Do active communities support activity, or support active people?
Residential self-selection in the estimation of built environment influences on physical activity

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Abstract

Janne E. Boone: Do active communities support activity, or support active people? Residential self-selection in the estimation of built environment influences on physical activity (Under the direction of Penny Gordon-Larsen, PhD)

In a growing body of research, the built environment, composed of "neighborhoods, roads, and buildings in which people live, work, and play," has been shown to be related to physical activity. While promising for physical activity promotion, substantial limitations must be addressed before built environment research can adequately inform policy recommendations. *To this end, we focused on three methodological challenges of particular concern for built environment research:* ***(1) quantitative characterization of a complex environment****,* ***(2) confounding*** *by other inter-related environment characteristics, and* ***(3) residential self-selection bias*** *resulting from systematic sociodemographic and behavioral differences among individuals selecting different types of neighborhoods.* We used data from the National Longitudinal Study of Adolescent Health, a nationally representative cohort of over 20,000 adolescents followed over seven years into young adulthood. A large scale geographic information system (GIS) linked community-level built (e.g., recreation facilities, land cover, street connectivity) and socioeconomic (e.g., median household income, crime rate) environment characteristics to individual-level sociodemographic and behavioral data in space and time.

Using factor analysis, we identified several built and socioeconomic environment constructs. We found that the socioeconomic environment is a potentially important confounder of built environment and physical activity relationships, but is often omitted in existing studies. We also show that commonly used built environment measures may act as proxies for complex environment constructs; for example, intersection density, typically used to indicate street connectivity, may represent general density of development. Lastly, in longitudinal analysis, we observed an increase in physical activity among males with a greater number of physical activity-related pay facilities and a decrease in physical activity among males and females with higher neighborhood crime rate. Other built environment characteristics were unrelated to physical activity. Additional analysis suggests that residential self-selection can attenuate, as opposed to magnify, environment-physical activity associations.

This research revealed complexities in the environment that have implications for analysis and interpretation of this and related research. Findings suggest that built environment characteristics may influence physical activity, yet raises additional questions to be answered by an evolving field.

To my parents, June and Jerry Boone

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List of Abbreviations

Add Health	National Longitudinal Study of Adolescent Health
CFA	Confirmatory Factor Analysis
CI	Confidence Interval
EFA	Exploratory Factor Analysis
ESRI	Environmental Systems Research Institute
FIML	Full Information Maximum Likelihood
GIS	Geographic Information Systems
GPS	Global Positioning System
ICC	Intraclass Correlation
MVPA	Moderate to Vigorous intensity Physical Activity
PA	Physical Activity
PCA	Principle Components Analysis
RMSE	Root Mean Square Error
SES	Socioeconomic Status
U.S.	United States
YMCA	Young Men's Christian Association
ZIP	Zone Improvement Plan postal codes

I. Introduction

A. Background

Evidence that built environment features such as parks and connected street networks can support active lifestyles holds tremendous promise for increasing physical activity levels and preventing obesity. Ultimately, built environment characteristics shown to influence physical activity can be used promote active lifestyles. However, substantial methodological limitations in existing research need to be addressed before this literature can adequately inform policy recommendations.

Potential residential self-selection bias, or bias resulting from already active individuals selecting activity-supporting neighborhoods, is considered a primary threat to causal inferences regarding the influence of the built environment on physical activity. Existing research is dominated by cross-sectional designs and little is known about the magnitude or direction of residential self-selection bias. Longitudinal designs can control for residential self-selection due to observed characteristics ***and*** unobserved characteristics that remain constant over time (e.g., inherent motivation to exercise) using fixed effects models or similar methods. The few existing longitudinal studies focus on changes in health and behavior following residential relocation, yet the environment can change around stationary individuals and exclusion of residentially stable households could lead to selectivity bias. However, cohorts with time-varying environment and individual behaviors have not previously been available.

Additionally, despite evidence that built environment characteristics related to physical activity may differ in children versus adults, built environment research in child and adolescent populations is limited. Most research is based in confined geographic areas, greatly limiting generalizability. Finally, built environment characteristics are inter-related and likely exert joint effects, but understanding of these complexities is limited due to the small range of built environment characteristics included in most studies. Furthermore, built environment patterning may shift across life stages but has not been studied in adolescents.

For the proposed research, we addressed these limitations by leveraging a unique Obesity and Environment database that comprises the first large scale geographic information system (GIS) to link community- and individual-level data in both space and time in a large ethnically diverse sample. The National Longitudinal Study of Adolescent Health (Add Health), a prospective cohort followed from adolescence to young adulthood, provides extensive individual-level health behavior and outcome data, as well as detailed time varying data on a wide range of community-level factors such as land use, recreation facilities, economic, climate, and crime data.

B. Research Aims

The overarching goal of this research was to estimate the influence of diverse built environment characteristics on physical activity during adolescence and young adulthood in a racially and ethnically diverse sample. We achieved this goal through the following aims:

1) **Describe the inter-relationships between built and socioeconomic environment characteristics in a nationally representative sample of adolescents.**
    a. Using exploratory factor analysis, identify multidimensional built and socioeconomic environment constructs from a large set of objective environment measures.
    b. Quantify the extent to which inter-related environment constructs confound cross-sectional, multivariate associations with physical activity.
    c. Create replicable measures for use in longitudinal analysis that account for inter-relationships and avoid collinearity.
2) **Estimate longitudinal effects of the built environment on physical activity and explore the role of potential biases.**

a. Use fixed effects models to estimate effects of several built and socioeconomic environment characteristics on physical activity while controlling for time invariant, unmeasured characteristics.
b. Assess the influence of residential self-selection bias due to time invariant, unmeasured characteristics on estimated environment-physical activity associations by comparing fixed effects and naïve estimates.
c. Assess the influence of selection bias related to conditioning on residential relocation by comparing fixed effects estimates in individuals who relocate residences versus those who remain in the same home.

II. Literature Review

The domestic (1-3) and global (4) increase in obesity prevalence and its associated morbidities and mortality (5-7) are well known. Individual-level obesity prevention strategies have achieved limited success (8), and recent attention has turned to broad environmental factors as targets for obesity prevention. In particular, associations between physical activity and community design characteristics have generated not only rapid growth in public health and transportation research (9-13), but also shifts in practice such as the creation of "new urbanist" neighborhoods and application of smart growth principles to community planning (14, 15).

However, research on environmental determinants of obesity and associated behaviors is in its infancy, warranting more detailed examination of these relationships in population subgroups and elucidation of methodological shortcomings in existing research. Without additional research that fill these methodological and conceptual gaps, policies and existing practices designed to encourage physical activity through changes to the built environment will remain without a solid scientific evidence base.

A. Determinants of Physical Activity

A rapidly growing body of research examines the role of a vast range of contextual factors in influencing how individuals move throughout the day (16, 17). The socio-ecologic framework in **Figure 1** depicts one major pathway linking behaviors to obesity, chronic disease, and related risk factors. While this example simplifies complex obesity and chronic disease etiologies, it is useful for theorizing and testing behavior determinants across levels of influence.

The socio-ecologic framework

The socio-ecologic framework describes five interactive levels of influence on health-related behaviors: intrapersonal, interpersonal, institutional/organizational, community, and public policy (18). Historically, health behavior interventions have focused on intrapersonal factors such as knowledge (19) and motivation (20), or interpersonal factors such as influence of a spouse's behavior (21), or organizational factors, such as workplace supports like onsite fitness equipment (22).

While neighborhoods can capture inter-personal influences (e.g., social support, social cues), the majority of neighborhood health research focuses on built and socioeconomic environments (23, 24). The importance of multiple levels of influence in public health (25) has been recognized in the past decade, starting with research showing increased coronary heart disease incidence associated with living in a disadvantaged neighborhood, independent of individual socioeconomic position (26). While each level can be influenced by any other level, public policy can potentially influence all levels and is arguably the ultimate goal of most neighborhood health research (27, 28).

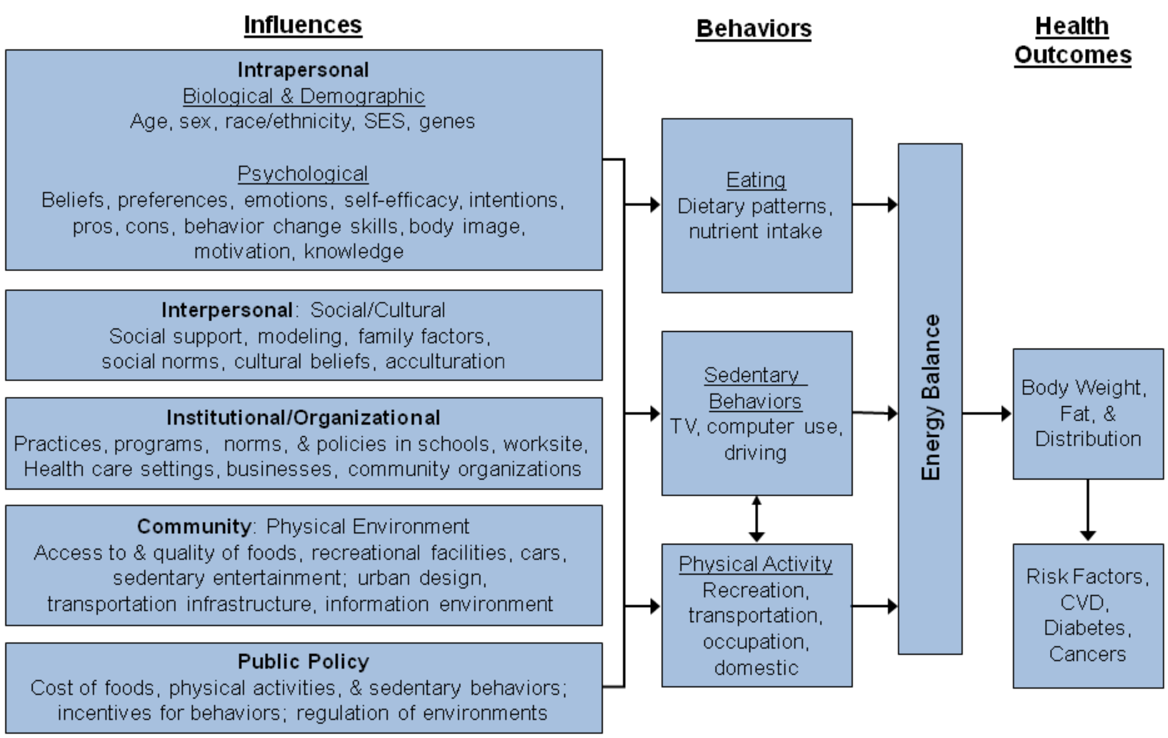

Figure 1 Relationships among diet, physical activity, and obesity within the socio-ecologic framework
Adapted from model developed at the National Heart, Lung, and Blood Institute Workshop: Predictors of Obesity, Weight Gain, Diet, and Physical Activity; August 2004, Bethesda MD

The built and socioeconomic environments

The built environment is a major component of community design comprised of aspects such as buildings, transportation systems, parks, and greenways. It is a particularly promising target for improving population health due to its apparent influence on physical activity and hence chronic disease prevention, as well as its existing linkages with local policies.

Researchers have found relatively consistent relationships between physical activity and urban sprawl (29), alternatively referred to as "walkability" (30), incorporating street connectivity measures, land use mix, housing density, and block lengths or retail floor area. Associations between physical activity and pedestrian and biking infrastructure such as sidewalks and bike lanes have been mixed (31, 32). Physical activity is related to access to recreational resources such as parks or physical activity facilities in youth (33) and adults (34, 35). Retail destinations such as shops and restaurants within walking distance are also correlated with walking behaviors (31, 36).

The socioeconomic environment, comprised of economic factors (e.g., poverty rate) and social factors (e.g., racial composition or crime and safety), are related to physical activity, obesity, and disease in existing research (37, 38).

Dynamic interactions within and between levels of influence

The socio-ecologic framework accommodates dynamic relationships among factors within and between levels of influence. Aspects of the built and socioeconomic environments are correlated (33) and appear to have independent relationships with physical activity (37). Built and socioeconomic environments may also interact: for example, high income neighborhoods may have greater local political influence to lobby for a community center or traffic calming measures, which could theoretically maintain or build social capital and improve socioeconomic indicators in the long run.

Additionally, the neighborhood environment may influence residents' perceptions of their neighborhood. An environment rich in activity opportunities may lower the perceived burden of engaging in physical activity (intrapersonal factor), act as a visual reminder to be active, or enforce activity as a cultural norm (interpersonal factors) (39). While we do not address perceived measures of the environment in our research, we assume any causal influence of the objective environment on physical activity occurs at least in part through perceptions of the environment (18), thus involving both intra- and interpersonal level factors. While agreement between perceived and objective measures of the environment is low (40, 41), the socio-ecologic framework remains useful as agreement may improve with better characterization of neighborhood boundaries and amenities.

Further, the dynamic relationships among socio-ecologic framework levels imply that intra- and interpersonal factors influence community-level exposures, either through changes in the environment around stationary residents, residential relocation, or some combination of the two. By way of simple example, the first mechanism (changes in the environment) would occur if the city opened a new basketball court in response to demand by community members. The second mechanism (residential relocation) would occur if those motivated to exercise choose to move into neighborhoods with parks or close access to fitness facilities. The latter example describes a major criticism of neighborhood health research and one focus of our study: residential self-selection (42). In other words, our concern about self-selectivity raises the question of whether addition of recreation options will enhance activity patterns in any selected neighborhood.

B. Research Gaps

Discussions of challenges and limitations to neighborhood health research have been previously published (42, 43). Of particular relevance to this project, heterogeneity of relationships by life stage and gender has been largely ignored, and many studies are conducted in small geographic areas with limited geographic variability and environment measures. Further, the literature is largely cross-sectional, which is particularly vulnerable to bias due to residential self-selection. We discuss each of these issues in the following sections.

Study populations used in existing research

Adolescence and young adulthood

Physical inactivity is an exceptionally consistent risk factor for obesity in both children (44, 45) and adults (46, 47). Additionally, as physical activity declines dramatically throughout adolescence (48-51) and young adulthood (52), obesity prevalence rises in parallel (53-56). The transition from adolescence to young adulthood is thus a critical period for weight gain as well as behavior change (53, 57-59), making this life stage a promising target for obesity prevention.

The majority of research on built environment effects on physical activity has focused on adults, and findings in child, adolescent (10, 33, 60), and elderly (61, 62) populations are largely similar with some key exceptions. Contrary to findings showing "sprawl" as a barrier to physical activity (63, 64), Nelson and colleagues reported higher physical activity in adolescents living in suburban neighborhoods (65). Likewise, de Vries and colleagues identified the number of parallel parking spaces as a positive correlate of physical activity in grade school children, theorizing that they may create an additional buffer between the sidewalk and street or reduce vehicle speed (66). Additionally, traffic safety appears to be a stronger predictor of active commuting (67, 68) and physical activity (69) in children than adults. These studies suggest that built environment characteristics supporting physical activity may be sensitive to the age of the target population. However, built environment research in children and adolescents is growing but still limited.

Sex differences

Differences in determinants of physical activity between males and females (70) may be even more pronounced in adolescence, when participation in organized physical activity is higher in males (71). Females may also be more influenced by safety concerns (72) and sociodemographic characteristics (70). Indeed, Eid and collegues found differences in urban sprawl-obesity associations by sex (73), and we found stronger built environment-physical associations in males in the Add

Health population in previous studies (74). However, few studies have examined sex-specific associations or sex interactions between the built environment and physical activity.

Geographic scope

Further, most existing research has been conducted in samples derived from confined geographic areas with limited racial and ethnic diversity (e.g., (14, 31, 61, 75)), making generalization of findings difficult. Study of built environment-health relationships in large, sociodemographically diverse samples residing in diverse environmental contexts, particularly in critical age groups, is an essential prerequisite to creating policies and environments that support physical activity.

Inter-relationships between built environment characteristics

Neighborhood environments are extremely complex, composed of a multitude of inter-related characteristics. Correlations between environmental characteristics pose two problems for assessing relationships with behavior. From a statistical perspective, traditional multivariate methods incorporating inter-related independent variables are susceptible to multicollinearity and violation of model assumptions. From a conceptual perspective, single characteristics likely operate not in isolation but as combinations of design features. Examination of patterning among environment variables is valuable not only for understanding how, and to what extent, environment characteristics are inter-related, but also for developing environment measures which account for inter-relationships and avoid multicollinearity.

Several methods can be used to examine inter-relationships among variables, including descriptive approaches, cluster analysis (or its maximum likelihood counterpart, latent class analysis), creation of summary variables that optimize relationships with an outcome of interest, and exploratory or confirmatory factor analysis. Descriptive analyses such as bivariate correlations or tabulations are a valuable first step for any of these analysis strategies, but are limited because they do not account for inter-relationships between three or more variables, and the resulting patterns can become prohibitively cumbersome with large sets of variables. In contrast, cluster analysis identifies mutually exclusive groups with similar patterning among numerous variables. For example, Nelson et al identified several clusters of adolescents characterized by various patterns of built and socioeconomic environment measures such as newer suburban and low socioeconomic status inner-city areas (65). However, the resulting patterns are categorical and data-driven, and thus not easily applied to longitudinal analysis or replication in external populations.

Additional approaches include index measures and reduced rank regression, which create summary variable(s) that explain the maximum amount of variance in the outcome variable(s). Indeed, to account for correlations between measures of urban form, Frank et al (30) developed a walkability index incorporating net residential density, street connectivity, and land-use mix; these components were weighted in a manner that maximized the explained variance in accelerometer-measured moderate physical activity duration per day. This walkability index has been examined in other samples (76), a necessary step because they were created by optimizing relationships with the outcome of interest. However, this walkability index does not incorporate recreational resources such as parks or fitness centers, which are also important elements of the built environment.

In contrast, factor analysis and principle components analysis (PCA) creates composite variables which best explain correlations between, and variation of, a set of variables, independent of the outcomes of interest. For example, Ewing et al and several other investigators (30, 41, 63) used PCA to create urban sprawl or similar summary measures. While PCA and exploratory factor analysis (EFA) are vulnerable to idiosyncratic patterns within a particular study population, they are valuable exploratory tools which, as opposed to confirmatory factor analysis, can accommodate a wider range of variable distributions and do not require extensive prior knowledge of the structure and relevant indicators of environment constructs. However, existing urban sprawl measures also do not incorporate physical activity facilities and were developed based on knowledge about patterning in adult populations and either on a small scale in small geographic areas or a large scale (e.g., counties) in larger geographic areas.

More generally, with these and few other exceptions (32, 61, 65), existing studies consider a single dimension of the built environment in relation to physical activity rather than the combined effect of multiple dimensions. Given the wide range of built and socioeconomic characteristics that are associated with physical activity, even characteristics weakly correlated enough to avoid multicollinearity may confound associations with physical activity. Therefore, concerns about multicollinearity and confounding must be balanced when estimating independent (or joint) effects of environment characteristics on physical activity.

In sum, greater understanding of how a broad range of built and socioeconomic environment characteristics are inter-related in demographically and geographically diverse adolescent populations is needed. Such knowledge will inform strategies to better account for correlations and potential confounding among environmental variables when estimating their independent associations with physical activity.

Residential self-selection: a major research gap

Potential bias due to residential self-selection has been identified as the primary limitation in built environment research (77) and is of particular concern in cross-sectional studies which predominate the existing literature. We refer readers to two excellent reviews on residential self-selection in the context of travel behavior: Bhat and Guo discuss several adjustment methods of control for residential self-selection and present their own simultaneous modeling strategy (78), and Mokhtarian and Cao review methodologies used to address "attitude-induced" residential self-selection, which is driven by travel or residential preferences (79). The following discussion builds on these reviews by incorporating perspectives from health research using epidemiologic and econometric methods.

Residential self-selection bias stems from concern that selection of a neighborhood may be related to both the neighborhood exposure and the health outcome of interest. A frequently overlooked point is that bias can result if factors driving residential selection are either directly or indirectly related to the exposure and outcome. In the context of built environment effects on physical activity, bias resulting from a direct relationship will result if already physically active individuals select neighborhoods based on their activity-supporting amenities. As an example of indirect relationships which may lead to bias, low income families may choose a neighborhood based solely on the affordability of housing; if these neighborhoods also contain inadequate physical activity resources and the families are less physically active (33), the built environment–physical activity relationship can be overestimated. Put simply, positive relationships between the built environment and physical activity can be attributed to (1) the effect of the environment on physical activity, (2) the effect of predisposition for physical activity, *or characteristics related to physical activity*, on residential choice, or (3) both.

Formally, consider the following model of physical activity (PA) as a function of vectors of environmental exposures of interest (E), sociodemographic characteristics (S), measured residential preferences (P), and unmeasured or unmeasureable characteristics that are related to PA (U). ε is an error term assumed to be random.

