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Neighborhood disadvantage and self-assessed health, disability, and depressive symptoms: longitudinal results from the Health and Retirement Study

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Abstract

Purpose—Using a longitudinal cohort, we assessed the association between neighborhood disadvantage and incidence of poor health and function in three domains.

Methods—Over 4,000 enrollees aged 55–65 in the national Health and Retirement Study were assessed biennially from 1998 through 2006 for incidence of: fair/poor self-rated health (SRH), elevated depressive symptoms, and limitations in five basic Activities of Daily Living (disability). Each analysis was restricted to subjects without that condition in 1994 or 1996. Neighborhoods (census tracts, time-updated for moves), were considered disadvantaged if they fell below the 25th percentile in an index comprising 6 socioeconomic status indicators. Repeated measures logistic regressions, inverse probability weighted to account for individual confounders, selective survival, and loss to follow-up, were used to estimate odds ratios (ORs) for incidence of each outcome in the wave following exposure to disadvantaged neighborhood.

Results—After covariate adjustment, neighborhood disadvantage predicted onset of fair/poor SRH (OR=1.32; 95% confidence interval 1.11, 1.57), but not disability (OR=0.98; 0.82, 1.16) or elevated depressive symptoms (OR=0.98; 0.83, 1.16).

Conclusions—Results confirmed prior findings that neighborhood disadvantage predicts SRH in a longitudinal context, but did not support an association between neighborhood disadvantage and onset of disability or elevated depressive symptoms.

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MeSH keywords

Neighborhoods; Self-Rated Health; Activities of Daily Living; Depressive Symptoms; Longitudinal Survey; Inverse Probability Weights; Marginal Structural Models

Introduction

Many studies have shown that residents of socioeconomically disadvantaged neighborhoods have worse health in several domains, including self-reported health (SRH), disability, and depression.(1) Most prior studies have been cross-sectional. Assessing whether these results can be replicated in longitudinal designs is recognized as a high priority for research on the health effects of neighborhoods.(2) Showing that neighborhood disadvantage predicts the onset of poor health provides stronger evidence that the associations may be causal, rather than strictly attributable to selection processes (i.e., people in poor health move to disadvantaged neighborhoods).

We evaluated whether neighborhood socioeconomic disadvantage predicted onset of fair/poor SRH, Activities of Daily Living (ADL) disability, and elevated depressive symptoms in Health and Retirement Study (HRS) participants.

Materials and Methods

Study population

HRS is a longitudinal, biennial-interview study initiated in 1992, when a nationally representative sample of non-institutionalized US adults born 1931–1941 was enrolled using a multi-stage sample design. The original response rate was 81.4% and response rates in subsequent waves have been between 85–90%. Details on the sample design and measurement validation in HRS have been previously published.(3–6) We analyzed data from the 1992 enrollment cohort, which sampled non-institutionalized people born 1931–1941. For each outcome, we included participants reported to be free of the respective condition in 1994 and 1996 (1994 was the first time all outcomes were assessed consistently) and followed these participants as a closed cohort through 2006 for development of the outcome. We repeated primary analyses including participants reported to be free of the condition in 1996 (regardless of their status in 1994), but results are not presented because they are very similar to the current findings.

Analyses for each outcome excluded those with prevalent cases of each condition at baseline, unknown exposure in 1996, missing core covariate data, or who did not provide any outcome assessments (e.g., dropped out before the first outcome assessment in 1998). Exclusions for each analysis are detailed in Table 1.

Measurement of health outcomes

SRH was assessed with the question “Would you say your health is excellent, very good, good, fair, or poor?” We dichotomized responses as fair/poor versus all other.

For consistency with prior research, we used the RAND variable coding for ADL disability and depressive symptoms. Detailed documentation of variable construction is available online.(7) ADL disability was defined as reporting “difficulty” with any of five ADLs: walking across a room; dressing, including putting on socks and shoes; bathing or showering; eating, such as cutting up food; getting in and out of bed; and using the toilet, including getting up and down.

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Scoring 3+ on an 8-item version of the Centers for Epidemiologic Study of Depression (CESD) scale qualified as elevated depressive symptoms.(8) Each item was phrased to elicit yes/no answers regarding feeling 8 symptoms “much of the time during the past week”: depressed; everything I did was an effort; sleep was restless; could not get going; felt lonely; enjoyed life; felt sad; was happy.(8,9)

Exposure measure

Our primary exposure was neighborhood socioeconomic status (NSES), based on census tract (CT) of residence in the wave prior to outcome assessment. NSES was operationalized with the RAND NSES Index(10), which comprised six NSES indicators, each linearly or geometrically interpolated between 1990 and 2000 Census years. CTs newly defined in 2000 were reassigned to correspond to 1990 definitions. Exposures measured in 1996 and 1998 were based on interpolated data. For exposures measured in 2002 and 2004, no interpolation was possible, so we carried forward the 2000 values.

