Assessing How Activity Space Exposures Influence Neighborhood Effects on Self-Rated Health

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Background

While the neighborhood effects literature is rich in its investigations of the association between residential context and health, theoretical and methodological challenges remain (for reviews, see Chaix et al. 2009; Cummins et al. 2007; Diez-Roux 2001; Picket and Pearl 2001; Sampson 2012). Notwithstanding significant improvements in the ability of researchers to detect place effects on health, very little is known about how exposure to the many contexts in which individuals conduct their daily lives (e.g., where they work, shop, seek healthcare) alters the impact of residential conditions on physical and mental health. Existing evidence of neighborhood effects has been rather inconsistent, often yielding weak and mixed results across a variety of health outcomes (Browning and Cagney 2002; Cagney and Browning 2004; Robert 1998). A continued focus on the neighborhood of residence may have contributed to these weak findings, as individuals' exposure to extralocal neighborhoods and activity spaces may suppress the influence of local conditions (see Crowder and South 2008; Inagami et al. 2007; Crowder et al. 2011).

Despite strong theoretical reasons to believe that exposure to other locations may moderate the association between residential context and health, the issue has received almost no attention in past research. Drawing from classic social disorganization theory, the neighborhood effects literature has implicated residential structural conditions (e.g., concentrated disadvantage) as being associated with unhealthy outcomes, and the social mechanisms (e.g., collective efficacy, institutional resources, social networks) through which they operate (Browning and Cagney 2002; Sampson 2012). The implication is that the structural characteristics to which individuals are exposed outside the residential neighborhood might not only directly influence health, but also modify the effects of residential context on health and well-being.

An assessment of how non-residential exposures shape the influence of local characteristics on health requires two important dynamics: space and time (see Kwan 2009). Indeed, prior work has shown that individuals not only frequently spend much of their day outside the residential environment (Buliung and Kanaroglou 2006; Kwan 2002), but they also perceive their neighborhood differently in terms of geographic size and scope (Lee and Campbell 1997; Pebley and Sastry 2009). It is equally salient to understand the temporal dimension of an individual's exposure to various contexts; however, previous research is largely cross-sectional and suffers from a lack of information on where respondents spend their time. Such spatiotemporal examinations should lend insight into the relationship between context and health and the ways in which neighborhood effects on health should be pursued more generally.

In this paper, we employ novel data to investigate the health impacts of residential context, and how individuals' exposures to characteristics outside the neighborhood influence the relationship between local neighborhood conditions and self-rated health. Using these unique data, we construct multiple measures of context, accounting for time and space, to systematically assess their relative contributions to individuals' health reports. Our analyses are guided by two research questions. First, what are the independent effects of residential and non-residential contexts on health? And second, how does exposure to activity spaces influence the relationship between residential context and health?

Data and Methods

This paper uses restricted-access longitudinal data (Version 2.5) from the Los Angeles Family and Neighborhood Survey (LAFANS). LAFANS was conducted in two waves, in 2000-2002 and 2006-2008, and is based on a stratified random sample of 65 neighborhoods (census tracts)[1] in Los Angeles County, including an oversample of poor neighborhoods. In Wave 1, an average of 41 households were randomly selected and interviewed within each tract, including an oversample of households with children under 18; both adults and children were sampled and interviewed. In Wave 2, an attempt was made to re-interview all children and adults in the sample – even if they moved out of the neighborhood – while a sample of newcomers into each neighborhood was interviewed.[2] LAFANS therefore combines the advantages of a panel study of individuals with the advantages of a repeated cross-section of neighborhoods. The final analytic sample of panel respondents who have valid data on all variables used in the study is 1,147. Panel weights are used in all analyses and are designed to make the sample representative of the Los Angeles County population age 18 and over, as well as to account for the attrition of Wave 1 respondents due to non-response (Peterson et al. 2011).