(1) $PA = \beta_0 + \beta_1 E + \beta_2 S + \beta_3 P + \beta_4 U + \varepsilon$

Typical analysis of associations between the built environment and physical activity include PA, E, and S using traditional multivariate adjustment of common sociodemographic measures. Some studies include P, which capture measured residential preferences that may influence residential choice. However, U is unmeasured and is thus omitted from the model, and variability in PA explained by U must be relegated to the error term in the model to form a composite error $\varepsilon^* = \beta_4 U + \varepsilon$. This is permissible if U is unrelated to E, S, and P. However, if ε^* is correlated with the independent variables, standard estimation methods will lead to biased estimates of the built environment variable coefficients (β_1) while also potentially distorting the estimates of the remaining coefficients in the equation (β_2, and β_3). Understanding these complex inter-relationships is essential for obtaining precise, robust, and unbiased estimates of neighborhood effects (80).

Components of U related to selection of a neighborhood may include unmeasured preferences for neighborhood characteristics related to physical activity amenities or other features such as schools, proximity to work or family, or other factors. These components may lead to residential self-selection bias, described as unmeasured confounders by epidemiologists and unobserved heterogeneity by economists (81).

Direct evidence of residential self-selection

Largely, the literature on environmental determinants of physical activity and obesity treats residential decisions as exogenous factors. However, the strong roles of race and income in residential selection are well documented in migration and residential mobility research (82, 83) as well as housing selection studies (84, 85). Coupled with the vast literature demonstrating socioeconomic and racial disparities in physical activity (86), existing knowledge supports the indirect residential self-selection bias mechanism. Further, recreation and other physical activity-related facilities are inequitably distributed across neighborhoods by race-ethnic and SES composition (33).

There is also evidence for the direct residential self-selection bias mechanism. For example, a recent market survey supports increasing yet varied preferences for denser, more centrally located neighborhoods (87). Consumers who prefer such neighborhoods might tend to have higher physical activity levels. Indeed, participants citing access to transit as an important reason for living in a "transit-oriented development" were almost 20 times more likely to use rail transit than those who did not cite this reason (88). Likewise, physical activity and belief that an activity-friendly community will support active transit have been shown to be significant predictors of desiring to live in an activity-friendly community (89). The microeconomic behavioral literature suggests that there may be peer neighborhood effects leading to self-selection or preference for neighborhoods resulting in race/ethnic stratification across neighborhoods, even in the situation of equivalent expenditures (and potentially amenities) across these neighborhoods (90).

While these studies provide evidence of residential selection bias, they rely on self-reported preference, belief, and behavior data which have important limitations. First, residential choices are determined by a virtually infinite set of variables such as affordability, convenience, and proximity to social support networks that may not be articulated by respondents, so reporting preference for activity-supportive communities has limited meaning (85, 91). Second, preferences are endogenous; unobserved factors such as financial constraints (i.e. affordability) may influence both self-reported preferences and selection of neighborhoods with amenities of interest. Failure to control for the endogeneity of preferences can result in biased estimates for the preference variables.

Strategies to control for residential self-selection bias

Associations between built environment factors and behavioral outcomes have been the topic of investigations across several fields including urban planning, transportation, economics, and epidemiology, each with their own methodological norms, culminating in recent and increased interdisciplinary research (9, 11, 92). To adjust for residential self-selection bias, these researchers have taken various approaches, including adjustment for self-reported residential preferences, adjustment for observed predictors of residential selection, longitudinal designs, and structural equations modeling.

While randomized controlled trials that experimentally assign families or amenities to neighborhoods (93) may help to address residential self-selection bias, experimental assignment of neighborhoods (or neighborhood characteristics) is not often financially or politically feasible. Therefore, we focus on advancements in statistical adjustment methods, availability of richer, longitudinal environmental datasets, and innovative study designs that have, and can continue to, vastly improve the validity of observational studies.

Control for attitudes and preferences. Attitude and residential preference data have been used in some of the first studies to attempt to control for residential self-selection in cross-sectional analyses. As described in greater detail by Mokhtarian and Cao (79), preference data have been used as control variables in multivariate models (94, 95) or to create variables reflecting the dissonance between residential preferences and objective neighborhood characteristics (96-98).

While these methods are innovative, they require the assumption that preference measures capture true preferences and are not influenced by current environment or transportation behaviors. As we have described, such assumptions may not hold. In studies of built environment determinants of physical activity, preferences and attitudes pose problems beyond those described for studying residential choice. Many economists view an individual's attitudes and preferences as being determined by many of the same factors that determine physical activity and residential selection. Additionally, reporting errors associated with self-reported preferences and behaviors are probably strongly correlated: those who value public transit might be more likely to over-state both their preference for and use of public transit. That is, unobserved factors (U and V) affect both preferences and self-reported physical activity-related behaviors.

For these reasons, self-reported residential preferences are likely endogenous and thus inadequate as control variables in the prediction of self-reported physical activity. There is a large literature on the topic of determinants of preference structure which is outside the purview of this discussion. Ultimately, it is possible that controlling for residential preferences may not only fail to correct for residential self-selection bias but may introduce additional bias due to correlation of errors in reported preferences and behaviors. While self-reported preferences may provide insights about the potential role of preferences in residential choice, this approach is not a substitute for other methods which are less vulnerable to endogeneity and correlated measurement errors.

Control for observed predictors of residential selection. An alternative approach is to control for predictors of observed residential selection using methods such as propensity scores (99, 100). Propensity score methods attempt to control for non-random selection into a treatment (or exposure) group in experimental or observational studies, more recently in the built environment literature. For example, using cross-sectional data, Boer et al. showed that cross-sectional associations between walkability measures and walking were attenuated after propensity score adjustment, in some cases near or past the null (15).

Propensity score methods model "treatment," defined in this context as living in a neighborhood with activity-supportive characteristics, as a function of measured covariates. These strategies model the probability of living in a particular environment, given individual characteristics. Resulting probabilities (propensity scores) are subsequently used as adjustment or matching variables in models predicting physical activity from environment characteristics. Propensity score methods were developed for binary treatments but can be expanded to multiple-level treatments. However, these methods are not always easily implemented. Indeed, Boer et al were forced to conduct a series of analyses comparing adjacent levels of built environment measures, adjusting for propensity scores reflecting the probability of living in areas with higher versus lower measures within each pair of levels (15). Alternatively, predicted probabilities can be incorporated into weighting variables (inverse-to-probability-of-treatment weighting), which offer the advantage of accommodating multi-level or continuously scaled "treatments" (101).

There are several advantages of propensity score methods over traditional covariate adjustment. The balance of covariates can be explicitly verified, and larger sets of covariates can be included in analysis. In the case of matching and weighting methods, selection bias induced by conditioning on common effects of the outcome and exposure (e.g. residential movement) can be avoided (102). However, propensity score methods only control for observed characteristics and assume adequate measurement of included variables. Therefore, they can control for residential selection bias only to the extent that covariates included in the treatment models capture determinants of selection into activity-supportive neighborhoods (103, 104). Unobserved characteristics correlated with the environment and physical activity will bias the obtained estimates. Thus, propensity score methods may not fully address residential self-selection.

Longitudinal designs. The most ideal *observational* designs are longitudinal, and assess changes in physical activity in relation to changes in the built environment. For example, Krizek took advantage of an annual panel survey that followed households who moved within a metropolitan area (105). Krizek used first difference models to estimate change in travel behavior as a function of change in the built environment resulting from residential relocation, finding that an increase in neighborhood accessibility was associated with a decrease in vehicle miles traveled. This study design controls for endogenous characteristics such as motivation for physical activity that *remain constant over time* by subtracting out time invariant components of U in the model above. To illustrate, consider an expansion of Model 1, which distinguishes variables that change (time variant) versus remain constant (time invariant) for individual i over time t:

$$(2)\ PA_{it} = \beta_0 + \beta_1 E_{it} + \beta_2 S_i + \beta_3 T_{it} + \beta_4 P_i + \beta_5 U_i + \beta_6 V_{it} + \varepsilon_i + \nu_{it}$$

S and T are vectors of observed time invariant and variant sociodemographic variables, respectively. U and V are vectors of unobserved time invariant and variant variables, respectively. U might include genetic determinants of propensity to exercise, while V might include factors such as desire to actively commute, which may change over time. Associated error terms are ε_i (random, person-specific error) and ν_{it} (random error for person i at time t). Recall that because U and V are unmeasured, and the variability in PA explained by U and V is captured in composite errors $\varepsilon_i^*=\beta_5 U_i + \varepsilon_i$ and $\nu_{it}^*=\beta_6 V_{it} + \nu_{it}$, respectively. Model 2 at time 1 subtracted from Model 2 at time 2 yields the following model, which is estimated by first difference models:

$$(3)\ (PA_{i2} - PA_{i1}) = \beta_1(E_{i2} - E_{i1}) + \beta_3(T_{i2} - T_{i1}) + (\nu_{i2}^* - \nu_{i1}^*)$$

Time invariant sociodemographics (S), measured preferences (P), and person-specific error (ε_i^*) subtract out of Model 3. In particular, ε_i^* captures unmeasured time invariant factors, which will no longer bias the estimates. ν_{it}^*, which may capture time unmeasured invariant factors, remains in the model, so first difference models (and fixed effects models) are vulnerable to endogenous characteristics that change over time. However, a recent study suggests that this remaining bias is not problematic: the relationship between sprawl and obesity was completely attenuated when estimated with first difference models (73), although we might expect stronger, more robust relationships between sprawl and a more proximate measure such as physical activity.

Additionally, the Krizek study is, to our knowledge, the only population-based longitudinal study examining the association between the built environment and physical activity. Others (29, 106, 107) have examined longitudinal associations between urban form and obesity or body mass index, although only Eid and colleagues (73) estimated true first difference models; other studies included time invariant characteristics or baseline measures in their models. However, while each of these studies use longitudinal individual-level sociodemographic and behavior data, the environment data was collected at one point in time. Therefore, these studies were restricted to individuals who moved between time periods in order to obtain variability in the environment variables, potentially leading to selection bias.

Summary. Each of the above described methods has made important contributions to understanding residential self-selection bias, and structural equations modeling strategies (instrumental variables, path analysis, and full information maximum likelihood methods; see Section VI.B) provide additional options. However, recent availability of our nationally representative, time-varying environment database can improve upon the few existing longitudinal studies. Replication of first difference (or fixed effects) estimates in a nationally representative sample containing residentially stable and mobile individuals is a logical next step toward understanding the role of residential self-selection bias.

C. Conclusion

The rapidly growing field of built environmental determinants of health behaviors and outcomes is at a crucial juncture. Without additional longitudinal analyses and an understanding of residential selection bias and methods to overcome such bias, environment-health research will be seriously limited. Our Obesity and Environment database, the first large scale GIS to link community- and individual-level data in both space and time in a large ethnically diverse sample, presents an unprecedented opportunity to develop a better understanding of built environment patterning in a critical life stage and the role residential selection bias in the relationship between built environment and physical activity.

III. Methods

A. Study Population and Data Sources

The National Longitudinal Study of Adolescent Health (Add Health) provides extensive behavioral and individual-level health outcomes collected at multiple time points that were linked and compared to environmental data derived from a geographic information system (GIS).

Add Health

Initially a school-based study, the core sample represents all adolescents attending U.S. public, private and parochial schools, grades 7-12, in the 1994-1995 school year, with special over-sampled groups (e.g., non-Hispanic blacks with a college-educated parent) [N=20,745]. From a primary sampling frame (all U.S. high schools), a stratified sample of 80 high schools and 52 junior high feeder schools was selected and surveyed in-school [N=90,000], with probability proportional to size. Adolescents were randomly selected from in-school survey respondents and school rosters for the Wave I in-home interview conducted in the 1994-1995 academic year (11-21 years). Wave II included all eligible adolescents who would have been in school for the 1995-1996 (excluding those who graduated in 1995). All located Wave I respondents (regardless of participation in Wave II) were eligible for Wave III (2001- 2002). A fourth wave is in progress and will provide future research potential.

GIS Database

Our Obesity and Environment database is a unique large scale GIS that links community-level data to individual respondent residential locations in both space and time. Community-level data include density and proximity to recreational facilities, land use pattern, population, economic, climate, and crime statistics, which were linked spatially and temporally to individual-level Add Health behavior and health outcomes data across the study periods.

Objective measures of the built environment

Objective measures of the built environment derived from GIS's have facilitated examination of built environment effects in large population studies. Such measures do not rely on resource-intensive neighborhood audits or other forms of direct observation, and avoid limitations of perceived measures of the environment (12, 108, 109). Many studies have demonstrated relationships between physical activity and GIS-derived measures such as connectivity, land use mix, population density (e.g., (30, 63, 64, 75, 76)) and access to resources (e.g.,(32, 36, 62)). Additionally, these measures are by definition easily quantifiable and thus particularly applicable to planning policies. While perception of environment is an important area of study and objective and perceived environments appear to be jointly associated with physical activity (40, 61, 110, 111) and thus comprise a promising emerging area of research, the study of GIS-derived measures remain important as they enable research in large, diverse samples, and provide quantitative measures that more easily translate into planning policies.

Scope and validity of the database

The Add Health GIS database is linked to individual respondent residential locations. Federal, private, and commercial sources of data were integrated into the GIS and linked spatially and temporally to respondent geocoded residential locations through complex human subject security procedures.

Residential mobility. 67% of Add Health respondents moved residences between Waves I and III, including 19% who moved to a different county and an additional 12% who moved to a different state. These data thus provided sufficient numbers of observations for longitudinal analysis of the health impacts of the built environment during adolescence and young adulthood.

Database validity. Environmental databases are vulnerable to errors due to incomplete records, of particular concern for parks, and out of date records. In the creation of respondent-specific environmental variables, geocoding error and inaccuracies in the street files are additional sources of error. For example, inaccurate placement of a facility or a residence along a street segment during the geocoding process may influence the calculated distance between the facility and a respondent, thus contributing to errors in the count of and distance to facilities. Of these environmental measures, only the physical activity facilities database has been validated for count, attribute, and positional accuracy. Additionally, out of date or otherwise inaccurate street files may contribute to unmatched addresses in the geocoding process, or may influence network distance due to new or closed streets. Validation of respondent specific facility counts, distance to facilities, or similar variables would require access to respondent-specific addresses, which is precluded by confidentiality agreements for Add Health. Ultimately, these potential errors are likely to be random, and are a tradeoff for data available for these two large populations.

Geocoding accuracy. At Wave I, residential locations for adolescents in the probability sample (n=18,924) were determined from the following sources, in order of priority: (1) geocoded home addresses with street-segment matches (n=15,480), (2) global positioning system (GPS) measurements (n=2,996), (3) ZIP/ZIP+4/ZIP+2 centroid match (n=205), (4) respondent's geocoded school location (n=243). At Wave III, residential locations for young adults in the probability sample (n=14,322) were determined from geocoded home addresses with street-segment matches (n=13,039), global positioning system (GPS) measurements (n=1,204), and ZIP/ZIP+4/ZIP+2 centroid matches (n=685). Individual-level and environmental measures differed for respondents located with GPS compared to other sources, reflecting rural locations in which Post Office Boxes or other addresses that cannot be geocoded. Otherwise, individual-level and environmental measures were similar across residential location source.

Spatial analytical methods

Point in polygon overlay analyses were used to identify census and metropolitan location areas to allow linkage of data at specified levels appropriate for each source dataset (e.g., census block, county). All spatial analyses were completed in ESRI ArcGIS (112) GIS and mapping software, and customized by the Carolina Population Center Spatial Analysis Unit with programming languages such as AML (113), Avenue (114), Python (115), Visual Basic (116), NetEngine (117), and C++ (118) to handle the data volume of this comprehensive and national GIS database. Quality assurance/control measures, such as manual, visual comparison of derived data against aerial photograph data were undertaken.

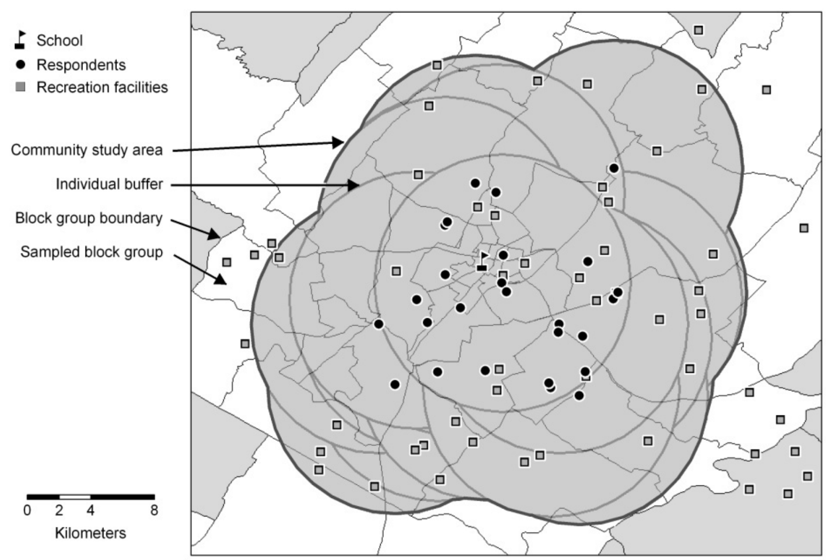

Figure 2. Example of one set of 8 km respondent buffers from the larger 42,857 census block groups (19% of U.S. block groups) of Add Health Wave I

Buffer-based neighborhoods

A series of respondent-specific environmental measures were created using a series of buffers surrounding the location of residence. A circle of 8-km radius was drawn around each respondent (**Figure 2**), based on empirical evidence that this distance would likely capture relevant physical activity and diet-related facilities (39, 119). Specifically, 25% of all trips are less than 1.61 km (75%

of these are by car), 62% of "social/recreational" trips are within 8.05 km (120) and 72% of walking trips are under 1 km (almost all are under 8.05 km) (119). Built environment characteristics and features within this 8-km buffer were then integrated into the GIS.

Advantage of buffer versus administrative neighborhood definitions. Despite substantial discussion regarding how to validly define a neighborhood using GIS-based data (43, 121, 122), administrative boundaries (e.g., counties, metropolitan statistical areas, ZIP codes, or census tracts or block groups) are, to date, the most commonly used definitions. While these administrative boundaries are readily and inexpensively available, they are somewhat arbitrary. Additionally, census geographies are designed to contain consistent population sizes, so their geographic size decreases as population density increases, resulting in dramatic variability in neighborhood size across regions. Finally, administrative boundaries disregard the respondents' location within the neighborhood. For example, for respondents who reside close to a block group boundary, resources in the adjacent block group may be closer than those in their own block group. These issues likely contribute substantial misclassification and ultimately attenuation of observed built environment-behavior relationships.

In contrast, neighborhood buffers define the neighborhood as the area within a given distance of the location of residence. Euclidean (circular) buffers are areas within a given straight-line distance from each respondent's residence (34, 123). Network buffers define the neighborhood as the area within a given distance along the street networks (30, 62), potentially providing a truer measure of proximity. Both types of buffers provide comparable neighborhood sizes and explicitly place the location of residence in the center of the neighborhood, thus avoiding misclassification related to administratively defined neighborhoods. In sum, buffer defined neighborhoods may help to reduce misclassification and enable more accurate and precise estimation of the effects of the built environment of health behaviors and outcomes.

Buffers and census units used in this project. Within the 8k buffer, 1, 3, 5, and 8k Euclidean and network buffer analyses were possible. Theoretically, the most appropriate buffer may differ among various built environment characteristics and resources. For example, pedestrian access is widely accepted as one-quarter mile network distance (124) and physical activity facilities are most likely to be used within a 5 km range (39). It is also likely that the relevant buffer size is smaller for children and adolescents than adults.

Therefore, as a precursor to this proposed study, we conducted cross-sectional analyses using 1, 3, 5, and 8 kilometer Euclidean buffers in Add Health Wave I (74). Total area was not available for network buffers, so all analyses used Euclidean buffers for built environment measures. We examined the distribution of each variable derived within each buffer definition and its association with physical activity, stratified by urbanicity, finding that intersection density within 1k buffers and count of physical activity facilities (not including parks) within 3k buffers were most strongly and consistently related to physical activity. Weighted facilities counts yielded associations intermediate to associations with buffer-specific, unweighted counts, so they did not appear to provide additional advantage. Additionally, population density within a 1k buffer was a stronger confounder than within 3k. Because we theorized that street connectivity, population density, and landscape patterning influence physical activity through similar mechanisms, we also used a 1k buffer for landscape patterning variables. Similarly, we treated parks as a type of physical activity facility and thus used counts of parks within a 3k buffer. To summarize, we used 3k buffers for physical activity resources and parks and 1k buffers for street connectivity, population density, and landscape patterning.

Census variables were calculated at the county, census tract, and block group levels. In other preliminary analysis (unpublished), census-tract level poverty, education, and racial composition were most strongly and consistently related to physical activity. Therefore, we used census tract-level measures for all census-based sociodemographic variables.

B. Analytical Variables

Environment measures

As described in the previous section, we analyzed environment variables calculated within buffers or census geographies selected based on preliminary analysis. Detailed descriptions and data sources of the following environment variables are presented in Section IV, **Table 1**.