The six variables in the RAND NSES index are: percent of adults age 26+ with less than high school diploma; percent male unemployment; percent of households with income below poverty; percent of households receiving public assistance; percent of female-heads among households with children; and median household income. Each variable was normalized using the mean and standard deviations of that variable for all US CTs. The normalized values were summed (those directly associated with disadvantage were reversed). For each model, we defined the “exposed” as individuals living in CTs in the lowest (most disadvantaged) 25% of the index. If information was missing for any of the six neighborhood variables, the index was missing.

Core and supplemental covariates

We considered variables that may confound the NSES-health relationship and variables that may influence loss-to-follow-up and survival. We distinguish between covariates that are “core” (baseline age; year of outcome assessment; black race; Hispanic ethnicity; sex; and years of education completed (0–17)) or “supplemental” (immediate recall of a 20-word list in 1994; and time-updated values of: household wealth in 1992 dollars, adjusted for household size and expressed as quintiles of the HRS sample pooled across all years; currently employed; married, widowed, divorced or separated, never married; and self-reported doctors’ diagnoses of hypertension and diabetes). For analyses of each outcome, the other two outcomes were also treated as supplemental covariates (e.g., for SRH, weighting models included disability and CESD score as covariates). In confounder adjustment models, we used continuous coding for SRH (range: 1–5) and CESD (range: 0–8) instead of the dichotomized versions which were used as the outcomes. These time-updated values were drawn from the interview preceding the exposure assessment.

We used standard RAND coding of wealth (total household excluding secondary residence). For the small fraction of respondents missing wealth, imputations were based on unfolding bracket estimates or demographic characteristics, and are detailed in RAND technical documentation.(7)

Methods of analysis

Exposure (residence in a disadvantaged neighborhood) was assessed at each biennial interview and used to predict odds of incidence of each health outcome during the subsequent two-year period (e.g. 1996 exposure status to predict new cases of fair/poor SRH reported in 1998) for up to 5 biennial interviews (through 2006). Respondents were censored after first report of the condition, death, or non-participation in an interview. Analyses were conducted with logistic regression, using robust variance estimates. Because the outcomes were generally rare, the odds ratios approximate relative risks. All models were conditioned on the core covariates identified above and weighted by the sample weights (provided by HRS to be representative of the age-eligible population) corresponding to the year of exposure measure.

In additional models, we used marginal structural models estimated with inverse probability of exposure weights (IPEWs) to account for baseline and time-varying confounding by supplemental covariates listed above.(11) Conceptually, the goal of inverse probability weighting (IPW) is to achieve statistical independence between the potential confounders and the exposure. Covariates that are statistically unassociated with the exposure are not likely to introduce confounding bias. This statistical independence is accomplished by estimating the probability of exposure, as predicted by the confounders, and weighting on the *inverse* of this probability. The IPEWs were calculated by estimating the probability of exposure to neighborhood disadvantage at each wave with logistic regression. These models were estimated in a data set pooled across all waves for which a respondent's outcome was observed, using values of both the core and supplemental covariates from the prior wave to predict exposure status in the current wave (e.g. 1994 covariates to predict 1996 exposure status). From this model, the probability of exposure was predicted; the inverse of this probability was the IPEW. We improved upon these basic weights by "stabilizing," a procedure that usually narrows the confidence interval (CI) for the effect estimate. Weights were stabilized by estimating a logistic regression predicting exposure status using only the core covariates. The product of the probability predicted by this model and the unstabilized weight is the stabilized weight. This approach to handling confounders avoids the potential bias of adjusting for individual characteristics that both mediate and confound the health effects of NSES, as may be the case for several of our supplemental covariates.

We also used IPWs to reduce potential bias from selective mortality and loss to follow-up. Stabilized weights for probability of survival were calculated in models identical to the probability of exposure models. Finally, we calculated stabilized loss-to-follow-up weights using parallel models to predict the probability of continuing study participation among those who survived. Final analytic models were weighted by the product of the exposure, survival, loss-to-follow-up, and sampling weights (details on estimating these models are published elsewhere).(10–12) Analyses were conducted with logistic regression, using robust variance estimates to provide 95% confidence intervals (CIs), to appropriately account for additional uncertainty associated with the weighting scheme.

For primary analyses, we show two models for each outcome. The first model (labelled "models with core covariates") is adjusted only for the core covariates and does not account for selective survival, loss-to-follow-up, or confounding using the supplemental variables. The second model incorporates the IPWs to account for confounding, selective survival, and loss-to-follow-up using the supplemental variables, including time-varying confounders (these models are labelled "models with supplemental covariates"). All analyses were conducted with SAS 9.2.