LAFANS is an excellent source of data for researching questions pertaining to neighborhoods and health. These restricted data not only provide census tract identifiers for where respondents reside, but also several important locations in respondents' daily lives, such as where they work, seek healthcare, and shop for groceries. This intricate level of detail allows us to create objective neighborhood characteristics based on tract of residence, as well as the many contexts to which individuals are exposed outside the residential area. Census 2000 and the 2005-2009 American Community Survey are the sources of data used to create neighborhood measures at both waves and appended to LAFANS respondent data.

Measures

In our analysis of *self-rated health*, the dependent variable comes from a 5-item question that asks the respondent to rate her/his health and ranges from poor (1) to excellent (5). Responses are collapsed into a dichotomous indicator where "poor/fair" are coded 1 and "good/very good/excellent" are coded 0. The simplistic nature of self-rated health notwithstanding, research has shown that respondents consider several factors when evaluating their overall health, such as health behaviors, health problems or lack thereof, and general physical functioning (Ferraro and Farmer 1999; Jylha 2009; Singh-Manoux et al. 2006).

There are four neighborhood measures: *concentrated disadvantage*, *residential stability*, *immigrant concentration*, and *population density*. The first three are indexes derived from a factor analysis with oblique rotation. Our focal independent variable, concentrated disadvantage, is made up of six variables (all proportions): persons under 18 years old, households on public assistance, female-headed households with children, persons without a high school degree, unemployment rate, and poverty rate. Residential stability combines measures of the proportion of owner-occupied housing units and the proportion of persons living in the same house as the prior year. The immigrant concentration index consists of the proportions of the population foreign-born and Hispanic, respectively. And finally, population density is the population (in 1000s) per square mile.

[1] While the originally-sampled 65 census tracts correspond to 1990 tract boundaries, this study uses 2000 tract boundaries for two reasons. First, the sample increases to 90 tracts, enhancing the power and variation for all analyses. In addition, 2000 tract boundaries align with the timeframe of the study.
[2] Panel sample members were followed even if they left the county, state, or country. However, these respondents were only eligible for a telephone interview rather than the standard in-person interview and were not asked health-related questions (Sastry et al. 2006).

In addition to using the home census tract as our measure of neighborhood context, we also construct three alternative contextual measures based on exposure. To calculate exposure, we use the LAFANS to ascertain the amount of hours spent in a week in each activity space – work, grocery store, place of worship, and healthcare. The total activity space hours are then subtracted from 168 (total hours per week) to arrive at the number of hours spent in the respondent's home neighborhood, which results in an exposure weight associated with each context. First, a single *global* measure of neighborhood context is a weighted average of *all* the contexts to which an individual is exposed. The other two time-weighted measures represent *residential* context and *activity space* context. Below is an illustration for concentrated disadvantage:

Context	Hours	Weight	Disadvantage
Home	120	.714	0.5
Work	40	.238	-0.85
Shop	3	.018	0.5
Worship	4	.024	0.1
Doctor	1	.006	-1
Total	168	1	

Global Disadvantage = .16
Residential Disadvantage = .36
Activity Space Disadvantage = -.20

Several individual-level variables shown to influence self-rated health are included in the analysis. Sociodemographic factors are age (measured in years), marital status (1=married), presence of children (1=yes), gender (1=female), and race/ethnicity (Non-Hispanic white, Hispanic, Non-Hispanic black, Non-Hispanic Asian/other). SES resources are family income (less than $25K; $25-50K; $50-75K; $75K and higher), educational attainment (less than high school; high school graduate; some college; college graduate and higher), and employment status (1=employed). Two final binary indicators represent whether the respondent was interviewed in Spanish and whether the respondent moved between waves (1=moved).

