Community Design, Street Networks, and Public Health

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ABSTRACT

What is the influence of street network design on public health? While the literature linking the built environment to health outcomes is vast, it glosses over the role that specific street network characteristics play. The three fundamental elements of street networks are: street network density, connectivity, and configuration. Without sufficient attention being paid to these individual elements of street network design, building a community for health remains a guessing game. Our previous study found more compact and connected street networks highly correlated with increased walking, biking, and transit usage; while these trends suggest a health benefit, this study seeks to strengthen that connection.

Using a multilevel, hierarchical statistical model, this research seeks to fill this gap in the literature through a more robust accounting of street network design. Specifically, we ask the following: what is the influence of the three fundamental measures of street networks on obesity, diabetes, high blood pressure, heart disease, and asthma? We seek to answer this question by examining 24 California cities exhibiting a range a street network typologies using health data from the California Health Interview Survey.

We control for the food environment, land uses, commuting time, socioeconomic status, and street design. The results suggest that more compact and connected street networks with fewer lanes on the major roads are correlated with reduced rates of obesity, diabetes, high blood pressure, and heart disease among residents. The outcome is a novel assessment of streets networks and public health that has not yet been seen but will be of great benefit to planners and policy-makers.

KEYWORDS

Street networks, physical activity, built environment, public health

INTRODUCTION

Inquiries into the built environment's impact on public health in the United States evolved appreciably over the last 150 years. In the early days of the U.S. Sanitary Commission, the focus was on just what the name implies: ensuring sanitary conditions in cities (Tise, 2013). Deaths from diseases such as cholera, tuberculosis, malaria, and typhoid fever were not formally linked to built environment issues such as poor sanitation and close proximities until the 1840s when a German doctor named Rudolf Virchow looked beyond medicinal answers and instead recommended solving these problems with changes to the built environment (Corburn, 2013). Frederick Law Olmstead, founding director of the U.S. Sanitary Commission, also understood this link between health and the built environment and brought similar lessons to military camps during the Civil War (Fisher, 2010). With the spread of manufacturing during the first and second industrial revolutions, the health/built environment discussion shifted toward industrial pollution (Rosen, 2003). Today, obesity and obesity-related diseases represent the bulk of the literature focusing on the connection between health and the build environment. Instead of being preceded by something as direct as industrial pollution, the obesity epidemic was instead preceded by a drastic shift in the way we lay out our communities.

Prior to the twentieth century, compact and connected street networks were long held as the standard upon which to build a city. Dating as far back as the earliest known existence of a gridded street network pattern in the city of Mehenjo-Daro, New Delhi, from at least 2,500 B.C. (Stanislawski, 1946). This thinking extended into the gridiron plans of the ancient Greeks and Romans to the organic, medieval patterns found across Europe and eventually in the New World. The Renaissance helped bring orthogonal, rectilinear networks back into vogue, and these street network patterns eventually found their way into early U.S. cities such as New Haven and Philadelphia in the mid-1600s. The trend continued across the U.S. and eventually expanded to suburban areas, particularly during the late 1800s in conjunction with the burgeoning use of streetcars. Despite some variation through the years, this approach to assembling cities saw a complete overhaul over the course of the 20th century. The compact and connected ways that we built our cities for the last few thousand years quickly evolved into much sparser, dendritic street networks, as depicted in Figure 1 (Southworth and Ben-Joseph, 1997). The existing literature suggests that our older cities can help facilitate less driving and more active transportation (Frank et al., 2007; Handy et al., 2002; Marshall and Garrick, 2010a; Pendola and Gen, 2007). But do they actually have a measurable public health benefit as well? Some researchers answer yes to this question (Davison and Lawson, 2006; Dunton et al., 2009; Frank et al., 2001; Grafova, 2008; Williams et al., 2012); other researchers find no significant relationship between built environmental variables and public health outcomes (Eid et al., 2008; Kirk et al., 2010; Sallis and Glanz, 2006). One potential reason for these discrepancies is that while most studies include a measure or two of street network design, no study of obesity or public health has accounted for the complete range of street network elements.

This research seeks to fill this gap in the literature by fully accounting for street network design so that we can better understand the role that street networks play in public health. Specifically, we ask the following: what is the influence of the three fundamental measures of a street network – street network density, connectivity, and configuration – on obesity, diabetes, high blood pressure, heart disease, and asthma? The study seeks to answer this question by examining 24 medium-sized California cities exhibiting a range a street network typologies via obesity and health data from the California Health Interview Survey (CHIS). In a previous study, we found

Figure 1 - Evolution of Community Design and Street Networks in the U.S.

more compact and connected street networks to be highly correlated with increased walking, biking, and transit usage (Marshall and Garrick, 2010a). While these trends suggest a public health benefit, this study seeks to better understand this link to actual health outcomes and health disparities. Health disparities are the differences in health by gender, race or ethnicity, education, income, sexuality, or geographic location that are *"not only unnecessary and avoidable but, in addition, are considered unfair and unjust"* (Braveman, 2006; U.S. DHHS, 2010; Whitehead, 1992). Using a multilevel, hierarchical statistical mode, we control for age, income, ethnicity, education, street design, commute distance, and proximity to fast food restaurants, grocery stores, big box stores, convenience stores, and fitness clubs. The result is a novel assessment of streets networks, community design, and public health that can better speak to questions of health disparities and the potential impact of the type of street network where one resides.

LITERATURE REVIEW

Data from the Centers for Disease Control and Prevention (CDC) suggests that more than half of the U.S. adult population fails to meet the minimum daily amount of recommended physical activity and that this percentage is higher than it was a generation ago (Centers for Disease Control and Prevention, 2005, 2011). U.S. workers now drive an average of 25.2 minutes each day as compared to 21.7 per day in 1990 (Pisarski, 2006), and the amount of time spent driving has been found to be a key factor impacting obesity risk (Jacobson et al., 2011). Today, over 68% of Americans over the age of 20 are overweight or obese; this number has increased from just 31.5% in 1960 (Ogden and Carroll, 2010b). Perhaps more critically, this issue now affects 1 in 3 children, which triples the percentage of overweight or obese children from just a generation ago (Ogden and Carroll, 2010a). Thus, this is likely to be the first generation with a shorter expected life span than their parents (Jackson and Sinclair, 2011). The good news is that even modest increases in physical activity have been shown to positively impact obesity rates, risk for certain chronic diseases, as well as mortality rates (Warburton et al., 2006; Wen et al., 2011).

The World Health Organization (WHO) estimates that insufficient physical activity contributes to 1.9 million annual deaths worldwide (Badland and Schofield, 2005). The literature suggests that the shift in industrialized nations toward a more sedentary lifestyle is linked to increasingly auto-dependent lifestyles, which in turn is linked to lower density developments and auto-friendly land uses (Centers for Disease Control and Prevention, 2011). As physical activity is removed from utilitarian transportation and commute times rise, it is often difficult to incorporate leisure-time physical activity into an individual's daily life (Badland and Schofield, 2005).

Over the course of the last several decades, the literature concerning the nexus between the built environment and public health has evolved. This evolution can be characterized by three points: i) studies in this area now include a broader range of variables from a larger number of disciplines; ii) these studies use more appropriate statistical methods such as multilevel, hierarchical models; and iii) they use more direct measures of health. We will organize this section around the last point by conducting an overview of the built environment literature related to travel behavior, physical activity, obesity, and finally, actual health disparities; evidence of the first two points will be integrated throughout these sections.