Results

Baseline characteristics of participants in each analysis are provided in Table 1. Crude risk of onset of each condition at each wave is shown in Table 2. The highest crude risk (11%) occurred in 1998 for elevated depressive symptoms.

In models adjusted only for core covariates, residence in a disadvantaged neighborhood predicted increased odds of onset of fair/poor SRH (OR=1.51; 95% CI: 1.30, 1.75)(Table 3). After applying IPWs to account for supplemental covariates, including household wealth, the OR for neighbourhood disadvantage remained statistically significant (OR=1.36; 1.15, 1.59).

Residence in a disadvantaged neighbourhood did not predict onset of elevated depressive symptoms, even when only adjusted for baseline characteristics (OR=1.07; 0.91, 1.27). Applying IPWs further attenuated the association to nearly null (OR=0.97; 0.81, 1.16). Onset of disability was associated with residence in a disadvantaged neighbourhood in models adjusted only for core covariates (OR=1.19; 1.00, 1.42) but the OR (0.97; 0.81, 1.16) was attenuated to the null after IPWs were applied.

Conclusion

In a nationally representative sample of adults aged 55–65 at baseline and followed up to 10 years, residence in a disadvantaged neighbourhood predicted onset of fair/poor SRH, but not onset of elevated depressive symptoms or ADL disability. Our study has several strengths compared to prior analyses of this association. Most importantly, we used a longitudinal design to examine the association between neighbourhood disadvantage and disease onset. Further, we use a nationally representative US sample. Finally, we used IPW methods to adjust for time-varying confounders. This approach has only rarely been applied in prior neighbourhoods research,(12,13) despite calls for such applications in recent methodological reviews.(2,14) IPWs circumvent a methodologic tension in the field: whether to adjust for covariates that may be both mediators and confounders of neighbourhood effects.

There may be additional confounders that were not considered in our analyses. Although it is commonly assumed that such confounders would spuriously inflate the relationship between neighbourhood disadvantage and poor health, some confounders could obscure neighborhood effects. Our study includes adults aged 55–65 who did not have each condition at baseline. The results are therefore not generalizable to individuals of other ages. This selection may also have left a restricted “hardy” sample. Statistical power is another limitation of our analyses. This is evident in the relatively wide 95% CIs for each of our parameter estimates, which include ORs of 1.16 for both elevated depressive symptoms and disability. Finally, we dichotomized the neighbourhood disadvantage measure as CTs below the 25^{th} percentile on an index of six objectively measured characteristics. Other measures of neighbourhood disadvantage, for example based on a threshold using an alternative percentile or constructed using subjectively perceived neighbourhood characteristics, may be more relevant to incidence of depression and disability.(15)

A recent review of neighbourhood effects on depression noted that 37 of 45 studies reported associations between neighbourhood characteristics and depressive symptoms, (15) but only 4 examined incidence of depression predicted by objective neighbourhood environment measures.(16–18) Only one of these found a main effect that persisted after covariate adjustment (OR=2.09; 95% CI 1.04–4.59).(16) The wide CIs in that study overlap substantially with the CIs in our analysis. An analysis of the Assets and Health Dynamics in the Oldest Old cohort found no relationship between change in symptoms and neighbourhood disadvantage after control for individual covariates.(17) In a cross-sectional analysis of 1994 HRS participants, Wight et al found neighbourhood disadvantage predicted higher levels of depressive symptoms.(17) The contrast between those findings and our results, based on the same cohort, suggest the earlier result may be attributable to differential selection into neighbourhoods. Alternatively, our analyses, which used neighborhood disadvantage two years previously to predict onset of each condition, may have failed to identify a short-term effect on depressive symptoms. We consider this an unlikely explanation because there was not usually substantial change in neighbourhood conditions within a two-year interval.

SRH is considered an important indicator of underlying health and mortality risk.(18) A review of 39 multilevel studies of neighborhood SES and SRH published between 1998 and 2005 found that nearly all studies reported that poor health was more common in disadvantaged neighborhoods, but all 39 were cross-sectional.(1) One prior longitudinal study found no relationship between neighborhood disadvantage and rate of change in SRH.(19) Our results are consistent with the findings of the cross-sectional studies but extend these to a longitudinal context.

Characteristics of the immediate residential neighborhood have been hypothesized to be particularly important for older adults. Our results indicate that in this sample of adults transitioning from late middle age to early old age, neighborhood disadvantage does not predict onset of depressive symptoms or disability. However, residents of disadvantaged neighborhoods were at higher odds of onset of fair/poor SRH.

