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Short- and Long-Term Impacts of Neighborhood Built Environment on Self-Rated Health of Older Adults

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Abstract

Background and Objectives: Proximity to health care, healthy foods, and recreation is linked to improved health in older adults while deterioration of the built environment is a risk factor for poor health. Yet, it remains unclear whether individuals prone to good health self-select into favorable built environments and how long-term exposure to deteriorated environments impacts health. This study uses a longitudinal framework to address these questions.
Research Design and Methods: The study analyzes 3,240 Americans aged 45 or older from the Panel Study of Income Dynamics with good self-reported health at baseline, and follows them from 1999 to 2013. At each biennial survey wave, individual data are combined with data on services in the neighborhood of residence (defined as the zip code) from the Economic Census. The analysis overcomes the problem of residential self-selection by employing marginal structural models and inverse probability of treatment weights.
Results: Logistic regression estimates indicate that long-term exposure to neighborhood built environments that lack health-supportive services (e.g., physicians, pharmacies, grocery stores, senior centers, and recreational facilities) and are commercially declined (i.e., have a high density of liquor stores, pawn shops, and fast food outlets) increases the risk of fair/poor self-rated health compared to more average neighborhoods. Short-term exposure to the same environments as compared to average neighborhoods has no bearing on self-rated health after adjusting for self-selection.
Discussion and Implications: Results highlight the importance of expanding individuals' access to health-supportive services prior to their reaching old age, and expanding access for people unlikely to attain residence in service-dense neighborhoods.

Keywords: Access to and utilization of services, Rural and urban issues, Methodology, Health

A growing literature has documented associations between neighborhoods and health, and built environment has been described as one key mechanism linking neighborhood context to health outcomes (Yen, Michael, & Perdue, 2009). Prior research indicates that proximity to built environments with many health-related goods and services is associated with improved health outcomes (Li, Fisher, Brownson, & Bosworth, 2005; Liu, 2007), while residence in commercially declined areas (those with a preponderance of liquor stores, pawn shops, and fast food outlets) may be a risk factor for poor health (Browning, Feinberg, Wallace, & Cagney, 2006). However, most researchers are wary of drawing strong claims that built environment impacts health from past work, in part because most prior studies do not account for two key methodological challenges. The first challenge is dynamic neighborhood selection, whereby individuals *self-select* into various neighborhood built environments. The second challenge is that of cumulative neighborhood exposure. Short-term health impacts of the current neighborhood built environment may differ from long-term impacts that accumulate over time, but few studies explore both. The purpose of this study is to examine the association between neighborhood built environment and the onset of fair/poor self-rated health among older adults. The study relies on nationally representative, longitudinal data from the Panel Study of Income Dynamics (PSID) over a 14-year period (1999–2013) matched with annually updated data from the Economic Census to addresses the challenges of dynamic neighborhood selection and short-term versus cumulative exposure.

Background

Associations between neighborhoods and health are not entirely explained by individual characteristics like race, education, or income. Therefore, many recent studies of health have drawn from the "neighborhood effects" literature to identify health predictors in the physical and social environment (Do, Wang, & Elliott, 2013; Malmström, Sundquist, & Johansson, 1999; Sharkey & Elwert, 2011; Wen, Hawkley, & Cacioppo, 2006). These studies consistently find that neighborhood structural factors like socioeconomic status, poverty, and employment rates are associated with individual health outcomes. However, it is theorized that these structural neighborhood factors operate through more direct mechanisms like social cohesion, stress, transportation, and access to services. A growing number of studies explore these specific mechanisms (Browning & Cagney, 2003; Browning et al., 2006; Li et al., 2005; Liu, 2007). These studies get closer to explaining *why* neighborhood conditions like poverty are associated with health. Such information is useful for the design and implementation of place-based changes to improve population health.

The built service environment—defined here as the geographic availability of health, retail, and recreational services in the neighborhood—is one specific mechanism that may link neighborhoods and health. This link may occur for at least three reasons. First, proximity to services like physicians, pharmacies, and supermarkets may directly improve health by making it easier to obtain medical care and purchase health-related goods like medications and healthy food. Indeed, geographic access to health care services has been positively associated with health and health care utilization (Hiscock, Pearce, Blakely, & Witten, 2008; Liu, 2007), and access to supermarkets has been associated with lower risk of obesity (Larson, Story, & Nelson, 2009). Proximity to other services might worsen health, as increased access to alcohol and fast food outlets has been linked to obesity, chronic disease, and injury (Campbell et al., 2009; Fuzhong et al., 2009). Second, the built service environment may influence health-related behaviors like diet and exercise. Increased recreational opportunities like playgrounds, parks, and gyms have been related to higher levels of physical activity (Li et al., 2005). Increased access to supermarkets has been associated with healthier diets (Larson et al., 2009), whereas increased access to alcohol and fast food has been linked to poor diet and excessive alcohol consumption (Campbell et al., 2009; Fuzhong et al., 2009). Third, the built service environment may influence neighborhood social processes like social interaction, social cohesion, and feelings of safety, all linked to health (Cornwell & Waite, 2009; Cramm, Van Dijk, & Nieboer, 2013). Community centers or parks may encourage or discourage interaction, depending on whether they appear well-maintained and free from crime. Similarly, high densities of liquor stores, pawn shops, and fast food may signal to residents that neighborhoods are unsafe (Skogan, 1990). An increased fear of crime is linked to worse health outcomes (Choi & Matz-Costa, 2017; Ross & Mirowsky, 2001) and risk factors for poor health like low physical activity and social isolation (Krause, 1996; Piro, Noss & Claussen, 2006). Collectively, prior work suggests that the built service environment is linked to health through multiple direct and indirect pathways that are often related and self-reinforcing. Based on this evidence, I hypothesize that:

H1: older adults with greater geographic access to health-supportive services (e.g., physicians, pharmacies, supermarkets, and recreational facilities) have better health outcomes.