Existing literature on the impact of the built environment on travel behavior, physical activity, and health outcomes is vast (Dannenberg et al., 2003; Ewing and Cervero, 2010; Frumkin et al., 2004; Jackson and Sinclair, 2011). Our literature review began by searching Google Scholar and TRID databases for broader keywords ('built environment,' 'community design,' or 'street networks' combined with 'travel/transportation,' 'active travel/transportation,' 'non-motorized travel,' as well as 'bicycling,' 'walking,' and 'physical activity/health'). These searches yielded hundreds of empirical studies and dozens of literature reviews on the subject.

One challenge in this process was interpreting what exactly scholars from across the various disciplines mean when using the somewhat general term: built environment. While the built environment might focus on the transportation infrastructure and land uses in some disciplines, other disciplines take it to include food sources and recreational opportunities (Sallis and Glanz, 2006). The intent of this study is to increase our understanding of the specific role that the street networks plays in health disparities; accordingly, we elected to focus on papers, literature reviews, and meta-analyses with findings applicable to street network characteristics, but with the understanding that other related factors should be recognized and controlled for. In addition to peer-reviewed, published literature, we also reviewed existing policy briefs and non-peer-reviewed literature on the subject. For instance, recent literature reviews from the Robert Wood Johnson Foundation as well as an international review for the Victoria Department of Transport (Australia) reached similar conclusions about the built environment playing a role in physical activity, obesity, and health outcomes.

Overall, it is evident that the existing research glosses over the role of specific street network characteristics, particularly in terms of how such variables were operationalized and which street network variables were found to be significant (or insignificant). The three fundamental elements of street networks (which will be covered in more detail in the data section) are: street network density, connectivity, and configuration (Marshall and Garrick, 2012). Without sufficient attention being paid to these individual elements of street network design, including their relationship to the numerous other factors impacting public health, trying to build a community with health outcomes in mind remains a guessing game. The remainder of this literature review investigates how those components are considered in relevant health-related built environment literature.

Street Networks and Travel Behavior

The most mature of the relevant built environment literature strands focuses on travel behavior. In a meta-analysis building upon their previous synthesis paper, Ewing and Cervero examined over 50 empirical studies (Ewing and Cervero, 2001, 2010). When characterizing the built environment, they stated that most early papers come with "*one big caveat: many differences among neighborhoods or activity centers get lumped into a single categorical variable, with a concomitant loss of information. These studies make no effort to isolate the effects of different* *land use and design features on travel decisions"* (Ewing and Cervero, 2001). In other words, neighborhoods were broadly categorized between two or three groupings such as "traditional" and "suburban", and then travel patterns were compared across neighborhoods. Ewing & Cervero identified at least fourteen such studies, while Saelens et al. (2003) cited another seven (Ewing and Cervero, 2001; Saelens et al., 2003). Broadly speaking, these papers gave some sense of street network differences but little was quantifiable. The papers that do begin to put numbers to built environment factors generally found significant correlations with outcomes such as mode share; however, Ewing and Cervero pointed out that these correlations come with many caveats based upon research design, data availability, appropriate methods and controls, as well as conceptual and theoretical issues (Ewing and Cervero, 2010).

In terms of papers that quantify street network characteristics, the existing travel behavior literature lacks consistency. For instance, Marshall and Garrick described a series of papers that discuss the importance of street connectivity but compute connectivity with a measure of street network density (Marshall and Garrick, 2012). On the other hand, many researchers used population density to measure street network density; while highly correlated in some cities, population density and street network density are not necessarily congruent (Marshall and Garrick, 2012). Ewing & Cervero's meta-analysis also included some specific street network measures, such as intersection density but not in combination with enough other measurements to fully characterize the full range of street network elements (Ewing and Cervero, 2010). Another limitation of the papers that attempt to measure the built environment – especially when compared to the earlier papers that broadly compared different neighborhoods – was the almost complete disregard for street network configuration. While the literature seemed to agree that more compact and connected street networks correlate with a reduction in driving, it remains difficult to understand the full impact of the street network due to the above issues.

Street Networks and Physical Activity

Sallis (2009) traces the history of scholarly contributions to physical activity and built environment research (Sallis, 2009). In terms of outcomes, Sallis notes that it was not until the mid-1990s when physical activity began replacing travel behavior in some papers, and prior to 2000, most physical activity studies focused strictly on recreational physical activity. Since then, this strand of research has evolved to include a broader range of physical activity outcomes.

With respect to measuring the street network, the trends in the physical activity papers were similar to the travel behavior research. Brownson, et al., in their literature review of measures of the built environment for physical activity, observed a great deal of variability in "*the operationalization of common GIS measures,*" including street network measures (Brownson et al., 2009). Forsyth, et al. stressed the importance of refined and consistent methods for measuring the street network to avoid over- or under-estimation of such characteristics on physical activity (Forsyth et al., 2008). For instance, connectivity and density consistently showed positive correlations with physical activity, but findings are often variable or conflicting (Davison and Lawson, 2006). Such conflicts may be due to the differences in operationalization of these variables and the penchant for relying on proxy measures (Badland and Schofield, 2005). Akin to the broad "traditional" and "suburban" categories from the above discussion of comparison studies, terms such as connectivity and density also tend to lack consistent definitions. While connectivity and density generally refer to similar concepts, the actual measures often aggregate or combine concepts like land-use mix and access to destinations, which obfuscate street network design differences.

Street Networks and Health Outcomes

The research related to actual health outcomes is also vast but comes with far less consensus than found in the travel behavior and physical activity strands. Some research suggests that there are significant correlations between the built environment and health (Davison and Lawson, 2006; Dunton et al., 2009; Frank et al., 2001; Grafova, 2008; Saarloos et al., 2009; Williams et al., 2012). Other researchers find no significant relationship between built environmental variables and, for instance, BMI or the body mass index (Eid et al., 2008; Kirk et al., 2010; Sallis and Glanz, 2006).

One issue has to do with what variables are included in the researcher's definition of the built environment. When inclusive of the surrounding food environment, it is significantly correlated with obesity and obesity-related illnesses (Bader et al., 2010; Lovasi et al., 2009; Wells and Yang, 2008). For instance, Black and Macinto used multilevel regression, controlling for a variety of variables, to find that the availability of local food and fitness amenities was associated with reduced obesity (Black and Macinko, 2010). They also found income to be an important factor, which is not uncommon in such health studies, as the literature more generally suggests that socioeconomic status (SES) variables significantly impact health outcomes. Income (Lovasi et al., 2009; Panter et al., 2010), age (Cutumisu and Spence, 2009; Kemperman and Timmermans, 2009; Li et al., 2009; Timperio et al., 2010), and race (Coogan et al., 2009; Haas and Rohlfsen, 2010) are all important factors that impact our understanding of the built environment and health. The overall impact of the built environment may vary by population and social group (Forsyth et al., 2009; Lovasi et al., 2009); thus, it is important to control for such SES and food environment variables in our study. This is critical when attempting to isolate the street network and street design factors of interest. While such factors have not been completely overlooked in the health and built environment literature, they have not yet been sufficiently measured and evaluated (MacDonald et al., 2010).

This literature review aimed to focus specifically on the impact of street network variables on travel behavior, physical activity, and health, and as such, on synthesizing a subset of the literature. Based on the inconsistent findings, especially regarding health outcomes, we argue that by utilizing more concise definitions and built environment metrics – specifically those metrics related to street network characteristics – scholars can more clearly identify significant trends. The importance of the street network as a defining characteristics of the built environment is understudied in comparison to other aspects of the built environment (Leck, 2006), and this paper aims to fill that gap.

