Activity Space Exposures and Adult Health: Dimensions of Community Social Organization as Underlying Mechanisms

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Introduction

In response to the relatively inconsistent and small neighborhood effects on health in the literature, recent developments have begun to integrate time and space into their conceptualization of neighborhoods (e.g., Inagami et al. 2007; Jones and Pebley 2014; Kimbro et al. 2017; Sharp et al. 2015). In general, these studies emphasize that including information on the full range of activity spaces to which individuals are exposed throughout the day and over time is critical for detecting contextual effects on health and well-being (Chaix et al. 2009; Kwan 2009). Indeed, not accounting for nonresidential contexts of exposure may overestimate the influence of the local neighborhood, given that activity spaces have been shown to attenuate or confound residential neighborhood effects (Chaix et al. 2017; Sharp et al. 2015). What is lacking in this recent work, however, is an investigation of the contextual and individual mechanisms that explain and shape residential and activity space exposure effects on health. Extant theory and empirical research suggests that dimensions of community social organization, including social cohesion, social capital, and social isolation may not only bear on self-rated health in direct fashion, but also potentially mediate or moderate the effects of residential and activity space conditions (Browning and Cagney 2003; Carpiano 2007).

In this study, I employ novel longitudinal data to examine whether and how contextual exposures—both inside and outside the residential neighborhood—affect self-rated health, with a particular focus on the role of community social organization mechanisms. Using these unique data, I construct multiple measures of context, weighted by the amount of time spent in each context, to systematically assess their relative impacts on adults' health reports. This research is guided by two research questions. First, to what extent do activity space structural characteristics alter residential neighborhood effects on self-rated health? And second, how do dimensions of community social organization mediate or moderate the health effects of activity space exposures?

Data and Methods

This paper uses longitudinal data 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 census tracts in Los Angeles County. The 65 tracts were sampled from three strata based on tract poverty level: very poor (tracts in the 90th or above percentile); poor (tracts in the 60-89th percentiles); and nonpoor (tracts below the 60th percentile). In Wave 1, LAFANS randomly selected and interviewed adults and children living in 3,085 households across the 65 sampled tracts. In Wave 2, an attempt was made to re-interview all respondents in the original sample, while also interviewing a sample of newly arrived residents in each neighborhood. Although sampled households were tracked even if they left the county, state, or country, telephone interviews were the sole interview method rather than the standard face-to-face interview and health-related questions were not asked (Sastry et al., 2006). Nonetheless, an important advantage of LAFANS is the ability to link a panel study of individuals with characteristics from repeated cross-sections of neighborhoods. The final analytic sample of panel respondents who have valid data on all variables used in the study is

1,095.[1] Panel weights are used in all analyses and are intended to make the sample representative of the LA County adult population at Wave 1 who reside in the county at Wave 2. Weights are a combination of the Wave 1 design weight and a Wave 2 attrition factor, and they adjust for the oversampling of tracts in the poorest strata of LA County, the oversampling of households with children, and the attrition of eligible Wave 1 panel members 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 contextual measures based on respondents' home tracts and those to which individuals are exposed outside the residential area. Decennial census (2000) and the American Community Survey (2005-2009) are the sources of data used to derive neighborhood structural measures (e.g., concentrated disadvantage), while the ZIP Code Business Patterns (2000 and 2007) databases are used to create neighborhood-level measures of social capital organizations that correspond to LAFANS Waves 1 and 2, respectively.[2]

Measures

The dependent variable is *self-rated health*, which comes from a 5-item question that asks the respondent to rate their overall health status, ranging from poor (1) to excellent (5). Responses are collapsed into a dichotomous indicator where "poor" and "fair" are coded 1 and "good," "very good," and "excellent" are coded 0 (see Sharp et al. 2015). 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 (e.g., Ferraro and Farmer 1999; Singh-Manoux et al. 2006).

There are four neighborhood-level structural measures: *concentrated disadvantage*, *residential stability*, *share of immigrants*, and *share of co-ethnics*. The first two are indexes derived from a factor analysis with oblique rotation. Concentrated disadvantage is made up of five variables (all percentages): households on public assistance, female-headed households with children, individuals without a high school degree, unemployment rate, and poverty rate. Residential stability combines measures of the percentage of owner-occupied housing units and the percentage of persons living in the same house as the prior year. I also include the percentage of the population who are foreign-born and the percentage of the population who are of the same ethnoracial category.