Analytical Strategy

Using these longitudinal data, we execute a series of multilevel cross-classified random effects logistic models (CCRELM) to examine how multiple contexts of exposure influence the likelihood of individual poor/fair health. Despite the multilevel design of LAFANS – respondents are nested within census tracts – the data lose their hierarchical nature because respondents move to different neighborhoods between waves. Failure to account for the cross-nesting of individuals and neighborhoods over time can bias standard errors and variance components estimates (Luo and Kwok 2012; Raudenbush and Bryk 2002).[3] The model is therefore estimated at two levels – time at Level 1 nested within individuals cross-nested within neighborhoods at Level 2. The Level 1 model is specified for the binary outcome poor/fair self-rated health Y_{tij}:

$$\log\,[\Pr(Y_{tij} = 1) / 1 - \Pr(Y_{tij} = 1)] = \pi_{0ij} + \pi_{1ij}x_{tij} + e_{tij} \qquad (1)$$

[3] Simulation studies have shown that as mobility rates increase, so do the relative biases of standard errors and variance components (Luo and Kwok 2012). A nontrivial share (37%) of the LAFANS analytic sample switched neighborhoods between waves, supporting the use of CCRELM in this study.

In this model, x_{tij} represents a measure of time, which is set equal to 0 at Wave 1 and 1 at Wave 2; π_{0ij} is the intercept and π_{1ij} represents the slope of change between waves; and e_{tij} is the within-individual error term. The Level 2 model represents the cross-classification of individuals and neighborhoods and is specified as follows:

$$\pi_{0ij} = \beta_{00} + \beta_{01}\mathbf{W}_i + \beta_{02}\mathbf{Z}_j + r_{0i} + \mu_{0j} \qquad (2)$$

$$\pi_{1ij} = \beta_{10}$$

where β_{00} and β_{10} are the average intercept and slope of change, respectively; β_{01} represents the coefficients for a vector of individual-level predictors $\mathbf{W}_i$; β_{02} represents the coefficients for a vector of neighborhood-level predictors $\mathbf{Z}_j$; r_{0i} is the random effect of individual *i* related to the intercept: and μ_{0j} is the random effect of neighborhood *j* related to the intercept.

An advantage of this strategy is that both associations and changes can be assessed among time-varying covariates. This is accomplished by including group-mean centered versions and mean values (over the two waves) to examine both the average effect and within-individual change of these predictors, while controlling for time-invariant covariates and secular change. This approach also provides a strong test of *contextual effects* because neighborhood-level predictors are centered on individuals over time, which importantly gauges the effect of changes in individuals' respective neighborhood surroundings whether they moved or not.

To assess the dynamic relationship between context and health, we run a series of CCRE logistic models predicting poor/fair self-rated health. As a baseline for comparison, we first examine the affect of concentrated disadvantage when the neighborhood is measured at the home census tract. Next, we assess a global measure of neighborhood disadvantage by combining activity space contexts with residential context. Finally, and most importantly, we investigate how activity space disadvantage shapes the relationship between residential disadvantage and the likelihood that individuals' report poor/fair health.

Results

Table 1 presents results from CCRE logistic models predicting individual poor/fair self-rated health in which neighborhood context is measured at the home census tract. As seen in Model 1, concentrated disadvantage has a strong and significant independent effect on the odds of an individual reporting poor or fair health. More specifically, on average, a one standard deviation increase in the concentrated disadvantage index is associated with a 93% increase ($e^{(.818)(.804)}$) in the odds of reporting poor/fair health. When the full range of individual- and neighborhood-level covariates is introduced in Model 2, the unhealthy effect of neighborhood disadvantage is attenuated but is still highly significant, which is in accord with what we currently know about disadvantage and health status (see Inagami et al. 2007).

In Table 2, we address prior limitations in the literature by conceptualizing the neighborhood as including exposure to the areas in which someone conducts many of their daily activities. Model 1 presents the independent effect of global neighborhood disadvantage on the log-odds of poor/fair health self-reports. Indeed, a one standard deviation increase in the average level of concentrated disadvantage is associated with more than double ($e^{(.976)(.804)}$) the log-odds of individual poor/fair health. Consistent with Table 1, controlling for an extensive array of individual and neighborhood characteristics partially explains the deleterious health impact of routine exposure to disadvantage, but the odds are still 72.6% higher ($e^{(.679)(.804)}$). Note, however, that our global measure of contextual exposure has slight suppressor effects compared to our neighborhood disadvantage effect in Table 1.

