

Stress and physical health: the role of neighborhoods as mediating and moderating mechanisms

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Abstract

Using data from the 1995 Detroit Area Study ($N = 1106$) in conjunction with tract-level data from the 1990 census, this paper evaluates the relationship between residential stability and physical health among black and white adults. Results suggest that neighborhood-level variation in health is primarily mediated by key sociodemographic characteristics of individuals (e.g., age, race, and socioeconomic status). However, a significant portion of health differentials across neighborhoods is due to disparate stress levels across neighborhoods. Further, high levels of neighborhood stability provide an important buffer to the otherwise deleterious effects of increased stress levels on adults' overall health.

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Introduction

In recent years, research emphasizing the composition and context of neighborhoods as an important mechanism contributing to population health differentials has increased dramatically (Duncan, Jones, & Moon, 1996; Robert, 1998; Robert, 1999; Pampalon, Duncan, Subramanian, & Jones, 1999; Subramania, Kawachi, & Kennedy, 2001; Macintyre, Ellaway, & Cummins, 2002; Morenoff & Lynch, 2002). This body of research denotes an important break from the theoretical and methodological individualism that until recently has defined mainstream social-scientific research into health related phenomena signaling, for some, a “new public health” (Baum, 1997). With a renewed interest in upstream social characteristics as the key determinants of health differentials (Martin & McQueen, 1989) this line of inquiry denotes a break from more traditional epidemiology and public health research because it explicitly focuses on differential access to material, social, and psychological resources, expo-

sure to deleterious pollutants and discriminatory actions as opposed to emphasizing specific health and disease outcomes, per se (Berkman & Kawachi, 2000a, b).

A number of neighborhood characteristics are believed to impact individuals' physical health, psychological well-being, and life chances in general (see Sampson, Morenoff, & Gannon-Rowley (2002) for a useful review of this research). This paper focuses on one particular aspect of neighborhood context that may have important consequences for adults' physical health: residential stability. Drawing on work involving the life-stress process (Lin & Ensel, 1989) and the growing body of work linking social integration and physical health status (Berkman, Glass, Brissette, & Seeman, 2000; Kawachi & Berkman, 2000) this paper posits that the health status for residents of more stable communities will be less affected by the effects of chronic and acute stressors compared to residents of communities with high rates of residential instability. In short, the potentially salubrious nature of residential stability is tested as an important buffer to the otherwise deleterious effects associated with stress on adults' physical health.

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Stress, neighborhoods, and health

Stress provides an important conceptual and physiological link between an individual's social context and their physical health status (McEwen, 1998) and research involving individuals' exposure to social stressors and their overall well-being has increased notably in recent years (e.g., Baum, Garofalo, & Yali, 1999; Brunner & Marmot, 1999; Landale, Oropesa, Llanes, & Gorman, 1999; Turner & Lloyd, 1999; Dohrenwend, 2000; Boardman, Finch, Ellison, Williams, & Jackson, 2001). The relationship between social stressors and physical health is best understood in reference to the fight-or-flight response in which the body prepares for an emergency situation by producing cortisol and other glucocorticoid hormones. The release of these hormones, while important during an emergency, may have the unintended effect of adversely impacting individual's physical health. If people face too many stressors, or encounter stressors for too long, the otherwise functional role of cortisol production has the unintended effect of breaking down important physiological processes. This process, described as allostasis or allostatic load may have deleterious associations with cardiovascular, metabolic, immune systems, brain activity, or central nervous system functioning (McEwen, 1998).

Given the physiological emphasis on this stress–health relationship, the stress process has been operationalized almost exclusively as a characteristic of individuals. However, because residential context may shape individual's exposure to stressors (Schulz et al., 2000a, b; Massey & Shibuya, 1995), researchers interested in the relationship between stress and health have been increasingly sensitive about including information on individuals' neighborhoods in their analyses. Previous research finds that residents of poor communities are more likely to experience stressful life events such as death of a loved one, job loss, and criminal victimization (Fang, Madhavan, Bosworth, & Alderman, 1998; Massey & Shibuya, 1995; Krivo & Peterson, 1996). Similarly, Aneshensel and Sucoff (1996) find that residents of "multiproblem" areas were more likely to perceive ambient risks such as crime, violence, noxious pollutants, failing infrastructure, and graffiti. Neighborhood disadvantage may also be associated with a higher incidence of social strain though negative social interactions with others and/or the experiencing discriminatory behaviors from individuals (Schulz et al., 2000a, b) and institutions (Kirschenman & Neckerman, 1991; Anderson, 1990). The convergence of research relating stress to health with neighborhood specific processes that are believed to affect physical health denotes an important and relatively new contribution to social scientific inquiry into population health differences.