Key to this analysis is adjudicating the effects of several measures representing dimensions of community social organization, including *social cohesion* and *social capital* at the neighborhood level, and *social isolation* at the individual level. *Social cohesion* captures the extent to which residents feel a general closeness within the neighborhood in terms of mutual trust and willingness to help each other. Specifically, five LAFANS questions tap whether respondents perceive their neighborhood as close-knit, trustworthy, helpful, amicable, and sharing common values. Responses are based on a Likert-type scale ranging from (1) "strongly agree" to (5) "strongly disagree" and items are reverse-coded so that higher values reflect stronger cohesion. *Neighborly exchange* is based on three questions tapping the frequency of contacts with neighbors that involve doing favors, giving advice to each other, and being

[1] Listwise deletion is used rather than a multiple imputation procedure because missing data accounts for only 7.8% (N = 92) of the sample. These respondents do not vary systematically from those with complete data.

[2] ZIP codes were converted to census tracts via crosswalk files generated from the Missouri Census Data Center's MABLE/Geocorr2K application (http://mcdc2.missouri.edu/websas/geocorr2k.html).

vigilant of each other's property when left unattended. A fourth question asks about the number of neighbors the respondent talked with for at least ten minutes. For the first three questions, responses range from (1) "often" to (4) "never" (reverse-coded), while the values of the last question are (1) "none", (2) "1 or 2", (3) "3 to 5", and (4) "6 or more." *Organizational participation* taps whether the respondent participated in local voluntary association during the past year across nine types of groups, such as a neighborhood block meeting, civic group, labor union, or ethnic pride group. To arrive at the three neighborhood-level measures, I execute three-level item response models—items nested with individuals nested within tracts—and use the resulting Empirical Bayes adjusted intercept (EB residuals) (e.g., Carpiano 2007). *Social capital organizations* represents the density of a number of organizations (number of establishments per square mile), including civic, advocacy, ethnic, and religious organizations; the final measure comes from summed z-scores and is then logged. From the individual-level, social isolation is captured by two measures. *Fear of the neighborhood* is a 4-item question capturing how dangerous respondents feel it is to walk around the neighborhood after dark, ranging from (1) "completely safe" to (4) "completely dangerous," and it dichotomized such that "completely" and "somewhat" dangerous are coded as 1 and "completely" and "somewhat" safe are 0. *No local friends* is a binary indicator of whether respondents answer "none" to the question regarding how many friends reside in their current neighborhood.

Using LAFANS respondent data, I follow prior work and estimate the amount of time spent in both residential and non-residential (activity space) locations (see Sharp et al. 2015). While not an exact account of an individual's duration of exposure to each contextual environment, survey questions help serve as proxies for the average time spent conducting routine activities (work, grocery store, worship, healthcare) in a given week.[3] I also estimate the amount of hours spent commuting to work during a given week. The total amount of respondents' time spent in their activity spaces and traveling to work is subtracted from the total hours per week (168) to arrive at the hours per week spent in the residential neighborhood. Exposure weights for each context are then derived by taking the number of hours spent in each context and dividing by 168 hours (which includes sleep time). I construct two time-weighted measures of context: *residential* and *activity space* (non-residential) context exposure by taking the unweighted contextual measure (e.g., concentrated disadvantage) from each LA County census tract that corresponds to the respondent's residential and activity census tracts and apply the exposure weight to arrive at a new residential disadvantage score as well as a total activity space disadvantage score. For more detailed information on the creation and application of exposure weights, see Kimbro et al. (2017) and Sharp et al. (2015). All neighborhood-level structural measures and social capital organizations have corresponding activity space measures, while neighborhood social organization measure only include residential exposure versions, given that these are based on survey questions pertaining to the current neighborhood of residence.

