Associations of multidimensional socioeconomic and built environment factors with body mass index trajectories among youth in geographically heterogeneous communities

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ABSTRACT

Understanding contextual influences on obesity requires comparison of heterogeneous communities and concurrent assessment of multiple contextual domains. We used a theoretically-based measurement model to assess multidimensional socioeconomic and built environment factors theorized to influence childhood obesity across a diverse geography ranging from rural to urban. Confirmatory factor analysis specified four factors—community socioeconomic deprivation (CSED), food outlet abundance (FOOD), fitness and recreational assets (FIT), and utilitarian physical activity favorability (UTIL)—which were assigned to communities (townships, boroughs, city census tracts) in 37 Pennsylvania counties. Using electronic health records from 2001 to 2012 from 163,820 youth aged 3–18 years from 1288 communities, we conducted multilevel linear regression analyses with factor quartiles and their cross products with age, age^2, and age^3 to test whether community factors impacted body mass index (BMI) growth trajectories. Models controlled for sex, age, race/ethnicity, and Medical Assistance. Factor scores were lowest in townships, indicating less deprivation, fewer food and physical activity outlets, and lower utilitarian physical activity favorability. BMI at average age was lower in townships versus boroughs (beta [SE]) (0.217 [0.027], $P < 0.001$) and cities (0.378 [0.036], $P < 0.001$), as was BMI growth over time. Factor distributions across community types lacked overlap, requiring stratified analyses to avoid extrapolation. In townships, FOOD, UTIL, and FIT were inversely associated with BMI trajectories. Across community types, youth in the lowest (versus higher) CSED quartiles had lower BMI at average age and slower BMI growth, signifying the importance of community deprivation to the obesogenicity of environments.

1. Introduction

Obesogenic environments are theorized to play an important role in obesity risk (Swinburn et al., 1999). Through physical and social features, community environments act as "risk regulators" that constrain or facilitate health-related behaviors affecting energy balance, including eating and physical activity (Glass and McAtee, 2006). The community environment has a unique influence on youth, who have different activities and less autonomy compared to adults (Ding et al., 2011; Krizek et al., 2004). The home neighborhood is a key location in supporting youth physical activity (Carlson et al., 2016) and influences youth food purchasing and fast food consumption (Forsyth et al., 2012; He et al., 2012). Since adiposity and obesity-related risk behaviors established in childhood often persist into adulthood (Howe et al., 2015) and living in obesogenic environments at multiple life stages may cumulatively impact obesity risk (Lippert et al., 2017), youths' community

contexts can have long-term health implications.

A complex literature has linked residential features with obesity-related behaviors and risk among youth, as illustrated by numerous reviews (Carter and Dubois, 2010; Casey et al., 2014; Cobb et al., 2015; de Vet et al., 2011; Ding et al., 2011; Dunton et al., 2009; Feng et al., 2010; Safron et al., 2011). With some exceptions (DeWeese et al., 2018; Nau et al., 2015a; Nelson et al., 2006; Saelens et al., 2012, 2018; Wall et al., 2012), most studies have evaluated individual indicators (such as fast food density) or composite measures of a single domain (such as measures of multiple food outlet types) in relation to youth behavior or weight-related outcomes. One takeaway from this body of research is a lack of consistent findings for any individual indicator or composite measure. Such inconsistencies may be partly explained by confounding by other, unmeasured environmental features that are spatially correlated but that influence adiposity through different mechanisms (Feng et al., 2010; Leal et al., 2012; Meyer et al., 2015; Nau et al., 2015a). Single indicators or domains do not capture the variety of structures that interact to create obesogenic environments, motivating studies that evaluate a range of environmental measures (DeWeese et al., 2018; Meyer et al., 2015; Wall et al., 2012). Accounting for area-level socioeconomic conditions, a likely confounder of built environment-obesity relations, is also critical (Leal et al., 2012). Additionally, most studies have been conducted in homogeneous geographies, largely urban areas (Boone-Heinonen and Gordon-Larsen, 2012; Feng et al., 2010), but relationships between environmental factors and obesity-related behaviors likely vary across geographic contexts (Boone-Heinonen and Gordon-Larsen, 2012; Schwartz et al., 2011; Stewart et al., 2016). To understand place-based impacts on health, community variation is essential, for only by assessing heterogeneous communities can a full range of community conditions be evaluated (Feng et al., 2010; Richardson et al., 2012).

We assessed community factors from four domains theorized to influence obesity across a diverse geography (Boone-Heinonen and Gordon-Larsen, 2012; Carroll-Scott et al., 2013; Nau et al., 2015a). We used confirmatory factor analysis to integrate multiple environmental indicators into a theory-based measurement model that specified these domains, including one socioeconomic environment factor (community socioeconomic deprivation [CSED]) and three built environment factors (food outlet abundance [FOOD], utilitarian physical activity favorability [UTIL], and fitness and recreational assets [FIT]). We evaluated associations of the four factors with body mass index (BMI) trajectories among youth in three community types—townships, boroughs, and city census tracts—that represent a rural to urban gradient.

2. Methods

To evaluate community factors theorized to influence obesity risk, we conducted a retrospective cohort study among 163,820 youth across 37 counties in Pennsylvania, USA. Institutional Review Boards from Geisinger and the Johns Hopkins Bloomberg School of Public Health approved the study and waived informed consent.