STUDY BACKGROUND

The goal of this paper is to explore the complex relationships between street network design and key indicators of health including obesity, diabetes, high blood pressure, heart disease, and asthma. The study was based on an extensive built environment dataset originally collected for a road safety project of California cities with populations ranging from 30,000 residents to just over 100,000 (Marshall and Garrick, 2009, 2010a, 2011a, 2012; Marshall and Garrick, 2010b, 2011b). The following cities were selected from a set of over 150 California cities to best represent a geographically diverse collection of twelve of the safest medium-sized cities and twelve of the least safe based upon the road fatality rate:

Safer Cities

- Alameda
- Berkeley
- Chico
- Cupertino
- Danville
- Davis
- La Habra
- Palo Alto
- San Luis Obispo
- San Mateo
- Santa Barbara
- Santa Cruz

Less Safe Cities

- Antioch
- Apple Valley
- Carlsbad
- Madera
- Morgan Hill
- Perris
- Redding
- Rialto
- Temecula
- Turlock
- Victorville
- West Sacramento

The cities are all from California because we originally wanted to ensure consistency in the safety data, which is collected differently by each state. This reasoning is equally essential for the health data. Street network measures – including measures of street network density, street connectivity, and street patterns – were combined with street design characteristics, the California Health Interview Survey (CHIS), as well as travel behavior data and socioeconomic data from the Census and American Community Survey. This information was geo-coded in a GIS database in order to conduct a comprehensive spatial analysis.

DATA

Health Outcomes Data

Cross-sectional health data was collected from the California Health Interview Survey (CHIS) for the years 2003, 2005, 2007, and 2009. With a range in sample size from 42,000 to 51,000 adults, CHIS is one of the most extensive health-based telephone survey in the country of civilian households selected through random digit dialing (UCLA Center for Health Policy Research, 2009). The sample for this analysis was restricted to adults, 18 years and older due to data restrictions. For the CHIS adult sample, the interview response rate was 60%, which is comparable to telephone surveys carried out by the National Center for Health Statistics. The health outcomes (obesity, diabetes, high blood pressure, heart disease, and asthma) represent the fraction of respondents self-reporting that particular disease (obesity was determined as BMI≥30.0 via self-reported height and weights).

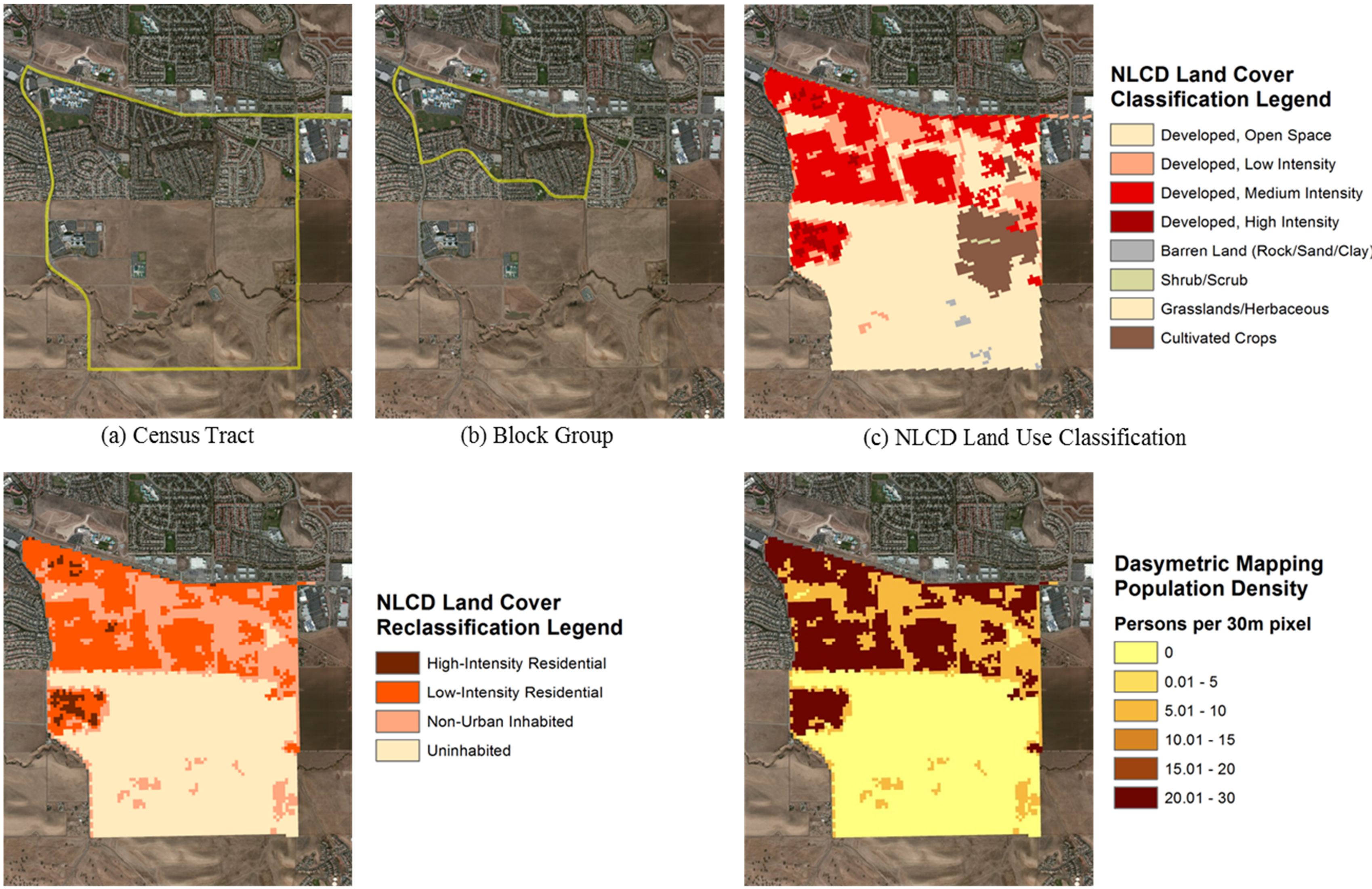
To protect individual privacy, individual person level data were aggregated to the census tract level by CHIS personnel. In investigating the applicability of this level of geography for our study, we identified many instances where the census tract boundary extended beyond developed edges and well into uninhabited and low density areas. In other words, population density is not homogenous across many census tracts (Mennis, 2003). Figure 2a depicts an example of this problem for a census tract from Antioch, CA, where the development intensities across the census tract are quite diverse. With a population of 6,489, the calculation of population density would be quite different depending upon the area used for the denominator; if using the entire census tract, the population density is 1,750 people/sq. mi. but would be more than triple that if we focus on the corresponding highly developed block group shown in the top-left of Figure 2b.

This issue of heterogeneous population distributions is not uncommon with health-related data, and unfortunately, such aggregated data can mask trends and the spatial variation of health disparities (IEHIAS, 2013). A frequent solution is to employ spatial disaggregation techniques such as simple area weighting, mask area weighting, or stochastic allocation (Gallego, 2010; IEHIAS, 2013). More advanced spatial disaggregation techniques typically differ from the simpler methods in that they incorporate supplementary data to enable the disaggregation. For instance with population-based disaggregations, land use data is particularly useful (Gallego, 2010; Gallego et al., 2011; Mennis, 2003; Sleeter and Gould, 2008). One such technique is dasymetric mapping. Dasymetric mapping techniques originated more than 150 years ago, but with the advent of GIS has become the subject of renewed interest and study over the last few decades (Eicher and Brewer, 2001). The fundamental idea behind dasymetric mapping is to depict the underlying data of zonal boundaries (i.e. census tract) by dividing them into internally homogenous zones (Eicher and Brewer, 2001). Dasymetric mapping is often used with population-based data, to the point where the U.S. Geological Survey (USGS) and the European Environment Agency publish dasymetric population density grids for researchers (Gallego, 2010; Sleeter and Gould, 2008).