Also included in the analysis are a number of individual/household-level controls that have been implicated in prior studies of place and adult health. Sociodemographic measures are *marital status* (1=married), *households with children* (1=yes), *age* (measured in years at Wave 1), *length of residence* (logged number of years at current address), *race/ethnicity* (Non-Hispanic white, Native-born Hispanic, Foreign-born Hispanic, Non-Hispanic black, Non-Hispanic Asian/other), and *gender* (1=female). Socioeconomic characteristics are *family income* (adjusted to 2007 dollars and logged), *education* (measured in years), *employment status* (1=employed), and *insurance status* (1=uninsured). I also control for whether the respondent *moved* between waves (1=moved).

[3] Respondents could report up to three jobs that they were presently working, and could report multiple locations (census tracts) for each particular job (e.g., multiple job sites), as well as grocery stores, physician offices, health clinics, and places of worship. In Wave 1, respondents were permitted to report up to three locations and four in Wave 2.

Analytical Strategy

To examine the relationship between contextual exposure, community social organization, and self-rated health, I run a series of cross-classified linear probability models (LPM). The use of cross-classified modeling is warranted because these data lose their hierarchical nature as respondents relocate to different neighborhoods across the study period (i.e., individuals become cross-nested in neighborhoods over time).[4] Prior work has established that this can lead to biased estimates of standard errors and variance components (Luo and Kwok 2012). The model is therefore estimated at two levels—time (survey wave) at Level 1 nested within individuals cross-nested within neighborhoods at Level 2.

Because this study is concerned with how changes in activity space and residential exposures influence and shape the likelihood of reporting poor or fair health, I report within-person and between-person effects. This is accomplished by entering the mean values of these time-varying predictors across the two waves at Level 2 and the deviation from the mean at Level 1. This approach is similar to hybrid-effects models that combine random-effects (between-person) and fixed-effects (within-person) approaches into a single model (Allison 2009; Firebaugh et al. 2013; Sharp et al. 2015). An important advantage of this strategy is the ability to ascertain the effects of time-invariant and time-varying predictors, while controlling for secular change.

Results

Table 1 presents results from cross-classified linear probability models predicting individual poor/fair self-rated health. Beginning with residential structural exposure effects in Model 1, concentrated disadvantage in the home neighborhood is associated with a higher probability of poor health reports. For example, a one standard-deviation increase in residential disadvantage exposure is associated with an elevated risk of reporting poor/fair health by 12.5 percentage points, net of other residential neighborhood covariates. Likewise, living in neighborhoods with higher shares of immigrants and those that experience less residential turnover is associated with worse health. With respect to within-person change, neighborhoods in which immigrants increased their local presence during the study period significantly increases the likelihood of changing health status to good or better health to fair or poorer health.

Adding activity space exposures in Model 2 reveals that those who are exposed to higher levels of disadvantage, on average, across their activity locations are at a heightened risk (20 percentage points higher) of perceiving their health in poor or fair terms. Exposure to higher share of immigrants outside the residential neighborhood is associated with reporting significantly *better* health, while increasing shares of co-ethnics in one's activity spaces raises the probability by 40 percentage points of downgrading one's health status. It is apparent that, as in previous work, activity space effects attenuate residential effects on health, particularly for residential immigrant composition, and tend to operate as confounders of residential exposure effects (see Chaix et al. 2017; Sharp et al. 2015). After LAFANS respondent information is controlled for in Model 3, the between-person effects of residential and activity space immigrant shares are no longer statistically significant, as well as activity space disadvantage. But now living around other co-ethnics is associated with a greater probability of reporting poor/fair health. More work is needed on the findings of Model 3, but it seems that it is the ethnoracial and immigrant characteristics of individuals both in the residential neighborhood and activity locations that are driving the contextual exposure effects witnessed in Model 2.

[4] Indeed, a nontrivial share (37%) of respondents switched neighborhoods between waves (i.e., moved to a different census tract by the second wave).

Model 4 of Table 1 assesses the role of community social organization in the context-health relationship. In terms of direct impacts, living in neighborhoods that are socially cohesive is associated with better health perceptions, even when accounting for the full range of neighborhood- and individual-level variables. Yet, an increase in exposure to social cohesion slightly increases the likelihood of reporting worse health by the end of the study period. Although neighborly exchange and organizational participation do not significantly affect self-rated health, residents are benefiting from increasing density of social capital organizations. Social isolation is particularly detrimental to health evaluations; being afraid or living increasingly in fear of the neighborhood increases poor/fair health, and transitioning from having at least some friends to having no friends living in the residential neighborhood increases the probability of reporting poorer health.