An important aspect of the stress–health relationship involves individual's access to social resources. The bulk of research on the relationship between social resources and health focuses on the main effects associated with distinct pathways such as social influence, social engagement, direct "person-to-person" contact, and indirect access to material resources (Berkman et al., 2000). Less common is any evaluation of the way in which the effects associated with social resources may vary depending on individual's level of stress or exposure to stressors. Lin and Ensel (1989) describe the life-stress process where social resources reduce exposure to known stressors as well as moderate and at times eliminate the unhealthy effects associated with stress in general. Following their stress-buffering hypothesis, this paper posits that the nature of individual's immediate residential context may exacerbate or suppress the negative impact that stress has on health. Specifically, ritualized and routine interactions with neighbors may not only provide a sense of consistency and coherency in one's life, but neighbors may also provide direct or indirect access to other important resources that can be tapped during stressful times.

Research questions

This paper addresses the four following research questions:

- (1) Do stress levels and physical health status vary across neighborhoods?
- (2) To what extent does the non-random distribution of stress across neighborhoods account for neighborhood variation in health?
- (3) Does the effect of stress on adults' health vary across neighborhoods?
- (4) Do social resources associated with neighborhood stability account for the neighborhood-to-neighborhood variation in the effect associated with stress?

Several related multilevel modeling techniques (discussed at greater length below) are used to address each research question and the findings from these models are presented in Tables 1–3.

Methods

Data

Individual-level data: Individual-level data come from the 1995 Detroit Area Study (DAS). The 1995 DAS is one of a series of studies from the Survey Research Center and the Department of Sociology at the University of Michigan. Each DAS poses a unique set

of research questions and is headed by different principal investigators every year. The primary investigators of the 1995 DAS, James Jackson and David Williams, were primarily interested in identifying the social influences on individual health outcomes and individual's access to important health resources. These data come from a multistage area probability sample of 1139 adult respondents 18 years of age and older residing in Wayne, Oakland, and Macomb counties in Michigan including the city of Detroit. Face-to-face interviews were completed between April and October 1995 by University of Michigan graduate students in a research training practicum in survey research and professional interviewers from the Survey Research Center and the overall response rate was 70%. The small number of Hispanic ($n = 11$), Asian American ($n = 15$), Native American ($n = 4$) respondents, and respondents who reported another race/ethnicity ($n = 3$), have been dropped from the present analyses because of small sample sizes. These deletions, which allow for more meaningful comparisons between African-American and non-Hispanic white respondents, yields a final N of 1106.

Neighborhood-level data: Respondent's neighborhoods are operationalized as census tracts. Census tracts are specifically designed to be demographically homogeneous and are generally considered to be an appropriate operationalization of one's "neighborhood". Tract boundaries are relatively stable over time and they generally contain between 3000 and 8000 residents. Of the 1088 census tracts in the Detroit Tri-County Area, DAS-95 respondents come from 139 of these tracts. Data describing these neighborhoods were extracted from the 1990 decennial census file 3A (CD-ROM version) and then merged with the individual-level records from the DAS-95.

Measures

Physical health status is operationalized with a composite of three standardized scores tapping respondents' overall health (see Ross and Mirowsky (2001) for a similarly constructed dependent variable). First, morbidity taps the number of chronic and serious health conditions that individual respondents reported. Respondents were asked to indicate if a doctor had told them that they had any of the following: (a) stroke; (b) heart attack or other heart problem; (c) diabetes; (d) cancer; (e) arthritis; (f) stomach ulcers; (g) asthma; (h) liver trouble; (i) kidney problem; (j) chronic bronchitis; (k) blood circulation problem; (l) high cholesterol; or (m) high blood pressure. The number of "no" responses were summed across individual respondents to form a measure of positive physical health. Second, respondents were then asked "how much do these health problems usually interfere with your life activities?" Functional

health is measured with responses to this question that ranged from (1) "a lot" to (4) "not at all". Third, self-rated health is measured with a variable in which respondents were asked to rate their physical health from (1) "poor" to (5) "excellent". This measure is widely used in medical sociology and public health research and the concurrent validity of this measure is consistently supported (Idler & Benyamini, 1997; Benyamini & Idler, 1999). These three measures of health were standardized and then summed ($\alpha = 0.82$) to create the dependent variable used in the present analyses where higher values reflect better health.