For the purposes of our effort, we employed the USGS methodology in GIS. This approach is specifically intended for reassigning census tract-level population data to another set of overlapping zones and employs the National Land Cover Database as the ancillary dataset (Sleeter and Gould, 2008). The basic steps included reclassifying the land use and land cover (LULC) codes (shown in Figure 2c) into one of four population-based categories, which are depicted for our Antioch example in Figure 2d. We then broke the census tracts down into relatively homogenous zones using the USGS-published GIS script, based upon published areal weighting and empirical sampling techniques (Mennis, 2003; Sleeter and Gould, 2008). This step results in a raster grid highlighting areas with homogenous population densities, which is illustrated in Figure 2e. Area ratios combined with the original health outcome data allow us to calculate the number of people within each zone afflicted with each disease. We then intersect these zones with the block group layer and again use area ratios to calculate the adjusted health rates. Table 1 compares the original data to the dasymetric adjusted data; the population-weighted overall disease rates remain similar. Spatially, the result is a set of health outcomes that will minimize the masking of health disparities during the analysis phase.

Table 1 - Comparison of Health Outcome Rates, Weighted by Population

	Original Health Outcomes (census tract level)	**Dasymetric Adjusted Health Outcomes (block group level)**	Difference
Proportion of Obese Respondents	19.7%	19.3%	-1.8%
Proportion of Respondents with Diabetes	6.3%	6.2%	-1.6%
Proportion of Respondents with High Blood Pressure	24.9%	24.3%	-2.4%
Proportion of Respondents with Heart Disease	6.1%	6.4%	4.9%
Proportion of Respondents with Asthma	12.9%	13.1%	1.7%



(a) Census Tract

(b) Block Group

(c) NLCD Land Use Classification

(d) NLCD Land Use Reclassification

(e) Dasymetric Mapping Result

Figure 2 - Dasymetric Mapping Example

Street Network Data

While many of the papers covered in the literature review point to both increased network density and connectivity as desirable, few successfully differentiate between these two network qualities with quantifiable measures. In some papers, network density and connectivity measures were mistakenly used interchangeably, and in most papers, network configuration was ignored altogether (Marshall and Garrick, 2012). So in order to best characterize street networks, we created a straightforward set of measures for the three essential street network characteristics of interest:

i. Street connectivity
ii. Street network density
iii. Street configuration

While there are abundant indices, ranging from very simple to overly complex, available to measure both connectivity and network density, stepwise statistical analysis helped identify variables resulting in the strongest models: intersection density for street network density; and the link-to-node ratio for street connectivity. Intersection density tallies the total number of nodes or intersections, including dead ends, and divides it by the area. Higher values signify higher network densities. The link-to-node ratio divides the total number of links (i.e. road segments between intersections) by the total number of nodes (i.e. intersections) (Ewing, 1996; Handy et al., 2003; Litman, 2005). Using the 2012 North American Detailed Streets GIS layer from ESRI[1], we calculated both intersection density and the link-to-node ratio for the typical street network as well as for the same network but including pedestrian-only connections and alleys as well[2]. Alleys are also included in the intersection density measure used by LEED-ND (Council, 2009). This latter set of network density and connectivity measures – with alleys and pedestrian-only connections included – proved stronger in the health statistical models.

Neither intersection density nor the link-to-node ratio imparts any sense of configuration. To resolve this, we adapted a chart from Stephen Marshall's book *Streets and Patterns* that emphasizes the major street network structure separately from the minor street network, depicted in Figure 3 (Marshall, 2005). To facilitate replication, major streets were classified as those falling between A20 and A39 under the Feature Class Code (FCC) classification schema used by the Census. The A20 series includes all primary roads that are not limited access roads, while the A30 series includes all secondary or connecting roads; in other words, the major streets are essentially the arterial and collector roads. Understanding the role of the major streets in the network helped facilitate the manual classification of each of the over 1,000 block groups into one of the eight representative configuration types. Although Marshall's categories do not accommodate every possible pattern, they do provide a straightforward visual classification that can help differentiate between the most common configuration types. Actual city patterns are often more complex than the representative configurations; so while actual street networks were not always exact replicas of the representative diagrams, there were only a handful of the over 1,000 block groups that were not able to be confidently classified. Table 2 displays the descriptive data for the analysis.

Street Data

We collected the following street design characteristics for every major street segment (based on the street categorization methodology above) using Google Earth and Google Street View:

- Total number of lanes

[1]*Please note that the 2000 Census TIGER files were used to calculate street network measures in our prior street network papers.*

[2]*Please note that street network density and connectivity measures in our prior papers did not include non-automobile streets or alleys; as a result, the values reported in this paper are typically higher than those reported in previous papers.*

- Outside shoulder width
- Raised median (0 = no, 1 = yes)
- Painted median (0 = no, 1 = yes)
- On-street parking (0 = no, 1 = yes, 0.5 = along one side of street)
- Bike lanes (0 = no, 1 = yes, 0.5 = along one side of street)
- Sidewalks (0 = no, 1 = yes, 0.5 = along one side of street)

This data was field verified in six cities via a sample of major streets. For use in the statistical model, we aggregated the data to the block group level.

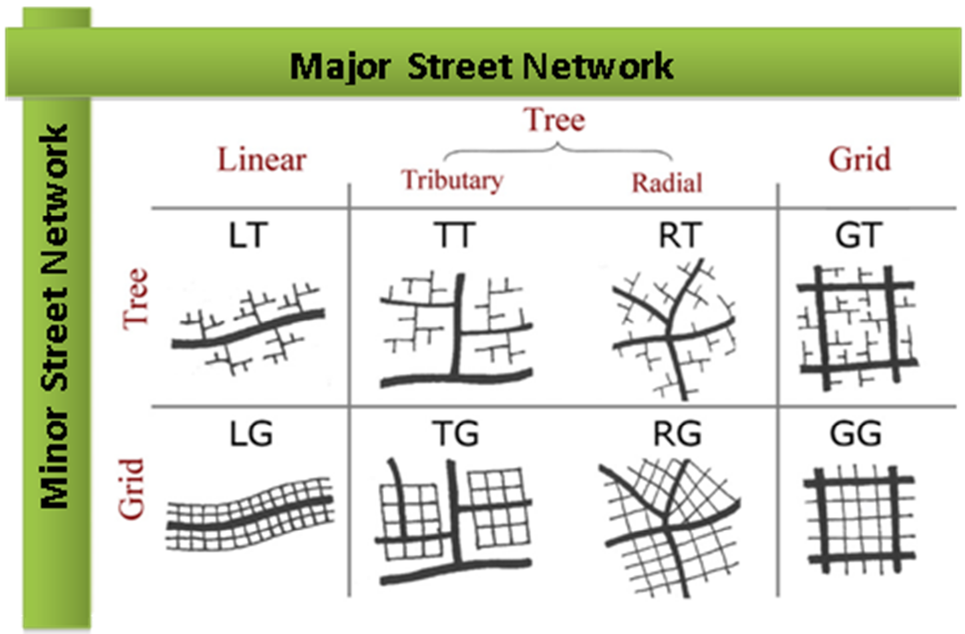


Figure 3 - Street Configuration Classifications, Adapted from S. Marshall [65]

Land Use Data

As discussed in the literature review, it is imperative for built environment/health studies to account for the food environment. Hence, we purchased land use data from InfoUSA. This data included addresses for every restaurant, grocery store, big box store, and fitness club in the 24 cities. We geocoded these land uses into GIS and disaggregated the restaurants into two categories: one for fast food restaurants and one for all other restaurants. Each land use category (i.e. fast food restaurants, other restaurants, grocery stores, fitness clubs, and big box stores) was aggregated and counted at both the block group and city levels of geography. We define a big box store as a retail use with a single building occupying 40,000 square feet or more. Big box stores typically serve large market areas, possess very large parking lots, and can sometimes diminish the pedestrian environment, which could negatively impact active transportation and health outcomes.