2.1. Study population

Using previously described data collection methods (Nau et al., 2015b; Schwartz et al., 2014, 2016a, 2016b), we obtained electronic health record data on all youth ages 3 to 18 years with an outpatient visit to a Geisinger primary care provider between January 2001 and February 2012 who had valid height and weight measurements and a successfully geocoded address. Geisinger is a large integrated health system in Pennsylvania whose primary care patients represent the age and sex distribution of the region's general population (Casey et al., 2016).

Youths' addresses were assigned to one of 1288 communities. Community types were defined using a previously evaluated definition, combining minor civil divisions (townships, boroughs, cities) with city

census tracts (Schwartz et al., 2011). This definition provides a sociologically valid and policy-relevant representation of non-urban areas, since townships and boroughs are governed by local policies that can influence the socioeconomic and built environment. Census tracts provide relevant spatial resolutions by which to divide heterogeneous and densely populated cities. Mean population density and land use mix are lowest in townships (the most rural community type), higher in boroughs (small towns), and highest in cities.

2.2. Electronic health record data collection

We obtained electronic health record data on height and weight (for BMI calculations) and socio-demographics, including sex, age at BMI measurement, race/ethnicity (non-Hispanic white, black, Hispanic, other), and history of Medical Assistance (needs-based insurance status that serves as a proxy for low household socioeconomic status (Casey et al., 2017)). Biologically implausible values for weight- and height-for-age and weight-for-height were deleted using the Centers for Disease Control and Prevention 2000 Growth Charts SAS Program (CDC, 2012). To avoid prevalent disease sampling bias, we randomly selected one BMI per youth per age-year; thus, youth provided multiple BMIs over the study period.

2.3. Confirmatory factor analysis

The confirmatory factor analysis model specified four latent constructs, or factors, hypothesized to underlie obesogenic or obeso-protective community environments. CSED, previously associated with youth BMI in our region (Nau et al., 2015b), characterized the degree of socioeconomic disadvantage. FOOD characterized the density, diversity, and accessibility of food outlets, considering all types of food outlets in order to capture the overall abundance of food options. Given the plethora of food options at any given outlet (Lucan, 2015), we hypothesized that an environment characterized by a greater density of food outlets of any type may encourage dietary intake. UTIL characterized utilitarian physical activity favorability, which influences active transport, and FIT characterized the density and diversity of fitness and recreational facilities and the number of parks, which influences leisure time physical activity (Sallis et al., 2012). A comprehensive panel of 29 candidate indicators was selected from archival data (InfoUSA, Dun & Bradstreet, U.S. Census, Pennsylvania Department of Transportation) from the year 2000 and assigned to the four factors based on theory and prior literature. After omitting highly correlated indicators and transforming skewed variables, the model was estimated using weighted-least squares. Paths allowing for correlation between factors and for residual correlation between selected pairs of similar indicators were added as needed to assure acceptable model fit. Factor scores were estimated using the Maximum A Posteriori method (Skrondal and Laake, 2001). Model invariance across community types was adequate, indicating the factors were sufficiently robust in measuring the four constructs in each community type. Fig. 1 provides detailed exposition of the factor model, including fit indices.