H2: older adults residing in areas with commercial decline (e.g., liquor stores, pawn shops, and fast food) are at increased risk for poor health.

Despite the important contributions of prior studies, health impacts of the built environment are still inconclusive. Unlike the studies described previously, many other studies investigating links between heath and aspects of the built environment report no associations (for example, see work by Lehning, Smith, & Dunkle, 2014, on grocery stores and Carlson et al., 2012 on recreational facilities). These mixed findings may arise from inconsistencies in how prior research has addressed two key methodological challenges: dynamic neighborhood selection and short-term versus cumulative neighborhood exposure.

Dynamic neighborhood selection is an implicit selection process whereby individual characteristics, including health, may influence neighborhood choice, which in turn affects future outcomes like health. The types of moves made in later life differ substantially by health status (Litwak & Longino, 1987). Compared to healthier individuals, individuals in poor health have higher rates of residential mobility (Friedman et al., 2016; Miller et al., 1999), but are less likely to escape disadvantaged neighborhoods with their move (Arcaya, Graif, Waters, & Subramanian, 2016). Healthier older adults, who also tend to be younger, wealthier, and more often married, are more likely to make moves motivated by lifestyle factors like leisure, public transportation, and shopping, compared to movers in poor health (Wilmoth, 2010). Exposure to particular types of neighborhoods may not only directly affect health, but may also impact the assets that residents have for future residential moves. As a result, the people who maintain or gain residence in advantageous neighborhoods as a partial virtue of their health may be able to further delay health declines.

Most studies attempt to address selection bias by controlling for a host of individual characteristics (like age, race, marital status, and income) predictive of both residential location and health. Indeed, failing to control for individual-level confounders runs the risk of overestimating neighborhood impacts on health. But that solution is imperfect, as time-varying individual characteristics are influenced by prior neighborhood context, and controlling for them ultimately leads to underestimating or "controlling-away" the complete impact of neighborhoods (Nandi, Glymour, Kawachi, & VanderWeele, 2012; Robins, 1999). Alternative strategies that better deal with selection have recently gained momentum in the neighborhoods literature (Kravitz-Wirtz 2016; Sharkey & Elwert, 2011; Wodtke, Harding, & Elwert, 2011). These studies first model neighborhood selection to obtain the probability of living in neighborhoods of various types, and then adjust for these probabilities in a second model predicting the outcome of interest. These are known as marginal structural models (MSMs) with inverse probability of treatment (IPT) weights. They are a means of incorporating the indirect effects of neighborhoods while still adjusting for neighborhood selection. While neighborhood studies employing MSMs have not focused specifically on the built environment, they have generally found that neighborhood-health associations are robust to selection bias (Glymour, Mujahid, Wu, White, & Tchetgen Tchetgen, 2010; Sharkey & Elwert, 2011). Some have also found that conventional regression underestimates the impact of neighborhoods on health compared to MSMs (Do et al., 2013). Such studies provide important clues about underlying selection processes. However, these studies have largely explored neighborhood poverty or levels of disadvantage, rather than the built environment. The results are not necessarily transferable, as different selection processes may govern different neighborhood characteristics. For instance, movers may specifically select neighborhoods for a built environment feature (e.g., seeking out neighborhoods with parks), but they may be unaware of the actual poverty rate. In this example, there is stronger potential for selection bias associated with the built environment than with poverty. Thus, it is important to investigate built environment on its own to evaluate this study's third hypothesis:

> *H3*: observed links between neighborhood built environment and health persist after accounting for dynamic neighborhood selection.

The long period over which dynamic neighborhood selection unfolds draws attention to potential long-term impacts of neighborhoods. Especially with health, there may be a distinction between short-term impacts of neighborhoods and impacts that accumulate over many years. Cross-sectional studies (Lehning et al., 2014; Subramanian, Kubzansky, Berkman, Fay, & Kawachi, 2006) and even some longitudinal studies (Glymour et al., 2010) of neighborhood effects on health focus on short-term exposure by measuring characteristics of the neighborhood concurrently or in the 1 or 2 years immediately prior to the measurement of health. Recent studies have begun to explore long-term effects by calculating cumulative averages from longitudinal data of neighborhood characteristics experienced over a long period of time. Studies employing this technique have documented health impacts of long-term exposure to neighborhood disadvantage (Clarke et al., 2014) and neighborhood poverty (Do et al., 2013), but they have not examined the built environment. Furthermore, very few researchers compare short- and long-term exposure, with the exception of Do and colleagues (2013), who find that long-term exposure to neighborhood poverty is more strongly linked to mortality than short-term exposure. Research is needed comparing short- and long-term health impacts of the built environment, but related studies suggest length of exposure may be an important conceptual consideration. Based on previous evidence, I hypothesize that:

> *H4*: cumulative exposure to health-supportive services and commercial decline is more strongly associated with health than short-term exposure.

The current study relies on longitudinal data to investigate associations between health and the built environment. In doing so, this study contributes to the ongoing debate of whether neighborhood-health associations represent causal connections or selection biases. It does so for the built environment, a neighborhood characteristic that has yet to be explored with models that better account for selection or cumulative exposure. By focusing on a different aspect of the neighborhood than prior studies, this study also addresses the possibility that selection and cumulative exposure are more important for some neighborhood characteristics than for others. Finally, by focusing on a specific mechanism linking neighborhoods and health, this study can provide valuable insight into direct, actionable ways to create neighborhood contexts that support healthy aging, through improving built environments.