Physical activity facilities/resources were obtained from a commercially purchased time-varying national dataset containing street addresses and 8-digit Standard Industrial Classification codes (SIC). The database was validated against a field-based census of recreational facilities and resources, and demonstrated high overall agreement between commercial and field data in an urban and non-urban setting. Moreover, the patterns of error observed in the commercial data suggested that estimates of environment-health outcomes would not be substantially altered (125). Youth organizations are comprised primarily of YMCA's; due to the virtual duplication in these variables, YMCA's were excluded from analysis. All analyses used unweighted counts of facilities within 3k buffers.

Local parks and recreation areas <200 acres were hypothesized to more strongly influence routine activities than regional or national parks. Counts of local parks within 3k of each respondent residence were extracted from the parks component of ESRI StreetMap Pro. This data source has not been validated, and there is evidence that electronic sources of parks do not capture all parks; however, these data provide comparable parks information in our nationally representative population.

Several ***street connectivity*** measures were calculated from the ESRI StreetMap 2000 dataset within 1k buffers. ***Population counts*** were calculated by averaging census block-group population counts, weighted according to the proportion of block-group area captured within 1k and 3k buffers; ***population density*** was calculated by dividing by the corresponding buffer area (square kilometers).

Land cover data were derived from the software package Fragstats (126) based on the national land cover dataset. Total area, mean patch size, patch count, and patch density were available for each of six land pattern classes: (1) water or perennial ice, (2) low & medium density developed, (3) high density developed, (4) recreational developed, (5) undeveloped/natural, and (6) agricultural. Fractal dimension indices and patch density of recreational and undeveloped land cover were also included in analysis.

Measures of the socioeconomic environment included the following: ***neighborhood sociodemographics*** included median household income (1990 measures inflated to 2000 dollars); proportion of households below poverty and owning (versus renting) their homes; proportion of persons with at least a college education, of minority race/ethnicity was determined from the 1990 and 2000 U.S. Census. Non-violent and violent ***crimes*** per 100,000 population was assessed from Uniform Crime Reporting data, which reports county-level measures.

Physical activity (outcome)

Physical activity was the outcome of interest for this study because we hypothesize that it is the outcome most directly related to the built environment. Add Health interviews employed a standard activity recall that elicited weekly frequency (bouts) of the following activities. (1) *working around the house*, such as cleaning, cooking, laundry, yardwork, or caring for a pet; (2) *hobbies*, such as collecting baseball cards, playing a musical instrument, reading, or doing arts and crafts; (3) *sedentary activities*, such as watching television or videos, or play video games; (4) *roller-blading, roller skating, skate-boarding, or bicycling*; (5) *playing an active sport*, such as baseball, softball, basketball, soccer, swimming, or football; (6) *exercise*, such as jogging, walking, karate, jumping rope, gymnastics or dancing; (7) *hang out* with friends. Skating & cycling, exercise, and active sports correspond with moderate-vigorous physical activity (MVPA); total number weekly bouts of these leisure activities was analyzed as MVPA bouts. This activity recall was modeled after self-report questionnaires that were validated in other large-scale epidemiologic studies with regard to physical activity (127, 128).

Individual-level covariates

Multivariate analyses analyzing physical activity as an outcome adjusted for the following individual-level characteristics: ***Race/ethnicity*** was self-reported at baseline (Wave I): respondents were classified as white, black, Asian, Native American, or Hispanic based on adolescent self-report and parental report. ***Age*** was calculated based on self-reported date of birth and interviewer-recorded interview date. ***Sex*** was self-reported at each study period and was used as a stratification variable or examined as a potential effect modifier due to known sex differences in determinants of physical activity. ***Socioeconomic position*** in young adulthood can be characterized by a complex array of behaviors and achievements (129, 130) which are likely predictors of residential relocation, so we used parent-reported household income and highest education attained to indicate socioeconomic position in both waves.

C. Sample weights and survey clustering

While multi-level (hierarchical) modeling has been encouraged for examining neighborhood effects on health (131), these methods are most appropriately applied to administrative or other boundary-defined neighborhoods. This project used buffer-defined built environment measures, which are individual-level exposures.

While census tracts and counties could be considered additional levels for neighborhood-level sociodemographic variables, they are not nested within schools, the primary sampling unit and therefore a more important source of clustering. That is, in Add Health, students were sampled from a stratified sample of schools, rather than from a sampling frame of neighborhood units such as census units. Indeed, MVPA intraclass correlations within census tracts and counties were minimal in Wave I (0.04 within census tracts, 0.03 within counties) and even smaller in Wave III, after many respondents moved away from the school from which they were sampled (0.03 within census tracts, 0.02 within counties). Furthermore, sparse, unbalanced observations within census tracts is another concern for multilevel models (132), with an average of 8.1 individuals (median=2, range=1 to 287 per census tract) at Wave I and an average of 2.4 individuals (median=1, range=1 to 108 per census tract) at Wave III. We therefore used single-level regression models which corrected for complex survey sampling. All descriptive analyses and, where possible, regression analyses were weighted for national representation.

IV. Built and socioeconomic environments: patterning and associations with physical activity in U.S. adolescents

A. Abstract

Inter-relationships among built and socioeconomic environmental characteristics may result in confounding of associations between environment exposure measures and health behaviors or outcomes, but traditional multivariate adjustment can be inappropriate due to collinearity.

We used principle factor analysis to describe inter-relationships between a large set of geographic information system-derived built and socioeconomic environment measures for adolescents in the National Longitudinal Study of Adolescent Health (Add Health; Wave I, 1995-96, n=17,441). Using resulting factors in sex-stratified multivariate negative binomial regression models, we tested for confounding of associations between various built and socioeconomic environment characteristics and moderate to vigorous physical activity (MVPA). Finally, we used knowledge gained from factor analysis to construct replicable environmental measures that account for inter-relationships and avoid collinearity.

We identified three built environment constructs (homogenous landscape and development intensity with large counts of either pay or public facilities) and two socioeconomic environment constructs (advantageous economic environment, disadvantageous social environment). In regression analysis, confounding of built environment-MVPA associations by socioeconomic environment factors was stronger than among built environment factors. In fully adjusted models, MVPA was negatively associated with homogenous land cover in males [exp(coeff) (95% CI): 0.91 (0.86, 0.96)] and intensity (pay facilities) in females [exp(coeff) (95% CI): 0.91 (0.85, 0.98)]. Single proxy measures (Simpson's diversity index, count of pay facilities, count of public facilities, median

household income, and crime rate) representing each environmental construct replicated associations with MVPA.

In conclusion, environmental characteristics are inter-related, and both the built and SES environments should be incorporated into analysis in order to minimize confounding. Single environmental measures may be useful proxies for environmental constructs in longitudinal analysis and replication in external populations, but more research is needed to better understand mechanisms of action, and ultimately identify policy-relevant environment characteristics with causal influence on physical activity.

B. Introduction

Numerous aspects of the built environment such as physical activity facilities (e.g., parks, recreation centers) (34, 133), "walkability" (76, 134), and neighborhood socioeconomic status (SES) (38, 135, 136) are related to physical activity and other key health behaviors and outcomes (37, 137, 138). However, built and SES environments are theoretically and empirically correlated; for example, physical activity facilities are more common in wealthier neighborhoods (33) and streets may be more connected in the poor inner-city (139). Therefore, neighborhood health studies that examine single or narrow sets of environmental characteristics are vulnerable to confounding by other environmental variables.

While strong correlations between environmental measures raise concerns about potential confounding, they also preclude extensive covariate adjustment due to collinearity. Pattern analysis techniques, such as factor analysis, are a common strategy for overcoming collinearity and accounting for the potentially interactive effects of environmental characteristics (105, 139-142). However, because the resulting factors are data-driven and population specific, analyzing the resulting factors longitudinally or in external populations is not straightforward. Finally, while replicable "walkability" and "urban sprawl" index measures are available (30, 63) they do not incorporate other potentially important environmental determinants of physical activity such as availability of physical activity facilities (33, 34). Further, most work has been in constrained geographic areas (30) or large geographic units such as counties (63).

Using nationally representative data on U.S. adolescents, a group at risk for dramatic declines in physical activity (50, 51), we sought to (1) describe inter-relationships between a large set of built and SES environment measures in a nationally representative sample of adolescents, (2) quantify the extent to which inter-related environment measures confound associations with moderate to vigorous physical activity (MVPA), and (3) demonstrate a strategy for using pattern analysis results to construct replicable environmental measures that accounts for inter-relationships and avoids collinearity. While this study is largely exploratory, we hypothesized that (1) inter-relationships between and among built and SES environment measures would be substantial, (2) both built and SES environment measures would confound built environment associations with MVPA, and (3) indicator measures with the largest loadings in exploratory factor analysis (EFA) would adequately represent each environment factor.

C. Methods

Study population and data sources

We used cross-sectional Wave I data from The National Longitudinal Study of Adolescent Health (Add Health), a cohort study of 20,745 adolescents representative of the U.S. school-based population in grades 7 to 12 (11-22 years of age) in 1994-95. Add Health included a core sample plus subsamples of selected minority and other groupings collected under protocols approved by the Institutional Review Board at the University of North Carolina at Chapel Hill. The survey design and sampling frame are described elsewhere (143).

Neighborhood-level variables were created using a geographic information system (GIS) that links community-level data to Add Health respondent residential locations in space and time. Residential locations for adolescents in the probability sample (n=18,924) were determined from the following sources, in order of priority: (1) geocoded home addresses with street-segment matches (n=15,480), (2) global positioning system (GPS) measurements (n=2,996), (3) ZIP/ZIP+4/ZIP+2 centroid match (n=205), (4) respondent's geocoded school location (n=243). Individual-level and environmental measures differed for respondents located with GPS compared to other sources, reflecting rural locations in which Post Office Boxes or other addresses that cannot be geocoded. Otherwise, individual-level and environmental measures were similar across residential location source. Residential locations were linked to attributes of the circular area within 1, 3, 5, and 8.05 kilometers (k) of each respondent residence (Euclidean neighborhood buffer) and block group, tract, and county attributes from U.S. Census and other federal sources, which were merged with individual-level Add Health interview responses.

To facilitate national representation of adolescent neighborhood environments, missing environmental data (n=463, 2.4%) was the only exclusion criterion for environmental patterning analyses, resulting in 18,461 adolescents. In estimation of associations with MVPA, exclusions included self-reported pregnancy (n=401) or mobility disability (n=122) and Native Americans due to small sample size (n=156); of the remaining sample (18,248), those with missing analytic variables (n=366 missing individual-level variables, 433 missing environmental variables, 8 missing both) were also excluded for an analytical sample of 17,441 adolescents.

Study variables

GIS-derived environmental characteristics

We examined built and SES environment measures with conceptual relevance or evidence of physical activity relationships in existing literature; see **Table 1** for variable definitions and data sources and additional details below. While our environmental variables were created within various neighborhood buffers or Census geographies, we used neighborhoods (e.g., 1 or 3k buffer, or Census tracts) consistent with the strongest associations with MVPA in previous analysis (74).

PA facility counts were obtained from a commercial dataset of U.S. businesses validated against a field-based census of PA facilities in an urban and non-urban setting; results demonstrated high overall agreement between commercial and field data (125). Facilities were classified according to 8-digit Standard Industrial Classification (SIC) codes into overlapping types (**Table 1**). Several measures of ***landscape diversity and complexity*** (144) were created by analyzing national land cover data using the software package Fragstats (126). We examined several measures of ***street connectivity*** calculated based on classical graph theory (145). High ***street connectivity*** provides numerous route options and is characterized by dense, parallel routes, many intersections, and few cul de sacs and dead end streets (11). Census population counts within 1k buffers were calculated as averages weighted according to the proportion of the block-group area captured within 1k, then divided by the buffer area to obtain ***population density***.

SES environment measures included economic (median household income and proportion of persons below poverty, college degree or greater) and social (proportion minority race/ethnicity, and owning their homes; crime rate) environment characteristics.

Individual-level self-reported behaviors and sociodemographics

Weekly frequency (bouts) of MVPA (skating & cycling, exercise, and active sports) was ascertained using a standard, interview administered activity recall based on questionnaires validated in other epidemiologic studies (146).

Individual-level sociodemographic control variables included age at Wave I interview, self-identified race (white, black, Asian, Hispanic), parent-reported annual household income and highest level of education (<high school, high school or GED, some college, ≥college degree), and administratively determined U.S. region (West, Midwest, South, and Northeast). Distributions of these variables in the analytical sample are reported in **Table 2**.

Statistical analysis

Exploratory Factor Analysis (EFA)

EFA was used to describe the inter-relationships among a large set of built and SES environment characteristics (**Table 1**). Our final results used the principle factors estimator because it did not impose distributional constraints, and oblique rotation (oblimin, gamma=0) because environmental constructs are theoretically and empirically correlated. The maximum likelihood estimator (applied to variables with acceptable distributions; also corrected for sampling design and weights) and alternative oblique rotation methods yielded similar results. The number of factors was guided by the Kaiser Criterion (Eigenvalue>1), scree plots, and interpretability. Variables with weak loadings (<0.4) on all factors and variables of interest with substantial cross-loadings (>0.3) were removed from the EFA model. If two or fewer variables loaded strongly on a single factor, corresponding variables were removed from analysis. To address negative Eigenvalues, percent variance explained by each factor was calculated using the trace of the correlation matrix as the divisor (147).

EFA of SES environment variables was conducted separately using the same procedure. This approach facilitated comparison between more readily modifiable built environment characteristics and less modifiable SES environment measures.

Regression analysis

We fit two sets of regression models to estimate the relationships (1) among the resulting built and SES environment factors and (2) between the built and SES environment factors and MVPA. Because street connectivity measures did not load onto factors but are built environment features of interest, we selected one index (alpha) that was not highly correlated with the built environment factors to examine as a single variable in our models. Buffer-based measures are individual-level variables, and while census tracts and counties could comprise a second level in multi-level analysis, they are not nested within schools, the primary sampling unit and therefore a more important source of clustering. Intraclass correlations (ICC) for ln(MVPA) were minimal (0.03 for census tract, 0.02 for county, 0.05 for school; ICC's are not definable for Poisson distributed outcomes (148)). Furthermore, sparse, unbalanced observations within census tracts is another concern for multilevel models (132), with an average of 8 individuals (median=2, range=1 to 287 per census tract). We therefore used single-level regression models which corrected for complex survey sampling and were weighted for national representation. All statistical analyses were conducted in Stata version 10.1.

First, we used crude linear regression to model each built environment factor and alpha street connectivity index as a function of SES environment factor quartiles. Second, to investigate confounding of built environment-MVPA associations by other built and SES environment variables, we fit a series of negative binomial regression models estimating weekly MVPA bouts as a function of built environment factor quartiles, controlling for cumulative sets of variables in Models 1-4. Model 1 included built environment factors separately, Model 2 incorporated individual-level sociodemographic variables, Model 3 further incorporated all three built environment factors and alpha, and Model 4 further added a 1-dimensional SES environment factor. In Model 5, a 2-dimensional SES environment construct replaced the 1-dimensional factor. Models were sex-stratified due to sex differences in physical activity determinants shown in previous studies (74). Quartiles accounted for non-linearity and, in contrast with continuous variables with higher-order terms, facilitated comparability with parallel analysis using single measures to represent each factor. Results are reported as exponentiated coefficients, representing the proportion increase in MVPA bouts compared to the lowest quartile.

Confounding was quantified based on percent change in coefficient [100*(current model – previous model)/previous model] between each model and the preceding model for built environment characteristics; Models 4 and 5 were compared to Model 3. Because large percent changes reflect negligible absolute changes when coefficients are very small, confounding was defined as >±20%

change in coefficient, and percent change was omitted if coefficients remained within ±0.04, corresponding to the approximate magnitude of marginally statistically significant coefficients.

As suggested by Riitters and colleagues (149), we evaluated single environmental measures that could potentially serve as proxies for their respective constructs by replicating Models 1-5 above using single measures representing each factor. Selection of measures was guided by strength of factor loadings and conceptual considerations. Simpson's diversity index was selected to represent the homogenous landscape factor for interpretability; because it was negatively correlated with the homogenous landscape factor, quartiles were reverse-coded for comparability. For the intensity factors, the counts of each type of facility were unstable, so non-overlapping pay facility types (instruction, member, and public fee) were summed. For public facilities, public (rather than youth) facilities were selected because their relevance may carry longitudinally into adulthood. To separate the availability of resources from density, Model 6 uses alternative facilities variables calculated as the number of facilities per 1,000 population.

D. Results

Patterning of the built and socioeconomic environments

The geographic diversity of the Add Health population is demonstrated by several measures of variability for built and SES environment variables included in the final factor solutions and subsequent analysis (**Table 3)**. Built environment measures were inter-correlated, loading onto three factors explaining 70.8% of variation (**Table 4**). Landscape variables loaded onto a single *homogeneous landscape* factor (high scores indicate non-diverse landscape) and two development *intensity* factors representing the degree of high intersection and population density and counts of either pay or public physical activity facilities (high scores indicate high development intensity). Conceptually, we expected correlation between facilities counts and population and intersection density, so cross-loadings for population and intersection density were retained. Unweighted correlations with *homogeneous landscape* were -0.03 and -0.02 for *intensity (pay facilities)* and *intensity (public facilities)*, respectively; and 0.58 between *intensity (pay facilities)* and *intensity (public facilities)*. Other street connectivity indices did not load onto any factors and were therefore removed from factor analysis.

Two SES environment factors (**Table 5**; unweighted correlation -0.43; 59.5% of variation explained) were consistent with our theorized constructs. One represented *advantageous economic environment* (high scores indicate low poverty, high college and median household income), the other characteristics generally corresponding with less desirable health outcomes (*disadvantageous social environment*; high scores indicate high proportion of racial/ethnic minorities and renters and high crime). Because the second factor marginally met inclusion criteria (Eigenvalue=0.97), a 1-dimensional SES factor was also examined (43.3% of variation explained).

Relationship between built and SES environments

Using factor scores generated from factor analysis, we examined built environment constructs as a function of the 2-dimensional SES environment constructs. Street connectivity indices measured a built environment feature of interest but were not derived into the final factor solution, thus we examined one street connectivity index (alpha) as a single variable in this and subsequent analysis. Built environment factors or alpha street connectivity index varied across quartiles of SES factors (**Table 6**). Interestingly, the two SES environment factors were inversely related, but both were positively associated with the intensity factors. SES factors were inconsistently associated with less homogeneous landscape and the minority factor was positively associated with connectivity.

MVPA and built and SES environment factor scores: associations and confounding

Next, we examined MVPA as a function of built and SES environment factor scores. By sequentially adjusting for additional variables in Models 1 through 5, we tested for confounding by individual-level and environmental characteristics, quantified by the percent change in coefficients (**Tables 7 and 8**; negative percent changes indicate attenuation of the association). In crude models (Model 1), the highest built environment factor and alpha street connectivity index quartiles were associated with up to an 11% change in weekly MVPA bouts compared to the lowest quartile. Adjustment for individual-level covariates (Model 2) attenuated or magnified these relationships, particularly for intensity (pay facilities). The magnitude and direction of associations often varied by sex: MVPA was most strongly related to landscape homogeneity in males and to the intensity factors in females. Inclusion of all four built environment measures demonstrated confounding by other built environment features, but the absolute change in estimates were small (Model 2 vs. 3).

SES environment factors were also related to MVPA, with up to an 11% change in MVPA for the highest versus lowest SES factor quartile in fully adjusted models (Models 4 and 5). Comparison of Model 3 to Models 4 and 5 indicated confounding of MVPA associations with Intensity (public facilities) and alpha by SES environment measures. The 2-dimensional SES factor (Model 5) influenced these associations to a greater extent than the 1-dimensional SES factor (Model 4). However, absolute changes in estimates were small. The significant built environment-MVPA associations were otherwise relatively robust.

MVPA and built and SES environment <u>single measures</u>: setting the stage for longitudinal settings and external study populations

Because factors are data-driven and population specific, we used knowledge gained from factor analysis to identify measures replicable in future Add Health waves or external populations. Associations between MVPA and representative indicator measures (selected based on empirical and conceptual rationale as per Methods, and noted in **Tables 3 and 4**) in **Table 9** (Models 3 & 5) are generally consistent with corresponding factor score-MVPA associations, suggesting that the single measures adequately represent the underlying construct. In one exception, percent minority was not as strongly related to MVPA, and did not influence built environment-MVPA associations as much as the disadvantageous social environment factor (data not shown). Crime rate reproduced the relationships with MVPA and was therefore used to represent disadvantageous social environment (**Table 9)**.

The emergence of "intensity" factors suggests that facilities counts may reflect a general density of development and resources. Model 6 used alternative facilities variables scaled by population, generally attenuating facilities-MVPA associations.

E. Discussion

Neighborhood environments that may encourage or discourage physical activity are complex and multidimensional, but most existing research examines single or only a few aspects of the environment. Our study shows inter-relatedness of environmental characteristics in nationally representative adolescent population and reveals several patterns of built and SES environments reflecting constructs consistent with research in adult populations. Further, we show important correlations between these environments that appear to result in confounding to estimated associations with MVPA, demonstrating the complexity of potential environmental influences on physical activity.