Five sociodemographic controls are used in all multivariate models: (1) *age* is a continuous variable measured in years; (2) *sex* is measured with a dummy variable coded 1 for female and 0 for male respondents; (3) *race* is measured by respondent self-identification and is coded 1 if respondents indicated that they were African-American and 0 if they indicated that they were non-Hispanic and white; (4) *marital status* is measured with a dummy variable coded 1 if respondents reported that they were married at the time of the interview and 0 if otherwise; and (5) *socioeconomic status*. This variable is a composite of the following four important characteristics tapping respondents direct access to socioeconomic resources: (a) *income to needs ratio*. Information provided by respondents on their yearly family incomes and family size is used in conjunction with Federal Guidelines for 1995 poverty definitions to create a variable that indicates respondent's yearly incomes relative to the official poverty line for a family of their size (US Department of Health and Human Services, 2000); (b) *education* is measured with a continuous variable tapping the number of years of education; (c) *total assets* is measured with response to the following question: "Suppose you need money quickly and you cashed in all of your family's checks and savings accounts, and any stocks and bonds, and real estate (including your principle home). If you added up what you got, about how much would this amount to?" Responses ranged from (1) \$0–499 to (9) \$200,000 or more; (d) *Work Status* is measured with responses to a series of questions. Respondents were asked the following: (a) "have you ever held a regular job for pay?"; (b) "as an official part of your job, (do/did) you supervise the work of other employees, have responsibility for, or tell other employees what work to do?"; (c) do/did you hold a managerial position at your place of employment"; (d) "would that have been a top, upper, middle, or lower managerial position?"; (e) "did someone else supervise your work?"; and (f) "at your work place (do/did) you participate in making decisions about such things as the products or services offered, the total number of people employed, budgets, and so forth?". Values for this variable ranged from 0 (respondents who had not ever held a regular job for pay and respondents

who had held a job for pay but did not report that they had any managerial roles) to 7 (respondents who reported that they supervised others, had a top level managerial position, were not supervised by others, and participated in the decision making process. Respondents' income to needs ratio, education, assets, and work status were then standardized and socioeconomic status represents the mean value of these standardized scores ($\alpha = 0.66$).

Respondent's exposure to acute and chronic stressors was tapped with by response to the following 10 questions. Respondents were asked if the following had occurred in the past year: (a) had "been the victim of a serious physical attack or assault"; (b) were "robbed" or had their "home burglarized"; (c) had anyone in their household "unemployed for longer than 3 months"; (d) had "serious financial problems or difficulties"; or (e) anyone close to them die. Respondents with three or more affirmative responses were coded as "high-acute stress". They were also asked if they had any problems in the past "month or so": (a) "problems with your children"; (b) "hassles at work"; and (c) "trouble balancing work and family demands". They were also asked "how difficult is it for you to meet the monthly payments on your bills? Responses ranged from (1) "not difficult at all" to (5) "extremely difficult". Last, respondents were asked to report the frequency of "problems with muggings, burglaries, assaults, or anything else like that around here". Responses to this question ranged from (1) "never" to (5) "very often". Each variable was standardized and then measure Stress represents the mean of these standardized scores ($\alpha = 0.69$).

Finally, residential stability is measured with two pieces of information from respondents census tracts: (1) the percent of residents that own their home; and (2) the percent of residents that resided in the same dwelling five years earlier. These two characteristics are highly correlated with one another in the Detroit Area ($r = 0.73$).

Analyses: multilevel modeling of health outcomes

In the introduction of an important new text, Berkman and Kawachi (2000a) provide a useful review of the development and proliferation of research associated with the field deemed "social epidemiology". They define social epidemiology as "the branch of epidemiology that studies the social distribution and social determinants of states of health" and specifically highlight "socioenvironmental exposures that may be related to a broad range of physical and mental health outcomes" (p. 6). While theoretical treatments and empirical documentation of the social determinants of health is nothing new to social scientists (e.g.,

Durkheim's (1897) *Suicide*), the area of Social Epidemiology, according to Berkman and Kawachi (2000b), is. Berkman and Kawachi (2000a) list *contextual multilevel analysis* as one of the guiding principals of social epidemiology because health and health related behaviors are understood as social phenomena that vary across meaningful social categories. Therefore, the analysis of individual-level health differentials should incorporate data from various levels of aggregation. In other words, individuals are not isolated and independent from one another. They are nested within particular social contexts (i.e., families, households, schools, neighborhoods, and workplaces). And while individuals from the same social context differ with respect to their personal resources they nevertheless share the same exposure to these contextual (e.g., neighborhood) health risks.