Design and Methods

Sample

This study utilizes data from the PSID for the years 1999 to 2013. The PSID is a nationally representative, longitudinal study of U.S. families that began in 1968 and has continued to follow individuals from the core sample and their descendants over time. Respondents were interviewed biennially from 1999 to 2013. The sample consists of community-dwelling adults aged 45 and older at baseline (1999) who are designated as a household head or spouse and in good self-reported health. Data are structured as a series of person-periods, each referring to the 2-year period between successive PSID interviews. The analytical sample includes 15,372 person-periods, corresponding to 3,240 unique respondents who range in age from 45 to 104.

Measures

Self-Rated Health

Health status is represented by self-rated health, a subjective measure that encompasses mental and physical health (Diener, Suh, Lucas, & Smith, 1999) and is predictive of objective health outcomes like disability, morbidity, and mortality (Idler & Kasl, 1995; Mossey & Shapiro, 1982). Self-rated health responses are dichotomized so that a value of "1" indicates fair or poor self-rated health and "0" indicates excellent, very good, or good self-rated health. Only respondents in excellent, very good, or good health at baseline (1999) are included in the analysis. The outcome of interest is the first onset of fair or poor self-rated health, occurring between 2001 and 2013. Person-periods after the first onset of fair/poor health are excluded from the analysis. Respondents in the sample are observed an average of 4.5 person-periods, corresponding to 9 years, before the onset of fair/poor health. Respondents range in age from 46 to 99 at the time of fair/poor health onset.

Built Environment

To guide the measurement of neighborhood built environment, I reviewed the literatures on neighborhood service environments and neighborhood disadvantage. While there is general agreement on the types of services that are salient for health, it is more difficult to determine how to specify the service measures (e.g., as categories or continuous measures). Prior research suggests that environmental effects on health are generally nonlinear and often only emerge in the most disadvantaged living conditions (Do et al., 2013; Krause, 1996). For this reason, researchers often create categories (generally defined by medians or percentiles of the variable of interest) to represent levels of neighborhood exposures (Kravitz-Wirtz, 2016; Sharkey & Elwert, 2011; Subramanian et al., 2006; Wodtke et al., 2011). This allows for comparisons of living in the most disadvantaged category to the other categories. Furthermore, it allows for estimating the probability of living in each neighborhood category, a necessary component of the MSMs.

For these reasons, I constructed a five-category typology of built environment, based on the density of health-supportive services and commercial decline in respondents' zip codes. Services are identified by their NAICS industry classification codes using year-specific data from the Economic Census (1999–2013). Zip codes are based on the Census Bureau's delineation of 5-digit ZIP Code Tabulation Areas. Health-supportive services density is constructed by summing the number of supermarkets (NAICS 44511), pharmacies (NAICS 44611), health care services (NAICS 621), hospitals (NAICS 622), residential care facilities (NAICS 623), senior services (NAICS 62412), and recreational facilities (NAICS 71394) in the zip code and dividing by the zip code population. Commercial decline is constructed by summing the number of liquor stores (NAICS 4453), pawn shops (NAICS 45331), and fast food outlets (NAICS 722513) in the zip code and dividing by the zip code population. Less than 1% of person-periods are missing values for zip code services and are multiply imputed. Zip code population and other aggregate demographics are obtained from the 1990, 2000, and 2010 Decennial Censuses, using linear interpolation for non-census years.

Table 1 describes the categorization, based on quartiles of health-supportive services density and commercial-decline density. The resulting categories include: *high density*: zip codes with high densities of health-supportive services and commercial decline; *low density*: zip codes with low densities of health-supportive services and commercial decline; *service dense*: zip codes with high density of health-supportive services and low density of commercial decline; *commercially declined*: zip codes with low density of health-supportive services and high density of commercial decline; and *average*: zip codes with medium densities of health-supportive services and commercial decline. There are a few zip codes that have unusually high service densities despite having only a few establishments, because they have very small populations. To minimize the impact of these outliers, I restrict the *high-density* and *service-dense* categories to those with at least five health-supportive services, and the *high-density* and *commercially declined* categories to those with at least five commercially declined services. In addition, places with one or zero health-supportive and commercially declined services are automatically categorized as *low density*. Importantly, the results are fairly robust to alternate specifications of the neighborhood categories. A more restrictive typology,

Table 1. Zip code built environment typology

		Commercial decline density—quartiles			
		1st	2nd	3rd	4th
Health-supportive service density—quartiles	1st	Low density	Low density	Commercially declined	Commercially declined
	2nd	Low density	Average	Average	Commercially declined
	3rd	Service dense	Average	Average	High density
	4th	Service dense	Service dense	High density	High density

where only the 1st and 4th quartiles are considered nonaverage, results in stronger effects but substantively similar results to those presented here. A less restrictive typology, where categories are dichotomized to above or below and the median and the "average" category is eliminated, results in weaker effects than those presented here. I ultimately chose the current specification because it provides conservative estimates while still allowing some neighborhoods to be classified as "average".

To examine short-term impacts of the built environment, a single-point-in-time typology is constructed for each wave prior to the measurement of self-rated health. Long-term impacts are examined with a cumulative typology, calculated from a running average of health-supportive services density and commercial decline density that is averaged from all survey waves from the baseline up to and including the prior wave. Both typologies would be unnecessary if individuals rarely moved between neighborhood categories, as most people could be characterized with a single, time-invariant neighborhood measure. However, many sample respondents experience a change in neighborhood category, either through a residential move or through changes in the surrounding neighborhood. About 40% of the sample at any point in time lives in a neighborhood category that is different than their baseline category.