Insights about the environment gained from pattern analysis

Factor analysis revealed patterning in built and SES environments not necessarily apparent from examining sets of single measures. Our findings suggest that factor analysis can be used to identify inter-relationships between environmental measures and corresponding sets of variables too tightly correlated to analyze simultaneously as individual measures, while less inter-correlated environmental characteristics can be analyzed using traditional multivariate methods.

Inseparability of environmental features. Several environmental characteristics were strongly linked. For example, it is intuitive that more physical activity facilities are located in areas with greater population and intersection densities, and Cervero and colleagues (142) introduced the concept of intensity, representing dense population and resources and interpreted as a measure of density. It is therefore important to adjust for density in estimation of physical activity facilities' effects, yet statistical adjustment may be inappropriate due to strong correlation between density measures and facilities counts. Instead, we found that ratios of physical activity facilities per 1,000 population was a useful strategy for separating density from count of facilities, similar to Diez Roux and colleagues (34). Further, intersection density is a common measure of street connectivity (30, 150-152), but may reflect the general density of development. Indeed, dense, gridded streets are common in city centers (153), which represent a multitude of built, economic, social, cultural, and other features.

In contrast, other street connectivity measures did not load onto factors in our study, indicating that they were not strongly correlated with each other or with other aspects of the built environment. Our results contrast with other studies showing constructs with multiple connectivity index indicators (139, 140). This discrepancy may be explained by the national scope of Add Health as opposed to one or more metropolitan areas in the studies noted. Connectivity indices are ratios of various components such as number of intersections, street segments, and route alternatives, so they may reflect different constructs in areas with high versus low component values to varying extents. Likewise, Ewing et al (63) reported a single principle component representing urban sprawl characterized by residential density, land use mix, and street accessibility in a national sample, but their study was also limited to metropolitan areas and used block size measures rather than connectivity indices to represent street accessibility. Alternatively, our buffer-defined areas may have influenced intersection and street segment counts, particularly in rural areas with few streets, altering the meaning of the connectivity indices.

Dimensionality of environmental constructs. Factor solutions distinguished different dimensions of similar constructs, which in turn were differentially related to MVPA. Building on prior research showing higher MVPA in Census block groups with more physical activity-related facilities (33), factor analysis identified two types of facilities which were related to MVPA in different ways. For example, in females, MVPA was negatively associated with intensity (pay facilities) but marginally positively associated with intensity (public facilities) in fully adjusted models. Likewise, two SES environment factors emerged, one reflecting economic and education characteristics, the other reflecting social characteristics. These factors were correlated but appear to be differentially related to the built environment and MVPA, with corresponding implications for their role in confounding, discussed in the next section.

Importance of incorporating many aspects of the environment when estimating neighborhood effects on physical activity

Factors allowed a wide range of environmental measures to be simultaneously incorporated into the analysis, revealing confounding by environment characteristics. In particular, built and SES factors were strongly associated, and adjustment for SES environment factor(s) resulted in changes to several built environment-MVPA associations. Further, the 2-dimensional SES environment construct was a stronger confounder of associations between MVPA and intensity (public facilities) and, in females, street connectivity, compared to the 1-dimensional construct. Such confounding could reflect placement of public facilities in areas of greatest need. Likewise, high street connectedness is common in poor inner-city areas where physical activity may be influenced by social contexts particularly relevant to females such as crime (72), which is better captured by the 2-dimensional SES environment construct.

Mutual confounding among built environment characteristics was stronger in males, but absolute changes to estimates were small and did not change potential conclusions made from the results. Theorized behavior-specific effects (154) suggest that street connectivity might influence active transportation (16) while physical activity facilities may be stronger supports for leisure time exercise. In this scenario, weak associations between the given outcome and alternative built environment measures would minimize confounding. Additionally, the built environment factors are multidimensional and account for correlations between built environment measures; individual built environment measures may confound other measures loading onto the same factor, but strong correlations preclude formal testing of this hypothesis.

These findings suggest that failure to adjust for both economic and social aspects of the SES environment may lead to biased estimates of some built environment-MVPA associations. Fortunately, census variables are readily available. In contrast, relatively weak confounding by other built environment characteristics is encouraging for studies that do not have the wide range of measures used in this study. However, where present, mutual confounding was negative; that is, simultaneously adjusting for multiple built environment measures magnified the associations. The degree of confounding by built and SES environment characteristics in our study may have been minimized by weak built environment-MVPA relationships, but in studies showing stronger associations, omission of additional built environment characteristics may lead to more substatial underestimation of effects. Additionally, consistent with the multitude of health behavior determinants, associations between the environment and physical activity in the extant literature are generally weak, so even small degrees of confounding may influence conclusions drawn from this research.

Forging ahead with replicable measures into longitudinal settings and external populations

Factor analysis demonstrated inter-relationships between built and SES environment characteristics. The resulting multidimensional factors allowed us to simultaneously examine a large set of measures with respect to MVPA. In a next step, we used the knowledge gained from factor analysis to create simplified measures (**Table 9**) that incorporate inter-relationships, yet are more easily replicable for future studies. We emphasize that our simplified measures represent the set of variables identified in pattern analysis and should be interpreted as such. In fact, replication of regression results with single indicators demonstrates that these measures, which are often analyzed on their own, may act as proxies for underlying environmental constructs.

Two branches of investigation are needed to better understand the potential causal effects of these measures. First, these simplified measures can be used in longitudinal analyses and examination in external populations. Longitudinal study design can establish temporality and better address bias due to residential self-selection (79, 155). As opposed to other strategies such as scale measures, they are readily understandable and examined in prior research, and selection of single indicators reduces the number of measures needed to replicate findings in other populations. Additionally, due to the potentially bidirectional, dynamic relationships between various built and SES characteristics, investigation of interactions and mediation is needed. For example, street connectivity and land cover diversity may have synergistic effects, and crime may mediate, rather than confound, relationships between built and SES environment measures and physical activity.

Second, investigation of mechanisms leading to the observed associations will help to distinguish between proxies and policy-relevant determinants of physical activity. For example, we found that crime rather than racial composition drove the association between the minority factor and MVPA, but how crime might influence physical activity, or if yet another characteristic is the causal agent, is unknown. Research incorporating psychological measures (e.g., self-efficacy and perceived barriers) or detailed audit-based environment data (e.g., aesthetics and quality of facilities) can improve understanding of behavioral mechanisms. Such research may reveal additional layers, possibly showing our multidimensional environmental constructs as proxies for more qualitative inter-personal or cultural aspects of the environment.

Determining whether patterning of environmental measures is similar in other populations is an important next step. We examined patterning of environmental measures in a nationally representative sample of adolescents. Yet adults without children in the household may reside in neighborhoods with different environmental attributes, potentially altering observed patterning. If patterning in other age groups differs substantially from the Wave I Add Health population, our simple measures may have limited ability to represent the constructs in this study and thus must be tested before applying them in other populations.

We found differences in built environment-MVPA associations by sex, which is consistent with previous work showing differences in physical activity determinants for males versus females

(70). Homogenous landscape appears to be a negative correlate of MVPA for males but not females, possibly because males may be more likely to be active outdoors (156) with less regard to safety or other concerns. Intensity (pay facilities) was associated with lower MVPA in females but not males. On the other hand, count of public facilities corrected for population was associated with higher MVPA in females but not males, perhaps also due to safety concerns addressed by access to facilities. It will be valuable to determine whether these sex differences are maintained into adulthood, when overall physical activity levels are lower (50).

Further investigation of the dose-response relationship between built environment and MVPA is another opportunity for future research. We found non-linear associations between the four aspects of the built environment and MVPA. The strongest associations were generally observed for the largest quartile, which contained very large factor score or measure values. Using quartile measures allowed comparability between associations with factors versus single indicators, but closer examination of dose-response and shape of the relationship is warranted. Shifts in the shape of the dose-response relationships – often alternating between monotonic and U-shaped – with additional covariates add complexity and should be further examined.

Limitations and Strengths

Limitations include cross-sectional study design, which do not imply causality. Yet, we identified replicable measures that set the stage for longitudinal analyses. Second, we examined overall leisure time physical activity frequency, which does not distinguish between possible behavior-specific effects (e.g. associations with active transit versus exercise) (154) or incorporate physical activity duration or intensity. Third, there was some temporal mismatch between individual-level interviews (1995-96) and GIS data sources (e.g., StreetMap 2000, 1992 land cover dataset), but our GIS is unique in providing historical data approximately contemporaneous with multiple survey waves. Our county-level crime measure was crude, yet it provided an objective measure of safety available across the U.S. that was strongly associated with MVPA. Fourth, despite the extensive number of environmental variables analyzed, we did not consider quality of facilities, perceived environment measures, or other potential psychological mediators. Fifth, we did not address urbanicity, which may be an important moderator (74, 157, 158) of built environment-MVPA relationships, but we examined measures applicable longitudinally during periods in which individuals may move in or out of urban areas.

These limitations are balanced with several strengths. We examined a wide range of environment measures in a nationally representative sample of adolescents, an understudied population. We explicitly examined and compared built and SES environment characteristics, which were strongly related. Finally, we used pattern analysis methods to not only investigate inter-relationships, but also to inform the creation of replicable measures.

Conclusion

Our study demonstrates substantial inter-relationships between environmental characteristics and suggests that many aspects of the built and SES environments should be incorporated into analysis in order to minimize confounding. Further, commonly used built environment measures may reflect more general environmental patterning and should be interpreted as such. Examination of how a broad range of environmental characteristics mutually influenced relationships with physical activity suggested complex mechanisms involving a myriad of social and cultural factors. Finally, we present simplified, replicable measures that are cross-sectionally related to physical activity in adolescents. Better characterization of the environment, longitudinal analysis, and exploration of mechanisms in future studies can increase our understanding of built environment features that should be targeted in physical activity promotion policy.

Table 1. Built and socioeconomic environment measures:[1] data sources and variable descriptions

Data source (year); Measure	Geographic Area[2]	Variable description
ESRI StreetMap (2000)		
Street connectivity		
Alpha index[3]	1k	Ratio of observed to maximum possible route alternatives between nodes (intersections); high values indicate high connectivity.
Beta index[3]	1k	Ratio of links (connections between nodes) to nodes; high values indicate high connectivity.
Cul de sac density[3]	1k	Number of cul de sacs (single-link nodes) per square kilometer; low values indicate high connectivity.
Cyclomatic index[3]	1k	Number of route alternatives between nodes; high values indicate high connectivity.
Gamma index[3]	1k	Ratio of observed links to the maximum number of links; high values indicate high connectivity.
Intersection density	1k	Number of 3- or more-way intersections (≥links in a single node) per square kilometer
Commercial database of U.S. businesses (1995)		
Physical activity facilities		
Instruction (count)	3k	Dance studios, basketball instruction, martial arts
Member (count)	3k	Athletic club and gymnasium, tennis club, basketball club
Outdoor (count)	3k	Sporting and recreation camps, swimming pools
Public (count)	3k	Public beach, pools, tennis courts, recreation centers
Public fee (count)	3k	Physical fitness facilities, bicycle rental, public golf courses
Youth organization (count)	3k	Boy/Girl Scouts, youth centers
ESRI StreetMap Pro, parks component (2003)		
Parks (count)	3k	Local parks and recreation areas, classified by Census Bureau classification code
National land cover dataset (1992)		
Landscape diversity		
Mean patch size	1k	Total land patch area divided by the number of patches
Root mean square error (RMSE) patch size	1k	Square root of the sum of the squared deviations of each patch area from the mean patch area, divided by the number of patches
Land patch density	1k	Number of land patches per hectare
Simpson's diversity index	1k	Represents the probability that any two pixels selected at random would be different patch types.
Contagion index	1k	Measures texture based on aggregation and interspersion of land patch types
Perimeter-fractal dimension	1k	Measures perimeter and shape complexity
Patch richness[3]	1k	Number of different patch types (classes)
Mean shape index[3]	1k	Mean shape index, which measures patch shape and compaction.
Mean fractal dimension index[3]	1k	Measures perimeter and shape complexity across a range of spatial scales (patch sizes)

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Table 1, continued

Data source (year); Measure	Geographic Area[2]	Variable description
U.S. Census (1990)		
Population count	1k	Count of persons within buffer
% below poverty	CT	Percent of persons living in housedholds with income below the federal poverty level
% minority	CT	Percent of persons with race/ethnicity other than white non-Hispanic
Median household income	CT	Median household income
% homeowners	CT	Percent of households who own (versus rent) their homes
Uniform Crime Reporting data (1995)		
Crime rate	Co	Number of non-violent and violent crimes per 100,000 population

[1]From the National Longitudinal Study of Adolescent Health Obesity Environment Database
[2]Examined in exploratory factor analysis but excluded from final factor solutions based on criteria described in Methods
[3]1k, 3k = 1 and 3 kilometer Euclidean buffer; CT=census tract; Co=County. Selected neighborhood definitions were selected because they yielded the strongest associations between environment measures and physical activity in previous analysis.

Table 2. Individual-level characteristics by sex [mean/% (SE)][1]

		Males	Females
Count		8,747	8,694
Race/ethnicity (%)			
	White	68.1 (2.9)	68.3 (3.0)
	Black	16.1 (2.2)	16.0 (2.1)
	Asian	3.5 (0.7)	3.4 (0.7)
	Hispanic	12.4 (1.8)	12.3 (1.8)
Parent education (%)			
	<High school	15.0 (1.4)	15.6 (1.4)
	High school/GED	32.3 (1.2)	33.2 (1.2)
	Some college	28.5 (0.9)	26.9 (0.9)
	College or greater	24.3 (1.6)	24.2 (1.6)
Region (%)			
	West	15.0 (1.4)	15.7 (1.4)
	Midwest	31.1 (2.2)	32.7 (2.6)
	South	39.2 (1.8)	38.0 (1.9)
	Northeast	14.7 (1.0)	13.6 (0.9)
Age (mean)		15.5 (0.1)	15.3 (0.1)
MVPA (mean # weekly bouts)		4.1 (0.1)	3.3 (0.1)
Household income (mean)		42.9 (1.5)	43.3 (1.5)

[1] National Longitudinal Study of Adolescent Health, Wave I (1995-96), n=17,441.
GED, Graduate Equivalency Degree; MVPA, moderate to vigorous physical activity; SE, standard error

Table 3. Built and socioeconomic environment characteristics: descriptive statistics[1]

Measure	mean (SE)	minimum	25th percentile	median	75th percentile	maximum
Street connectivity						
Alpha index	0.32 (0.01)	-8	0.22	0.30	0.38	8
Intersection density	29.50 (1.64)	0	8.6	26.7	44.6	168.1
Population density	1,393 (178)	0.03	129	772	1,777	29,961
Landscape diversity						
Mean patch size	30,203 (1,572)	7,411	14,209	19,158	30,794	315,000
RMSE patch size	171,513 (6,873)	21,151	88,185	131,701	205,798	939,810
Land patch density	52.4 (1.7)	3.2	32.5	52.2	70.4	134.9
Simpson's diversity index	0.54 (0.01)	0.01	0.45	0.58	0.67	0.83
Contagion index	48.2 (0.9)	9.1	36.2	45.8	57.8	98.3
Perimeter-fractal dimension	1.48 (0.01)	1.06	1.44	1.50	1.54	1.67
Physical activity facilities						
Instruction	2.3 (0.2)	0	0	1	3	100
Member	2.0 (0.2)	0	0	1	3	52
Outdoor	1.2 (0.1)	0	0	1	2	15
Public	0.9 (0.1)	0	0	0	1	22
Public fee	1.4 (0.1)	0	0	1	2	22
Youth organization	1.3 (0.2)	0	0	0	2	38
Parks	4.7 (0.5)	0	0	1	8	44
Census measures						
% below poverty	0.15 (0.01)	0	0.06	0.11	0.21	0.85
% ≥college education	0.11 (0.01)	0	0.05	0.08	0.14	0.60
% minority	0.25 (0.02)	0	0.03	0.12	0.37	1
Median household income	29,766 (942)	4,999	21,003	28,193	35,708	150,001
% homeowners	0.68 (0.01)	0	0.57	0.72	0.83	0.98
Crime rate	5,473 (237)	108	3,523	5,528	6,975	13,723

[1] National Longitudinal Study of Adolescent Health, Wave I (1995-96), n=18,461. Excludes built environment characteristics examined but not included in subsequent analysis

RMSE, root mean square error; SE, standard error

Table 4. Built environment factor loadings resulting from exploratory factor analysis[1]

	Homogenous landscape	Intensity (pay facilities)	Intensity (public facilities)
RMSE patch size	**0.98**	--	--
Contagion index	**0.90**	--	--
Simpson's diversity index	**-0.90**[2]	--	--
Mean patch size	**0.87**	--	--
Land patch density	**-0.82**	--	--
Perimeter-fractal dimension	**-0.81**	--	--
Intersection density	-0.20	**0.49**	0.33
Population density	--	**0.40**	**0.50**
Facilities - instruction	--	**0.82**[2]	--
Facilities - member	--	**0.81**[2]	--
Facilities - outdoor	--	**0.80**	--
Facilities - public fee	--	**0.73**[2]	--
Facilities - public	--	--	**0.96**[2]
Facilities – youth organization	--	--	**0.90**[2]
Parks	--	**0.40**	0.34

[1] National Longitudinal Study of Adolescent Health, Wave I (1995-96), n=18,461.Obtained from exploratory factor analysis using a principle factors estimator and oblique oblimin (gamma=0) rotation. Unweighted correlations with *non-diverse landscape* were -0.03 and -0.02 for *intensity (pay facilities)* and *intensity (public facilities)*, respectively; and 0.58 between *intensity (pay facilities)* and *intensity (public facilities).*
[2] Indicator variable(s) used to represent corresponding factor in **Table 9**
--For clarity, loadings with absolute value <0.2 were omitted
RMSE, root mean square error

Table 5. Socioeconomic environment factor loadings resulting from exploratory factor analysis[1]

	2 factor solution		Alternative: 1 factor solution
	Advantageous economic environment	Disadvantageous social environment [2]	Advantageous socioeconomic environment
Median household income	**0.89**[3]	--	**0.82**
% ≥college education	**0.80**	--	**0.56**
% below poverty	**-0.63**	0.40	**-0.85**
% minority	--	**0.72**	**-0.60**
Crime rate	--	**0.70**[3]	-0.38
% homeowners	0.22	**-0.56**	**0.62**

[1] National Longitudinal Study of Adolescent Health, Wave I (1995-96), n=18,461.Obtained from exploratory factor analysis using a principle factors estimator and oblique oblimin (gamma=0) rotation. Unweighted correlations between *Advantageous economic environment* and *Disadvantageous social environment* factors was -0.43

[2] Marginally met inclusion criteria (Eigenvalue=0.97)

[3] Indicator variable(s) used to represent corresponding factor in **Table 9**

--For clarity, loadings with absolute value <0.2 were omitted

Table 6. Crude associations between built environment factor scores and socioeconomic environment factor quartiles [coeff (95% CI)][1]

	Homogenous landscape	Intensity (pay facilities)	Intensity (public facilities)	Connectivity (alpha)
Advantageous economic environment score quartile (1=referent, lowest income category omitted)				
2	-0.13 (-0.50, 0.23)	0.43 (0.24, 0.62)*	0.16 (-0.03, 0.35)	0.00 (-0.07, 0.06)
3	-0.38 (-0.78, 0.01)	0.58 (0.34, 0.82)*	0.20 (-0.02, 0.43)	-0.02 (-0.09, 0.06)
4	-0.46 (-0.89, -0.03)*	0.87 (0.61, 1.13)*	0.36 (0.15, 0.57)*	-0.06 (-0.13, 0.01)
Disadvantageous social environment score quartile (1=referent, lowest minority, crime category omitted)				
2	0.09 (-0.17, 0.36)	0.35 (0.22, 0.48)*	0.34 (0.22, 0.45)*	0.06 (0.00, 0.13)*
3	-0.25 (-0.48, -0.02) *	0.65 (0.36, 0.94)*	0.61 (0.40, 0.82)*	0.03 (-0.02, 0.09)
4	-0.18 (-0.59, 0.24)	1.31 (1.00, 1.63)*	1.39 (1.04, 1.74)*	0.09 (0.03, 0.16)*

[1]National Longitudinal Study of Adolescent Health, Wave I (1995-96), n=18,461. Based on linear regression modeling each built environment factor from **Table 4** (or street connectivity variable) as a function of quartiles of Advantageous economic and Disadvantageous social environment factor scores (**Table 5**). Referent category is lowest quartile.
CI, confidence interval; coeff, coefficient
*Statistically significant ($p<0.05$)

Table 7. Assessment of confounding to associations between built and socioeconomic environment factor score quartiles and weekly bouts of MVPA, males (n=8,747) [exp(coeff) (95% CI) [change in coefficient[2]][1]