As part of this work, a number of land use and built environment variables were calculated and investigated but were unable to be used in the final models due to high correlation with other tested variables. The variables in the final models were selected to maximize model significance. Some of these variables include: population, population density, employment density, mode share data, centerline length of streets per unit area, and block size.

Socioeconomic Status (SES) Data
SES data collected from the U.S. Census and American Community Survey included income, age, ethnicity, and level of education. Income is at the household level in continuous categories of $10,000s. The age categories for those 18 years or older were weighted and averaged by the mid-point of each categorization level. Ethnicity categories were aggregated to create a variable representing the total non-white percentage. For level of education, we aggregated the data into an education index score. Scores ranged from zero to four in terms of the highest level of education received, with: less than a high school diploma = 0; high school degree = 1; bachelor's degree = 2; master's or professional degree = 3; doctorate = 4. Thus, a score of 2.0 indicates that the average adult level of education for the specified area is a bachelor's degree.

Table 2 - Descriptive Statistics (selected variables) and Multi-Level Model Hierarchy

	Variable	Mean	SD	Min	Max
Health Outcomes (N=1,044)					
Health Variables	Proportion of Obese Respondents	0.18	0.13	0.00	0.84
	Proportion of Respondents with Diabetes	0.06	0.07	0.00	0.57
	Proportion of Respondents with High Blood Pressure	0.24	0.12	0.00	0.84
	Proportion of Respondents with Heart Disease	0.06	0.06	0.00	0.47
	Proportion of Respondents with Asthma	0.13	0.10	0.00	0.84
Level 1; Block Group Level (N=1,044)					
Street Network Variables	Intersection Density (int./sq. mi. for pedestrian network)	181	99	0	1,258
	Link to Node Ratio (for pedestrian network)	1.76	0.42	0.25	5.00
	Dead End Density	48	49	0	470
	Bisecting or Adjacent Limited Access Highway (0, 1)	0.26	0.44	0.00	1.00
	Curvilinear Streets (0, 1)	0.17	0.37	0.00	1.00
	Distance from City Center (mi.)	1.84	1.41	0.00	8.98
	% One-Way Roads	0.12	0.14	0	0.79
Major Street Design Variables	Avg. Total # of Lanes on Major Streets	2.97	1.12	0	7.34
	Avg. Outside Shoulder Width on Major Streets (ft.)	1.68	2.57	0	12.00
	% of Major Street Length with Painted Median	3.75	5.74	0	44.42
	% of Major Street Length with Raised Median	2.21	3.32	0	20.00
	% of Major Street Length with On-Street Parking	0.50	0.40	0	1.00
	% of Major Street Length with Bike Lane	0.27	0.35	0	1.00
	% of Major Street Length with Sidewalk	0.83	0.31	0	1.00
Land Use Variables	# of Fast Foot Restaurants	0.87	2.15	0	20.00
	# of Total Restaurants	4.13	9.27	0	116.00
	# of Convenience Stores	0.09	0.30	0	2.00
	# of Grocery Stores	0.43	0.82	0	7.00
	# of Fitness Clubs	0.24	0.64	0	6.00
	# of Big Box Stores	0.03	0.22	0	3.00
SES Data	% Non-White	29.72	18.13	0.00	81.02
	Median HH Income (10,000s)	7.02	3.85	0	22.73
	Level of Education Score	1.46	0.55	0	3.41
	Median Age	36.51	8.32	19	75.10
	Avg. Travel Time to Work (min)	26.71	7.95	0	51.58
Level 2; City Level (N=24)					
Street Network Variables	Intersection Density (int./sq. mi. for pedestrian network)	150.10	43.16	45.04	207.73
	Link to Node Ratio (for pedestrian network)	1.44	0.11	1.21	1.69
	Dead End Density	43.86	19.41	13.89	87.05
	% of City's Block Groups with Gridded Neighborhood	0.24	0.22	0	0.78
	% of Block Groups Bisected by a Highway	0.26	0.20	0	0.68
	% of Block Groups with Curvilinear Streets	0.17	0.22	0	0.91
Major Street Design Variables	% One-Way Roads	0.13	0.05	0.03	0.24
	Avg. Total # of Lanes on Major Streets	2.93	0.61	2.17	4.43
	Avg. Outside Shoulder Width on Major Streets (ft.)	1.67	1.45	0.21	7.39
	Avg. Raised Median Width (ft.)	3.75	2.62	0.52	11.27
	Avg. Painted Median Width (ft.)	2.11	1.53	0.38	6.05
	Proportion of Major Street Length with On-Street Parking	0.33	0.16	0.03	0.58
	Proportion of Major Street Length with Bike Lane	0.21	0.21	0.00	0.96
	Proportion of Major Street Length with Sidewalk	0.60	0.18	0.16	1.04
Land Use Variables	# of Fast Foot Restaurants	41.42	15.24	13.00	82.00
	# of Total Restaurants	221.30	95.18	78.00	428.00
	# of Convenience Stores	4.06	2.12	0	10.00
	# of Grocery Stores	23.24	12.12	7.00	48.00
	# of Fitness Clubs	12.67	7.74	2.00	31.00
	# of Big Box Stores	1.56	1.51	0	5.00
SES Data	Household Income	51,622	19,527	29,359	114,064

METHODS

We summarized the approach to assessing streets networks and the built environment in the data section; additional details can be found in our previous papers (Marshall and Garrick, 2009, 2010a, 2011a, 2012; Marshall and Garrick, 2010b, 2011b). This section describes the statistical methodology.

The fundamental research question for this paper – whether street network characteristics and street design features are associated with health disparities – is tested using a multilevel hierarchical random effect statistical model, which over the last fifteen years has become accepted practice for researchers conducting spatial health studies (Burton et al., 2009; Healy, 2001; Li et al., 2005; Radenbush and Bruk, 2002; Rundle et al., 2007; Subramanian et al., 2003). Our data is considered multilevel since it consists of health and built environment records on the first level that can be clustered into a second level of geography, in this case at the city level. The concept behind a multilevel hierarchical model is linking a pair of statistical models in order to simultaneously allow a focus on both micro-level and macro-level relationships as well as the interaction between the two (Healy, 2001). This type of structure helps account for spatial autocorrelation and the fact that respondents in the same areas share the characteristics of those areas, which would violate the independence assumption of an ordinary least squares (OLS) regression (Ewing et al., 2003). If we did not take this into account, the standard errors of regression coefficients that we are seeking to associate with our community design and street network characteristics would be underestimated (Ewing et al., 2003).

The following represents the hierarchical structure:

Level 1: Between-Block Group Disparities

Level 2: Between-City Differences

The first level of the model includes the health outcomes, SES data, and built environment characteristics of each block group, which can be modeled as a function of the characteristics of the block groups plus stochastic random error (Ewing et al., 2003). This equates to each city having a specific regression equation portraying the association between the characteristics and health outcomes of the block group. For the second level, the intercept and coefficients are modeled in terms of city characteristics plus random error (Ewing et al., 2003).

The level 1 model tested health outcomes as a function of the city mean using the following form:

$$Y_{ji} = \beta_{0j} + \beta_{1j}x_{ij} + r_{ij} \qquad r_{ij} \sim N(0, \sigma^2)$$

where Y_{ji} is the outcome for block group i in city j, and x_{ij} is a fixed covariate. β_{0j} represents the mean level of the outcome in city j, and β_{1j} represents the effect of the block group-level variable on the outcome in city j.