Covariates

Covariates of self-rated health are included in the analyses as either time-invariant or time-varying characteristics. Time-invariant covariates include race, sex, age, marital status, years of education, family income, family size, homeownership, whether the respondent's household is headed by a female, and employment status of the household head, all measured at baseline. Baseline health measures are also included to adjust for prior health history and its impact on neighborhood selection. They include number of chronic conditions ever diagnosed (cancer, arthritis, diabetes, lung disease, asthma, hypertension, heart disease, heart attack, or stroke), number of functional limitations (difficulty walking, getting in/out of bed, using the toilet, getting outside, eating, dressing, and bathing), body mass index, frequency of physical activity per week, and whether the respondent currently smokes. Time-varying covariates are measured in the prior survey wave or as a running average of all previous survey waves. They include family income, family size, marital status, female-headed household, homeownership, employment of the household head, whether the household head retired or became unemployed, and whether the respondent became widowed or divorced. Up to 4% of values of the individual covariates are missing and are multiply imputed. To account for possible confounding of built environments with other neighborhood attributes, models also control for structural characteristics of zip codes derived from census data. These are population, land area, population density, location in a metropolitan area, percent poor, percent college-educated, and percent non-white.

Statistical Methods

Results are initially estimated with conventional logistic regression models predicting the onset of fair/poor self-rated health with baseline and time-varying covariates. The contribution of selection bias is then evaluated by comparing results of the conventional models to MSMs utilizing IPT weights. The MSM method proceeds in two steps. In step 1, the treatment assignment (built environment category) is modeled. Prior-wave neighborhood built environment category, baseline covariates, baseline built environment category, and time-varying covariates are used to predict the respondent's probability of residing in each built environment category in the current wave. Respondents are then assigned a treatment weight, following the procedure for calculating and stabilizing IPT weights outlined in Wodtke, Harding, and Elwert (2011). The weighting process essentially creates a pseudopopulation that upweights individuals whose neighborhood exposure is underrepresented (compared to what would have been observed through random assignment), and downweights individuals whose neighborhood exposure is overrepresented. Within this pseudopopulation, treatment and time-varying confounders are no longer associated (Cole & Hernán, 2008).

The IPT method is also frequently used to account for selective attrition (Glymour et al., 2010; Kravitz-Wirtz, 2016). In this study, respondents are censored if they die, are lost to follow-up, are institutionalized, or are no longer a designated household head or spouse. To account for potential attrition bias, censoring weights are generated using the same process and covariates described for calculating the neighborhood weights. The final weights used in the analysis are the product of multiplying the stabilized censoring weight and the stabilized neighborhood weight for each respondent in each survey year.

In step 2, the generated weights are used as probability weights in a logistic regression equation estimating effects of the built environment (captured with the single-point-in-time and cumulative measures) on the probability of fair/poor self-rated health onset. The equation is referred to as a MSM because it models the *marginal* distribution of potential outcomes after adjusting for time-dependent confounders (Robins, 1999). Results utilizing the single-point-in-time measure and the cumulative measure are compared to assess differences in short- versus long-term impacts of the built environment. All regression models use Huber-White clustered standard errors to account for multiple observations of the same individual over time and clustering of spouses within households.

Results

Table 2 reports descriptive statistics of the sample in the baseline year of 1999. All respondents were in good self-reported health at baseline. On average, respondents were just older than 56 years, 48% were male and 52% were female, most were non-Latino white (76%), most were married (76%) and employed (69%), and their annual family incomes were $79,261. Respondents at baseline had been diagnosed with less than one chronic condition and had less than one functional limitation on average, an overall indicator of their good health. The most common built environment category at baseline was average (41%), followed by low density (30%), high density (13%), service dense (12%), and commercially declined (3.3%).

Table 3 reports descriptive statistics of time-varying characteristics separately for person-periods in which the respondent remained in good self-rated health and person-periods characterized by the onset of fair/poor health. Differences between those in good versus fair/poor health for all reported statistics are statistically significant at the 99% confidence level, with the exception of job loss and retirement. Respondents experiencing the onset of fair/poor health are older on average than respondents remaining in good health. They have family incomes that are on average about $30,000 lower, are more likely to be recently widowed or divorced, and are less likely to own their home compared to respondents in good health. Differences in the built environment by health status are prevalent. Those in good health are more likely to currently live in high-density or service-dense environments, where they have the greatest access to health-supportive services. In contrast, respondents experiencing the onset of fair/poor health are more likely to reside in low-density or commercially declined areas.

Table 2. PSID sample characteristics at baseline (1999)

Characteristics	Mean/%	SD
Age, mean	56.56	10.83
Years of education, mean	13.60	3.69
Family income ($), mean[a]	79,261	98,321
Family size, mean	2.63	1.33
Male, %	48.02	
Married, %	76.08	
Female-headed household, %	17.31	
Homeowner, %	83.77	
Race/ethnicity, %		
White, non-Latino	76.30	
Black, non-Latino	17.96	
Asian, non-Latino	1.51	
Other, non-Latino	0.71	
Latino, any race	3.52	
Employment status, head, %		
Employed	68.89	
Retired	24.48	
Unemployed	1.48	
Disabled	2.28	
Other	2.87	
Chronic conditions, mean	.81	1.02
Functional limitations, mean	.08	0.43
Body mass index, mean	27.19	4.86
Frequency of physical activity per week, mean	7.45	16.26
Smoker, %	16.17	
Built environment category, %		
High density	13.43	
Low density	30.46	
Service dense	11.64	
Commercially declined	3.30	
Average	41.17	
N (unique respondents)	3,240	

Note: First of 10 imputation data sets.
[a]Family income is standardized to the year 2000 consumer price index.