Quartile [median (min, max)]	Model 1	Model 2	Model 3	Model 4	Model 5
Homogenous landscape score					
1 [-0.86 (-1.43, -0.68)]	1	1	1	1	1
2 [-0.49 (-0.68, -0.27)]	0.98 (0.93, 1.04)	0.98 (0.93, 1.03)	0.98 (0.93, 1.03)	0.98 (0.93, 1.03)	0.98 (0.93, 1.03)
3 [0.00 (-0.27, 0.35)]	0.97 (0.90, 1.03)	0.95 (0.91, 1.00) [34%]	0.95 (0.91, 1.00) [-3%]	0.95 (0.91, 1.00)* [9%]	0.95 (0.91, 1.00)* [7%]
4 [1.04 (0.35, 5.45)]	0.92 (0.87, 0.99)*	0.92 (0.88, 0.97)* [7%]	0.91 (0.86, 0.96)* [14%]	0.91 (0.87, 0.96)* [-4%]	0.91 (0.86, 0.96)* [-2%]
Intensity (pay facilities) score					
1 [-0.82 (-1.45, -0.68)]	1	1	1	1	1
2 [-0.51 (-0.67, -0.25)]	1.05 (0.99, 1.11)	1.04 (1.00, 1.09) [-11%]	1.02 (0.98, 1.07) [-53%]	1.01 (0.97, 1.06)	1.02 (0.98, 1.06)
3 [-0.01 (-0.25, 0.37)]	1.03 (0.97, 1.09)	1.01 (0.96, 1.06)	1.01 (0.96, 1.07)	1.00 (0.95, 1.06)	1.01 (0.95, 1.07)
4 [0.94 (0.37, 13.96)]	1.07 (1.00, 1.14)*	1.02 (0.97, 1.08) [-64%]	1.05 (0.98, 1.12) [96%]	1.04 (0.98, 1.12) [-7%]	1.05 (0.98, 1.12) [-1%]
Intensity (public facilities) score					
1 [-0.74 (-1.25, -0.67)]	1	1	1	1	1
2 [-0.58 (-0.67, -0.39)]	1.02 (0.98, 1.07)	1.01 (0.97, 1.05)	0.99 (0.95, 1.03)	0.99 (0.95, 1.03)	0.99 (0.95, 1.04)
3 [-0.06 (-0.39, 0.41)]	0.97 (0.91, 1.02)	0.95 (0.91, 1.00)* [33%]	0.93 (0.87, 0.98)* [64%]	0.93 (0.88, 0.99)* [-8%]	0.95 (0.89, 1.01) [-27%]
4 [1.15 (0.41, 9.76)]	1.05 (0.99, 1.11)	1.03 (0.98, 1.08) [-49%]	1.00 (0.94, 1.07)	1.02 (0.96, 1.08)	1.03 (0.96, 1.10)
Street Connectivity (alpha)					
1 [0.17 (-8.00, 0.21)]	1	1	1	1	1
2 [0.26 (0.21, 0.30)]	1.00 (0.94, 1.06)	0.99 (0.93, 1.04)	0.98 (0.93, 1.04)	0.99 (0.95, 1.05)	0.99 (0.95, 1.04)
3 [0.34 (0.30, 0.38)]	0.97 (0.91, 1.03)	0.95 (0.91, 1.01) [45%]	0.96 (0.91, 1.01) [-5%]	0.97 (0.93, 1.02) [39%]	0.97 (0.93, 1.02) [-40%]
4 [0.45 (0.38, 8.00)]	0.95 (0.90, 1.02)	0.95 (0.90, 1.01) [2%]	0.98 (0.93, 1.03) [-57%]	1.00 (0.95, 1.05)	1.00 (0.95, 1.05)
Advantageous economic environment score[3]					
1 [-1.07 (-2.58, -0.67)]				1	1
2 [-0.29 (-0.67, 0.03)]				1.04 (0.99, 1.09)	1.01 (0.96, 1.07)
3 [0.22 (0.03, 0.52)]				1.04 (0.98, 1.11)	1.04 (0.99, 1.09)
4 [0.88 (0.52, 5.99)]				1.11 (1.04, 1.18)*	1.06 (0.99, 1.13)

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Quartile [median (min, max)]	Model 1	Model 2	Model 3	Model 4	Model 5
Disadvantageous social environment score					
1 [-0.94 (-1.37, -0.67)]					1
2 [-0.38 (-0.67, -0.09)]					0.96 (0.92, 1.00)
3 [0.10 (-0.08, 0.46)]					0.95 (0.89, 1.01)
4 [1.09 (0.46, 3.38)]					0.94 (0.88, 1.01)

[1]National Longitudinal Study of Adolescent Health, Wave I (1995-96). Based on sex-stratified negative binomial regression models; value represents proportion increase in MVPA bouts. Referent category is lowest quartile.
[2]Change in coefficient reflects change in coefficient [(current model –previous model)/previous model]*100 for built environment characteristics only. Model 5 coefficients are compared to Model 3 coefficients. Change in estimates were omitted if both coefficients were <±0.04. Negative percent changes indicate attenuation of the association.
[3]Ranges for 1-dimensional factor quartiles: (1) -1.17 (-3.50, -0.61); (2) -0.11 (-0.61, 0.15); (3) 0.35 (0.15, 0.61); (4) 0.92 (0.61, 4.56)
Model 1: Built environment characteristics separately, crude associations
Model 2: Built environment characteristics separately, adjusted for individual-level sociodemographics (age, race, parental education, household income, region)
Model 3: Built environment characteristics in the same model, adjusted for individual-level sociodemographics
Model 4: Built environment characteristics in the same model, adjusted for individual-level sociodemographics and 1-dimensional neighborhood SES factor
Model 5: Built environment characteristics in the same model, adjusted for individual-level sociodemographics and for 2-dimensional neighborhood SES factor
CI, confidence interval; exp(coeff), exponentiated coefficient; MVPA, moderate to vigorous physical activity
*Statistically significant (p<0.05)

Table 8. Assessment of confounding to associations between built and socioeconomic environment <u>factor score quartiles</u> and weekly bouts of MVPA, <u>females</u> (n=8,694) [exp(coeff) (95% CI) [change in coefficient[2]][1]

Quartile [median (min, max)]	Model 1	Model 2	Model 3	Model 4	Model 5
Homogenous landscape score					
1 [-0.86 (-1.43, -0.68)]	1	1	1	1	1
2 [-0.49 (-0.68, -0.27)]	1.04 (0.98, 1.11)	1.03 (0.98, 1.09) [-21%]	1.04 (0.99, 1.10)	1.04 (0.99, 1.10)	1.04 (0.98, 1.10)
3 [0.00 (-0.27, 0.35)]	1.01 (0.96, 1.08)	1.00 (0.96, 1.05)	1.02 (0.97, 1.06)	1.01 (0.97, 1.06)	1.01 (0.97, 1.06)
4 [1.04 (0.35, 5.45)]	0.98 (0.91, 1.06)	0.99 (0.95, 1.04)	1.02 (0.97, 1.08)	1.02 (0.97, 1.08)	1.02 (0.96, 1.08)
Intensity (pay facilities) score					
1 [-0.82 (-1.45, -0.68)]	1	1	1	1	1
2 [-0.51 (-0.67, -0.25)]	1.02 (0.95, 1.09)	0.98 (0.93, 1.02)	0.96 (0.91, 1.01)	0.96 (0.91, 1.01) [11%]	0.96 (0.91, 1.02) [-2%]
3 [-0.01 (-0.25, 0.37)]	1.06 (0.99, 1.14)	1.01 (0.96, 1.06) [-83%]	0.99 (0.93, 1.05)	0.98 (0.92, 1.04)	0.99 (0.93, 1.05)
4 [0.94 (0.37, 13.96)]	0.97 (0.89, 1.05)	0.93 (0.88, 0.99)* [115%]	0.91 (0.84, 0.98)* [-32%]	0.91 (0.85, 0.97)* [0%]	0.91 (0.85, 0.98)* [-8%]
Intensity (public facilities) score					
1 [-0.74 (-1.25, -0.67)]	1	1	1	1	1
2 [-0.58 (-0.67, -0.39)]	0.98 (0.91, 1.06)	0.96 (0.91, 1.02)	0.96 (0.91, 1.02) [13%]	0.96 (0.91, 1.02) [-2%]	0.97 (0.91, 1.02) [-17%]
3 [-0.06 (-0.39, 0.41)]	1.00 (0.93, 1.08)	0.98 (0.93, 1.04)	1.01 (0.95, 1.08)	1.01 (0.95, 1.08)	1.04 (0.98, 1.11)
4 [1.15 (0.41, 9.76)]	0.94 (0.86, 1.03)	0.96 (0.90, 1.03) [-40%]	1.02 (0.94, 1.10)	1.03 (0.95, 1.11)	1.06 (0.98, 1.14) [188%]
Street Connectivity (alpha)					
1 [0.17 (-8.00, 0.21)]	1	1	1	1	1
2 [0.26 (0.21, 0.30)]	1.00 (0.93, 1.07)	0.99 (0.93, 1.05)	0.98 (0.92, 1.05)	0.99 (0.92, 1.06)	0.99 (0.93, 1.06)
3 [0.34 (0.30, 0.38)]	0.99 (0.93, 1.06)	0.99 (0.94, 1.05)	0.99 (0.93, 1.06)	1.00 (0.94, 1.07)	1.01 (0.95, 1.08)
4 [0.45 (0.38, 8.00)]	0.89 (0.83, 0.97)*	0.92 (0.87, 0.98)* [-28%]	0.91 (0.85, 0.98)* [14%]	0.92 (0.86, 0.99)* [13%]	0.93 (0.87, 1.00) [27%]
Advantageous economic environment score[3]					
1 [-1.07 (-2.58, -0.67)]				1	1
2 [-0.29 (-0.67, 0.03)]				1.04 (0.98, 1.10)	0.99 (0.94, 1.04)
3 [0.22 (0.03, 0.52)]				1.02 (0.96, 1.10)	1.02 (0.96, 1.09)
4 [0.88 (0.52, 5.99)]				1.07 (0.99, 1.14)	1.04 (0.98, 1.11)

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Quartile [median (min, max)]	Model 1	Model 2	Model 3	Model 4	Model 5
Disadvantageous social environment score					
1 [-0.94 (-1.37, -0.67)]					1
2 [-0.38 (-0.67, -0.09)]					0.95 (0.90, 1.00)
3 [0.10 (-0.08, 0.46)]					0.93 (0.87, 1.00)*
4 [1.09 (0.46, 3.38)]					0.91 (0.84, 0.98)*

[1]National Longitudinal Study of Adolescent Health, Wave I (1995-96). Based on sex-stratified negative binomial regression models; value represents proportion increase in MVPA bouts. Referent category is lowest quartile.
[2]Change in coefficient reflects change in coefficient [(current model –previous model)/previous model]*100 for built environment characteristics only. Model 5 coefficients are compared to Model 3 coefficients. Change in estimates were omitted if both coefficients were <±0.04. Negative percent changes indicate attenuation of the association.
[3]Ranges for 1-dimensional factor quartiles: (1) -1.17 (-3.50, -0.61); (2) -0.11 (-0.61, 0.15); (3) 0.35 (0.15, 0.61); (4) 0.92 (0.61, 4.56)
Model 1: Built environment characteristics separately, crude associations
Model 2: Built environment characteristics separately, adjusted for individual-level sociodemographics (age, race, parental education, household income, region)
Model 3: Built environment characteristics in the same model, adjusted for individual-level sociodemographics
Model 4: Built environment characteristics in the same model, adjusted for individual-level sociodemographics and 1-dimensional neighborhood SES factor
Model 5: Built environment characteristics in the same model, adjusted for individual-level sociodemographics and for 2-dimensional neighborhood SES factor
CI, confidence interval; exp(coeff), exponentiated coefficient; MVPA, moderate to vigorous physical activity
*Statistically significant (p<0.05)

Table 9 Association between representative built, social, and economic environment measure quartiles and weekly bouts of MVPA [exp(coeff)][1]

Quartile [median (min, max)]	Males (n=8,747) Model 3	Males (n=8,747) Model 5	Males (n=8,747) Model 6	Females (n=8,694) Model 3	Females (n=8,694) Model 5	Females (n=8,694) Model 6
Simpson's Diversity Index[2]						
1 [0.71 (0.66, 0.83)]	1	1	1	1	1	1
2 [0.62 (0.58, 0.66)]	0.96 (0.92, 1.01)	0.96 (0.91, 1.01)	0.96 (0.92, 1.01)	1.03 (0.97, 1.09)	1.03 (0.97, 1.09)	1.03 (0.97, 1.09)
3 [0.53 (0.46, 0.58)]	0.91 (0.88, 0.95)*	0.91 (0.88, 0.95)*	0.92 (0.88, 0.95)*	1.03 (0.98, 1.09)	1.03 (0.98, 1.09)	1.02 (0.97, 1.08)
4 [0.33 (0.01, 0.46)]	0.91 (0.86, 0.95)*	0.91 (0.86, 0.95)*	0.91 (0.87, 0.95)*	1.00 (0.94, 1.06)	1.00 (0.94, 1.06)	0.99 (0.94, 1.05)
Count of pay facilities						
1 [0 (0, 1)]	1	1	1	1	1	1
2 [3 (2, 4)]	1.02 (0.98, 1.06)	1.01 (0.98, 1.05)	1.03 (0.97, 1.10)	0.96 (0.92, 1.01)	0.96 (0.91, 1.01)	0.93 (0.87, 0.99)*
3 [7 (5, 9)]	1.02 (0.98, 1.07)	1.02 (0.98, 1.07)	0.99 (0.95, 1.04)	0.97 (0.92, 1.02)	0.97 (0.92, 1.01)	0.95 (0.91, 0.99)*
4 [14 (10, 174)]	1.04 (0.99, 1.09)	1.05 (1.00, 1.10)	1.03 (0.99, 1.08)	0.92 (0.86, 0.98)*	0.92 (0.87, 0.98)*	0.96 (0.91, 1.01)
Count of public facilities[3]						
1 [0 (0, 0)]	1	1	1	1	1	1
2 [1 (1, 1)]	0.96 (0.91, 1.01)	0.96 (0.91, 1.02)	1.05 (0.99, 1.12)	1.02 (0.97, 1.08)	1.03 (0.98, 1.08)	1.03 (0.95, 1.12)
3 [3 (2, 20)]	1.02 (0.97, 1.06)	1.04 (0.99, 1.08)	1.00 (0.96, 1.04)	1.05 (0.99, 1.10)	1.07 (1.02, 1.13)*	1.04 (1.00, 1.08)
Street Connectivity (alpha)						
1 [0.17 (-8.00, 0.21)]	1	1	1	1	1	1
2 [0.26 (0.21, 0.30)]	0.97 (0.92, 1.03)	0.99 (0.94, 1.04)	0.99 (0.94, 1.04)	0.99 (0.93, 1.06)	1.00 (0.94, 1.07)	0.99 (0.93, 1.06)
3 [0.34 (0.30, 0.38)]	0.95 (0.90, 1.00)*	0.97 (0.93, 1.02)	0.97 (0.93, 1.01)	0.99 (0.94, 1.06)	1.02 (0.96, 1.09)	1.02 (0.96, 1.09)
4 [0.45 (0.38, 8.00)]	0.98 (0.93, 1.03)	1.00 (0.95, 1.05)	1.01 (0.96, 1.06)	0.92 (0.86, 0.99)*	0.95 (0.88, 1.02)	0.95 (0.88, 1.02)
Median household income[4]						
1 [1.7 (0.5, 2.1)]		1	1		1	1
2 [2.5 (2.1, 3.0)]		1.01 (0.97, 1.06)	1.00 (0.96, 1.05)		1.02 (0.97, 1.07)	1.02 (0.97, 1.07)
3 [3.4 (3.0, 3.8)]		1.03 (0.99, 1.08)	1.03 (0.98, 1.07)		1.04 (0.97, 1.11)	1.04 (0.98, 1.11)
4 [4.5 (3.8, 13.7)]		1.08 (1.02, 1.15)*	1.07 (1.01, 1.14)*		1.09 (1.02, 1.17)*	1.10 (1.03, 1.18)*

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Quartile [median (min, max)]	Males (n=8,747) Model 3	Model 5	Model 6	Females (n=8,694) Model 3	Model 5	Model 6
*Crime rate/100,000 population						
1 [2,629 (108, 3,647)]		1	1		1	1
2 [4,899 (3,696, 5,612)]		0.95 (0.90, 1.01)	0.96 (0.91, 1.01)		0.97 (0.92, 1.03)	0.98 (0.92, 1.03)
3 [6,177 (5,623, 6,975)]		0.94 (0.89, 0.99)*	0.96 (0.90, 1.01)		0.93 (0.86, 0.99)*	0.94 (0.88, 1.00)
4 [8,317 (7,084, 13,723)]		0.95 (0.91, 1.00)*	0.95 (0.91, 1.00)*		0.92 (0.86, 0.98)*	0.93 (0.87, 0.99)*

[1]National Longitudinal Study of Adolescent Health, Wave I (1995-96). Based on sex-stratified negative binomial regression models; value represents proportion increase in MVPA bouts. Referent category is lowest quantile. Environmental measures representing each factor were generally selected based on the highest loadings, with the following exceptions: non-overlapping pay facility types (instruction, member, and public fee) were summed, public (rather than youth) facilities were selected for longitudinal relevance; and crime rate replicated MVPA associations more closely than percent minority, the highest loading variable. For brevity, only Models 3, 5, and 6 are presented; their names are retained to be consistent with **Tables 7 and 8**.
[2]Negatively associated with homogenous land cover factor, so reverse coded to for comparability
[3]Tertiles
[4]In 10,000's
Model 3: Built environment characteristics in the same model, adjusted for individual-level sociodemographic variables
Model 5: Built environment characteristics in the same model, adjusted for individual-level sociodemographics, median household income, and crime rate
Model 6: Built environment characteristics (facilities counts scaled by population) in the same model, adjusted for individual-level sociodemographics, median household income, and crime rate
CI, confidence interval; exp(coeff), exponentiated coefficient; MVPA, moderate to vigorous physical activity
*Statistically significant (p<0.05)

V. Residential self-selection bias in the estimation of built environment effects on physical activity between adolescence and young adulthood

A. Abstract

Built environment research is dominated by cross-sectional study designs, which are particularly vulnerable to residential self-selection bias resulting from unmeasured characteristics related to neighborhood choice and health-related outcomes. This study used cohort data from the National Longitudinal Study of Adolescent Health (Wave I, 1994-95; Wave III, 2001-02; n=12,797) and a time-varying geographic information system to estimate longitudinal relationships between moderate to vigorous physical activity (MVPA) bouts and several built and socioeconomic environment measures from adolescence to young adulthood. After controlling for measured and time invariant unmeasured characteristics using within-person estimators (fixed effects models), MVPA was higher with greater physical activity pay facilities per population in males, and lower with higher crime rates in males and females; other associations were null or in the counter-intuitive direction. Comparison of within-person estimates to estimates not adjusted for unmeasured characteristics suggested that residential self-selection can bias associations toward the null, as opposed to its typical characterization as a positive confounder. Additionally, differential environment-MVPA associations by residential relocation status suggest that selection bias may be a concern in studies examining changes following residential relocation. The authors discuss complexities of adjusting for residential self-selection bias and selectivity of residential relocation, particularly during the adolescent to young adult transition.

B. Introduction

Built environment characteristics, such as walkability (29, 60) and availability of recreation centers (33, 34), are associated with physical activity (PA) in a growing literature. However, existing research is dominated by cross-sectional studies, which are particularly vulnerable to residential self-selection bias, as unmeasured neighborhood selection factors related to both built environment exposures and PA could contribute to observed associations (79, 155).

Longitudinal designs can address residential self-selection bias by establishing temporality and controlling for unmeasured characteristics. In two key longitudinal studies (73, 105), investigators used "first difference" models to estimate the influence of urban form on travel behavior or obesity. First difference models and a similar method, "fixed effects" models, use within-person estimators to control for unmeasured characteristics that remain constant throughout the study period (148, 155, 159) (e.g., genetics or resilient attitudes toward exercise) by analyzing variation in the exposure and outcome within person, over time. Within-person estimation is particularly valuable when confounders are difficult to measure (e.g., residential selection factors), and, as described by Glymour, is most appropriate for exposure-outcome relationships with short lag times (160) such as theorized built environment influences on PA and, to a lesser extent, body weight.

Prior longitudinal studies (29, 73, 105, 107) examined changes in behavior (or body weight) in response to changes in urban form resulting from residential relocation. However, the environment can change around stationary residents. Furthermore, residential relocation is generally triggered by events such as marriage or change in employment (161), which may also influence health-related behaviors. Therefore, restriction based on residential relocation is a potential source of selection bias (102).

In this study, our primary objective was to estimate within-person effects of several built and socioeconomic environment characteristics on moderate to vigorous PA (MVPA) in a nationally representative sample with time-varying geographic information system (GIS) environment measures.

Secondary objectives were to (a) assess the influence of time invariant, unmeasured characteristics on environment-PA associations by comparing within-person estimates to alternative estimates which do not address unmeasured characteristics (naïve estimates), and (b) explore selectivity related to residential relocation. We hypothesized that (1) greater MVPA bouts would be related to higher landscape diversity, pay and public facilities counts, street connectivity, and median household income and to lower crime rates; (2a) controlling for time invariant, unmeasured characteristics would attenuate estimated effects, and (2b) environment-MVPA associations would vary by residential relocation status.