Research on health-related neighborhood effects build on what some call a "exposure-resource framework" (Lynch & Kaplan, 2000, p. 21), because individual's residential areas directly and indirectly affect access to *resources* (Edin & Lein, 1997; Wilson, 1996) while at the same time shaping individual's *exposure* levels to any number of known health risks (LaVeist & Wallace, 2000; Ringquist, 1997). Identifying the source of variability in health outcomes across particular social contexts is important to health researchers because it not only suggests that changes in individual's social contexts will have a salubrious impact on a large number of persons but also provides a geographically defined, discrete, target population for health-related interventions. While the relative impact associated with macro-level changes on an individual's life chances compared to more direct modification of individual's personal resources may be small, the social impact associated with improving the health of several thousand persons compared to one individual is quite large indeed.

$$Y_{ij} = \gamma_{00} + u_{0j} + e_{ij}. \quad (1)$$

Multilevel modeling techniques are particularly useful in identifying residential areas in which known health risks have a more pronounced impact on an individual's health status. In other words, traditional multivariate techniques illustrate *what's* important but multilevel models also illustrate *where* these processes may be most acute. The most basic multilevel model equivalent to a one-way ANOVA with random effects and is presented in Eq. (1). Here, γ_{00} represents the grand mean for the population of scores and two sources of error are specified: u_{0j} and e_{ij} . The first is simply an offset to grand mean for the j th neighborhood and e_{ij} is an offset for the i th observation in the j th neighborhood. If, for example, the average health level in a neighborhood is identical to the mean health for the total sample then estimate for u_{0j} is simply zero. Alternatively, neighborhoods with higher mean health levels than expected are scored positively

and those with lower health levels receive negative values of u_{0j} . Together, the two sources of error can be used to calculate a simple statistic called the intra-class correlation coefficient (ρ). This value, presented in Eq. (2), describes the relative contribution of level-2 (σ_u^2) residual variance to the total residual ($\sigma_u^2 + \sigma_e^2$) variance. As Snijders and Bosker (1999, p. 17) state, “(t)his parameter is called a correlation coefficient, because it is equal to the correlation between values of two randomly drawn micro-units in the same, randomly drawn, macro-unit”

$$\rho = \frac{\sigma_u^2}{\sigma_u^2 + \sigma_e^2}, \tag{2}$$

$$Y_{ij} = \gamma_{00} + \gamma_{10}x_{ij} + u_{0j} + e_{ij}. \tag{3}$$

This approach can be easily extended to include both individual-level and neighborhood-level covariates in simple and multivariate regression models (see Eq. (3)). The levels-1 and -2 residual variance estimates are particularly helpful because they help to *document* the neighborhood-specific nature of all variables used in the analyses. More importantly, the multivariate extension of this modeling approach enables researchers to *explain* neighborhood variation in the dependent variable with the piecewise inclusion of levels-1 and -2 predictor variables. If level-2 residual error is operationalized as the “neighborhood effect”, then controls that are hypothesized to be related to neighborhoods and to the outcome variable that reduce the size of this error estimate can be thought of as *mediators* of the observed neighborhood effect. Snijders and Bosker (1999, p. 103) describe this reduction as the level-2 “R-Square” (R_2^2) by Eq. (4). Here, the variance components with subscript f refer to the full model estimates and those with an r subscript refer to the reduced model (with fewer covariates). If the number of observations per level-2 unit varies, then the harmonic mean or the average number respondents per level two units can be used as an appropriate estimate of n

$$R_2^2 = 1 - \frac{(\sigma_{ef}^2/n) + \sigma_{uf}^2}{(\sigma_{er}^2/n) + \sigma_{ur}^2}. \tag{4}$$

In addition to random intercepts, multilevel models also allow researchers to estimate random slopes. Eq. (5) presents a multilevel model similar to the random intercept model (Eq. (3)), however, this equation provides an additional parameter estimate (u_{1j}) that describes the extent to which the estimated effect of the independent variable x_{ij} varies across neighborhoods. In this model, the parameter estimate γ_{10} describes the average effect of x_{ij} across all neighborhoods and u_{1j} can be thought of as an “offset” to this effect. If the estimate for γ_{10} is positive, then positive values of u_{1j} indicate that the effect of x_{ij} is stronger in a particular neighborhood and negative values of u_{1j}

indicate that the effect of x_{ij} is less pronounced in these neighborhoods.

$$Y_{ij} = \gamma_{00} + \gamma_{10}x_{ij} + u_{0j} + e_{ij} + u_{1j}x_{ij}. \tag{5}$$

As others have demonstrated (e.g., Duncan et al., 1996; Pampalon et al., 1999; Subramania et al., 2001), multilevel modeling parameter estimates can be used to address the research questions presented earlier. Here, the baseline random intercept in the dependent variable is operationalized as the “neighborhood effect”. This helps to address the first research question. In other words, to investigate the extent to which health levels vary across neighborhoods, simply calculate the intra-class correlation coefficient (ρ). The magnitude of this coefficient (bounded between 0 and 1) will address this concern and this approach is preferable to the standard method of including contextual predictors to identify neighborhood effects because it does not rely on the researcher to “choose” the correct level-2 variable (e.g., poverty rate, unemployment rate, percent female headed households, etc.). Likewise, clustering of similar values for the primary independent variable is important information for researchers to have as well. Therefore, an unadjusted intra-class correlation coefficient is calculated for stress because stress is hypothesized to be an important mediator between area of residence and physical health status.