To get at structural differences in the types of built environments, Table 4 shows how each built environment category is characterized by census demographics. High-density built environments are indeed denser (in terms of population) than average places, and they have higher rates of college degrees, are more racially diverse, and are almost exclusively within metropolitan areas. A quintessential example of a neighborhood that would be categorized as high density is Brooklyn, New York. In contrast, low-density environments have sparse populations that are less racially diverse and have lower rates of college degrees compared to most other places. They are exemplified by many of the nation's small towns, and also by outlying areas of some larger metros. Service-dense places are perhaps the most advantaged category, with below-average poverty rates and above-average rates of college degrees. Places like San Mateo, California, would be classified as service-dense. Finally, commercially declined places are perhaps the most disadvantaged. They have large populations, the highest population densities, poverty rates near 20%, the lowest rate of college degrees, and are predominately non-white. As an example, several inner-city Detroit neighborhoods would be classified as commercially declined.

The logistic regression results further describe the health impacts of these environments. Table 5 compares results from conventional regression models with MSMs incorporating IPT weights. Panel 1 shows the set of models focusing on short-term exposure. To be most comparable with the MSMs, the conventional models control for the same baseline and time-varying covariates. The conventional models show no short-term impacts of neighborhood built environment on health. This is consistent with other studies reporting no effects (Carlson et al., 2012; Lehning et al., 2014), but to date, it has been unclear whether "over-controlling" for individual covariates previously influenced by neighborhood selection has led to the lack of significant findings. However, the corresponding MSM, which better accounts for selection, also shows no short-term health impact of the built environment. This stage of the analysis shows no

Table 3. Time-varying characteristics, by self-rated health

Time-varying characteristics	Self-rated health	
	Remain good/very good/excellent	Onset of fair/poor
Age (*prior wave*), mean (SD)	62.09 (9.85)	65.31 (12.18)
Family income ($) (*running average*), mean (SD)[a]	87,860 (97,661)	58,328 (67,499)
Family size (*running average*), mean (SD)	2.52 (1.15)	2.43 (1.28)
Married (*running percent of person-periods*), %	79.05	69.17
Female-headed household (*running percent of person- periods*), %	15.09	23.71
Homeowner (*running percent of person-periods*), %	87.45	78.80
Employed, head (*running percent of person-periods*), %	59.92	40.39
Recently retired, head (*prior wave*), %	6.48	7.84
Recently unemployed, head (*prior wave*), %	1.20	1.87
Recently widowed/divorced (*prior wave*), %	1.79	3.17
Built environment category (*single-point-in-time*), %		
High density	11.27	10.35
Low density	32.41	36.19
Service dense	8.56	7.28
Commercially declined	2.65	4.85
Average	45.11	41.32
Built environment category (*running average*), %		
High density	14.30	11.75
Low density	24.86	29.66
Service dense	5.62	6.06
Commercially declined	2.16	4.76
Average	53.06	47.76
N (person-periods)	14,300	1,072

Note: First of 10 imputation data sets. Differences by self-rated health are statistically significant at $p < .01$, with the exception of recently retired and unemployed, which are not significantly different.
[a]Family income is standardized to the year 2000 consumer price index.

Table 4. Zip code built environment categories and census characteristics

Built environment category	Census characteristics						
	Population (median)	Square miles (median)	Persons per square mile (median)	% Located in MSA	% Poor (mean)	% College-educated (mean)	% Non-white (mean)
High density	10,803	5.73	2,310.19	97.27	12.86	32.73	31.53
Low density	7,423	55.25	143.43	85.76	12.19	21.35	25.58
Service dense	7,440	6.67	1,675.03	86.13	10.97	31.74	26.56
Commercially declined	24,309	7.20	3,519.65	98.44	19.17	18.84	54.07
Average	14,552	10.24	1,422.96	96.13	12.07	29.58	29.81

Note: First of 10 imputation data sets.

evidence that over-controlling for selection obscures short-term built environment impacts. Rather, it suggests that built environments may not be associated with health in the short-term.

Table 5, panel 2, shows corollary results for longer-term environmental exposures. The same outcome variable (onset of fair/poor self-rated health) is predicted by the built environment category experienced, on average, by the respondent across every wave since the baseline. For respondents in the last wave, this amounts to 14 years of exposure. Results from the conventional model show that respondents with long-term exposure to low-density or commercially declined environments are at heightened risk of poor health compared to respondents in average environments. However, the corresponding MSM suggests that the conventional results for low-density environments should be interpreted with caution. The MSM reports no significant difference between low-density and average environments. Rather, it suggests that residential patterns, whereby individuals prone to poor health move to (or stay in) low-density environments, explains the apparent association between low-density neighborhoods and poor health. In contrast, the association between health and commercially declined neighborhoods persists in the MSM, even with the

Table 5. Logistic regression estimates of the short- and long-term effects of built environment on first onset of fair/poor self-rated health (N = 15,372)