The expected random effects level 2 model allows the intercept and slope to vary across cities. The level 2 model corresponding to a level 1 random coefficients model is as follows:

$$\begin{aligned} \beta_{0j} &= \gamma_{00} + u_{0j} \\ \beta_{1j} &= \gamma_{10} + u_{1j} \end{aligned} \qquad \begin{pmatrix} u_{0j} \\ u_{1j} \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \tau_{00} & \tau_{01} \\ \tau_{01} & \tau_{11} \end{pmatrix} \right)$$

where γ_{00} represents the overall average outcome level (at $x_{ij} = 0$), and γ_{10} is the average effect of block group variables on the outcomes. Also, the city level community data and street network information were added as fixed effects in this model in order to permit for the potential varying and cross influence of block group level and city level built environment characteristics. For instance, one could imagine that living in a compact and connected block group might make more of a difference in a city of similar structure as compared to a city characterized by a sparse, disconnected street network; this modeling structure facilitates the testing of such questions related to the differing public health impact of neighborhood walkability as compared to citywide walkability. The statistical analyses were completed with SAS 9.3 using the PROC MIXED procedure command. The variables used in the final models were selected in an effort to maximize model significance using the AIC value. Statistical significance at three levels (i.e. $p<.10$, $p<.05$; and $p<.01$) is noted by the asterisks in Table 3. This methodology is common to other studies attempting to concurrently display the results of multiple statistical models (Chatman, 2013). With respect to multicollinearity, none of the variables used in the final models had a Pearson correlation coefficient higher than 0.5.

RESULTS

Table 3 portrays the statistical results of the four multilevel health models, as we did not find statistical significance with the asthma model. The health outcome for:

- Model 1 is obesity;
- Model 2 is diabetes;
- Model 3 is high blood pressure (HBP); and
- Model 4 is heart disease.

The variables tested will be discussed via the following categories: street network characteristics, street design features, land use and the food environment, and SES variables. The interaction between street network and SES factors has shown to sometimes be correlated with health (Boone-Heinonen et al., 2011). While parsing out those interactions is challenging due to the number of confounding relationships, we tested all such relevant interactions terms (between every combination of street network and SES variables) and found no significant interactions. Also, the hierarchical terms (corresponding to the variability in slopes) are significant in every model; this means that we cannot reject the null hypothesis that there is no difference in slopes across cities for the associated health outcomes.

Street Network Characteristics

The street network variables represent the three fundamental characteristics of a street network: i) street network density; ii) street connectivity; and iii) configuration.

Increased intersection density, a measure of street network density, is significantly correlated with: a reduction in obesity at the block group level; and a reduction in all four disease rates at the city level (which corresponds to the intersection density for the entire city).

Rather than report elasticity measures, Table 4 and Table 5 calculate the percent change in the expected disease rate based upon changing the level of a single variable and holding all other variables at their mean. This percent change is based upon the expected disease rate with respect to a reference value close to the mean value of that variable and is mathematically the same as elasticity measures, but easier to visualize (Noland and Quddus, 2004). These results focus solely on the influence of intersection density while holding all other variables constant at their mean value. Regarding street network density, for example, the results suggest that reducing intersection density at the block group level from 144 intersections per square mile (equivalent to a 12-by-12 grid) to 81 (equivalent to a 9-by-9 grid) is associated with, on average, a 2.8% increase in obesity. The same drop in intersection density across the entire city (as opposed to the block group level) corresponds with the following: a 33.4% increase in obesity, a 42.4% increase in diabetes, a 12.9% increase in HBP, and a 19.7% increase in heart disease. These results suggest that citywide intersection density is more important to health outcomes than at the block group level; in other words, better health outcomes are more strongly associated with living in a compact city than a compact neighborhood surrounded by a sparse city. This is an important result in that many new developments focus on building urban enclaves with high intersection densities in the middle of more suburban environments. Such developments have many benefits but may not be optimal for public health where our results suggest that the overall character of the city makes a bigger difference.

Findings regarding street connectivity demonstrate similar trends to street network density with an increased link-to-node ratio at the block group level being significantly associated with lower rates of obesity and heart disease. The link-to-node ratio was not found to be significant in any models at the city level. Comparing a block group with a high level of street connectivity to that of an average level (link-to-node ratio of 2.25 vs. 1.75), we would expect an 8.6% lower rate of obesity and a 6.7% lower rate of heart disease. Thus, more compact and connected street networks are significantly associated with improved health outcomes.

The categorical variable representing street configuration was only significant in the obesity and HBP models; specifically, we found only two street network patterns to exhibit significant differences from the network reference type, 'TT' (tree-like major streets and tree-like minor streets). These two network patterns were 'GG' (gridded major streets and gridded minor streets) and 'RG' (radial major streets and gridded minor streets). Holding all other variables at their mean value (including both intersection density and the link-to-node ratio), we would expect a 1.0% increase in obesity for a 'GG' network and 47.6% increase for an 'RG' network at the block group level. It is worth noting that 26 out of the 1,044 block groups were designated as an 'RG' pattern type, as the gridded network from our cities tended to be more orthogonal. For HBP, both the 'GG' and 'RG' networks were associated with almost a 10.5% drop, as compared to the 'TT' reference type.

We also accounted for the differences in how these various network configurations tend to be built in practice by holding all variables at their overall mean other than street network density, connectivity, and configuration. For intersection density and the link-to-node ratio, we used the mean value of each particular configuration and found that: the 'GG' network is associated with improved obesity, HBP, and heart disease; and the 'RG' network is associated with increased obesity but lower rates of HBP and heart disease. These expected rates are shown at the bottom of Table 4.

Whether or not the streets were curvilinear was not significant in any model.

Street Design Features

Most of the street design features were not significant in the health models; however, the average number of lanes on the major streets was significant in Models 1, 2, and 4. Wider major streets with more driving lanes were indicative of increased obesity and diabetes rates. This result seems sensible when considering that wider major street may be indicative of an inferior pedestrian environment. However, the presence of additional lanes on the major streets was also associated with reduced heart disease. This result appears counter-intuitive but could suggest differences in access to health care and diagnoses, as studies suggest the rate of undiagnosed heart disease is much higher than the rate of undiagnosed diabetes (Lloyd-Jones et al., 2010).

At the block group level, averaging six lanes instead of two on the major streets suggested a 28.9% increase in obesity but a similar sized decrease in heart disease (Table 4). This same change to the major roads at the city level was associated with a 366.6% increase in diabetes. In the same diabetes model (Model 2), we found that the presence of bike lanes on the major roads was associated with lower rates. Raising the percentage of bike lanes on major roads from 0% to 40% was associated with a 47.6% decrease in the diabetes rate.

Land Use and the Food Environment

In terms of the food environment, more fast food restaurants were associated with a lower HBP rate at the block group level and a higher diabetes rate at the city level. The presence of a single big box store at the block group level was associated with a 13.7% rise in obesity rates and a 24.9% increase in the diabetes rate, as shown in Table 5. In terms of other food environment variables: the presence of a grocery store at the block group level was associated with a slight decrease in HBP; and more convenience stores at the city level were associated with an increase in both the obesity and diabetes rates. Just two additional convenience stores in a city over the average number were associated with a 16.9% increase in obesity and a 29.1% rise in diabetes. The other measured land use element, fitness clubs, was significant in the obesity model at the city level. A city with a relatively high number of fitness clubs (20) correlated with a 24.5% drop in obesity rates as compared to a city with an average number (12).