2.4. Statistical analysis

Analysis goals were to: 1) evaluate associations of the four community factors, separately and together, with youth BMI trajectories; and 2) assess how associations differed by community type (township, borough, city). We first examined correlations (Spearman's rho) between community factors (as continuous variables), overall and separately by community type. We also examined distributions of youth across community types and community factor quartiles. Because factor distributions across community types did not overlap, it was necessary to stratify all regression analyses by community type to avoid violations of non-positivity. We did not re-quartile factors for each community type so as to make results between strata more comparable. Due to the
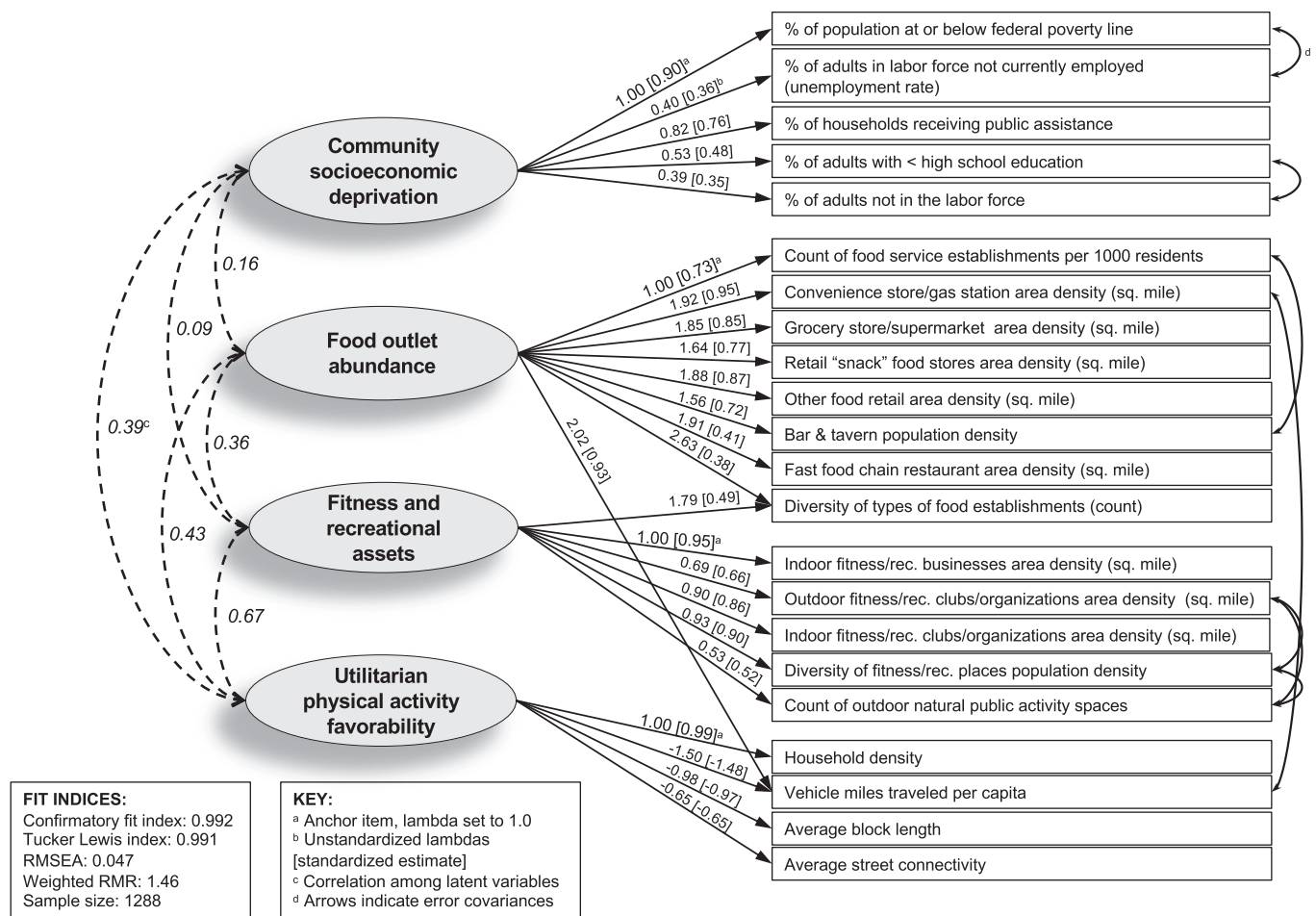
Fig. 1. Figure illustrating community factors and their composite indicators, as specified through confirmatory factor analysis among 1288 Pennsylvania communities. Abbreviations: RMSEA, root mean square error of approximation; RMR, root mean square residual.

small number of observations in some factor quartiles following stratification, reference groups necessarily differed by community type to avoid imprecise and unstable estimates. We then used mixed effects linear regression models to evaluate associations of community factors with BMI trajectories over time. We first evaluated the relation between community type and BMI trajectories, omitting community factors. Next we evaluated single domain models that included factors (quartiled) as main effects one domain at a time, with the exception that FOOD, UTIL, and FIT models were adjusted for CSED to account for potential confounding by area socioeconomic conditions. We then evaluated combined (four factor) models.

The regression models specified BMI as the dependent variable to model growth curve trajectories of BMI by age. Models included fixed-effects for population mean-centered age, age^2, and age^3. These age polynomials allowed for sufficiently flexible modeling of BMI trajectories, an important consideration since BMI does not increase in a linear pattern as youth age. To accommodate correlations between serial BMI measurements within youth and allow BMI trajectories to vary across youth, random intercepts and slopes for age and age^2 were included. These were allowed to co-vary with unstructured covariance (Nau et al., 2015b; Schwartz et al., 2014, 2016a, 2016b). The results presented include beta coefficients with 95% confidence intervals (CI) for the main effects of factor quartiles (interpreted as differences in BMI at average age of the study sample, roughly 10.8 years) and for cross product terms between factor quartiles and all age terms (with statistically significant terms indicating differences in BMI trajectories over time). All models were adjusted for sex, race/ethnicity, and Medical Assistance (yes vs. no); interactions between these covariates and all

age terms were included to allow covariate associations with the outcome (BMI) to vary by age. For the combined (four-factor) models, we used Wald tests to evaluate the global significance of each factor (including the factor quartiles and age interaction terms) and we calculated variance inflation factors to test for potential collinearity between the community factors (all values were < 4, suggesting collinearity was not a concern). Analyses were conducted using Stata version 13.1 (StataCorp LP, College Station, TX).

3. Results

The 163,820 study youth provided 524,862 BMI measurements. Median age at first visit was 8.8 years, with a median first BMI measurement of 18.0 kg/m². The majority of youth were non-Hispanic white, representing the racial/ethnic makeup of the study region (Table 1). Factor scores from the confirmatory factor analysis were lowest in townships, indicating less community socioeconomic deprivation, fewer food and physical activity outlets, and lower utilitarian physical activity favorability as compared to boroughs and cities.

Correlations between community factors varied by community type but were highest for FOOD and UTIL and for FOOD and FIT (Appendix Table A). The distribution of youth across quartiles of the community factors differed substantially by community type: township youth were concentrated in the first three quartiles of CSED, FOOD, and UTIL and borough and city youth were concentrated in the highest factor quartiles for all factors (Fig. 2).