C. Methods

Study population and data sources

We used Wave I (1994-95) and III (2001-02) data from The National Longitudinal Study of Adolescent Health (Add Health), a cohort study of 20,745 adolescents representative of the U.S. school-based population in grades 7 to 12 (11-22 years of age) in 1994-95 followed into adulthood. Add Health included a core sample plus subsamples of selected minority and other groupings collected under protocols approved by the Institutional Review Board at the University of North Carolina at Chapel Hill. The survey design and sampling frame have been discussed elsewhere (143).

A GIS linked community-level data to Add Health respondent residential locations determined in Wave III from geocoded home addresses with street-segment matches (n=13,039), global positioning system (GPS) measurements (n=1,204), and ZIP/ZIP+4/ZIP+2 centroid match (n=685) among 14,322 Wave III respondents in the probability sample; analogous Wave I information is published elsewhere (162). Differences in individual-level and environmental measures across location sources were consistent with greater reliance on GPS or ZIP codes (compared to geocodes) among rural respondents, who often use Post Office Boxes or other addresses that could not be geocoded. Residential locations were linked to attributes of circular areas of various radii surrounding each wave-specific respondent residence (Euclidean neighborhood buffer) and block group, tract, and county attributes from time-matched U.S. Census and other federal sources, which were merged with individual-level Add Health interview responses.

Of 18,924 Wave I respondents in the probability sample, 6% refused participation and 19% could not be located or were unable to participate for other reasons, leaving 14,322 Wave III respondents. Exclusions included mobility disability (n=87) or self-reported pregnancy at Wave I or III (n=578) and Native Americans due to small sample size (n=121). Of the remaining sample (n=13,546), those missing individual-level variables (n=272), environmental variables (n=472), or both (n=5) were excluded. Those excluded due to missing data (n=749) were similar to the analytical sample (n=12,797) with regard to Wave I and III individual sociodemographics, MVPA, and environmental variables; exceptions were lower census tract-level median income and Wave III landscape diversity, and higher Wave III MVPA in excluded respondents (data not shown).

Study variables

GIS-derived environmental characteristics

We examined variables calculated within neighborhoods (e.g., 1 or 3k buffer, or census tracts) consistent with the strongest associations with MVPA (74) and shown to adequately represent multidimensional environmental constructs (162). Detailed variable definitions have been described previously (162). ***Residential relocation*** (move vs. not move) was defined as greater than ¼ mile Euclidean distance between Wave I and III residential locations.

PA facilities were obtained from a commercial dataset of U.S. businesses (Wave 1: 1995, Wave III: 2001) validated against a field-based census (125). Facilities were classified according to 8-digit Standard Industrial Classification codes. Population counts within 3k buffers were calculated by averaging census block-group population counts, weighted according to the proportion of block-group area captured within 3k. Pay (member, instruction, public fee) and public facilities counts within 3k were divided by population count/10,000 to obtain ***pay*** and ***public facilities counts per 10,000 population***.

Simpson's Diversity Index, an indicator of ***landscape diversity*** and complexity (144), was calculated within 1k based on national land cover data (Wave I: 1992, Wave III: 2001) using Fragstats software (126) and represents the probability that any two randomly selected pixels are different land patch types. ***Alpha index*** calculated within 1k from StreetMap 2000 files indicated the degree of street connectivity (145), which provides numerous route options and is characterized by dense, parallel routes, many intersections, and few cul de sacs and dead end streets (11).

The socioeconomic environment was represented by census tract-level ***median household income*** (U.S. census, Wave I: 1990, inflated to 2000 dollars using the Consumer Price Index; Wave III: 2000), and county-level ***non-violent and violent crime rate*** per 100,000 population obtained from Uniform Crime Reporting data (Wave I: 1995, Wave III: 2001).

Individual-level self-reported behaviors and sociodemographics

Weekly frequency (bouts) of MVPA (skating & cycling, exercise, and active sports) was ascertained at Waves I and III using a standard, interview administered activity recall based on questionnaires validated in other epidemiologic studies (146). The Wave III questionnaire was modified to include age-appropriate activities, so Wave III bouts were scaled for comparability with Wave I (163).

Individual-level sociodemographic control variables included Wave I self-identified race (white, black, Asian, Hispanic), parent-reported annual household income and highest education attained (<high school, high school or GED, some college, ≥college degree), and administratively determined U.S. region (West, Midwest, South, and Northeast); and age at Wave I and III interviews. Socioeconomic position in young adulthood can be characterized by a complex array of behaviors and achievements (129, 130) which are likely predictors of residential relocation, so we used parent income and education to indicate socioeconomic position in both waves.

Statistical analysis

Descriptive analysis

Individual-level and environment variables were compared by residential relocation status (95% confidence level) using adjusted Wald tests and design-based F-tests for continuous and categorical variables, respectively, weighted for national representation and corrected for complex survey design. Some environmental variables were skewed, so we report median and interquartile range and performed statistical tests on natural-log transformed pay and public facilities counts and median household income.

Regression analysis

Within-person effects of built and socioeconomic environment measures on MVPA bouts from adolescence (Wave I) to young adulthood (Wave III) were estimated using fixed effects Poisson regression (Objective 1). Fixed effects (versus first differences) accommodate nonlinear models, as required for our dependant variable (weekly counts of MVPA bouts). Fixed effects models analyze deviations of the outcome and exposures from person-specific means, but, as demonstrated elsewhere (73, 155, 159), interpretation of the coefficients is unchanged from traditional regression models.

"Random effects" estimates incorporate both between- and within-person variation and thus do not control for unmeasured characteristics (naïve estimation; Objective 2a). Fixed and random effects estimates were tested formally using the Hausman specification test. All models were fit using the xtpoisson function in Stata 10.1 (164), which provided comparable estimates but does not accommodate probability weights. Sample weighted, school cluster-corrected, within-person estimates obtained using an alternative method (159) were substantively similar, but comparable random effects estimates were not possible given the available software. School-level clustering was corrected in random effects models by including school indicator variables (165); fixed effects regression models within-person variation, which is not influenced by higher-level clustering.

The MVPA bouts distribution was overdispersed (the standard deviation was larger than assumed by the Poisson distribution), but the conditional likelihood for the negative binomial distribution required for fixed effects models is problematic (159). However, additional error terms in random and fixed effects models (148) and correction for school-level variation may help to address overdispersion by allowing for sources of variability not included in a standard Poisson model; further, estimates from cross-sectional Poisson and negative binomial models are virtually identical (166).

Buffer-based environment measures were individual-level variables. While census tracts or counties could comprise a third level in multi-level analysis, they are not nested within schools, our primary sampling unit and more important source of clustering. Data within census tracts and counties were unbalanced and sparse (132), and intraclass correlations were small ($\leq$0.03 within census tracts, $\leq$0.02 within counties).

Natural log transformations of environment measures linearized relationships with MVPA bouts in preliminary analysis. Because both the dependent and independent variables are logged, random and fixed effect model coefficients were interpreted as elasticities, or the percent change in MVPA bouts predicted from a 1% change in the independent variable. Time invariant individual-level variables were included in random effects models but are not estimated in fixed effects models. Time varying age was included in both models. Sex interactions with each environmental variable were tested; for comparability, interaction terms were retained if significant (Wald $p<0.10$) in the random or fixed effects model. Further interaction with residential relocation status (Objective 2b) in fixed effects models was examined by including significant (Wald $p<0.10$; lower order terms were retained) two- and three-way interactions between residential relocation status, sex, and each environment measure.

D. Results

Individual-level and environment characteristics are presented in **Tables 10** and **11**, respectively. 68.8% (SE 1.2%) of the analytical sample moved between Waves I and III (data not shown), and changes in environmental measures observed between Waves I and III (**Table 11**) provided sufficient variability for estimation of within-person effects, even for non-movers.

Random and within-person estimates indicated that with more pay facilities in the neighborhood, MVPA bouts were higher in males but lower in females (**Table 12**). MVPA bouts was negatively associated with crime and, for males in random effects models, with median household income. Landscape diversity, public facilities, and alpha index were unrelated to MVPA.

Random effects and within-person model coefficients were significantly different (Hausman $p<0.0001$), indicating that unexplained variation was correlated with the independent variables. Compared to random effect estimates, within-person elasticities were almost two times larger for pay facilities and, in males, over two times larger for crime rate. Negative random effects for median household income (in males) and crime (in females) were attenuated by the within-person estimator (**Table 12**).

Several associations varied by residential relocation status and sex (**Table 13**). Elasticities between MVPA bouts and crime were substantially larger in non-movers than movers, and landscape diversity was negatively associated with MVPA bouts only in male non-movers. Sex- and relocation-specific associations between public facilities and MVPA bouts varied in magnitude and direction, but none were statistically significant. Model coefficients and p-values corresponding to **Tables 12** and **13** are reported in **Tables 14** and **15**, respectively.

E. Discussion

We investigated longitudinal relationships between several built and socioeconomic environment characteristics and MVPA bouts in a prospective study of adolescents as they transition into young adulthood. To our knowledge, ours is the first study to examine built environment changes resulting from either residential relocation or changes around stationary residents. After adjusting for unmeasured time invariant characteristics, pay facilities were related to greater MVPA bouts in males, and higher crime was related to fewer MVPA bouts in males and females. Other associations were null or in the counter-intuitive direction. However, as described below, several methodological issues should be considered when interpreting our results and designing future longitudinal studies. In particular, comparison of random and within-person effects estimated conflict with the hypothesized direction of residential self-selection bias, and differences in within-person estimates by residential relocation status have implications for selection bias.

Built environment findings in the Add Health population

In contrast to a vast body of literature showing relatively consistent cross-sectional associations between the built environment and PA (16, 17), many cross-sectional (166) and random effects associations were weak or null in the Add Health population. Possible methodological explanations for these differences are discussed elsewhere (74, 162, 166) and include our nonspecific MVPA measure (154), buffer-based environment measures, and complications related to broad geographic variation and measurement of complex environments. Of course, null associations may reflect a lack of causal effects in adolescents, young adults, or the general population. Eid and colleagues also found weak longitudinal associations between urban sprawl and obesity in a national study population (73); however, we expected a stronger, more robust relationship with PA, a more proximal outcome. Ultimately, several naïve estimates (cross-sectional and random effects) were null or counterintuitive, so corresponding within-person estimates do not appear to result from adjustment for unmeasured time invariant characteristics.

Residential self-selection bias: upward, downward, or more complex?

Residential self-selection is typically presented as a positive confounder which may create or magnify associations between the built environment and PA (78, 79, 155). This characterization assumes that the hypothesized built environment promoters of PA are: (1) preferred by, or correlated with other neighborhood characteristics selected by people with higher PA levels (e.g., high performing schools), or (2) uncommon in areas selected by people with generally lower PA (e.g., lack of resources in affordable neighborhoods). These assumptions are supported by disproportionate allocation of recreation resources to more affluent neighborhoods (33, 167-169) and by attenuation of relationships between urban form and health-related outcomes by first difference models (73) and other adjustment methods (79, 96, 170).

However, some PA-promoting features may be less common in advantaged areas. For example, pay facilities may encourage PA but may be more common in commercial centers potentially selected less often by advantaged families (with higher PA levels). In this scenario, residential self-selection factors are negative confounders, consistent with stronger positive estimated within-person (versus random) effects of pay facilities on MVPA in males.

On the other hand, among females in this study, random effects models underestimated a *negative* within-person effect of pay facilities on MVPA bouts, suggesting that both pay facilities and self-selection factors operate in the opposite direction in females versus males. Alternatively, pay facilities may reflect another environment characteristic that more plausibly functions differently by sex. For example, pay facilities could reflect commercial activity and employment opportunity; through influences on perceived safety, females with sufficient resources may choose to live closer to work but encounter PA barriers related to dense development. Overall, these results suggest that residential self-selection may magnify or attenuate built environment-PA associations and involves multifaceted relationships among complex environments and sex-specific determinants of residential relocation and PA.

Furthermore, the direction of confounding has implications for the common concern that positive environment-PA associations may be due to selection of neighborhoods based on their activity-related amenities (79). Such a mechanism implies positive confounding, yet may not imply the absence of causal effects. That is, the selected amenities may help active individuals to maintain or increase their activity levels, formally defined as “effect in the treated” (171). Alternatively, placement of activity-related amenities in areas of greatest need implies "effect in the untreated." Investigation of such heterogeneous effects can help to understand the potential value of various built environment modification strategies.

Within-person estimators applied to a life transition period

Within-person estimators control for unmeasured characteristics that remain constant over time, a major strength for addressing residential selection factors, which are challenging, if not impossible, to measure accurately (155). However, within-person estimators do not control for time *varying* unmeasured characteristics. Further, null associations do not necessarily imply that bias has been fully addressed because residential self-selection may attenuate estimated relationships.

In the general population, residential relocation is typically triggered by events such as marriage, childbearing, or employment opportunities (161), which may lead to changes PA determinants, thus comprising time varying, potentially unmeasured confounders. Such events characterize the adolescent to young adulthood transition (172) but are rare in adolescence, providing insufficient variability to analyze as time varying measures and leaving a potentially large proportion of bias unaddressed. For example, magnification of negative crime-MVPA associations by within-person estimation in males could be explained by movement into urban centers (with higher crime) for employment, which may limit leisure time and thus PA. Additionally, unmeasured residential selection factors relevant to parents in Wave I but respondents in Wave III may contribute additional bias.

Further, random effects and within-person estimation assume constant causal effects between time points (160), a questionable assumption during periods of shifting PA determinants. Cross-sectional Wave I and III associations were different (166), though further evaluation of potential causal effects in adolescents versus young adults should be further investigated.

Similar residential relocation triggers occur throughout middle and later adulthood, with similar implications if they are not sufficiently measured. On the other hand, previous neighborhood characteristics are the most powerful predictors of subsequent neighborhood characteristics (82, 173), suggesting that key unmeasured characteristics remain constant, and may be shared between generations. Within-person effects are also particularly valuable for capturing theorized short-term effects (relative to time periods typically studied) (160). In sum, within-person estimation has limitations, but is a valuable approach for addressing residential self-selection bias.

Restriction by residential relocation status: an additional source of bias?

These issues suggest that restriction or stratification by residential relocation status may result in selection bias. In the adolescent to young adulthood transition, biases related to residential stability may be at least as strong as residential relocation: those remaining in the parent's home may do so for reasons also associated with health behaviors (e.g., care for young children, inability to find employment, or attendance at a local college), and neighborhoods change systematically (e.g., disadvantaged groups more often live in neighborhoods with less advantageous environment trajectories (82)). Indeed, individual characteristics differ between movers and non-movers in this and prior studies (174).

These hypothesized biases are consistent with comparisons by residential relocation status: greater landscape diversity (perhaps reflecting uneven development patterns) was related to fewer MVPA bouts only in male non-movers, and negative crime-MVPA associations were stronger in non-movers than movers. However, other environment-MVPA associations were similar by relocation status. Overall, associations were weaker or equivalent in movers than non-movers, but these patterns could be reversed in adulthood when residential stability is the norm. Future research should examine analytical methods to address residential relocation status without inducing selection bias through covariate adjustment or stratification (102).

Strengths and limitations

Limitations of this study include the methodological concerns raised above. Our definition of residential relocation may have misclassified respondents who moved a short distance or moved but returned to the same location by Wave III, and did not capture duration of residence. Second, changes in socioeconomic environment variables around a given location may have resulted from shifts in census boundaries between 1990 and 2000. Third, loss to follow-up and missing data could have led to biased estimates. Finally, the direction of effect remains ambiguous, as we examined simultaneous changes in the environment and in MVPA bouts.

However, our unique time-varying environment database captures residential locations of a large, nationally representative population followed through a critical life stage. By including six built and socioeconomic environment measures shown to adequately represent key environmental constructs, we addressed environmental confounders while avoiding collinearity (162). Our longitudinal data was used to address residential self-selection bias and explore bias related to residential relocation.

Conclusions

After controlling for residential self-selection bias using within-person estimators, MVPA bouts were related only to pay facilities in males and crime in males and females in the expected directions. Our results suggest that the magnitude and direction of residential self-selection bias can vary across environmental and individual characteristics. Within-person estimators are valuable for controlling for residential self-selection bias, but their application to major life transitions is complex. Further research and development of methods that can address predictors of residential relocation while simultaneously controlling for unobserved measures are needed.

Table 10. Sociodemographic characteristics in adolescence and young adulthood: descriptive statistics, by residential relocation status [mean/% (SE)][1]

	Male				Female			
	Total (n=6291)	Movers (n=4110)	Non-movers (n=2181)	p[2]	Total (n=6506)	Movers (n=4506)	Non-movers (n=2000)	p[2]
MVPA - Wave I (mean, bouts/week)	4.1 (0.1)	4.1 (0.1)	4.3 (0.1)	0.05	3.3 (0.1)	3.3 (0.1)	3.5 (0.1)	0.05
MVPA - Wave III (mean, bouts/week)	1.9 (0.0)	1.8 (0.1)	2.0 (0.1)	0.05	1.3 (0.0)	1.2 (0.0)	1.4 (0.1)	0.06
Age – Wave I (mean)	15.5 (0.1)	15.7 (0.1)	15.2 (0.1)	<0.001	15.3 (0.1)	15.4 (0.1)	14.9 (0.1)	<0.001
Age – Wave III (mean)	21.9 (0.1)	22.1 (0.1)	21.6 (0.1)	<0.001	21.7 (0.1)	21.8 (0.1)	21.3 (0.2)	<0.001
Parental household income – Wave I (mean, in 10,000's)	43.1 (1.5)	43.1 (1.7)	43.0 (1.4)	0.9	44.6 (1.6)	44.0 (1.7)	46.1 (1.8)	0.06
Race/ethnicity (%)				<0.001				0.009
White	68.3 (2.9)	71.0 (2.8)	62.8 (3.7)		70.0 (2.9)	71.7 (2.8)	65.8 (3.7)	
Black	15.6 (2.1)	15.5 (2.2)	15.8 (2.4)		14.9 (2.0)	14.9 (2.1)	15.1 (2.2)	
Asian	3.6 (0.7)	2.9 (0.6)	5.1 (1.2)		3.3 (0.7)	2.9 (0.6)	4.1 (1.1)	
Hispanic	12.4 (1.8)	10.6 (1.6)	16.2 (2.7)		11.8 (1.8)	10.5 (1.6)	15.0 (2.8)	
Highest parental education (%)				0.09				0.8
<High school	14.7 (1.4)	13.7 (1.3)	16.9 (1.9)		15.2 (1.4)	15.3 (1.4)	14.9 (1.8)	
High school/GED	31.5 (1.3)	31.8 (1.5)	31.0 (1.6)		32.4 (1.2)	31.9 (1.4)	33.5 (1.6)	
Some college	28.5 (1.0)	28.5 (1.1)	28.4 (1.4)		26.9 (0.9)	27.0 (1.1)	26.6 (1.4)	
College or greater	25.3 (1.7)	26.1 (1.9)	23.7 (1.9)		25.6 (1.7)	25.8 (1.8)	24.9 (1.9)	
Region (%)				0.008				0.001
West	15.6 (1.4)	15.4 (1.6)	16.0 (2.0)		16.4 (1.4)	15.7 (1.5)	18.2 (2.3)	
Midwest	30.2 (2.3)	31.8 (2.8)	26.7 (2.2)		32.5 (2.6)	33.8 (2.9)	29.5 (3.0)	
South	39.7 (1.8)	40.5 (2.2)	38.1 (2.5)		36.7 (1.8)	38.7 (2.2)	32.0 (2.4)	
Northeast	14.5 (0.9)	12.2 (1.1)	19.2 (1.9)		14.3 (1.0)	11.8 (1.3)	20.3 (2.1)	

[1] National Longitudinal Study of Adolescent Health, Wave I (1994-95) and Wave III (2001-02). Residential relocation defined as >1/4 mile Euclidean distance between Wave I and Wave III residential locations

[2] Test of difference between movers and non-movers in males and females determined from adjusted Wald tests (continuous variables) and design-based F-tests (categorical variables), weighted and corrected for clustering

GED, Graduate Equivalency Degree; MVPA, moderate-vigorous physical activity (bouts per week); SE, standard error

Table 11. Baseline and changes in built and socioeconomic environment characteristics between adolescence and young adulthood: descriptive statistics, by residential relocation status[1]

Measure (geographic area[3])	Movers (n=8,616) mean (SE)	Movers (n=8,616) median (IQR)	Non-movers (n=4,181) mean (SE)	Non-movers (n=4,181) median (IQR)	p[2]
Landscape diversity (1k)					
Baseline	0.53 (0.01)	0.58 (0.43, 0.67)	0.54 (0.01)	0.58 (0.46, 0.67)	0.3
Change (Wave III-Wave I)	-0.01 (0.01)	-0.02 (-0.15, 0.12)	-0.04 (0.01)	-0.03 (-0.14, 0.06)	0.002
Pay facilities, count/10k population (3k)					
Baseline	2.65 (0.23)	1.71 (0.00, 3.74)	2.42 (0.20)	1.61 (0.34, 3.40)	1.0
Change (Wave III-Wave I)	1.97 (0.20)	1.36 (-0.06, 3.97)	2.10 (0.23)	1.02 (0.06, 3.04)	0.07
Public facilities, count/10k population (3k)					
Baseline	0.30 (0.05)	0.00 (0.00, 0.29)	0.28 (0.05)	0.00 (0.00, 0.31)	0.7
Change (Wave III-Wave I)	0.32 (0.05)	0.00 (0.00, 0.53)	0.18 (0.05)	0.00 (0.00, 0.30)	0.02
Alpha street connectivity (1k)					
Baseline	0.31 (0.02)	0.30 (0.22, 0.38)	0.33 (0.02)	0.30 (0.22, 0.38)	0.4
Change (Wave III-Wave I)	-0.002 (0.019)	-0.006 (-0.097, 0.076)	-0.018 (0.016)	-0.003 (-0.023, 0.012)	0.5
Median household income, $1,000's (CT)					
Baseline	38.9 (1.3)	36.9 (27.4, 46.9)	41.2 (1.3)	39.7 (28.7, 52.0)	0.002
Change (Wave III-Wave I)	0.17 (0.99)	1.88 (-7.92, 9.83)	2.40 (0.35)	2.48 (-1.53, 5.80)	0.03
Crime, per 100,000 population (Co)					
Baseline	5,298 (247)	5,369 (3,072, 6,975)	5,546 (238)	5,528 (3,647, 6,459)	0.005
Change (Wave III-Wave I)	-553 (170)	-676 (-1,944, 309)	-878 (161)	-1,081 (-1,645, -350)	0.005

[1] National Longitudinal Study of Adolescent Health, Wave I (1994-95) and Wave III (2001-02). Residential relocation defined as >1/4 mile Euclidean distance between Wave I and Wave III residential locations

[2] Test of difference between movers and non-movers in males and females determined from adjusted Wald tests (continuous variables) and design-based F-tests (categorical variables), weighted and corrected for clustering. statistical tests were performed on natural log-transformed pay facilities, public facilities, and median household income to correct for skewness.