If significant variation in the dependent variable is identified then the inclusion of covariates can help to identify the source of the variation (see Pampalon et al. (1999) for a similar approach). These covariates allow us to answer the second question regarding the source of neighborhood-level variation. Moreover, individual-level predictors can be conceptually considered as potentially important “mediators” of the observed neighborhood effect. In other words, reduction in the magnitude of the level-2 residual can and should be attributed to individual-level characteristics and not simply neighborhood characteristics (as is typically the case). In addition, it is also the case that the effects of a particular individual-level characteristic may vary in magnitude depending on what neighborhood an individual resides in. Random slope coefficients from multilevel models allow researchers to test and model this type of variation and help to address the third research question. Lastly, cross-level interactions provide important information about the source of slope coefficient variability. Here, the effect of stress is expected to interact with levels of neighborhood stability and this interaction should significantly reduce the variance of this random slope (σ_{u2}^2).

It is often the case that the range of possible level-2 predictors limits researchers abilities to account for neighborhood-level variation. In these cases, Duncan et al. (1996, p. 821) argue that “*predictions* of place-specific intercepts and slopes can be obtained

and since these are made using the entire sample of places they are more precise than those from a traditional approach in which each place is estimated separately". In other words, the parameter estimates from multilevel models are particularly helpful for researchers interested in systematic social observation (Sampson & Raudenbush, 1999) as a method of inquiry because they can be used to identify neighborhoods in which the estimated net effect of a health risk and physical health is either more pronounced or non-existent. All multilevel models are estimated with SAS 8.1 PROC MIXED (Littell, Milliken, Stroup, & Wolfinger, 1996).

Results

Table 1 presents unadjusted multilevel residual variance estimates and the subsequent intra-class correlation coefficients for the dependent variable (health) and the primary independent variable (stress). According to these estimates, 12.4% and 9.1% of the variance in stress levels and physical health, respectively, is due to unmeasured characteristics of respondents' neighborhoods. In short, these results provide an affirmative response to the first research questions: *do stress and physical health status vary across neighborhood?* This first step is important because it suggests that

Table 1
Unadjusted multilevel variance components and intra-class correlation estimates: stress and physical health

	Independent variable (stress)	Dependent variable (physical Health)
σ_u^2 : Level 2 residual variance	0.024 (0.005)	0.597 (0.176)
σ_e^2 : Level 1 residual variance	0.169 (0.008)	5.959 (0.269)
ρ : Intra-class correlation	0.124	0.091

Source: 1995 Detroit Area Study (N = 1106). All data have been weighted to reflect sampling design.

Table 2
Multilevel modeling parameter estimates: stress, neighborhood stability, and health

	1	2	3	4	5
Intercept	0.059 (0.150)	-0.049 (0.146)	-0.076 (0.148)	-0.073 (0.148)	-0.057 (0.147)
Individual-level					
Age	-0.068*** (0.003)	-0.076*** (0.004)	-0.077*** (0.004)	-0.076*** (0.004)	-0.076*** (0.004)
Female	-0.175 (0.135)	-0.181 (0.133)	-0.112 (0.132)	-0.119 (0.132)	-0.129 (0.132)
Non-hispanic black	-0.207 (0.189)	-0.015 (0.182)	-0.006 (0.183)	-0.022 (0.184)	-0.002 (0.183)
Socioeconomic status	0.564*** (0.104)	0.537*** (0.101)	0.562*** (0.101)	0.567*** (0.102)	0.551*** (0.101)
Married	0.194 (0.144)	0.156 (0.141)	0.164 (0.141)	0.162 (0.141)	0.155 (0.141)
Stress		-1.077*** (0.161)	-1.065*** (0.193)	-1.065*** (0.192)	-1.011*** (0.192)
Neighborhood-level					
Residential stability				-0.083 (0.081)	-0.020 (0.085)
Cross-level interactions					0.550** (0.205)
Stress × stability					
σ_e^2	4.640***	4.505***	4.336***	4.338***	4.313***
$\sigma_{Intercept}^2$	0.249**	0.179*	0.191*	0.192*	0.192*
$\sigma_{\beta_{stress}}^2$			0.875*	0.851*	0.844*
R_2^2	0.579	0.696	0.700	0.700	0.702

Source: 1995 Detroit Area Study (N = 1106). Cell entries represent unstandardized parameter estimates from multi-level linear models. All Data have been weighted to reflect sampling design. ***p < 0.001, **p < 0.01, *p < 0.05.