Table 1

Characteristics of youth aged 3–18 years and communities in analysis, Pennsylvania, USA, 2001–2012.

|	No. (%) unless otherwise indicated		
	Townships	Boroughs	Cities
Youth	89,831 (100)	49,371 (100)	24,618 (100)
Male	45,748 (50.9)	24,553 (49.7)	12,145 (49.3)
Age at first BMI, median (IQR)	8.8 (4.2, 13.9)	8.8 (4.1, 14.0)	8.8 (4.3, 14.0)
Race/ethnicity			
Non-Hispanic white	83,555 (93.0)	45,955 (93.1)	20,018 (81.3)
Black	3128 (3.5)	2895 (11.8)	1680 (3.4)
Hispanic	753 (0.8)	450 (0.9)	662 (2.7)
Other	1478 (1.6)	637 (1.3)	560 (2.3)
Missing	917 (1.0)	649 (1.3)	483 (2.0)
History of medical assistance	23,672 (26.4)	18,746 (38.0)	12,879 (52.3)
First BMI (kg/m^2), median (IQR)	17.9 (15.9, 21.8)	18.0 (16.0, 22.1)	18.2 (16.1, 22.5)
Communities	719	373	196
Population density in 2000 (people/mile^2), median (IQR)	131 (67, 255)	2737 (1591, 3727)	6668 (3725, 8739)
Confirmatory factor analysis scores, median (IQR)			
Community socioeconomic deprivation	−0.34 (−0.60, −0.07)	0.14 (−0.16, 0.51)	0.81 (0.41, 1.30)
Food outlet abundance	−0.09 (−0.29, 0.12)	0.49 (0.32, 0.65)	0.56 (0.40, 0.70)
Utilitarian physical activity favorability	−0.24 (−0.59, 0.03)	0.78 (0.55, 1.46)	1.18 (0.96, 1.55)
Fitness and recreational assets	0.04 (−0.58, 0.66)	1.12 (0.50, 1.60)	0.89 (0.42, 1.17)

Abbreviations: BMI, body mass index; IQR, interquartile range.

### 3.1. Community type and youth BMI trajectories

BMI (at average age of the study sample) was significantly lower in townships compared to boroughs and cities, after controlling for covariates (beta [CI]) (boroughs: 0.217 kg/m^2 [0.163, 0.270]; cities: 0.378 kg/m^2 [0.307, 0.450]). Significant interaction terms of community type with age ($P < 0.001$) indicated that on average, living in townships was associated with modestly slower BMI growth over time (Appendix Fig. A).