[3] Geographic areas consistent with the strongest associations with moderate to vigorous physical activity (bouts per week) in a previous analysis were selected for each variable.

1k and 3k, radius of Euclidean neighborhood buffer in kilometers (k); CT, Census Tract; Co, County; IQR, Interquartile Range; SE, standard error

Table 12. Random and within-person effect estimates[1] of built and socioeconomic environment characteristics on MVPA between adolescence and young adulthood [elasticity (95% CI)]

	Random Effects[2]	Within-Person Effects[2]
Landscape diversity	-0.004 (-0.024, 0.016)	-0.025 (-0.051, 0.002)
Pay facilities (count/10k population)		
Males	0.024 (0.006, 0.042)*	0.047 (0.023, 0.071)*
Females	-0.026 (-0.045, -0.007)*[3]	-0.046 (-0.072, -0.019)*[3]
Public facilities (count/10k population)	0.006 (-0.024, 0.036)	-0.008 (-0.045, 0.029)
Alpha Index	-0.009 (-0.113, 0.095)	0.002 (-0.152, 0.155)
Median household income[4]		
Males	-0.042 (-0.077, -0.008)*	0.005 (-0.046, 0.056)
Females	0.025 (-0.012, 0.061)[3]	-0.051 (-0.104, 0.002)
Crime (per 100,000 population)		
Males	-0.071 (-0.106, -0.037)*	-0.165 (-0.209, -0.120)*
Females	-0.065 (-0.102, -0.029)*	-0.020 (-0.071, 0.030)[3]

[1]National Longitudinal Study of Adolescent Health, Wave I (1994-95) and Wave III (2001-02), n=12,797.
[2] Estimated from Poisson random and fixed effects regression modeling MVPA as a function of natural log-transformed built and socioeconomic environment measures. Fixed effects models adjusted for time varying age and do not estimate parameters for time invariant individual-level variables; random effects models additionally adjusted for time invariant sex, race, parental income and education, and region.
[3]Statistically significant (p<0.1) interaction with sex; sex interactions were included if significant in either random or fixed effects models.
[4]Wave I values inflated to 2000 U.S. dollars
CI, Confidence Interval; MVPA, moderate-vigorous physical activity (bouts per week)
*Statistically significant elasticity (p<0.05)

Table 13. Variation in within-person effect estimates[1] of built and socioeconomic environment characteristics on MVPA between adolescence and young adulthood by residential relocation status,[2] [elasticity (95% CI)]

		Movers	Non-movers
Landscape diversity			
	Males	0.006 (-0.033, 0.044)	-0.143 (-0.219, -0.067)*
	Females	-0.018 (-0.062, 0.026)	-0.033 (-0.124, 0.059)
Pay facilities (count/10k population)			
	Males	0.048 (0.023, 0.073)*	
	Females	-0.050 (-0.077, -0.022)*	
Public facilities (count/10k population)			
	Males	-0.042 (-0.097, 0.012)	0.032 (-0.076, 0.139)
	Females	0.037 (-0.023, 0.098)	-0.090 (-0.232, 0.052)
Alpha Index		-0.006 (-0.159, 0.148)	
Median household income[3]		-0.023 (-0.060, 0.014)	
Crime			
	Males	-0.143 (-0.190, -0.096)*	-0.234 (-0.317, -0.151)*
	Females	-0.012 (-0.065, 0.041)	-0.103 (-0.190, -0.016)*

[1]National Longitudinal Study of Adolescent Health, Wave I (1994-95) and Wave III (2001-02), n=12,797. Estimated from Poisson fixed effects regression modeling MVPA as a function of natural log-transformed built and socioeconomic environment measures, adjusted for time varying age; fixed effects models do not estimate parameters for time invariant individual-level variables.
[2]Residential relocation was defined as greater versus less than ¼ mile Euclidean distance (Mover (n=8,616) and Non-mover (n=4,181), respectively) between Wave I and III respondent locations. 3- and 2-way interactions between sex, residential relocation status, and environment measures were included if statistically significant ($p<0.1$); if a 3-way interaction was significant, all corresponding 2-way interactions were retained.
CI, Confidence Interval; MVPA, moderate-vigorous physical activity (bouts per week)
[3]Wave I values inflated to 2000 U.S. dollars
*Statistically significant elasticity ($p<0.05$)

Table 14. Model coefficients and significance for random and within-person effect estimates[1] of built and socioeconomic environment characteristics on MVPA between adolescence and young adulthood

	Random effects[2]		Within-person effects[2]	
	Coefficient (95% CI)	p	Coefficient (95% CI)	p
Landscape diversity	-0.004 (-0.024, 0.016)	0.69	-0.025 (-0.051, 0.002)	0.06
Pay facilities (count/10k population)	0.024 (0.006, 0.042)	0.01	0.047 (0.023, 0.071)	<0.001
Female*Pay facilities[3]	-0.050 (-0.073, -0.027)	<0.001	-0.093 (-0.127, -0.060)	<0.001
Public facilities (count/10k population)	0.006 (-0.024, 0.036)	0.70	-0.008 (-0.045, 0.029)	0.67
Alpha street connectivity	-0.009 (-0.113, 0.095)	0.86	0.002 (-0.152, 0.155)	0.98
Median household income[4]	-0.042 (-0.077, -0.008)	0.02	0.005 (-0.046, 0.056)	0.84
Female*Median household income[3]	0.067 (0.024, 0.110)	0.002	-0.056 (-0.129, 0.017)	0.13
Crime (per 100,000 population)	-0.071 (-0.106, -0.037)	<0.001	-0.165 (-0.209, -0.120)	<0.001
Female *Crime[3]	0.006 (-0.030, 0.042)	0.73	0.144 (0.079, 0.210)	<0.001

[1] National Longitudinal Study of Adolescent Health, Wave I (1994-95) and Wave III (2001-02), n=12,797. Corresponds to estimates reported in **Table 12**.
[2] Estimated from Poisson random and fixed effects regression modeling MVPA as a function of natural log-transformed built and socioeconomic environment measures. Fixed effects models adjusted for time varying age and do not estimate parameters for time invariant individual-level variables; random effects models additionally adjusted for time invariant sex, race, parental income and education, and region.
[3]Sex interactions were included if significant (p<0.1) in either random or fixed effects models.
[4]Wave I values inflated to 2000 U.S dollars
CI, Confidence Interval; MVPA, moderate-vigorous physical activity (bouts per week)

Table 15. Model coefficients and significance for within-person effect estimates[1] of built and socioeconomic environment characteristics on MVPA between adolescence and young adulthood by residential relocation status[2]

	Coefficient (95% CI)	*P*
Landscape diversity	-0.143 (-0.219, -0.067)	<0.001
Mover*Landscape diversity	0.149 (0.064, 0.234)	0.001
Female*Landscape diversity	0.110 (-0.008, 0.228)	0.07
Mover*Female*Landscape diversity	-0.134 (-0.266, -0.003)	0.04
Pay facilities (count/10k population)	0.048 (0.023, 0.073)	<0.001
Female*Pay facilities	-0.098 (-0.133, -0.063)	<0.001
Public facilities (count/10k population)	0.032 (-0.076, 0.139)	0.56
Mover*Public facilities	-0.074 (-0.193, 0.045)	0.22
Female*Public facilities	-0.122 (-0.298, 0.054)	0.18
Mover*Female*Public facilities	0.202 (0.010, 0.394)	0.04
Alpha street connectivity	-0.006 (-0.159, 0.148)	0.94
Median household income[3]	-0.023 (-0.060, 0.014)	0.23
Crime (per 100,000 population)	-0.234 (-0.317, -0.151)	<0.001
Mover*Crime	0.091 (0.007, 0.175)	0.03
Female*Crime	0.131 (0.065, 0.197)	<0.001

[1] National Longitudinal Study of Adolescent Health, Wave I (1994-95) and Wave III (2001-02), n=12,797. Corresponds to estimates reported in **Table 13**. Estimated from Poisson fixed effects regression modeling MVPA as a function of natural log-transformed built and socioeconomic environment measures. Fixed effects models adjusted for time varying age and do not estimate parameters for time invariant individual-level variables.

[2]Residential relocation was defined as greater versus less than ¼ mile Euclidean distance (Mover (n=8,616) and Non-mover (n=4,181), respectively) between Wave I and III respondent locations. 3- and 2-way interactions between female sex, residential relocation, and environment measures were included if statistically significant (p<0.1); if a 3-way interaction was significant, all corresponding 2-way interactions were retained.

[3]Wave I values inflated to 2000 U.S. dollars

CI, Confidence Interval; MVPA, moderate-vigorous physical activity (bouts per week)

VI. Synopsis

The overall purpose of this research was to better understand whether "active communities support activity, or support active people." That is, we sought to estimate the extent to which built environment characteristics typically used to characterize "active communities" influence physical activity. Because the goal of built environment research is to inform policies and strategies intended to promote physical activity and health through community design, elucidation of and correction for major threats to causal inference are critical but, to date, generally overlooked objectives. Ultimately, building strong evidence for causality is needed to not only build political support for policies and funding, but also, once support is won, to reduce the possibility that vast resources dedicated for community infrastructure changes will fail to result in corresponding improvements in physical activity levels and related public health outcomes.

Unfortunately, the issues that make causal conclusions so important also make randomized controlled trials, the strongest evidence for causal inference, generally infeasible. Randomized assignment of built environment changes faces political barriers and high financial costs, and randomized assignment of families to different neighborhoods involves practical and ethical concerns. Further, such randomized strategies and analogous natural experiments involve self-selected samples, for whom in this context we might expect systematic loss to follow-up, with associated concerns about generalizability and selection bias, respectively. While randomized trials and natural experiments are important for estimating causal effects, much can be learned from observational studies. We therefore focus on existing and potential contributions, as well as opportunities for improvement, of observational research.

This research addressed several threats to causal inference in observational built environment research stemming from the complexity of the environment and discretion of individuals and households over where they live. Specifically, we explored complex patterning in the environment, estimated the degree to which associations between physical activity and built environment characteristics are confounded by other aspects of the built and socioeconomic environments, and examined the magnitude and direction of residential self-selection bias after applying one adjustment strategy.

In the following sections, we review our findings, how they contribute to understanding of these issues, and future research needed to address the limitations in our studies and strengthen causal inference in built environment research. We end by discussing a series of policy-relevant knowledge gaps and corresponding research strategies using Add Health and similar study populations as well as complimentary approaches.

A. Do active communities support activity? But first, what is an active community?

The concepts of "active communities," "healthy places," and their converse, "urban sprawl" have intuitive appeal, but are difficult to quantify. Neighborhood environments are tremendously complex, involving inter-relationships between commonly measured built and sociodemographic aspects, less quantifiable markers of social disorder and cohesion, quality and aesthetic appeal of physical attributes, cultural and attitudinal influences of the broader community, and potentially unmeasureable aspects such as attitudes of leaders in various social hierarchies.

In this study, we investigated complexities in the neighborhood environment using a large set of commonly used built and sociodemographic environment characteristics. We describe how these environment features are inter-related and discuss implications for measurement and future research needs.

Review of environment construct findings

Our first step was to use factor analysis to identify natural patterning among existing, commonly used measures of the built and socioeconomic environments. Factor analysis served two purposes: first, as a data reduction technique that allowed us to examine inter-relationships among physical activity and constructs underlying the broad range of built and socioeconomic environment variables available in our environment database; second, to reveal environment patterning and guide the selection of a reduced set of measures for subsequent analyses. This is the first study to conduct factor analysis on both physical-activity related facilities and walkability measures. We identified three built environment constructs (homogeneous landscape and two development intensity constructs) and two socioeconomic environment constructs (advantaged economic environment and disadvantaged social environment).

The two development intensity constructs were characterized by high population and intersection density and distinguished by for-pay versus public facilities, which were differentially related to both physical activity and to socioeconomic aspects of the environment. We found that several dimensions of land cover pattering (diversity, complexity, and uniformity) represented a single landscape pattern construct. Socioeconomic environment constructs were consistent with our hypothesized dimensions: advantaged economic environment (high median household income, low neighborhood poverty, high education) and social variables typically associated with poorer health (high proportion of racial/ethnic minorities and renters, high crime rate). Finally, correlations between these environments appear to confound estimated associations with MVPA, demonstrating the complexity of potential environmental influences on physical activity.

In the following sections, we discuss the implications of these findings for interpretation of previous, current and future research findings, and analytical strategies for future studies. We also describe research opportunities to advance measurement of the environment and address related limitations of our research, primarily regarding the scope of measures included and potential proxy effects.

Implications for existing environment measures

Factor analysis findings have implications for studies analyzing environment characteristics representing our constructs as single measures. In particular, the intensity constructs reflect population density, intersection density, and physical activity facilities, each examined as single measures in other studies. We also showed that physical activity was similarly associated with the environment constructs and single, representative indicator measures. Therefore, while intersection density is often used as an indicator of street connectivity and physical activity facility counts are assumed to represent active recreation opportunities, both may act as proxies for general development intensity.

By calculating pay and public physical activity facilities counts scaled by population, we attempted to separate physical activity facilities, the characteristic of interest, from population density. Other representative indicator measures which replicated associations with physical activity included the Simpson's Diversity Index (representing the landscape homogeneity construct), median household income (advantaged economic environment), and crime rate (social environment characteristics typically associated with poorer health).

Insights gained from measured environment characteristics. While our study revealed multidimensional constructs underlying several environment measures, these constructs appear to represent additional complexities in the environment. Even among measured environmental characteristics, we found that the socioeconomic environment influenced several of the associations between built environment constructs and physical activity. For example, in cross-sectional analysis in females, adjustment for the social environment magnified the positive association between public facilities intensity and physical activity: higher public facilities intensity construct scores were related to higher physical activity (albeit not significantly) only after adjusting for social environment, presumably because public facilities were more common in disadvantaged areas.

Our assessment of confounding by other measured environment characteristics suggests that inconsistent findings in existing literature may, in part, result from differences in control variables across studies. Many studies only control for individual-level characteristics, others for one or two environment characteristics. The immediate implication is that studies should control for a wide range of potential confounders (conceptually or empirically justified), to the extent that collinearity is avoided.

Possible influences of unmeasured characteristics. Our multidimensional constructs may also reflect additional, *unmeasured* environmental characteristics. In particular, our intensity constructs are consistent with previous "walkability" measures, except that physical activity facilities in our study may represent land use mix or retail floor area in prior studies. Therefore, it is possible that physical activity facilities could represent the degree of commercial activity (pay facilities) or public services (public facilities). It is also possible that development intensity reflects degree of urbanicity, another intuitive yet difficult to define concept. Similar explanations could be applied to any built environment measure used in this or other studies.

The ambiguity of existing environment measures suggests two simultaneous, interacting trajectories of research. First, as described in the next section, identification of causal agents of behavior change requires a better understanding of underlying mechanisms and the "real world" environments represented by existing measures. Second, existing environment measures, which appear to represent more complex constructs associated with physical activity in many study populations and settings, can be used to investigate various biases and statistical adjustment methods (described in Section VI.B).

Distinguishing proxies and causal agents: the start of a long journey?

A basic requirement for estimating causal effects is valid and reliable measurement of hypothesized outcomes and exposures. In this study, measurement of physical activity has developed over half a century of research. In contrast, built environment research is relatively young and its associated measures are, as discussed above, correspondingly crude. While some of our environment measures have been used for several decades, they were originally developed to study other outcomes (e.g., landscape diversity effects on wildlife migration patterns) and have only recently been used to study urban form and physical activity.

On the other hand, physical activity measurement began much like the current state of health-related neighborhood measurement. For example, higher coronary heart disease risk in bus, trolley, and train drivers (who sat down during the workday) compared to conductors (who walked up and down the aisles) provided some of the first evidence that physical activity may protect against heart disease (175). In retrospect, these early indicators of physical activity were crude, but they are similar to neighborhood environment measures in that they compare naturally occurring patterning to an outcome of interest and, more optimistically, will continue to evolve with future research. Key areas of future research include:

Development of a conceptual framework. While physical activity measurement remains challenging, physical activity measures can be validated within a framework of known physiologic responses established in controlled experimental settings. In contrast, the built and socioeconomic environments are hypothesized to influence behavior within newly developing frameworks which may, in fact, depend on the constraints and freedoms of free-living individuals. That is, choices such as auto versus bike transit are influenced by a complex web of factors including time and budget constraints (176, 177), preferences, and perhaps community design; without time and budget constraints, we expect that the role of community design in such decisions would change dramatically. Such complexities, along with conflicting disciplinary norms and perhaps distraction by the multitude of other methodological challenges may explain the lack of progress in establishing a working conceptual framework.

A conceptual framework describing theorized mechanisms of influence on physical activity can guide validation and improvement of environment measures. Within the socio-ecologic framework (Section II) commonly used in public health-based built environment research, community-level factors such as neighborhood amenities may influence individual-level factors such as perceived barriers and facilitators to various types of physical activity behaviors, which may in turn influence physical activity. However, current measures of the neighborhood environment are remarkably *unrelated* to perceptions of the environment. Furthermore, such theories lack specificity with regard to *how* the environment influences behavior. For example, street connectivity is theorized to influence behavior by providing more route options, hence reducing distance and travel time. Do we hypothesize that this mechanism operates through deliberate decisions (I walk to the store because there is a short and direct route to get there), subconscious choice (I walk to the store because it seems easier than driving), or creation of other barriers (I walk to the store because there are too many stop lights and it is too difficult to park)? As described by King and colleagues (178), sociological theories provide more specific, testable mechanisms. For example, the theory of physical incivilities posits that broken windows and similar visual cues connote a feeling of disorder, which will discourage use of public spaces such as sidewalks and parks (178). However, existing sociological theories appropriately focus on social, rather than built aspects of the environment.

In the absence of a conceptual framework, neighborhood environment measures are implicitly validated against the outcomes of interest. The result is a collection of environment measures which are associated with physical activity, without understanding their mechanisms or in some cases of what is being measured. Development of a conceptual framework may be facilitated by a better understanding of how our environment measures correspond with the "real world" environment indicated by more detailed objective data, and research using perceived environment measures and qualitative data.

Comparison to detailed objective data. Environmental measures can also be collected with neighborhood audits, in which researchers collect information via direct observation (walking or driving through the neighborhood). While neighborhood audits add an element of subjectivity on the part of the observer, they use standard protocols and audit tools and minimize correlated errors that may result when respondents report both environments (perceived measures) and behaviors. Furthermore, neighborhood audits provide detail about the environment not apparent from GIS data such as sidewalks, tree cover, aesthetics, social disorder (e.g., graffiti, poorly maintained properties), and quality of facilities. Neighborhood audits are labor intensive and thus conducted in small geographic areas, but exploration of how GIS-based measures correspond with audit-based measures can help to understand what each GIS-measure represents. For example, our above described hypothesis that pay facilities may reflect commercial activity and perhaps busy, unpleasant streets could be tested with neighborhood audit data.