Table 3 shows a series of CCRE logistic models where we gauge the effects of residential context and activity space disadvantage on poor/fair self-rated health. The substantive pattern is again clear. Residential disadvantage significantly increases the probability that an individual will evaluate their health in an unsatisfactory manner. The logits in both Models 1 and 2 are on par with those witnessed in Table 2, underscoring the role of activity space exposures as suppressors of standard neighborhood effects. Model 3 tests the relationship between exposure-weighted non-residential disadvantage and personal health assessment. Specifically, a one standard deviation increase in residential disadvantage, on average, is associated with a 67.5% increase ($e^{(.642)(.804)}$) in the log-odds of poor self-rated health, net of controls. Though both of the effects for average status and individual change for activity space disadvantage are marginally nonsignificant ($p < .08$), they produce effects in the opposite directions such that exposure to disadvantage outside the local neighborhood is associated with poor/fair health (15.2%), but being exposed to a one standard deviation *change* in activity space disadvantage raises the likelihood of changing from good health to poor/fair health by 15.9% ($e^{(-1.61)(.107)}$ – 1*100), all else equal.

The possibility might exist, however, that exposure to neighborhoods outside a person's local surroundings might modify or condition the relationship between neighborhood disadvantage and poor/fair health reports. To test this supposition, we interact residential disadvantage with activity space disadvantage in Model 4 of Table 3 and find a significant and negative coefficient. To better illustrate this relationship, we graph the interaction in Figure 1. What is striking about the graph is that individuals living in the most disadvantaged neighborhoods perceive their health to be worse when they spend time in more advantaged neighborhoods than in more disadvantaged ones. This paradoxical finding suggests that being routinely exposed to areas that are markedly more advantaged than individuals' home environments leads to a sense of relative neighborhood deprivation that might manifest in worse health ratings. Alternatively, residents of highly disadvantaged neighborhoods might be able to garner unique resources in the forms of social capital and interpersonal networks that actually result in more favorable reported health.

Ongoing Research

While our analyses of context and self-rated health are largely completed, we are seeking to further refine our approach as necessary. One area that needs more contemplation, which is a significant innovation, is in the change portion of the study. Our findings on individual change are generally nonsignificant, which is not that surprising given the short of amount of time between waves to change from poor/fair to good/very good/excellent and vice versa. We plan to address this issue by executing CCRELM without centering, which will produce coefficients similar to a standard person-period longitudinal analysis with standard errors adjusted for clustering. Another opportunity to explore is examining residential and activity space disadvantage as categorical measures and computing each respondent's relative disadvantage based on the quartile of home disadvantage relative that of the non-residential environment.

Table 1. Multilevel Cross-Classified Random Effects Logistic Models of Standard Neighborhood Context Predicting Poor/Fair Health, LAFANS

	Model 1						Model 2					
	Average Status			Individual Change			Average Status			Individual Change		
	b	SE		b	SE		b	SE		b	SE	
Standard Neighborhood Context												
Concentrated disadvantage	.818	(.100)	***	.008	(.195)		.530	(.145)	***	.085	(.223)	
Residential stability							-.073	(.221)		.132	(.250)	
Immigrant concentration							-.409	(1.078)		4.206	(1.697)	*
Population density							.001	(.016)		-.033	(.021)	
Individual-level												
Time-Varying Covariates												
Age (years)							.044	(.008)	***	-.310	(.129)	*
Married							-.066	(.215)		.631	(.473)	
Presence of children							.695	(.268)	**	-.300	(.322)	
Family income (Ref: Less than $25,000)												
$25,000-$50,000							-.386	(.311)		.708	(.271)	**
$50,000-$75,000							-.292	(.400)		.245	(.358)	
$75,000 and higher							-.935	(.411)	*	.077	(.440)	
Education (Ref: Less than high school)												
High school graduate							-.727	(.296)	*	1.011	(.866)	
Some college							-.673	(.311)	*	.870	(.984)	
College graduate							-2.173	(.411)	***	-2.845	(1.183)	*
Employed							-.581	(.253)	*	-.576	(.284)	*
Spanish speaker							-.368	(.363)		.157	(.469)	
Fixed Covariates												
Race/Ethnicity (Ref: Non-Hispanic white)												
Hispanic							-.708	(.344)	*			
Non-Hispanic black							-.181	(.387)				
Non-Hispanic Asian/other							-.750	(.411)				
Foreign-born							.789	(.313)	*			
Female							.281	(.197)				
Moved between waves							.268	(.207)				
Wave	.328	(.133)	*				2.526	(.875)	**			