3.2. Single domain models

In all community types, there was higher BMI at average age when comparing higher CSED quartiles to the lowest quartiles. In townships, youth in the first (versus fourth) quartile of CSED had an average of 0.58 higher BMI units. In boroughs and cities, youth in the fourth (versus first) quartile of CSED had an average of 0.39 and 0.91 lower BMI units, respectively. Youth in communities in the lowest CSED quartiles also had significantly lower BMI growth than those in communities in higher quartiles (Fig. 3). These associations remained
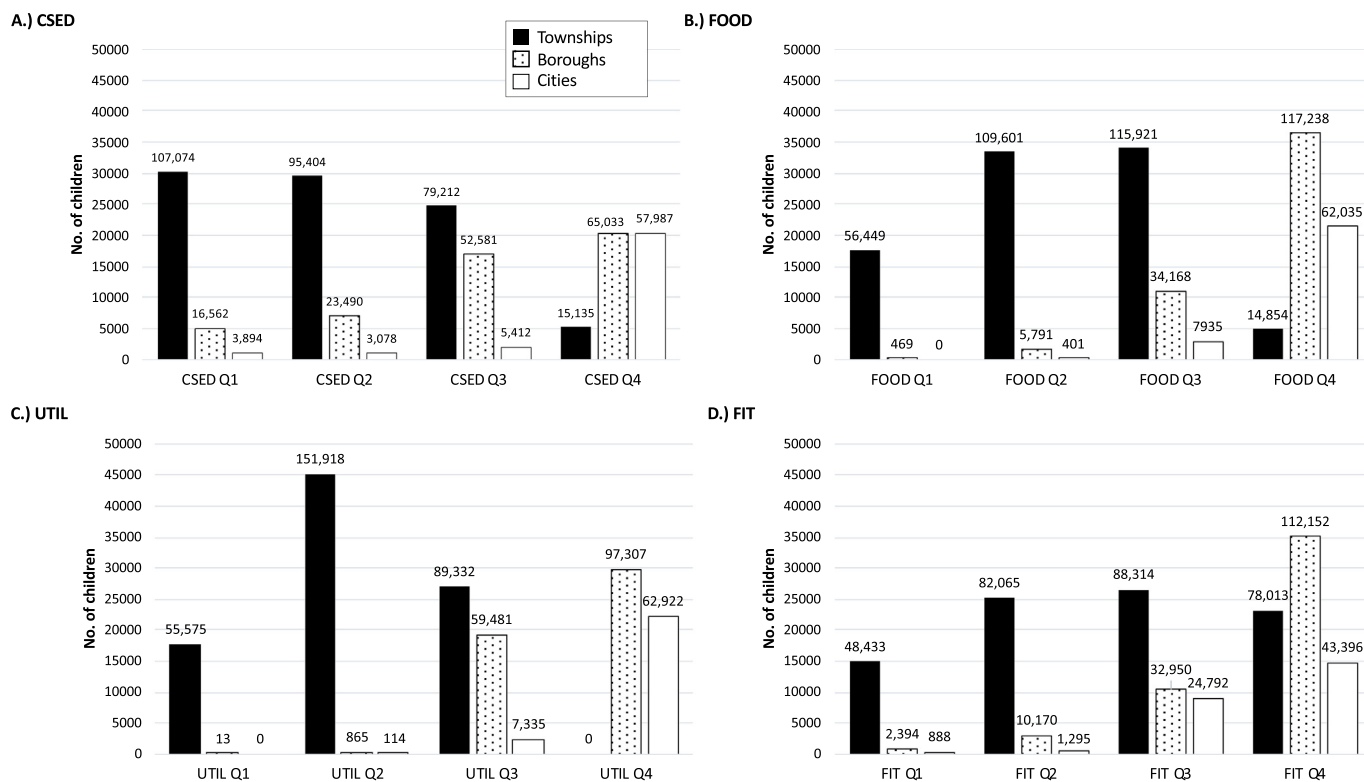
Fig. 2. Distribution of youth participants aged 3–18 years in Pennsylvania, USA, 2001–2012, across quartiles of community factors by community type. Numeric labels above each bar represent the number of body mass index measurements. Abbreviations: CSED, community socioeconomic deprivation; FOOD, food outlet abundance; UTIL, utilitarian physical activity favorability; FIT, fitness and recreational assets; Q, quartile.
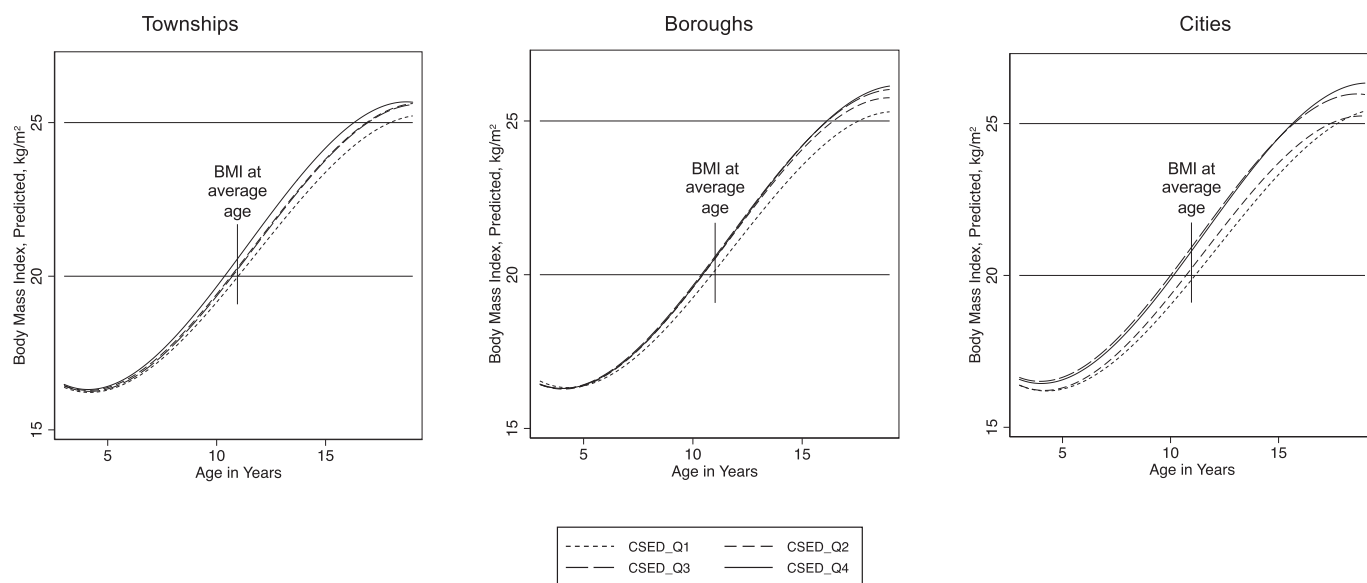
Fig. 3. Body mass index predictions among youth aged 3–18 years in Pennsylvania, USA, 2001–2012, by CSED quartiles in townships, boroughs, and cities. Each prediction model controlled for age (centered; linear, quadratic, and cubic terms), sex, race/ethnicity, and Medical Assistance, and age interaction terms for each of these covariates, as described in the Methods. Abbreviations: BMI, body mass index; CSED, community socioeconomic deprivation; Q, quartile.

consistent in models that added UTIL, FIT, and FOOD (results not shown).