Table 3
Tract specific slope and intercept estimates

Random effects	Neighborhood A	Neighborhood B
Intercept (U_0)	0.131* (0.062)	-0.439*** (0.109)
Stress (U_1)	-1.879** (0.647)	1.227* (0.596)
Number of observations	10	9

Source: 1995 Detroit Area Study ($N = 1106$).

Note: Tract specific estimates u_{1a} and u_{1b} are obtained from Table 2, Model 5.

All data have been weighted to reflect sampling design. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

disparate levels of stress across neighborhoods may partially mediate the observed neighborhood variation in average health levels. However, because stress is associated with characteristics that are also associated with health and well-being, it is important to partial out these confounding effects. This is where multivariate mixed modeling techniques are particularly useful. Accordingly, Table 2 presents estimates from five nested multilevel regression models in which baseline estimates for sociodemographic characteristics are followed by a similar model that controls for stress levels, controls for neighborhood stability, and a cross-level interaction between stress and neighborhood stability. As expected, age ($b = -0.068$, $p < 0.001$) and socioeconomic status ($b = 0.564$, $p < 0.001$) are both strongly related to physical health status. The controls variables in Model 1 reduce the level-2 residual variance from 0.597 (Table 1) to 0.249 resulting in a R^2_2 of 0.579. In other words, nearly 58% of the variation in physical health status across neighborhoods is due to the non-random distribution of these individual-level characteristics across neighborhoods. Given that there is significantly more residential segregation by socioeconomic status compared to age, it is likely that the bulk of this effect is due to socioeconomic status.

The next model (Model 2, Table 2) presents estimates for one of the key research questions of this paper: to what extent does the non-random distribution of stress across neighborhoods account for neighborhood variation in physical health? Net of individual-level socio-demographic characteristics, stress is negatively and significantly related to physical health status among adults ($b = -1.077$, $p < 0.001$). Moreover, this control reduces the level-2 residual variance estimate from 0.249 to 0.179. By the formula provided above, this reduction yields a R^2_2 of 0.696. In other words, even after controlling for individual-level characteristics for age, sex, race, socioeconomic status, and marital status, variation in stress levels across neighborhoods explains a significant proportion of the remaining level-2 residual variance.

The third question deals the potential of neighborhoods to act as moderators between stress and physical health: does the effect of stress on adults' health vary across neighborhoods? In other words, individuals may face the same number and intensity of stressors but the likelihood that stress will adversely affect one's health may depend on where you live. To assess this possibility, Model 3 in Table 2 presents estimates from a multilevel model in which the effect of stress is allowed to vary across neighborhoods (i.e., random slope). The significant estimate ($\sigma_{u1}^2 = 0.875$) suggests that the magnitude of the stress effect varies from neighborhood to neighborhood. In other words, neighborhoods moderate the impact of stress on adult's physical health. The results presented in Models 4 and 5 attempt to account for this variation and address the final question in these analyses: do social resources associated with neighborhood stability account for the neighborhood-to-neighborhood variation in the effect associated with stress? According to the estimates presented in Model 5, the estimated effect of stress ($b = -1.011$, $p < 0.001$) does depend on the stability of respondents' neighborhoods. Specifically, the parameter estimate ($b = 0.550$, $p < 0.01$) suggests that the effect of stress on physical health is less pronounced among individuals residing in relatively stable neighborhoods. Said differently, the negative effect of stress on physical health is even stronger among individuals residing in unstable neighborhoods (i.e., high turnover and low homeownership). This is important because the results from Model 4 do not illustrate a main effect of residential stability on individuals' health. Residential stability only appears to be a significant predictor of adults' health when considering adults' stress levels.

It is also important to note that this interaction only reduced the random slope estimate from 0.875 to 0.828 suggesting that other (unmeasured) characteristics of individual's neighborhoods may help to explain this variation.¹ The inclusion of cross-level interaction terms is the typical strategy employed by researchers to explain random slope variability however, when data come from a single-city another interesting method exists that may help explain this variation. Table 3 presents the random intercept (u_{0j}) and random slope estimate for stress (u_{1j}) from Model 5 in Table 2 for two extreme tracts. These

¹ Ancillary analyses (results not shown) controlled for a number of relevant socioeconomic characteristics at the census-tract level (e.g., poverty rates, percent of adults with less than a high school education, percent female headed households, and percent unemployed). None of these level-2 characteristics were significantly associated with physical health status and none of these characteristics moderated the main effects associated with stress. As a result, these controls were not included in the final models presented in Table 2. Results from these analyses are available from the author upon request.