	Conventional model		MSM	
1. Short-term exposure	Odds ratio	SE	Odds ratio	SE
Single-point-in-time				
Built environment category (ref = Average)				
High density	1.050	.131	.805	.125
Low density	1.115	.092	.993	.103
Service dense	0.977	.139	.868	.150
Commercially declined	1.319	.241	1.531	.388
	Conventional model		**MSM**	
2. Cumulative exposure	Odds ratio	SE	Odds ratio	SE
Running average				
Built environment category (ref = Average)				
High density	.985	.113	.882	.132
Low density	1.224*	.110	1.187	.153
Service dense	1.314	.204	.952	.189
Commercially declined	1.493*	.288	1.851*	.517

Note: Combined estimates from 10 multiple imputation data sets. All models include all baseline and time-varying individual and zip code covariates, although their effects are not reported.
*$p < .05$.

adjustment for neighborhood selection. More specifically, the MSM indicates the odds of fair/poor health onset are 1.851 times larger for residents of commercially declined environments compared to residents of average environments. In contrast, there is no observed difference in the odds of fair/poor health between high-density, low-density, service-dense, and average neighborhoods.

Discussion

This study contributes to growing evidence that built environment, and neighborhood context more generally, impacts healthy aging. The analysis builds on recent research showing that health-supportive services and neighborhood commercial decline influence health outcomes for older adults, while addressing some of the shortcomings of prior work. By investigating data from a longitudinal, nationally representative sample in models that deal with selection and cumulative exposure, this study provides more comprehensive evidence of the associations between built environment and health beyond the evidence contained in prior studies.

The evidence presented here suggests that older adults in commercially declined neighborhoods are at increased risk for poor health compared to older adults in average neighborhoods. This provides support for the first hypothesis (that lack of access to health-supportive services diminishes health) and the second hypothesis (that commercial decline diminishes health), with one important caveat: it is the *combination* of lack of health services and commercial decline that has the most meaningful impact on health. Neighborhoods that have *either* limited services *or* commercial decline are no riskier for health than average neighborhoods. In contrast, neighborhoods with a lack of desirable services along with prolific signs of disorder significantly diminish health compared to average neighborhoods. A potential explanation is that health services and commercial decline interact—high rates of commercial decline may render the few existing health resources relatively unusable. For example, residents of commercially declined neighborhoods may feel unsafe leaving their homes or traveling to the few nearby physicians or supermarkets. Residents of other neighborhoods may feel safe because signs of disorder are few or are balanced out by more desirable amenities. The results confirm prior evidence that older adults who face difficulty accessing health services are at greater risk for health declines (Hiscock et al., 2008; Liu, 2007; Larson et al., 2009), but also suggests that an important piece of the "difficulty" with access may be related to neighborhood disorder. Future research should work to untangle the complex and possibly reciprocal relationships between neighborhood services and disorder. The findings also underscore the idea that health impacts often only emerge in the most disadvantaged environments (Do et al., 2013; Krause, 1996). Thus, policies should prioritize expanding health-supportive services in underserved neighborhoods coupled with reducing commercial decline in such neighborhoods, so that all older adults have unfettered access to at least an average level of services. Devoting resources to improving neighborhoods beyond this point is likely to produce diminishing returns for population health.

The third hypothesis (that the health effects of built environments persist after accounting for dynamic neighborhood selection) is supported for long-term effects only. This suggests that short-term effects of the built environment reported in prior studies may actually be driven by selection processes, such as healthier individuals moving out of neighborhoods that lack health services for better areas. But in the long-term, the impacts of built environments appear to accumulate, impacting not only current health but future residential selections, and in turn, future health. More work needs to be done to better understand the selection processes that sort healthier individuals into advantageous neighborhoods and individuals prone to poor health into deteriorated neighborhoods. But it is also apparent that selection may not fully explain long-term associations between neighborhoods and health, supporting the idea of an independent cumulative neighborhood effect. From a policy perspective, these findings suggest that resources for expanding access to services may be most impactful if directed towards people unlikely to attain residence in age-friendly environments on their own.

The fourth hypothesis is also supported, as cumulative exposure to commercially declined neighborhoods seems to matter much more than short-term exposure (if short-term exposure matters at all, as this study did not detect any short-term effects). The cumulative impacts may reflect the direct health consequences of living many years with limited access to physicians, healthy foods, and other health resources. But they may also reflect the aggregate effect of prior residential choices, whereby prior neighborhood context influenced health directly and also indirectly through ongoing residential choices. Given that existing research on built environments and health primarily focuses on recent surroundings, a priority for future research should be investigating residential histories and cumulative environmental exposures. This is especially important in light of evidence that few residents of high-poverty neighborhoods experience upward residential mobility (Sharkey, 2013). Furthermore, because the impact of built environment on health may unfold over a long period of time, researchers exploring short-term measures should be cautious of concluding that built environments have no impact on health. From a policy perspective, these results underscore the need for a long-term outlook in the development of "age-friendly" neighborhoods. Policies and practices supporting age-friendly environments may need to be enacted before the people they intend to help reach old age. Furthermore, short-term changes likely cannot undo years of exposure to disadvantaged built environments.

This study has several limitations. Most important, environmental exposure is determined solely by geographic availability of services, ignoring other important considerations like cost, quality, and transportation (Huang, Rosenberg, Simonovich, & Belza, 2012). I utilize zip code boundaries in part by necessity, to align with the industry data. But zip codes may vary greatly internally and may not adequately capture older adults' activity spaces. A related limitation is that this study does not directly identify the specific behaviors linking neighborhood services to health. It remains unclear whether, for example, lack of health-supportive services diminishes health because people are less likely to visit a physician, eat healthy foods, exercise, or some combination of these and other behaviors. Another limitation has to do with the measurement of self-rated health. The associated categories (i.e. "fair", "poor", "good", etc.) may not mean the same to different individuals or even to the same individual over time. Furthermore, the factors that give rise to poor health may be variably related to neighborhoods. Some individuals may fall into poor health for reasons that have little to do with their neighborhood, but this study does not distinguish among the underlying conditions leading to health declines. Future research should explore whether neighborhood impacts on health are sensitive to different conceptualizations of health.