***p < .001; **p < .01; *p < .05. N = 2,294 person-periods.

Table 2. Multilevel Cross-Classified Random Effects Logistic Models of Global Neighborhood Context Predicting Poor/Fair Health, LAFANS

	Model 1					Model 2				
	Average Status			Individual Change		Average Status			Individual Change		
	b	SE		b	SE	b	SE		b	SE	
Global Context											
Concentrated disadvantage	.976	(.112)	***	.019	(.213)	.679	(.173)	***	-.098	(.253)	
Residential stability						-.028	(.235)		.033	(.259)	
Immigrant concentration						-.132	(.199)		.395	(.322)	
Population density						.002	(.017)		-.008	(.022)	
Individual-level											
Time-Varying Covariates											
Age (years)						.044	(.008)	***	-.322	(.130)	*
Married						-.071	(.215)		.539	(.470)	
Presence of children						.683	(.267)	*	-.321	(.322)	
Family income (Ref: Less than $25,000)											
$25,000-$50,000						-.375	(.311)		.684	(.270)	*
$50,000-$75,000						-.296	(.398)		.250	(.358)	
$75,000 and higher						-.910	(.409)	*	.086	(.440)	
Education (Ref: Less than high school)											
High school graduate						-.721	(.296)	*	1.037	(.869)	
Some college						-.660	(.310)	*	.891	(.987)	
College graduate						-2.167	(.409)	***	-2.868	(1.170)	*
Employed						-.505	(.254)	*	-.608	(.284)	*
Spanish speaker						-.367	(.363)		.210	(.468)	
Fixed Covariates											
Race/Ethnicity (Ref: Non-Hispanic white)											
Hispanic						-.692	(.348)	*			
Non-Hispanic black						-.225	(.388)				
Non-Hispanic Asian/other						-.737	(.413)				
Foreign-born						.792	(.311)	*			
Female						.264	(.197)				
Moved between waves						.279	(.206)				
Wave	.329	(.134)	*			2.571	(.883)	**			

***p < .001; **p < .01; *p < .05. N = 2,294 person-periods.

Table 3. Multilevel Cross-Classified Random Effects Logistic Models of Exposure-Weighted Context Predicting Poor/Fair Health, LAFANS

	Model 1				Model 2				Model 3				Model 4			
	Average Status		Individual Change		Average Status		Individual Change		Average Status		Individual Change		Average Status		Individual Change	
	b	SE	b	SE	b	SE	b	SE	b	SE	b	SE	b	SE	b	SE
Residential Exposure																
Concentrated disadvantage	1.015	(.121) ***	.097	(.225)	.703	(.187) ***	-.001	(.272)	.642	(.192) ***	.022	(.274)	.704	(.194) ***	.018	(.273)
Residential stability					-.125	(.262)	-.034	(.293)	-.133	(.265)	-.042	(.295)	-.163	(.266)	-.052	(.295)
Immigrant concentration					-.102	(.215)	.647	(.355)	-.126	(.217)	.685	(.357)	-.193	(.219)	.682	(.358)
Population density					.001	(.018)	-.024	(.023)	.002	(.019)	-.028	(.023)	.002	(.019)	-.028	(.023)
Activity Space Exposure																
Concentrated disadvantage									1.321	(.739)	-1.611	(.852)	2.390	(.885) **	-1.580	(.850)
Residential-Activity Space Interaction																
Home X Activity Space disadvantage													-2.498	(1.085) *		
Individual-level Covariates	No				Yes				Yes				Yes			