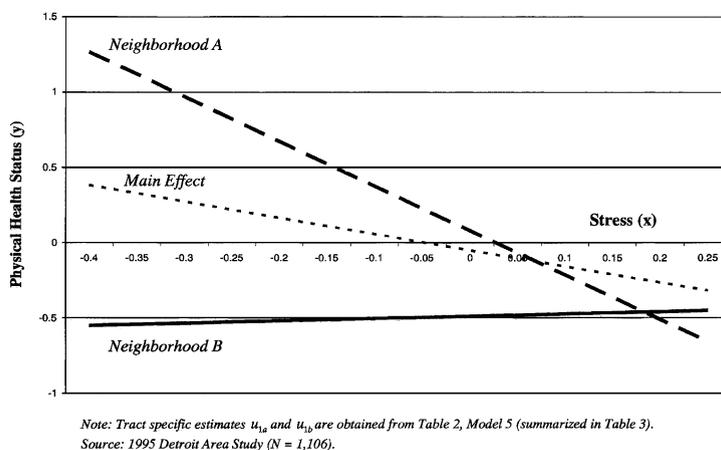


Fig. 1. Utilization of mixed modeling parameter estimates to identify neighborhood specific effects of known health risks.

estimates can be thought of as an offset to the main effect of stress. In other words, on average, stress is negatively related to health, but the magnitude of this effect ($b = -1.011$, $p < 0.001$) is more than twice as strong in Neighborhood A. Likewise, although the residents of Neighborhood B may face a similar number of social stressors, stress does not appear to affect their physical health; the tract-specific offset ($u_{1b} = 1.227$) eliminates the overall main effect. This relationship is illustrated in Fig. 1 where the dotted line represents the main effect of stress across all neighborhoods. The dashed line illustrates the more pronounced effect of stress among the residents of Neighborhood A and the solid line demonstrating virtually no effect of stress on health among the residents of Neighborhood B. Most importantly, the estimated average health levels for the residents of Neighborhood A are only higher than the corresponding levels in Neighborhood B until a certain level of stress. Beyond that point, the residents of Neighborhood B appear to fair better in terms of their health outcomes.

Generally, researchers will include statistical controls for various compositional and contextual characteristics of respondents' neighborhoods to account for this variation. However, this information is generally limited to socioeconomic and sociodemographic data obtained from the decennial census. At times additional information such as criminal activity (Sampson, Raudenbush, & Earls, 1997), pollution levels (Ringquist, 1997), and the presence of liquor outlets (Scribner, Cohen, Kaplan, & Allen, 1999; Scribner, Cohen, & Farley, 1998) may be included in this type of analyses but researchers are still dependent on the availability of contextual data sets to help account for tract to tract variation in individual-level effects. The approach presented here helps to identify two case study examples to elaborate on the observed relationships. This triangulative approach could then rely on systematic social observation methods (Sampson & Raudenbush, 1999) to identify

the source of this variability. In other words, what is it about some neighborhoods that may compound the already deleterious effects of stress on physical health (Neighborhood A)? Likewise, what formal and informal social organizations and institutions exist within particular neighborhoods that make this relationship less pronounced (Neighborhood B)?

Discussion

The findings presented in this paper identify significant variation in physical health status and stress levels across residential areas and controls for stress levels significantly reduce the observed neighborhood variation in health levels. More importantly, the impact of stress on physical health is found to be stronger among residents of relatively unstable neighborhoods. Social stressors are known risk factors for a number of adverse health outcomes and the findings presented here are important because they point to the important role that social resources—in this case stable residential context—may play as buffers to the otherwise negative impacts associated with acute and chronic social stressors. The stability of neighborhoods may play a crucial role in the formation of lasting and meaningful social networks that can provide important coping resources (Lin & Ensel, 1989) and the so-called “social capital” (Kawachi & Berkman, 2000). In addition, stable residential areas may independently impact an individual's health through social integration and sense of community (James & Schulz, 2001).