Socioeconomic Status

At least one SES variable was significant in each of the five health models. Since household income and education score were highly correlated, only the variable that resulted in a better AIC was used in the final model. We also tested a series of interaction terms to determine whether certain SES groups were more or less impacted by street network and street design factors but found no significant results.

With respect to income, higher income was associated with lower rates of obesity and lower rates of HBP. More specifically, results suggest an area with poverty level household incomes (~$20,000) as compared to an area of approximately average income for the sample cities (~$60,000) is associated with an 8.4% higher obesity rate and a 6.4% higher HBP rate (Table 5). Age was significant in Models 3 and 4, where a neighborhood with an older population was correlated with increased HBP and heart disease rates. The percent of non-white residents was significant in the diabetes model where an increase in the percentage of minorities was associated with an increase in diabetes. Average commute time was only significant in the obesity model but with a contrary effect to what has been seen in several notable studies (Frank et al., 2004; Hoehner et al., 2012; Lindstrom, 2008; Mobley et al., 2006; Pendola and Gen, 2007; Wen et al., 2006). Our results suggest that a longer commute is significantly associated with a lower obesity rate. Given that many of the cities investigated for this study are very well-known for their active transportation and high transit mode shares, the finding that a five minute longer commute is associated with a 3.6% decrease in obesity seems plausible. For instance in cities such as Davis – which boasts the highest bicycling to work mode share in the country – a longer commute, if walking or biking, might very well be associated with improved health outcomes.

To further investigate this hypothesis, we compared commute times to mode share statistics but did not find commute time to be highly correlated with any particular mode share. The only evidence of high correlation between commute time and mode share surfaced when we focused our analysis on the eight cities with bicycle commute modes share greater than 2.5% (i.e. Alameda, Berkeley, Chico, Davis, Santa Barbara, Santa Cruz, and San Luis Obispo). While bicycling and walking mode shares were still not highly correlated with commute time for this subset of cities, we found a Pearson correlation coefficient of 0.66 between transit mode share and the number of minutes commuting. High transit usage has been shown in other studies to be associated with increased physical activity (Besser and Dannenberg, 2005; Wener and Evans, 2007) and reduced BMI (MacDonald et al., 2010). Similar trends could be playing a role in our findings, which warrants future study with individualized health and travel behavior data so that all modes of transportation can be examined in greater detail to better explain these relationships.

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Table 3 - Results of Multilevel Hierarchical Models

Variable	Model 1 Obesity		Model 2 Diabetes		Model 3 HBP		Model 4 Heart Disease	
Intercept	0.4212	***	0.05057	*	0.2676	***	0.0991	***
Block Group Level								
'TT' = Citywide Tree-like, Neighborhood Tree-like *(reference value)*	0				0			
'GG' = Citywide Grid, Neighborhood Grid	0.001673				- 0.02541	**		
'GT' = Citywide Grid, Neighborhood Tree-like	0.007246				- 0.00364			
'LG' = Citywide Linear, Neighborhood Grid	- 0.0352				0.1439	**		
'LT' = Citywide Linear, Neighborhood Tree-like	0.007084				0.0384	**		
'RG' = Citywide Radial, Neighborhood Grid	0.08338	**			- 0.02563			
'RT' = Citywide Radial, Neighborhood Tree-like	- 0.00216				- 0.02876	*		
'TG' = Citywide Tree-like, Neighborhood Grid	0.01419				- 0.00304			
Intersection Density (intersections/mi^2)	- 0.00008	**						
Link to Node Ratio	- 0.03019	**					- 0.00846	*
Avg. Total # of Lanes on Major Streets	0.01184	**					- 0.00485	**
# of Fast Food Restaurants					0.003088			
# of Big Box Stores	0.02386	*	0.01444	*				
# of Grocery Stores					- 0.01181	**		
Median Household Income (10,000s)	- 0.00377	**			- 0.00397	**		
Median Age					0.002311	***	0.000632	**
% Non-White			0.000383	**				
Avg. No. of Minutes Commuting to Work	- 0.00129	**						
City Level								
Intersection Density (intersections/mi^2)	- 0.00096	**	- 0.00041	**	- 0.00051	**	- 0.0002	**
Avg. Total # of Lanes on Major Streets			0.02888	**				
% of Major Streets with Bike Lanes			- 0.07022	**				
# of Fast Food Restaurants			- 0.00113	**				
# of Fitness Centers	- 0.00548	**						
# of Convenience Stores	0.01476	**	0.008427	**				
Hierarchical Effects								
Intercept Variance	0.001973	**	0.000365	**	0.001106	**	0.00013	**
Model Fit								
Observations	1,018		1,044		1,018		1,043	
AIC	-1,584		-2,732		-1,360		-2,799	

* p <.10; ** p < .05; *** p< .01

Table 4 - Expected Change in Health Outcomes for Street Network and Street Design Variables

	Model 1		Model 2		Model 3		Model 4	
	Obesity		Diabetes		HBP		Heart Disease	
Base Rate of Disease (calculated using mean values for all variables)	17.5%	% Change	5.8%	% Change	24.5%	% Change	6.3%	% Change
Intersection Density (Block Group Level)								
81	**18.3%**	2.8%	-	-	-	-	-	-
144 (reference value)	**17.8%**	-	-	-	-	-	-	-
225	**17.2%**	-3.6%	-	-	-	-	-	-
324	**16.4%**	-8.1%	-	-	-	-	-	-
Intersection Density (City Level)								
81	**24.1%**	33.4%	**8.7%**	42.4%	**28.0%**	12.9%	**7.7%**	19.7%
144 (reference value)	**18.1%**	-	**6.1%**	-	**24.8%**	-	**6.4%**	-
225	**10.3%**	-43.0%	**2.8%**	-54.5%	**20.7%**	-16.6%	**4.8%**	-25.3%
324	**0.8%**	-95.5%	**-1.3%**	-121.2%	**15.7%**	-37.0%	**2.8%**	-56.2%
Intersection Density (Block Group & City Levels[1])								
BG City								
81 81	**24.9%**	35.6%	**8.7%**	42.4%	**28.0%**	12.9%	**7.7%**	19.7%
144 144 (reference value)	**18.4%**	-	**6.1%**	-	**24.8%**	-	**6.4%**	-
225 225	**10.0%**	-45.8%	**2.8%**	-54.5%	**20.7%**	-16.6%	**4.8%**	-25.3%
324 324	**-0.3%**	-101.8%	**-1.3%**	-121.2%	**15.7%**	-37.0%	**2.8%**	-56.2%
Link to Node Ratio (Block Group Level)								
1.50	**18.3%**	4.3%	-	-	-	-	**6.5%**	3.4%
1.75 (reference value)	**17.5%**	-	-	-	-	-	**6.3%**	-
2.00	**16.8%**	-4.3%	-	-	-	-	**6.1%**	-3.4%
2.25	**16.0%**	-8.6%	-	-	-	-	**5.9%**	-6.7%
Street Configuration (Block Group Level)								
TT (reference value)	**17.5%**	-	-	-	**24.5%**	-	-	-
GG	**17.7%**	1.0%	-	-	**22.0%**	-10.4%	-	-
RG	**25.9%**	47.6%	-	-	**22.0%**	-10.5%	-	-
Street Configuration as Typically Built (Block Group Level) via Int. Density, Link to Node Ratio, and No. of Lanes on Major Streets								
TT (reference value)	**18.2%**	-	-	-	**24.5%**	-	**6.0%**	-
GG	**15.5%**	-15.1%	-	-	**22.0%**	-10.4%	**5.6%**	-6.1%
RG	**23.9%**	31.0%	-	-	**22.0%**	-10.5%	**5.8%**	-2.6%
Total # of Lanes on Major Streets (Block Group Level)								
2 (reference value)	**16.4%**	-	-	-	-	-	**6.8%**	-
4	**18.7%**	14.5%	-	-	-	-	**5.8%**	-14.4%
6	**21.1%**	28.9%	-	-	-	-	**4.8%**	-28.7%
Total # of Lanes on Major Streets (City Level)								
2 (reference value)	-	-	**3.2%**	-	-	-	-	-
4	-	-	**8.9%**	183.3%	-	-	-	-
6	-	-	**14.7%**	366.6%	-	-	-	-
Total # of Lanes on Major Streets (Block Group & City Levels[2])								
BG City								
2 2 (reference value)	**16.4%**	-	**3.2%**	-	-	-	**6.8%**	-
4 4	**18.7%**	14.5%	**8.9%**	183.3%	-	-	**5.8%**	-14.4%
6 6	**21.1%**	28.9%	**14.7%**	366.6%	-	-	**4.8%**	-28.7%
% of Major Street Length with Bike Lanes (City Level)								
0%	-	-	**7.3%**	23.8%	-	-	-	-
20% (reference value)	-	-	**5.9%**	-	-	-	-	-
40%	-	-	**4.5%**	-23.8%	-	-	-	-