In townships, UTIL, FIT, and FOOD were significantly and inversely associated with BMI trajectories after controlling for CSED. Compared with youth in the second quartile of UTIL, those in the first quartile had an average of 0.17 higher BMI units and youth in the third quartile had an average of 0.28 lower BMI units. Compared with youth in the third quartile of FIT, those in the second quartile had an average of 0.20 higher BMI units and youth in the fourth quartile had an average of 0.38 lower BMI units. Contrary to expectation, youth in the third quartile of FOOD had significantly lower BMI at average age than those in the first or second quartiles of FOOD with an average difference of 0.36 and 0.42 BMI units, respectively. For each of these differences in BMI at average age, BMI growth over time also differed between groups
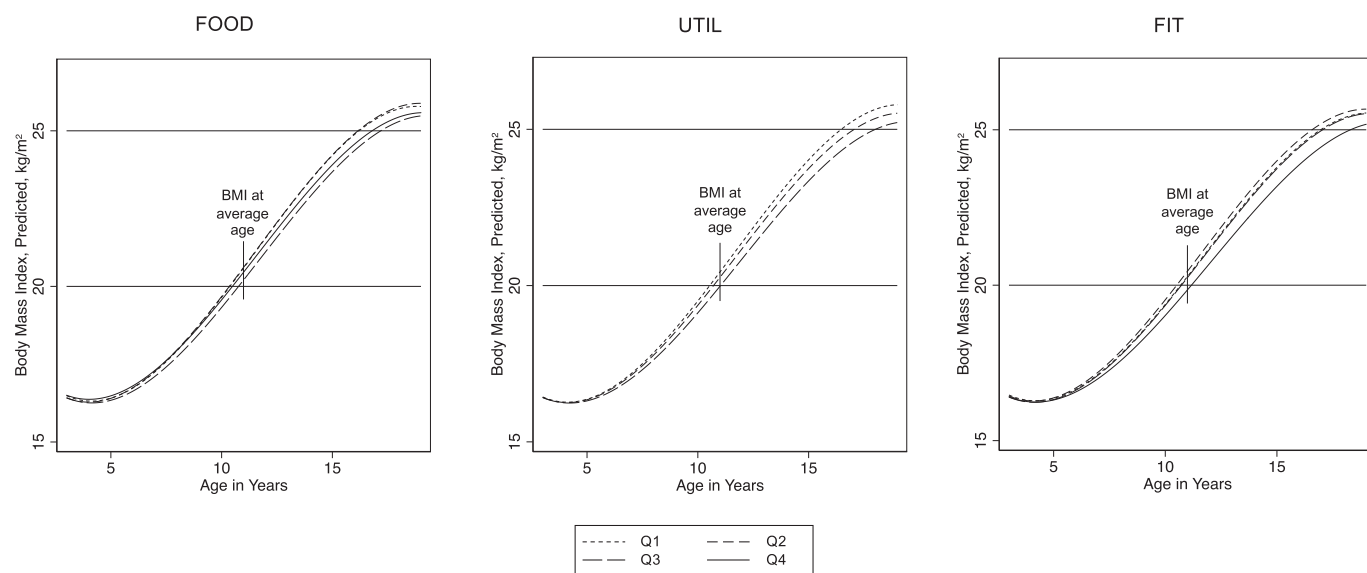
(Fig. 4).

In boroughs and cities, there were no associations between FOOD, UTIL, or FIT and BMI trajectories with the exception of a significant age-interaction term for FIT in boroughs.

Full results of single domain models, including factor-age interaction terms, are presented in Appendix Table B.

3.3. Combined (four-factor) models

In all community types, CSED-BMI associations remained consistent in combined models that included FOOD, UTIL, and FIT (Wald $P < 0.001$), with higher CSED quartiles (versus the lowest) associated with higher BMI at average age and faster BMI growth (Table 2).

In townships, associations remained consistent for the first (versus

Fig. 4. Body mass index predictions among youth aged 3–18 years in Pennsylvania, USA, 2001–2012, by FOOD, UTIL, and FIT quartiles in townships. Each prediction model controlled for age (centered; linear, quadratic, and cubic terms), sex, race/ethnicity, and Medical Assistance, age interaction terms for each of these covariates, and community socioeconomic deprivation, as described in the Methods. Abbreviations: FOOD, food outlet abundance; UTIL, utilitarian physical activity favorability; FIT, fitness and recreational assets; Q, quartile.

Table 2

Main effects[a] of associations of four-factor models[b] (CSED, FOOD, UTIL, and FIT) with differences in body mass index at mean age by community type[c] among youth aged 3–18 years in Pennsylvania, USA, 2001–2012.

	Community type					
	Model 1: townships		Model 2: boroughs		Model 3: cities	
	Beta	95% CI	Beta	95% CI	Beta	95% CI
CSED quartiles						
CSED-Q1	Ref		−0.421	−0.596, −0.247	−0.910	−1.279, −0.540
CSED-Q2	**0.253**	**0.175, 0.330**	−0.071	−0.214, 0.071	**−0.540**	**−0.865, −0.213**
CSED-Q3	**0.254**	**0.173, 0.335**	0.013	−0.094, 0.120	0.125	−0.126, 0.375
CSED-Q4	**0.607**	**0.459, 0.755**	Ref		Ref	
Global P value[d]	< 0.001		< 0.001		< 0.001	
FOOD quartiles						
FOOD-Q1	0.132	−0.070, 0.334	−1.142	−2.374, 0.089	NA	
FOOD-Q2	**0.176**	**0.051, 0.302**	−0.268	−0.697, 0.161	−0.989	−2.195, 0.218
FOOD-Q3	Ref		−0.045	−0.045, 0.088	**−0.291**	**−0.537, −0.044**
FOOD-Q4	**0.271**	**0.109, 0.434**	Ref		Ref	
Global P value	< 0.001		0.202		0.261	
UTIL quartiles						
UTIL-Q1	**0.144**	**0.040, 0.247**	**4.99**	**0.133, 9.849**	NA	
UTIL-Q2	Ref		0.496	−0.351, 1.344	0.109	−1.268, 1.486
UTIL-Q3	0.056	−0.050, 0.162	0.088	−0.028, 0.205	0.028	−0.230, 0.286
UTIL-Q4	NA		Ref		Ref	
Global P value	0.001		0.285		0.236	
FIT quartiles						
FIT-Q1	−0.081	−0.247, 0.085	0.500	−0.053, 1.053	**1.102**	**0.268, 1.935**
FIT-Q2	0.085	−0.023, 0.192	0.152	−0.111, 0.416	0.285	−0.260, 0.831
FIT-Q3	Ref		0.094	−0.045, 0.233	0.077	−0.072, 0.226
FIT-Q4	**−0.396**	**−0.499, −0.294**	Ref		Ref	
Global P value	< 0.001		0.003		0.140	