This paper addresses key shortcomings in the public health literature involving neighborhood effects. Specifically, as Morenoff and Lynch (2002) discuss, the bulk of the neighborhood effects studies “have been concerned with *whether* neighborhoods, and specifically the socioeconomic characteristics of neighborhoods, matter

for the health of individuals... we believe that research should begin to pay attention to the question of *why* neighborhoods matter” (p. 7). By positing individual-level characteristics as potentially important neighborhood-level mediators the analyses presented above help to address this frequently discussed problem. In short, the bulk of this research enters level-2 (compositional or contextual) predictors to *identify* the so-called neighborhood effects and then enters level-1 (individual-level) predictors to account for potentially confounding characteristics associated with particular neighborhoods. This approach is problematic because it relies on researchers to *choose* the correct neighborhood-level variables in order to identify neighborhood effects. Instead, this paper suggests that the baseline neighborhood-level residual be operationalized as the neighborhood effect and that the reduction in this variance be attributed to the mediating nature of specific, theoretically appropriate individual-level and neighborhood-level covariates. This method enables researchers to better understand *why* neighborhoods may matter, and provides a simple method to assess the relative importance of each predictor variable in terms of explaining neighborhood-level variation.

The findings linking social context to physical health that are derived from multilevel modeling procedures may also be important because they may help to provide information that will better help guide policies specifically aimed at ameliorating persistent health inequalities. The findings presented above are important for health-related policy makers because they not only highlight *what* characteristics to emphasize (e.g., stress), but equally important they suggest *where* policy makers might want to locate health-related resources to better ensure efficacious interventions to improve the health of at-risk populations. This information may improve the effectiveness of increasingly prevalent community-based health care facilities (O’Loughlin, Paradis, Gray-Donald, & Renaund, 1999). The explicit goal of the population perspective is to shift our understanding of health risks beyond an individual framework to a social context paradigm in which health risks such as health-related behaviors are seen as restricted by access to various resources, normatively patterned, and ultimately dependent on environmental opportunities to exhibit or engage in potentially unhealthy behaviors. Following this perspective, health-related policy interventions may emphasize not only health related behaviors but also target the amelioration of the social determinants of these health related behaviors.

Conclusion

Echoing the comments of other researchers in this area (Sampson et al., 2002; Macintyre et al., 2002), this

paper concludes with several suggestions regarding the collection of data on health and health related phenomena that will facilitate this type of research in the future. First, data should permit detailed examination of variation within and across important social contexts. Sociological theory takes the following rather obvious idea as an unmentioned point of departure: individuals are not isolated from one another. If this is the case why does the bulk of multivariate statistical models reduce all phenomena to individual differentiation? Increasing utilization of mixed modeling procedures help researchers *adjust* parameter estimates for dependence but, more importantly, they allow researchers to *model* this dependence as a function of individual and group-level characteristics. These methods more effectively describe complex social phenomena and force us to reconsider the theoretical underpinnings of the observed and unobserved relationships. The number of data sets that purposely sample multiple observations nested within the same neighborhood, classroom, workplace, or family is limited and those that do collect this type of data often do not contain any information that enables researchers to effectively test for contextual-effects.

Second, contextual information beyond socioeconomic and sociodemographic composition should be appended to individual-level data sets. Links between unhealthy characteristics of individual’s residential context such as proximity to liquor stores (Scribner et al., 1999) and exposure to known pollutants (Elreedy et al., 1999; Ringquist, 1997) and individual’s physical health have been established in a limited number of studies (see Robert (1999) for a review). More efforts should be made in the future to include contextual characteristics of respondent’s residential areas that are believed to impact their physical health, such as criminal activity, industrial production, traffic networks, political activity, health-care networks, and salutary goods and services (e.g., fresh produce). In this *way*, we may start to identify why neighborhoods matter rather than simply stating that they *do* (Sampson, Morenoff, & Rowley, 2002).

Third, increased efforts should be made to collect longitudinal data on individual’s health and their residential histories. At times, researchers are not clear about the direction of causality; although neighborhoods are posited to impact individuals’ health, it is also possible that health is an important neighborhood-selection criterion (i.e., persons who exhibit a greater frequency of risky behaviors such as drug use may select into neighborhoods because of these behaviors). In addition, of the large body of research documenting links between neighborhoods and physical health, no studies indicate how long it may take for a neighborhood to actually impact an individual’s health. Are there critical moments in individual’s lives when neighborhoods are more pronounced or, alternatively, are there

thresholds in the life cycle in which residential context simply does not matter? Likewise, contextual data should be appended to individual-level records that taps time-variant characteristics of neighborhoods. Here, it is important to remember that people change over time but so do neighborhoods (Quillian, 1999). We know very little about the processes relating neighborhood change (e.g., ‘gentrification’) to the health and well-being of relatively impoverished persons. Likewise, we know even less about the reciprocal nature of individual-level health and neighborhood stability or prosperity. Last, continued efforts should be made to oversample members of historically marginalized racial and ethnic groups. The black–white paradigm of the so-called “race relations” is becoming increasingly less useful for a general framework to understand all race/ethnic relations (Pedraza 1999), and future research should make a priority of including members of racial and ethnic groups that were previously underrepresented in large social surveys.

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