***p < .001; **p < .01; *p < .05. N = 2,294 person-periods.

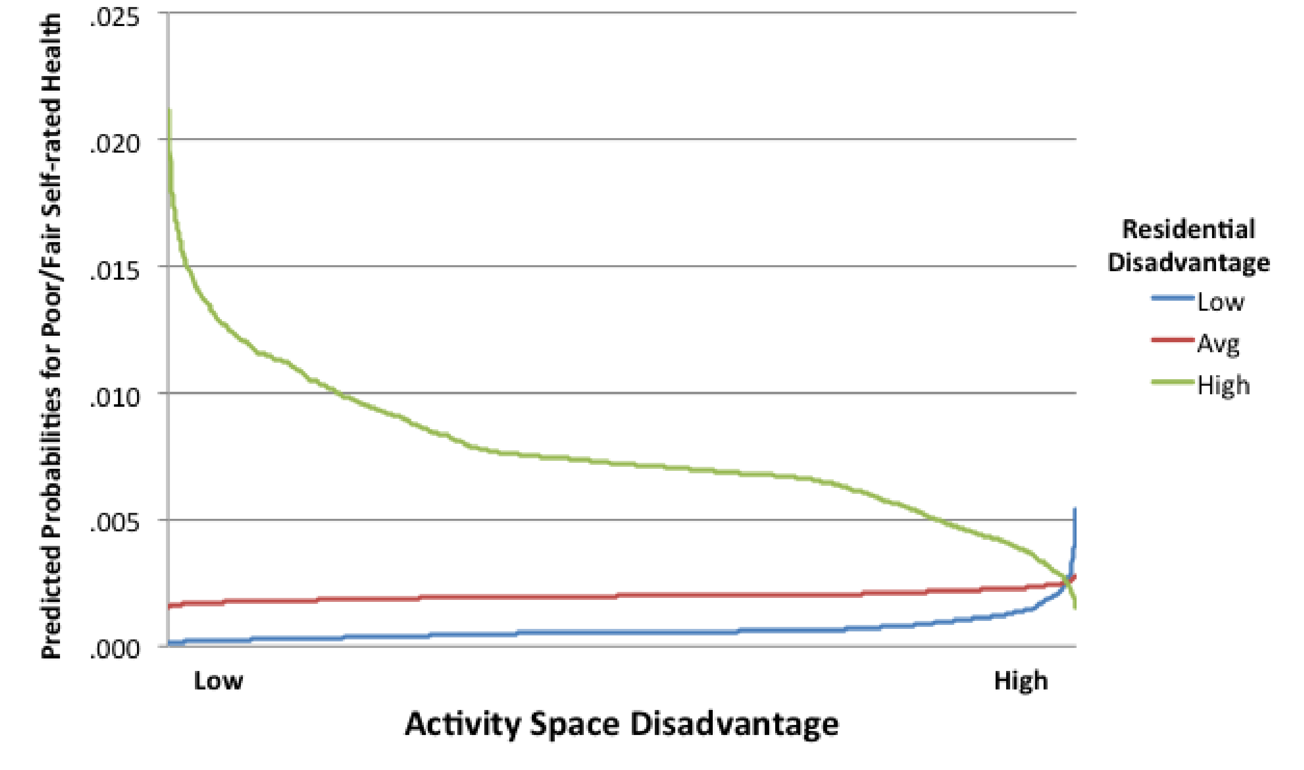

Figure 1. Effect of Residential Disadvantage on Poor/Fair Self-rated Health by Level of Activity Space Disadvantage