Abbreviations: CI, confidence interval; CSED, community socioeconomic deprivation; FOOD, food outlet abundance; UTIL, utilitarian physical activity favorability; FIT, fitness and recreational assets. NA indicates quartile could not be evaluated due to a lack of observations.

Boldface indicates statistical significance ($P < 0.05$).

[a] Full model results, including interaction terms for each community factor with age, age^2, and age^3, are provided in Appendix Table C.

[b] Each model controlled for age (centered; linear, quadratic, and cubic terms), sex, race/ethnicity, and Medical Assistance, and age interaction terms for each of these covariates, as described in the Methods.

[c] Due to the small number of observations in some factor quartiles, reference groups necessarily differed by community type.

[d] Global P values represent evaluation of factor quartiles and age interaction terms.

second) quartile of UTIL and the fourth (versus third) quartile of FIT in the combined model (Table 2). The first quartile of FOOD was attenuated, but the second and fourth (versus third) FOOD quartiles were associated with higher BMI. Wald tests were significant ($P < 0.01$) for all factors.

In boroughs, there was a statistically significant association between the first (versus fourth) quartile of UTIL (Table 2) not observed in the single domain model, but Wald testing indicated the association lacked global significance. Wald testing indicated a significant association for FIT ($P < 0.01$); primary differences appeared to relate to the trajectory shape, with faster BMI growth over time among youth in the first and second (vs. fourth) FIT quartiles. There remained no associations between FOOD and BMI trajectories in the combined model. In cities, Wald testing showed no globally significant associations between FOOD, UTIL, or FIT and BMI trajectories in combined models (Table 2).

Full results of combined models, including factor-age interaction terms, are presented in Appendix Table C.

4. Discussion

We evaluated how theoretically-based, multidimensional measures of four community environmental domains were associated with BMI trajectories among youth across heterogeneous communities. To our knowledge, this study is the first to use a formal measurement model to concurrently assess multiple domains of the socioeconomic and built environment in relation to youth obesity across a diverse geography. We observed lower BMI at average age and slower rates of BMI growth among youth in townships, even though these rural communities had more obesogenic built environments, with fewer physical activity

outlets and lower utilitarian physical activity favorability. However, townships had lower deprivation, and CSED was consistently associated with BMI trajectories across community types, signifying the major relative importance of community deprivation to the obesogenicity of environments.

This study highlighted the challenges of comparing heterogeneous communities. Though not new, this challenge is worth revisiting as efforts to aggregate geographically diverse cohorts progress (National Institutes of Health, 2019a, 2019b). Studies assessing neighborhood features across the U.S. have demonstrated substantial variation by urbanicity and sociodemographic factors (Boone-Heinonen et al., 2010; Richardson et al., 2012), indicating a need for large national studies, in combination with more geographically focused studies, to better explain contextual influences on obesity (Boone-Heinonen and Gordon-Larsen, 2012). Toward this end, we compared youth across a large region that included rural areas, small towns, and cities. As seen in our first model, which omitted community factors, community type was a strong predictor of youth BMI trajectories, suggesting particular features of townships may be obeso-protective. A direct comparison of youth across community types could, in theory, identify environmental features that explain this observation. However, the marked lack of overlap in the distribution of factors across community types led us to stratify analyses by community type to avoid regression extrapolation (which occurs when there is insufficient overlap between communities on individual- or place-based measures) (Oakes, 2004). The dissimilarity of community types in regard to community factors exemplifies the positivity violations that likely occur in place and health studies that pool data from heterogeneous places (Westreich and Cole, 2010). Additionally, environmental features may differentially affect

behaviors, such as walking, in different contexts (e.g., urban versus rural) (Stewart et al., 2016), in which case analyses that pool individuals across community types could obscure differential impacts of built environment features on health.

Our findings highlighted potentially obesogenic aspects of community environments. Most notably, greater CSED was consistently associated with higher youth BMI at average age and more rapid BMI growth over time in all community types, even when controlling for built environment factors (FOOD, UTIL, and FIT), as seen in combined models. These findings are consistent with past studies of neighborhood disadvantage and youth adiposity (Carter and Dubois, 2010) and our prior research in the study area (Nau et al., 2015b; Schwartz et al., 2011). The connection between CSED and obesity may be mediated through the built environment, as more deprived communities often lack resources that promote physical activity and healthy eating, such as recreational facilities and supermarkets (Lovasi et al., 2009; Schreier and Chen, 2013; Suglia et al., 2016). However, adjusting for FOOD, UTIL, or FIT did not attenuate CSED-BMI associations, suggesting an independent association. Similarly, Sharifi et al. (2016) found that food and physical activity environment features contributed less to racial/ethnic disparities in youth BMI than did neighborhood socioeconomic status. Dimensions of the social environment that influence obesity-related behaviors, such as crime and social capital, could also mediate the CSED-BMI relation (Carroll-Scott et al., 2013; Lovasi et al., 2009; Schreier and Chen, 2013; Suglia et al., 2016).