Conclusion

This study further clarified relationships between self-rated health and built environment by exploring both short-term and cumulative environmental exposure, and dealing with dynamic neighborhood selection. The findings add to growing evidence that residential context influences healthy aging. They also highlight the importance of expanding individuals' access to health-supportive services prior to their reaching old age, and expanding access for people unlikely to attain residence in service-dense neighborhoods. Future research should examine how other contextual factors—like crime, family and friendship networks, and housing—impact older adult health in the short-term versus the long-term, and how they are related to residential selection processes.

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Conflict of Interest

None reported.

References

Arcaya, M. C., Graif, C., Waters, M. C., & Subramanian, S. V. (2016). Health selection into neighborhoods among families in the Moving to Opportunity Program. *American Journal of Epidemiology*, **183**, 130–137. doi:10.1093/aje/kwv189

Browning, C. R., & Cagney, K. A. (2003). Moving beyond poverty: neighborhood structure, social processes, and health. *Journal of Health and Social Behavior*, **44**, 552–571. doi:10.2307/1519799

Browning, C.R., Feinberg, S.L., Wallace, D., & Cagney, K.A. (2006). Neighborhood social processes, physical conditions, and disaster-related mortality: The case of the 1995 Chicago heat wave. *American Journal of Sociology*, **71**, 661–678. doi:10.1177/000312240607100407

Campbell, C. A., Hahn, R. A., Elder, R., Brewer, R., Chattopadhyay, S., Fielding, J., … Middleton, J. C.; Task Force on Community Preventive Services. (2009). The effectiveness of limiting alcohol outlet density as a means of reducing excessive alcohol consumption and alcohol-related harms. *American Journal of Preventive Medicine*, **37**, 556–569. doi:10.1016/j.amepre.2009.09.028

Carlson, J.A., Sallis, J.F., Conway, T.L., Saelens, B.E., Frank, L.D., Kerr, J., … King, A.C. (2012). Interactions between psychosocial and built environment factors in explaining older adults' physical activity. *Preventive Medicine*, **54**, 68–73. doi:10.1016/j.ypmed.2011.10.004

Choi, Y.J., & Matz-Costa, C. (2017). Perceived neighborhood safety, social cohesion, and psychological health of older adults. *The Gerontologist*. Advance online publication. doi:10.1093/geront/gnw187

Clarke, P., Morenoff, J., Debbink, M., Golberstein, E., Elliott, M. R., & Lantz, P. M. (2014). Cumulative exposure to neighborhood context: Consequences for health transitions over the adult life course. *Research on Aging*, **36**, 115–142. doi:10.1177/0164027512470702

Cole, S. R., & Hernán, M. A. (2008). Constructing inverse probability weights for marginal structural models. *American Journal of Epidemiology*, **168**, 656–664. doi:10.1093/aje/kwn164

Cornwell, E. Y., & Waite, L. J. (2009). Social disconnectedness, perceived isolation, and health among older adults. *Journal of Health and Social Behavior*, **50**, 31–48. doi:10.1177/002214650905000103

Cramm, J. M., van Dijk, H. M., & Nieboer, A. P. (2013). The importance of neighborhood social cohesion and social capital for the well being of older adults in the community. *The Gerontologist*, **53**, 142–152. doi:10.1093/geront/gns052

Diener, E., Suh, E.M., Lucas, R.E., & Smith, H.L. (1999). Subjective well-being: Three decades of progress. *Psychological Bulletin*, **125**, 276–302. doi:10.1037/0033-2909.125.2.276

Do, D. P., Wang, L., & Elliott, M. R. (2013). Investigating the relationship between neighborhood poverty and mortality risk: A marginal structural modeling approach. *Social Science and Medicine (1982)*, **91**, 58–66. doi:10.1016/j.socscimed.2013.03.003

Friedman, E. M., Weden, M. M., Shih, R. A., Kovalchik, S., Singh, R., & Escarce, J. (2016). Functioning, forgetting, or failing health: Which factors are associated with a community-based move among older adults? *The Journals of Gerontology, Series B: Psychological Sciences and Social Sciences*, **71**, 1120–1130. doi:10.1093/geronb/gbv075

Fuzhong, L. , Harmer, P., Cardinal, B. J., Bosworth, M., & Johnson-Shelton, D. (2009). Obesity and the built environment: Does the density of neighborhood fast-food outlets matter?" *American Journal of Health Promotion*, **23**, 203–209. doi:10.4278/ajhp.071214133

Glymour, M. M., Mujahid, M., Wu, Q., White, K., & Tchetgen Tchetgen, E. J. (2010). Neighborhood disadvantage and self-assessed health, disability, and depressive symptoms: Longitudinal results from the health and retirement study. *Annals of Epidemiology*, **20**, 856–861. doi:10.1016/j.annepidem.2010.08.003

Hiscock, R., Pearce, J., Blakely, T., & Witten, K. (2008). Is neighborhood access to health care provision associated with individual-level utilization and satisfaction? *Health Services Research*, **43**, 2183–2200. doi:10.1111/j.1475-6773.2008.00877.x