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List of abbreviations

ADL	activities of daily living
CESD	Centers for Epidemiologic Study of Depression
CI	confidence interval
CT	census tract
HRS	Health and Retirement Study
IPTW	inverse probability of treatment weights
IPW	inverse probability weights
NSES	neighborhood socioeconomic status
OR	odds ratio
SES	socioeconomic status
SRH	self-rated health

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Table 1

Baseline characteristics of HRS participants.

	Fair/Poor Self-Rated Health Analyses		Elevated Depressive Symptoms Analyses		Limitations in Activities of Daily Living (Disability) Analyses	
	n/mean	**%/(std)**	**n/mean**	**%/(std)**	**n/mean**	**%/(std)**
Age-eligible sample	10273	100%	10273	100%	10273	100%
Exclusions						
Had condition at baseline in either 1994 or 1996	2556	25%	2397	23%	1306	13%
Condition not assessed at baseline in either 1994 or 1996*	2261	22%	2340	23%	1943	19%
Missing baseline covariates	158	2%	157	2%	156	2%
Missing exposure	783	8%	848	8%	1107	11%
Analytic Sample						
Unique individuals at baseline	4,515	100%	4,531	100%	5,761	100%
Unique census tracts at baseline	1,673		1,667		1,910	
Core Demographic Variables						
Male	1,975	44%	2,075	46%	2,657	46%
Black	620	14%	692	15%	909	16%
Hispanic	219	5%	245	5%	411	7%
Age	57.7	(3.2)	57.9	(3.2)	57.8	(3.2)
Years of education	13.0	(2.7)	12.9	(2.8)	12.6	(2.9)
Supplemental Variables at Baseline^						
Memory score (0–20)	8.4	(3.0)	8.3	(3.0)	8.2	(3.1)
Household wealth, median (interquartile range)	153,500	(263,000)	148,800	(261,000)	131,500	(245,500)
Marital status						
Married	3,479	77%	3,544	78%	4,432	77%
Widowed	306	7%	279	6%	392	7%
Divorced or Separated	571	13%	550	12%	724	13%
Never Married	159	4%	158	3%	213	4%
Diabetes diagnosis	241	5%	354	8%	448	8%
Hypertension diagnosis	1,372	30%	1,521	34%	1,961	34%
Self-rated health (1–5)	N/A		2.3	(1.0)	2.4	(1.0)

	Fair/Poor Self-Rated Health Analyses		Elevated Depressive Symptoms Analyses		Limitations in Activities of Daily Living (Disability) Analyses	
	n/mean	%/(std)	n/mean	%/(std)	n/mean	%/(std)
CESD score (0–8)	0.8	(1.4)	N/A		1.0	(1.7)
ADL disability (any limitations)	82	2%	127	3%	N/A	

Sample sizes differ across outcomes due to differences in the prevalence of each condition at baseline.

*Reasons not assessed include mortality before 1996, non-participation in 1994 or 1996, or did not complete specific survey items in either year.'

^Supplemental variables were used in the weighting models. All variables except memory were time-updated in the weighting models.

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Table 2

Number of respondents and new cases at each assessment wave.

	Fair/Poor Self-Rated Health			Elevated Depressive Symptoms			Disability		
Assessment Year	**Respondents at risk**	**New cases**	**Crude risk**	**Respondents at risk**	**New cases**	**Crude risk**	**Respondents at risk**	**New cases**	**Crude risk**
1998	4163	395	9%	4114	455	11%	5327	274	5%
2000	3768	189	5%	3659	273	7%	5053	204	4%
2002	3341	192	6%	3149	193	6%	4575	170	4%
2004	2960	174	6%	2767	146	5%	4175	158	4%
2006	2672	145	5%	2516	102	4%	3881	159	4%

Table 3

Odds ratios for incidence of fair/poor self-rated health, elevated depressive symptoms, or disability predicted by neighborhood disadvantage.

	Models with core covariates*		Models with supplemental covariates^	
	OR	95% CI	OR	95% CI
Fair/Poor Self Rated Health	1.51	(1.30, 1.75)	1.36	(1.15, 1.59)
Elevated Depressive Symptoms	1.07	(0.91, 1.27)	0.97	(0.81, 1.16)
Disability	1.19	(1.00, 1.42)	0.97	(0.81, 1.16)

*Adjusted for core variables: age, sex, race, Hispanic ethnicity, education, and interview wave. Sampling weights applied.

^Adjusted for core variables and inverse probability weighted to adjust for sampling, confounding, selective survival, or selective loss to follow-up modeled with baseline memory score, and time-updated household wealth quintile, work status, marital status, diabetes diagnoses, hypertension diagnosis (see text for details).