In preliminary analysis, we performed confirmatory factor analysis (CFA) on a limited set of environmental variables. The resulting poor model fit or failure to converge may be attributed to insufficient characterization of the environment. CFA requires extensive knowledge of factor structure and relevant indicators which have not yet been established in the context of built of socioeconomic environments. Perhaps neighborhood audit data can help to gain the requisite understanding of these details, making it possible to conduct CFA in other populations.

Beyond descriptive studies, neighborhood audit and GIS data can be used together to investigate independent, confounding, and moderating influences on physical activity. Suppose sidewalks are more common in areas with well-connected streets but encourage leisure walking regardless of street connectivity. Sidewalks would thus be an independent predictor of walking not captured in GIS-based analysis, and could confound associations with physical activity. Further suppose that street connectivity influences walking for transportation only if sidewalks are present; in the absence of neighborhood audit data, GIS-based research would underestimate associations between street connectivity and physical activity. Existing and future studies using audit-based measures are valuable in their own right, but can also help to interpret GIS measures.

Self-reported environments and qualitative research. As noted above, the socio-ecologic framework for built environment influences on physical activity theorizes that the built environment acts through perceptions of the environment, such as alteration of perceived barriers and facilitators to physical activity. While objective and perceived measures are relatively uncorrelated, this framework may still be viable. For example, perceived safety may be influenced by unrecorded verbal harassment or bullying, but uncorrelated with objective crime rate. That is, the objective measure may be insufficient. Understanding how relationships between perceived and objective environment measures vary across subgroups may help to generate hypotheses explaining their discordance.

Insights may also be gained from qualitative research (e.g., focus groups or in-depth interviews) in which neighborhood residents describe how they are impacted by their neighborhood environment. Qualitative data can provide understanding of decision making processes and the influences of less tangible aspects of the environment. Built environment influences may act through unconscious shifts in perceptions influenced by individual circumstances that might not captured in a perceived environment measure. Perceived and qualitative data can help to improve objective measures, develop and improve a conceptual framework, and provide initial insights into mechanisms and how perceived barriers and facilitators can be altered (e.g., shifts in cycling culture) within a given objective environment.

Of course, all of these data cannot be collected for every study, or even a single population-based study. But as a field, using a wide range of data and approaches can provide a more complete description of the environment, identify systematic biases, improve our measures and interpretation, and push us closer to identifying causal agents and mechanisms.

B. Do active communities support activity?

Residential self-selection bias is one of the most common criticisms of built environment research. It can be viewed as confounding by unmeasured individual characteristics related to both neighborhood selection and to physical activity. It is distinct from confounding by other environmental characteristics because it involves an inherently temporal sequence: if individuals were randomly assigned into neighborhoods, we could conceivably estimate causal effects using cross-sectional data if environmental confounders were adequately measured and controlled for in analysis, while longitudinal data is needed to adequately study residential self-selection bias.

In the vast majority of existing studies, the exposure and outcomes were measured at the same time and could be easily reversed, estimating characteristics and behaviors (exposures) of people who choose certain neighborhood features (outcome), rather than the influence of neighborhood features (exposure) on individual behaviors (outcome). Instead, we leveraged a unique longitudinal dataset to estimate changes in physical activity in response to changes in built and socioeconomic environment characteristics using within-person estimation.

Review of findings

After controlling for measured and time invariant unmeasured characteristics using within-person estimators (fixed effects models), physical activity was higher with greater physical activity pay facilities in males and lower with increased crime rate; other associations were null or in the counter-intuitive direction. Comparison of within-person and random effects estimates suggested that residential self-selection can bias associations toward the null, as opposed to their typical characterization as positive confounders in prior discussions (79, 96, 155). Additionally, differences in associations between built environment features and physical activity by residential relocation status suggest that restriction of analyses to movers only, as performed in prior studies, may induce selection bias.

In the following sections, we discuss the contributions of our research to understanding of residential self-selection bias and next steps that can address limitations in our study. Key limitations included complications related to the studying changes within the adolescent to young adult transition and lack of adjustment for time varying unmeasured characteristics.

What have we learned?

While within-person estimation of longitudinal effects of the built environment on physical activity is a major step forward, more must be learned to better understand "if active communities support activity." However, our methodological findings suggest additional research questions and can inform future longitudinal studies.

In particular, our finding that residential self-selection may bias associations toward or away from the null challenges common characterization of this problem. Understanding that residential self-selection can attenuate associations may impact framing of the problem and resulting adjustment techniques. For example, adjustment for neighborhood and travel preferences assumes that residential self-selection will create or magnify positive associations. It may also influence conclusions made by investigators, such as Eid and collegues (73), who concluded that attenuation to the null indicated that first differences models completely adjusted for residential self-selection bias. Additionally, evidence that residential relocation status may be either an effect modifier or a source of bias helps to interpret existing study findings and underscores the importance of time-varying environmental data.

The challenges related to the transition stage of the Add Health populations helped to clarify issues relevant to studies of any population. Specifically, we could not control for time varying characteristics related to major life transitions such as marriage and children due to lack of variability in the adolescent time point. However, even without this sparse data problem, the determinants and consequences of transition events are likely to change from adolescence to young adulthood; that is, their meaning changes between life stages. While this issue may be more pronounced in the adolescence to young adulthood transition, the meaning of life transition events may continue to shift throughout adulthood. Similarly, as discussed in a previous chapter, time-varying unmeasured confounders are not addressed by within-person estimation and may be particularly influential during the adolescence to young adulthood transition, but can also be problematic in other life stages.

Some important next steps and complementary research strategies

It will be valuable to replicate our within-person estimation methods in adult populations in which life transition events can be included as time-varying covariates, and in populations yielding stronger cross-sectional effects which will better indicate the influence of controlling for unmeasured time invariant characteristics. Explicit investigation of mobility patterns may help to estimate the direction and magnitude of bias and to identify important adjustment variables.

Alternative study designs are also valuable for controlling for residential selection bias. For example, natural experiments already underway have the advantage of testing relatively modest, feasible changes to the environment such as installation of a walking path or construction of a new planned community. On the other hand, investigation of the influences of larger scale characteristics may rely on observational studies.

Additionally, the following alternative adjustment methods can be used to adjust for time varying unmeasured confounders:

Instrumental Variables. Structural equations modeling accommodates endogenous variables by explicitly modeling error common to multiple equations of interest (e.g., determinants of residential selection and physical activity). One example is instrumental variables analysis, a traditional econometric approach to controlling for endogeneity. An instrument is a variable that (i) has a causal effect on the exposure, (ii) affects the outcome only through the exposure, and (iii) does not share common causes with the outcome (unobserved characteristics correlated with the instrument and the outcome) (179). While instrumental variables can be powerful in controlling for endogeneity due to unobserved characteristics, their effectiveness depends on the validity of the instrument. Violation of criteria ii or iii will introduce bias to the association between the exposure and outcome, which will be amplified if the instrument is only weakly associated with the exposure. While the Sargon test assesses the validity of the instrument, others note that criteria ii and iii are not empirically verifiable (179, 180).

In sum, the instrumental variables approach is promising, but introduces the challenge of identifying a valid instrument. Even if a potential instrument is not *explicitly* related to travel behavior (or physical activity), it may not be valid due to complex inter-relationships between various environmental characteristics and preferences, behaviors, and sociodemographics. Other researchers have suggested school quality, which may be an important driver of residential selection, or time lagged environmental variables as potential instruments.

Full information maximum likelihood (FIML). Other forms of structural equations modeling include FIML methods such as factor and path analysis, which can simultaneously test multiple pathways. Cross-sectional studies on the relationships among residential preferences, neighborhood characteristics, and behavior, show that attitudes and preferences are the strongest correlates of behavior and neighborhood environment (170, 181). Given the limitations of self-reported preferences, these findings are unsurprising. However, FIML will accommodate longitudinal data and is a powerful tool for testing dynamic pathways among individual characteristics, mobility, and neighborhood environments at multiple time points. This approach is underway by colleagues at the Carolina Population Center (155).

What if active communities support active people, too?

In addition to estimation of causal effects of the built environment on physical activity in the population, the following two questions illustrate another distinction: (1) among those who move into active communities, do features in that community help those individuals to be more active? And (2) among those who do not live in active communities, would they be more active if they lived in an active community? In other words, there may be heterogeneous effects, defined respectively as "effect in the treated" (in individuals with characteristics similar to those who live in active communities) and "effect in the untreated" (in individuals with characteristics similar to those who do not live in active communities) (171).

The concepts of effects in the treated and untreated are linked to the alternative adjustment methods described above and in previous sections. Instrumental variables estimate the effect in the treated (182). Additionally, while propensity score methods can only adjust for observed characteristics, they accommodate estimation of effects in various groups. In essence, propensity score-derived weights can be constructed to create a psuedopopulation with covariate patterns reflecting the treated, untreated, or total population (183, 184).

These distinctions have several policy implications. The typical characterization of residential self-selection bias is that individuals choose to live in neighborhoods which support their existing activity levels. However, if the activity-related amenities help those individuals to maintain or increase their physical activity levels (effect in the treated), meeting demand with *affordable* options for such environments may increase physical activity levels in the population. The most beneficial result to public health is an effect in the untreated, which is implied by efforts to increase activity-supportive amenities in communities in which physical activity levels are low.

C. Reconnecting with policy, people, and the real environment: some questions for future research

We addressed three questions regarding major vulnerabilities to causal inference in observational built environment research: (1) How do we adequately measure complex environments using quantitative data? (2) What environment features influence physical activity: built environment characteristics examined in existing research, or other correlated environmental characteristics? (3) To what extent can observed relationships between the environment and physical activity be explained by systematic sorting of individuals and households into different types of neighborhoods? Our research makes progress and suggests additional avenues of study that will provide more complete answers, but these are the first of many questions requiring answers before built environment research can provide practical guidance to policymakers.

Once we can identify environmental characteristics with sufficient evidence of causal effects on physical activity behaviors, many additional issues may be important for creation of policies within the realities of constrained resources and political environments. Understanding of such issues will require more nuanced measurement, study design, and analytical methods, and will benefit from more collaborative work among academic disciplines, planners, and policymakers. In the following sections, we discuss some key policy-relevant knowledge gaps, initial insights provided by and additional limitations of our current research, and opportunities for future studies using similar and complementary research methods.

What built environmental modifications should be made first (or simultaneously)?

In the context of limited resources, policymakers working to improve community design must target specific built environment characteristics among the wide array studied in existing research.

Relative strength of effects. Knowledge of the relative strength of effects among built environment characteristics will help to inform these decisions. The current study estimated elasticities, or the percent change in physical activity in response to 1% change in a given built environment measure, which provides a comparable metric across environmental characteristics measured on very different scales. While this is an improvement over estimates corresponding to changes in physical activity in response to 1 unit changes in environment measures, some built environment features are more easily modifiable than others. Effect estimates that incorporate resources required for modification of any given characteristic may provide valuable supplemental information, perhaps converting into changes in physical activity in response to a dollar value assigned to certain amount of environmental change.

Interactive effects. Another consideration is whether modifications to some built environment features should occur together, either to capitalize on synergistic effects that can maximize physical activity changes with a given investment, or to address environment features that only affect physical activity together. Our factor analysis results demonstrated strong correlations between built and socioeconomic environment measures, and the resulting factors suggest that the relationships with physical activity may occur through multidimensional constructs. That is, combinations of environment features, rather than any single characteristic, may influence behavior. Testing of interactions among the built and socioeconomic characteristics examined in this study would be an important next step. Assessment of whether single characteristics (e.g., crime rate, as opposed to the social environment construct) are independently related to physical activity may require stratified sampling strategies which compare neighborhoods similar on all but the characteristic(s) of interest (e.g.,(185)). Existing and future work investigating interactive effects between built and socioeconomic characteristics with aspects of the social and cultural environments (e.g., social norms, social support) is also an important element of this question.

How dramatic must built environmental modifications be to achieve a meaningful change in physical activity in the population?

A related issue is that a more complete understanding of expected changes in physical activity with various degrees of built environment changes will help to determine how drastic modifications to the built environment must be in order to expect change in behavior.

Dose response. Different dose response relationships imply various policy strategies and should thus be examined carefully: linear effects would suggest that incremental changes, which may be most politically and economically feasible, may be effective; saturation effects would imply a point of diminishing returns, of particular interest because we expect that costs rise exponentially with more extreme community design changes; threshold effects might indicate that a certain minimum investment is required for any amount of behavior change; and curvilinear effects could imply an optimal level for promoting physical activity. Many studies use categorical built environment variables, and among those using continuous measures, most appear to assume, rather than test for, linear dose response relationships.

In this study, we examined natural log-transformed environmental variables, which served to linearize their relationships with physical activity, thereby simplifying the longitudinal analysis by allowing us to examine changes in continuous variables and to calculate readily interpretable elasticities. Linearization by log transformation implies a saturation effect, but additional examination with more flexible models such as splines would be valuable. Log transformations also minimized the influence of large values of environment measures, but these values may be interesting in their own right, warranting further examination of whether they exert specific effects and of the environments in which they are found.

Regional versus neighborhood scale. A broader issue is the scale at which modifications should be made. While there are complex issues related to the modifiable areal unit problem (186, 187), in which aggregation of environmental measures within different areas can yield vastly different values for a given residential location, they are outside the scope of this discussion. Here we focus on regional- or metropolitan-level versus neighborhood-level changes. This study examined neighborhood-level characteristics, which may be more readily modifiable with regard to both resources and time. It is also likely that neighborhood-level effects are more susceptible to residential self-selection bias. Because inter-city or -state moves are expensive and are generally driven by employment or education opportunities or proximity to family and social networks, decisions regarding macro-level location are unlikely to be related to physical activity. In contrast, selection of a neighborhood is likely influenced by more local features such as school quality, affordability, or physical-activity related amenities.

Some existing studies examine metropolitan-level urban sprawl, which could independently influence physical activity through large-scale factors such as public and active transportation networks or city-wide culture. Macro-level environments are also more likely to capture residents' total activity space, comprised of the areas in which individuals spend their time including home, work, school, and friends and family. However, few studies have examined both macro- and neighborhood-level changes; understanding of their independent and interactive effects can inform optimal strategies for changing the built environment.

In what ways do we expect physical activity to change?

Modifications to the built environment may change any or all dimensions of physical activity (frequency, duration, intensity, and type), with implications for expected downstream health effects as well as complimentary environmental or transportation impacts with varying leverage for potential political support. Our physical activity measure captured weekly frequency (bouts) of moderate to vigorous leisure time physical activities, a tradeoff for the size and scope of the Add Health study.

Frequency and duration. The built environment may influence patterns of physical activity throughout the day or week. Active transit may be performed as many short bouts, while those exercising in a fitness center may perform longer, less frequent bouts, potentially with similar health benefits. Therefore, examination of frequency provided an incomplete understanding of the influence of the built environment of total amount of physical activity as well as the potential health benefits. More research is needed with more detailed physical activity measures.

Type and intensity. As discussed in recent literature (154), built environment features may exert behavior-specific effects in which, for example, street connectivity may influence active transportation but not leisure walking, and recreation centers may influence active sports but not cycling. Examination of specific types of physical activity may have yielded stronger, more robust results. Additionally, different types of physical activity correspond with different intensities and corresponding health benefits, so estimation of behavior specific effects could help to translate expected changes in physical activity to expected improvements in downstream health outcomes.

On the other hand, examination of total physical activity can complement type-specific analysis by addressing substitutive effects (11), in which active transit could be performed in place of structured exercise, yielding no net gain in total physical activity. However, to address substitutive effects, total physical activity measures should include a broad range of activities, including occupational, utilitarian, household, and leisure time activities.

Also of interest to policy makers are behaviors with potentially complimentary effects on other outcomes of policy interest. Even in the presence of substitutive effects *among physical activity types*, there is evidence that increases in active transportation has a positive influence on traffic congestion and air pollution (76). However, better understanding of the influence of urban form on substitutive effects *among transportation modes* (e.g., whether trips made using active modes are performed in place of, or in addition to, trips made by car) will be generated by current (188) and future transportation research.

The fifth dimension: location. Lastly, in addition to the traditional dimensions of physical activity, "location" is also an important dimension in built environment research. Studies already underway (189) will provide insights into *where* various types of physical activities take place, relative to one's home and in other areas in the community. This and similar work will also inform the extent to which focus on environments surrounding residential locations rather than work or school limits current studies.

Will built environmental modifications be more or less effective in different subpopulations or different types of communities?

We examined built environment features as predictors of physical activity in a large, nationally representative sample of adolescents as they age into young adults. National representation is a key strength when seeking federally allocated resources, and the sociodemographic and geographic diversity in our dataset accommodates examination and comparison of effects in population subgroups. Investigation of heterogeneous effects is important for understanding causality as well as for allocating resources to certain areas and populations to maximize return on investment and balancing equality and disparities considerations.

Life stages. It is likely that determinants of physical activity shift from adolescence, when structured sports and activities are readily accessible, to young adulthood, when physical activity may be more self-motivated or utilitarian. Residential mobility, preferences, and constraints are also likely to shift with age, which may result in varying influences of residential self-selection bias across age groups. Indeed, in prior analysis, we found differences in cross-sectional built environment-physical activity associations between Waves I and III. Greater understanding of causal effects from younger childhood through older adulthood will help to design and estimate potential impacts of built environment modifications.

Sex differences. We also found differences in environment-physical activity relationships between males and females in cross-sectional and longitudinal analysis. Such differences could arise from differences in physical activities (influenced by different built environment characteristics) common in males and females, sex differences in residential selection decisions, or from varying influences of perceived safety, social norms, or constraints related to sex-specific roles. Sex-related differences have implications for targeting modifications to address existing sex disparities in physical activity, and understanding of the underlying mechanisms may reveal other environmental modifications needed in conjunction with changes to the built environment.

Socioeconomic position. The influence of environment features may also vary by socioeconomic position. Differences in association by socioeconomic position could result from differential influences of environmental confounders (e.g., crime or culture) or residential selection, or from causal modifying effects. An example of causal modifying effects is that individuals with high socioeconomic position may be able to pay for a fitness club membership, have access to a car for travel to club sports events, or join an employer-sponsored walking group. In contrast, those with lower socioeconomic position may have fewer options and be more sensitive to their neighborhood environment. Like modification by sex, knowledge of effect modification by socioeconomic position may help to target built environment modifications and inform additional strategies to reduce socioeconomic disparities.

Urbanicity. In other analyses conducted in the Add Health population (74), we show that both the magnitude and shape of the dose response relationship varies by degree of urbanicity. Conceptually, built environment features may have varying relevance and relative influence in rural, suburban, and urban environments. “Walkability” characterized by well-connected streets and nearby retail destinations is perhaps irrelevant in rural areas, and relatively unimportant in urban centers where “walkability” is ubiquitous but safety is not.

Further study of urbanicity differences is needed but requires better strategies to define and identify intuitive types of environments such as the inner city and suburban developments. Such definitions are challenging in the Add Health dataset because, due to confidentiality concerns, analysts do not have knowledge of respondent locations relative to geographic markers (e.g., an urban center) or to each other. Gentrification in urban centers and movement of the poor to the urban fringe in recent decades adds further complexity; that is, we do not expect area-level socioeconomic indicators to be useful components in neighborhood definitions. Existing and future studies that focus on defined metropolitan areas will be valuable for teasing apart effects of proximity to urban centers (e.g., suburb, urban fringe, rural) versus built environment characteristics typically associated with urban centers (e.g., walkability).

Future research should also address selectivity into rural, suburban, and urban areas. Also shown in our prior research (74), this selectivity issue is further complicated by the non-comparability of the ranges of many built environment characteristics across urbanicity levels; density measures in particular were high in urban areas and low in non-urban areas, with little overlap between urban classifications. Therefore, adjustment for urbanicity ignores the selectivity issue and would rely almost entirely on extrapolation beyond the observed data and is therefore inappropriate. Our present research did not address urbanicity due to these concerns, particularly in a longitudinal setting where individuals can move in and out of urban areas. Exploration and, if needed, development of methods that will address selectivity related to urbanicity in cross-sectional and longitudinal settings is also an important area of future study.

More individual-level research. A better understanding of key activities performed and the barriers and facilitators of specific activities for each of these subgroups will help to both understand differences in built environment effects across subgroups and address needs related to modifiable aspects of the environment.

D. Conclusion

The built environment is a promising leverage point for obesity and chronic disease prevention and health promotion by facilitating active lifestyles. This study addressed several threats to causal inference in built environment research and provided substantive knowledge, insights into appropriate methodologies, and new questions that can move the field toward an understanding of whether "active communities support activity." We outlined an extensive set of knowledge gaps that constrain environmental policy solutions to the urgent problems of obesity and chronic disease as well as a broad range of environmental, social, and economic issues.

Solutions to these public health problems should not wait for the conclusion of optimally-designed, long-term prospective studies. Similarly, experimental designs are important components of the field, but have their own limitations related to generalizability, feasibility, time and resource intensity, and availability of natural experiment opportunities. Observational research has an important role in understanding of the direction and magnitude of biases so that existing and future cross-sectional or short-term (experimental or observational) study findings can be better interpreted, and for informing which environment changes should be tested in experimental settings. Indeed, coordination of diverse research efforts will be important for guiding policy solutions already in progress and in years to come.

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