Huang, D. L., Rosenberg, D. E., Simonovich, S. D., & Belza, B. (2012). Food access patterns and barriers among midlife and older adults with mobility disabilities. *Journal of Aging Research*, **2012**, 231489. doi:10.1155/2012/231489

Idler, E. L., & Kasl, S. V. (1995). Self-ratings of health: Do they also predict change in functional ability? *The Journals of Gerontology, Series B: Psychological Sciences and Social Sciences*, **50**, S344–S353. doi:10.1093/geronb/50B.6.S344

Krause, N. (1996). Neighborhood deterioration and self-rated health in later life. *Psychology and Aging*, **11**, 342–352. doi:10.1037/0882-7974.11.2.342

Kravitz-Wirtz, N. (2016). Cumulative effects of growing up in separate and unequal neighborhoods on racial disparities in self-rated health in early adulthood. *Journal of Health and Social Behavior*, **57**, 453–470. doi:10.1177/0022146516671568

Larson, N. I., Story, M. T., & Nelson, M. C. (2009). Neighborhood environments: Disparities in access to healthy foods in the U.S. *American Journal of Preventive Medicine*, **36**, 74–81. doi:10.1016/j.amepre.2008.09.025

Lehning, A. J., Smith, R. J., & Dunkle, R. E. (2014). Age-friendly environments and self-rated health: An exploration of Detroit elders. *Research on Aging*, **36**, 72–94. doi:10.1177/0164027512469214

Li, F., Fisher, K. J., Brownson, R. C., & Bosworth, M. (2005). Multilevel modelling of built environment characteristics related to neighbourhood walking activity in older adults. *Journal of Epidemiology and Community Health*, **59**, 558–564. doi:10.1136/jech.2004.028399

Litwak, E., & Longino, C. F. Jr. (1987). Migration patterns among the elderly: A developmental perspective. *The Gerontologist*, **27**, 266–272. doi:10.1093/geront/27.3.266

Liu, J. J. (2007). Health professional shortage and health status and health care access. *Journal of Health Care for the Poor and Underserved*, **18**, 590–598. doi:10.1353/hpu.2007.0062

Malmström, M., Sundquist, J., & Johansson, S. E. (1999). Neighborhood environment and self-reported health status: A multilevel analysis. *American Journal of Public Health*, **89**, 1181–1186. doi:10.2105/AJPH.89.8.1181

Miller, M. E., Longino, C. F. Jr, Anderson, R. T., James, M. K., & Worley, A. S. (1999). Functional status, assistance, and the risk of a community-based move. *The Gerontologist*, **39**, 187–200. doi:10.1093/geront/39.2.187

Mossey, J. M., & Shapiro, E. (1982). Self-rated health: A predictor of mortality among the elderly. *American Journal of Public Health*, **72**, 800–808. doi:10.2105/AJPH.72.8.800

Nandi, A., Glymour, M.M., Kawachi, I., & VanderWeele, T.J. (2012). Using marginal structural models to estimate the direct effect of adverse childhood social conditions on onset of heart disease, diabetes, and stroke. *Epidemiology*, **23**, 223–232. doi:10.1097/EDE.0b013e31824570bd

Piro, F. N., Noss, O., & Claussen, B. (2006). Physical activity among elderly people in a city population: The influence of neighbourhood level violence and self perceived safety. *Journal of Epidemiology and Community Health*, **60**, 626–632. doi:10.1136/jech.2005.042697

Robins, J.M. (1999). Association, causation, and marginal structural models. *Synthese*, **121**, 151–179. doi:10.1023/A:1005285815569

Ross, C. E., & Mirowsky, J. (2001). Neighborhood disadvantage, disorder, and health. *Journal of Health and Social Behavior*, **42**, 258–276. doi:10.2307/3090214

Sharkey, P. (2013). *Stuck in place: Urban neighborhoods and the end of progress toward racial equality*. Chicago, IL: University of Chicago Press.

Sharkey, P., & Elwert, F. (2011). The legacy of disadvantage: multigenerational neighborhood effects on cognitive ability. *AJS; American Journal of Sociology*, **116**, 1934–1981. doi:10.1086/660009

Skogan, W.G. (1990). *Disorder and decline: Crime and the spiral of decay in American neighborhoods*. Berkeley and Los Angeles, CA: University of California Press.

Subramanian, S. V., Kubzansky, L., Berkman, L., Fay, M., & Kawachi, I. (2006). Neighborhood effects on the self-rated health of elders: uncovering the relative importance of structural and service-related neighborhood environments. *The Journals of Gerontology, Series B: Psychological Sciences and Social Sciences*, **61**, S153–S160. doi:10.1093/geronb/61.3.S153

Wen, M., Hawkley, L. C., & Cacioppo, J. T. (2006). Objective and perceived neighborhood environment, individual SES and psychosocial factors, and self-rated health: An analysis of older adults in Cook County, Illinois. *Social Science and Medicine (1982)*, **63**, 2575–2590. doi:10.1016/j.socscimed.2006.06.025

Wilmoth, J. M. (2010). Health trajectories among older movers. *Journal of Aging and Health*, **22**, 862–881. doi:10.1177/0898264310375985

Wodtke, G. T., Harding, D. J., & Elwert, F. (2011). Neighborhood effects in temporal perspective. *American Sociological Review*, **76**, 713–736. doi:10.1177/0003122411420816

Yen, I. H., Michael, Y. L., & Perdue, L. (2009). Neighborhood environment in studies of health of older adults: A systematic review. *American Journal of Preventive Medicine*, **37**, 455–463. doi:10.1016/j.amepre.2009.06.022