To better understand the degree to which activity space characteristics modify and are modified by the effects of residential exposures and forms of community social organization. Figure 1 displays the interaction effect of neighborhood social cohesion and activity space disadvantage. As seen in the graph, in neighborhoods with average levels of social cohesion, individuals view their health worse when they spend time in highly disadvantaged areas compared to lower ones. The effect is magnified if one's residential neighborhood is inhabited by people who do trust each other, share the same values, and are willing to help one another. Figure 2 shows how the health impacts of local social capital organizations is moderated by levels of nonresidential exposure to disadvantage. More specifically, people who have highly disadvantaged activity spaces report worse health their low-disadvantaged counterparts, but people who have higher exposure to social capital organization in their home neighborhood tend to benefit if they also spend time in activity locations characterized by low disadvantage. This is an intriguing finding that requires additional work. Finally, in Figure 3 we see that whereas being socially isolated in the residential neighborhood leads to poorer health self-reports, having access to social capital organizations outside the local neighborhood is beneficial for health. It could be that these individuals are able to seek out associations that offer social support and, in turn, buffer the negative health effects of social isolation.

Ongoing Research

Though my analyses of contextual exposure, community social organization, and self-rated health are largely completed, I plan to further refine my approach as necessary. One area in need of attention is the nonsignificant results of the contextual mechanisms. In supplemental analyses, I plan to test different versions of the measures (i.e., categorical) in order to gain analytical leverage. Given the interesting preliminary findings regarding immigrant and co-ethnic neighborhood compositions, I plan to delve into different ethnoracial measures, such as neighborhood diversity measured as the entropy index, as well as including separate ethnoracial categories (e.g., % Hispanic, % Non-Hispanic Black). Further contemplation of the interaction results is needed as well.

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Table 1. Cross-Classified Linear Probability Hybrid Models Predicting Poor/Fair Health, LAFANS

	Model 1		Model 2		Model 3		Model 4	
	Between-Person	Within-Person	Between-Person	Within-Person	Between-Person	Within-Person	Between-Person	Within-Person
Residential Exposure								
Concentrated disadvantage	.125 *** (.023)	-.029 (.026)	.114 *** (.024)	-.032 (.026)	.082 *** (.025)	-.028 (.026)	.054 * (.028)	-.045 † (.026)
Residential stability	.067 * (.032)	-.019 (.027)	.042 (.032)	-.017 (.027)	-.001 (.032)	-.014 (.027)	.015 (.035)	-.040 (.028)
% Immigrants	.595 *** (.136)	.645 *** (.138)	.366 * (.144)	.645 *** (.141)	-.050 (.155)	.469 ** (.155)	-.141 (.158)	.541 *** (.160)
% Coethnics	.000 (.058)	-.105 (.100)	-.010 (.063)	-.079 (.102)	-.145 * (.066)	-.145 (.103)	-.104 (.066)	-.156 (.102)
Activity Space Exposure								
Concentrated disadvantage			.201 * (.085)	-.068 (.070)	.107 (.083)	-.086 (.069)	.111 (.084)	-.108 (.069)
Residential stability			.019 (.066)	-.005 (.054)	-.024 (.064)	-.023 (.053)	.000 (.066)	-.011 (.055)
% Immigrants			-.862 * (.337)	-.146 (.244)	-.033 (.355)	.102 (.250)	-.247 (.439)	-.058 (.314)
% Coethnics			-.242 (.238)	.399 * (.195)	-.189 (.234)	.383 * (.192)	-.243 (.233)	.315 † (.191)
Community Social Organization Dimensions								
Social cohesion							-.049 * (.023)	.024 † (.014)
Social capital								
Neighborly exchange							-.009 (.018)	-.007 (.011)
Neighborhood organizational participation							.013 (.017)	-.009 (.010)
Residential social capital organizations							-.002 (.018)	-.052 ** (.018)
Activity space social capital organizations							.015 (.016)	.006 (.012)
Social isolation								
Fear of the neighborhood							.059 † (.032)	.105 *** (.025)
No local friends							-.017 (.027)	.042 * (.020)
Individual controls included	No		No		Yes		Yes	