[1]Intersection density at block group level is signifcant in Model 1 and at the city level in all 4 Models.

[2]The avgerage total number of lanes on the major streets at block group level is signifcant in Models 1 and 2 and at the city level in Model 2.

Table 5 - Expected Change in Health Outcomes for Land Use and SES Variables

	Model 1		Model 2		Model 3		Model 4	
	Obesity		Diabetes		HBP		Heart Disease	
Base Rate of Disease (calculated using mean values for all variables)	16.4%	% Change	5.8%	% Change	24.5%	% Change	6.3%	% Change
Fast Food Restaurants (Block Group level)								
0	-	-	-	-	**24.3%**	-1.3%	-	-
1 (reference value)	-	-	-	-	**24.6%**	-	-	-
3	-	-	-	-	**25.2%**	2.5%	-	-
Big Box Stores (Block Group level)								
0 (reference value)	**17.4%**	-	**5.8%**	-	-	-	-	-
1	**19.8%**	13.7%	**7.2%**	24.9%	-	-	-	-
Grocery Stores (Block Group Level)								
0	-	-	-	-	**25.0%**	2.4%	-	-
0.5 (reference value)	-	-	-	-	**24.4%**	-	-	-
1	-	-	-	-	**23.8%**	-2.4%	-	-
Fast Food Restaurants (City Level)								
30	-	-	**7.1%**	18.8%	-	-	-	-
40 (reference value)	-	-	**6.0%**	-	-	-	-	-
50	-	-	**4.9%**	-18.8%	-	-	-	-
Fitness Clubs (City Level)								
4	**22.3%**	24.5%	-	-	-	-	-	-
12 (reference value)	**17.9%**	-	-	-	-	-	-	-
20	**13.5%**	-24.5%	-	-	-	-	-	-
Convenience Stores (City Level)								
2	**14.5%**	-16.9%	**4.1%**	-29.1%	-	-	-	-
4 (reference value)	**17.4%**	-	**5.8%**	-	-	-	-	-
6	**20.4%**	16.9%	**7.5%**	29.1%	-	-	-	-
Household Income (Block Group Level)								
$20,000	**19.4%**	8.4%	-	-	**26.5%**	6.4%	-	-
$40,000	**18.7%**	4.2%	-	-	**25.7%**	3.2%	-	-
$60,000 (reference value)	**17.9%**	-	-	-	**24.9%**	-	-	-
$80,000	**17.1%**	-4.2%	-	-	**24.1%**	-3.2%	-	-
$100,000	**16.4%**	-8.4%	-	-	**23.3%**	-6.4%	-	-
Age (Block Group Level)								
20	-	-	-	-	**20.7%**	-14.3%	**5.2%**	-15.3%
35 (reference value)	-	-	-	-	**24.2%**	-	**6.2%**	-
50	-	-	-	-	**27.6%**	14.3%	**7.1%**	15.3%
65	-	-	-	-	**31.1%**	28.7%	**8.1%**	30.6%
Percent Non-White(Block Group Level)								
0%	-	-	**4.7%**	-19.6%	-	-	-	-
30% (reference value)	-	-	**5.9%**	-	-	-	-	-
60%	-	-	**7.0%**	19.6%	-	-	-	-
Average Commute Time in Minutes (Block Group Level)								
15 min	**19.0%**	7.3%	-	-	-	-	-	-
20 min	**18.4%**	3.6%	-	-	-	-	-	-
25 min (reference value)	**17.7%**	-	-	-	-	-	-	-
30 min	**17.1%**	-3.6%	-	-	-	-	-	-

CONCLUSIONS

In the existing health and built environment literature, the characterization of street networks lacked consistent measures and classification systems, which has left our understanding of the relationship between street network design and health outcomes muddled. Accordingly, this research builds upon our prior work establishing appropriate measures of street network design elements so that we can better understand their role in promoting healthy communities. One of the challenges in connecting the built environment to health disparities is accounting for the vast number of other factors clouding these relationships. As a result, we also considered street design while controlling for land use, the food environment, and a range of socioeconomic status variables. In a series of multilevel hierarchical random effect statistical models, we found the more compact street networks correlated with reduced rates of obesity, diabetes, high blood pressure, and heart disease. Some critics point out that studies regarding health and community design fail to consider the potential for increased exposure to air pollution by those not in their cars. However, our study also explicitly considered the same set of independent variables with asthma rates as the dependent variable and found no statistically significant results.

Our categorical classification of street patterns was only significant in the obesity and HBP models and suggested that for the two most prevalent configurations, a full tree-like network and a fully gridded network, the latter was associated with a slightly higher obesity rate. When also accounting for the manner in which these two network types tend to be built in practice, we find improved rates for obesity, HBP, and heart disease for the 'GG' network as opposed to the 'TT' configuration.

It might not be common for people to explicitly contemplate health when selecting a place to live, but this research indicates it is worth considering. While it is likely possible to lead a healthy lifestyle is most any type of neighborhood, our findings suggest that people living in more compact cities tend to have better health outcomes. Whether these effects are caused by a healthier subset of the population self-selecting into certain types of places is unclear. Our previous research showed dramatic increase in utilitarian active transportation in compact and connected networks with smaller streets; on the other hand, neighborhoods without such characteristics have the potential to inhibit active transportation, even for someone with a penchant for it (Marshall and Garrick, 2010a). Such disparities in the ability to partake in utilitarian and/or recreational transportation may be a contributing factor to health disparities.

Despite the extensive literature cited, there is still much work to be done to solidify our understanding of the link between the built environment and health outcomes. In future research, we hope to overcome the limitations of our current study, specifically addressing the fact that our health outcomes were aggregated and self-reported. Also, given the cross-sectional nature of our study, showing causation is also not feasible. Thus, a longitudinal study would potentially enable us to speak upon street networks issues as a health intervention. Finally, it would be worth further investigating health outcomes with respect to commute times and how that relationship might with respect to mode choice. Such a study would be again be helped by individualized health and travel behavior data.

Nevertheless, our results suggest that the role of the street network and how we put together the bones of our communities should not be overlooked as a potential contributing factor to health outcomes. We hope that by refining the measurement and classification of street network characteristics, future researchers will be able to more accurately parse-out relative impacts of the built environment on health with greater clarity. Such refinements, along with increased access to high quality, objective measures of individual health and activity, as well as the built environment, can provide evidence-based recommendations for planners and policy-makers attempting to build communities that help improve health.

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