Physical activity-related factors were associated with youth BMI trajectories in townships, the most rural community type. Consistent associations in the combination model provided evidence of independent associations for UTIL and FIT. These findings suggest less walkable townships and those with fewer fitness and recreational opportunities may increase obesity risk, which is similar to findings from research in urban and suburban areas (Casey et al., 2014; de Vet et al., 2011; Ding et al., 2011; Saelens et al., 2018; Safron et al., 2011). Rural communities face numerous challenges to active transport (e.g., long distances, lack of sidewalks), and lower access to recreational opportunities impedes leisure time physical activity (Hansen et al., 2015). Given the underdevelopment of active living research on the rural built environment (Hansen et al., 2015), the associations of UTIL and FIT in townships are noteworthy. In boroughs and cities, the only observed association for these factors was a relation between lower FIT and higher BMI trajectories in boroughs. The limited range and general homogeneity of these factors within boroughs and cities likely constrained our ability to demonstrate associations. Observed, contrasting associations by community type also suggests a possible threshold effect.

Given the ubiquity of high calorie/nutrient poor foods across food outlet types, we hypothesized proximity to a greater density of food outlets of any type could encourage dietary intake. In the single domain model, lower food outlet abundance was associated with higher BMI trajectories in townships, opposite the hypothesized direction but consistent with research on rural food deserts and youth overweight (Schafft et al., 2009). Townships in higher FOOD quartiles may have represented those with access to supermarkets that offer nutrient-dense foods such as fruits and vegetables, although the role of supermarket proximity and obesity among youth has not been consistently demonstrated (Cobb et al., 2015). Furthermore, associations were not consistent when controlling for FIT and UTIL and these factors were highly correlated with FOOD in townships, suggesting the food environment may be difficult to disentangle from other community domains (Cobb et al., 2015; Leal et al., 2012). We observed no associations for FOOD in boroughs and cities. Potential associations may have been diluted if individual indicators such as supermarket and convenience store density had opposite effects on youth BMI. This is challenging to decipher as research has not shown consistent relations for most food outlet types and obesity among youth (Casey et al., 2014; Cobb et al., 2015). Detecting associations between the food environment and obesity is also challenged by the many behavioral and cultural factors that influence youth dietary patterns, including parental control over the home food environment (Poti and Popkin, 2011), as well as uncertainty regarding the causally-relevant geographic context in which individuals obtain food (Kwan, 2012).

One limitation of our study is the potential for confounding due to location-selection bias, in which individuals move into or out of areas based on residential preferences and financial or social considerations that are linked to their health (Boone-Heinonen and Gordon-Larsen, 2012). For example, physically active individuals may select neighborhoods conducive to these activities. Without measuring all relevant confounders related to neighborhood selection, estimated effects may be biased (Grafova et al., 2014). This study minimized potential for such bias by studying youth (who do not self-select into neighborhoods) and by studying the largely residentially stable population served by Geisinger (Casey et al., 2016; Feng et al., 2010). Our findings related to youth BMI trajectories are important, given the persistence of adiposity and obesity-related risk behaviors from childhood into adulthood (Howe et al., 2015); however, longitudinal research has suggested a cumulative impact of neighborhood disadvantage on obesity, demonstrating the importance of measuring obesity risk in relation to neighborhood entry and exit over the lifespan (Lippert et al., 2017). An additional limitation is our treatment of community measures as fixed rather than time-varying exposures. This may be a stronger limitation for particular community features; for example, food outlets are known to change over time in urban areas (Lucan et al., 2018), whereas other features such as block length or park locations are more static. We used data from multiple years to examine indices comprised of indicators from our community factors and found high correlations across years; thus, we decided that investment in conducting multiple confirmatory factor analyses across years was not justified. Using factors comprised of multiple indicators also helped overcome this limitation, since such metrics are more robust to secular trends than single indicators (Messer et al., 2006). Finally, although models controlled for Medical Assistance participation to address confounding by income, our results may be subject to residual confounding (Casey et al., 2017).

Study strengths included use of electronic health records to evaluate BMI trajectories across a large, diverse geography; the large number of youth and encounters; clinical measurement of height and weight; and use of a rigorous, comprehensive, and theory-based approach to measuring community domains that accounted for measurement error. As one of the first studies to evaluate associations of multidimensional obesity-related community domains across a heterogeneous geography, it highlighted the challenge of determining which community features contribute to obesogenic and obeso-protective environments when place-based measures lack overlap. Despite challenges to direct comparisons across community types, we found that within townships, the most rural community type, utilitarian physical activity favorability and fitness and recreational opportunities were key obeso-protective environmental features. Most notably, consistent associations for CSED and BMI across community types signified the importance of community deprivation in the constitution of obesogenic environments. As a "risk regulator," CSED may influence youth eating and physical activity behaviors, with concomitant impacts on adiposity.

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Declaration of Competing Interest

The authors declare there is no conflict of interest.

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