***p < .001; **p < .01; *p < .05; †p < .10. *N* = 2,190 person-waves. Robust standard errors in parentheses.

Figure 1. Predicted Probability of Reporting Poor/Fair Health by Levels of Neighborhood Social Cohesion and Activity Space Disadvantage

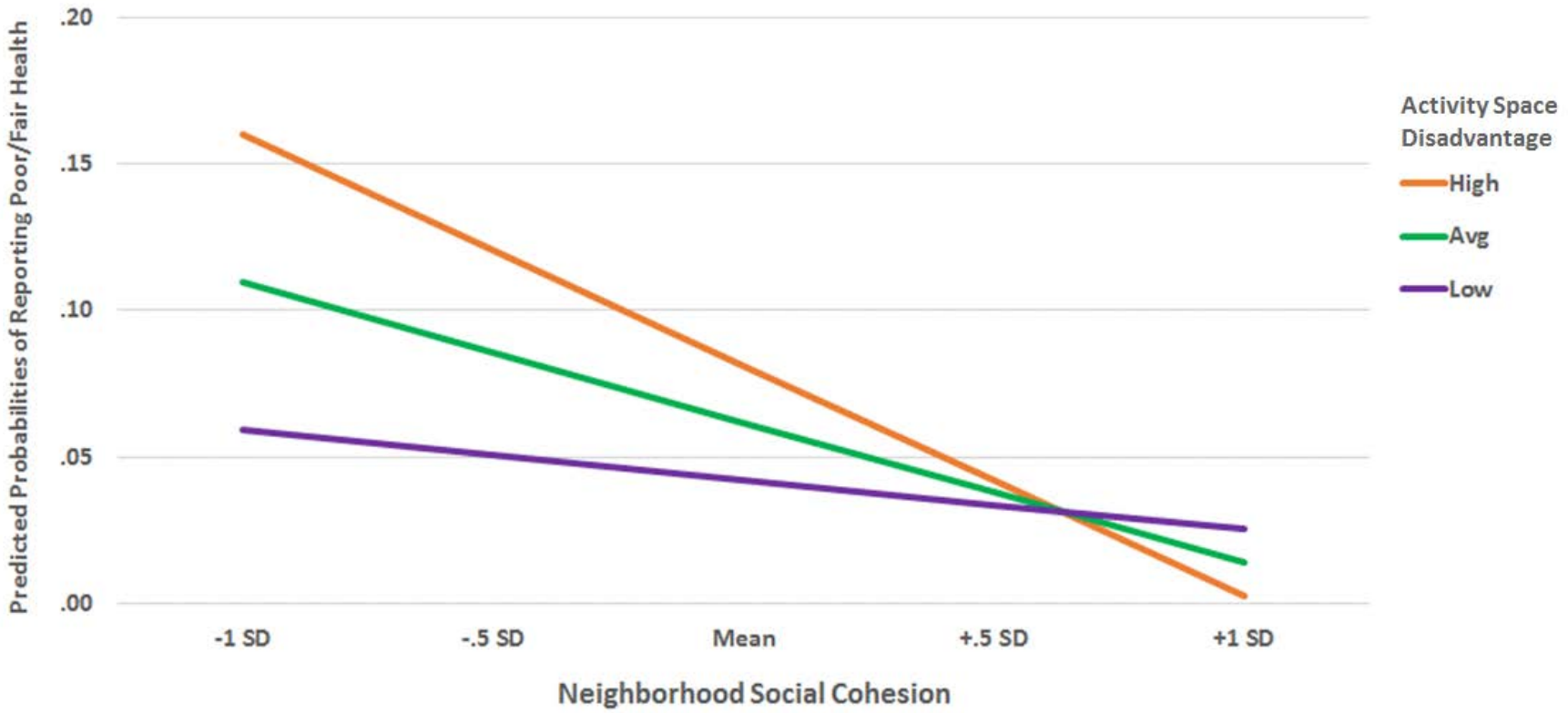

Figure 2. Predicted Probability of Reporting Poor/Fair Health by Levels of Residential Social Capital Organizations and Activity Space Disadvantage

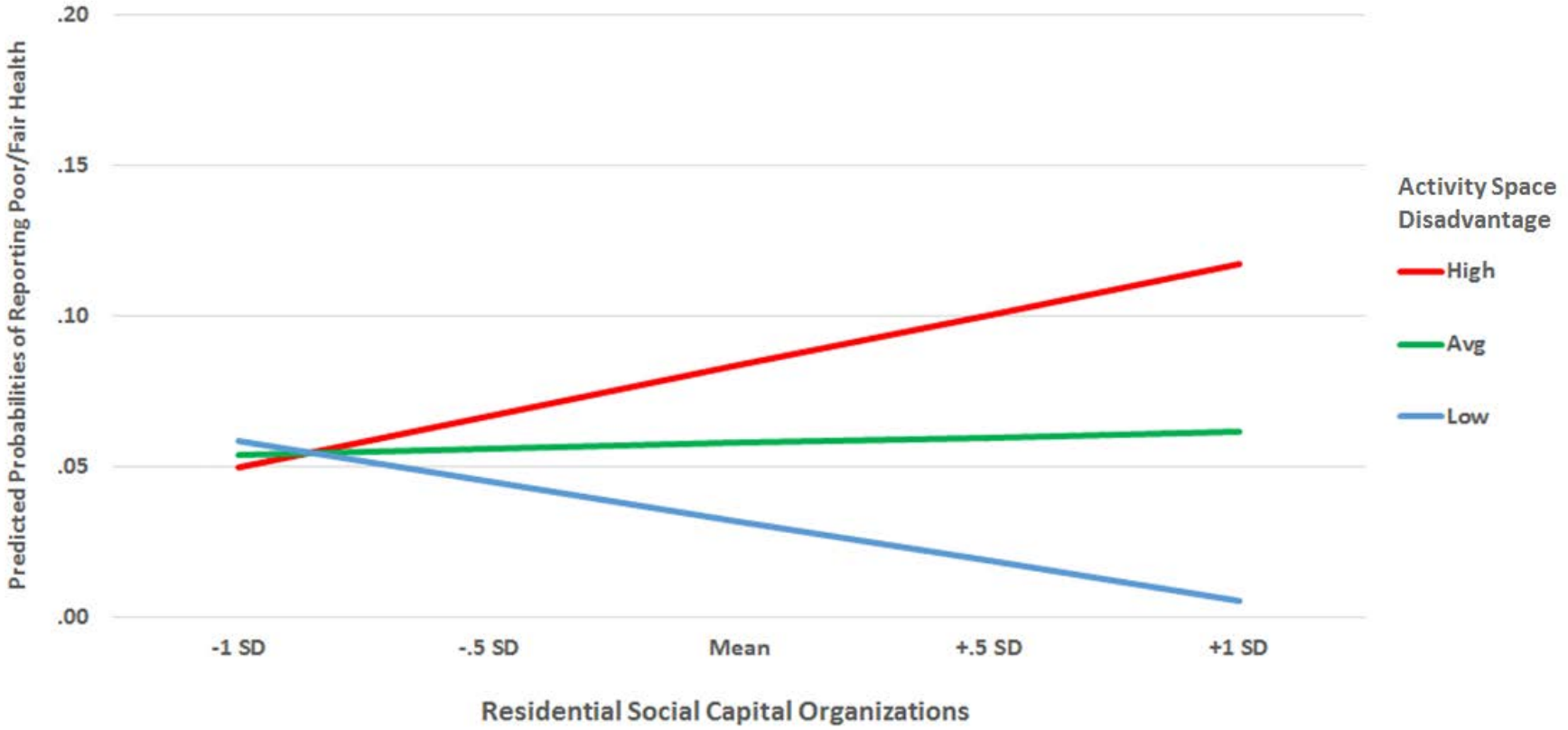

Figure 3. Predicted Probability of Reporting Poor/Fair Health by Presence of Neighborhood Friends and Activity Space Social Capital Organizations