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The Contribution Of Place To Disparities In Life Expectancy And Cardiovascular Outcomes

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THE CONTRIBUTION OF PLACE TO DISPARITIES IN LIFE EXPECTANCY AND CARDIOVASCULAR OUTCOMES

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Executive Summary

Socioeconomic disparities in health are well-documented, but the precise reasons for these disparities are poorly understood. Traditional explanations for health disparities focus on the influence of *person-level* disadvantages, such as those related to income, education, and health insurance status. However, the contribution of *place* to these health disparities is increasingly appreciated. By "place", we refer to the sum of the environmental and community-level factors that may contribute to health, as distinguished from person-level disadvantages associated with low socioeconomic status (SES).

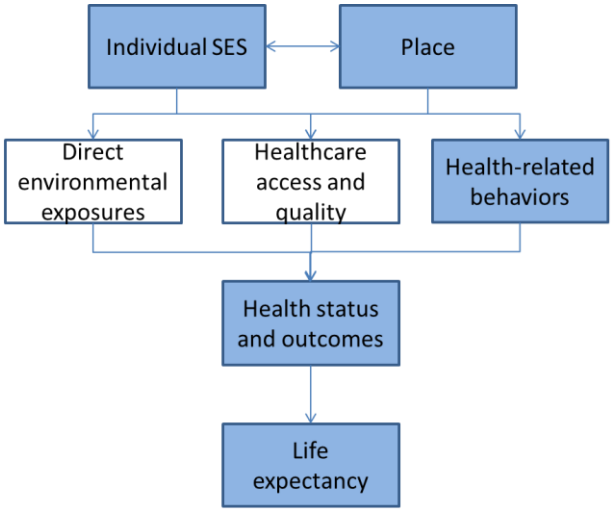
These contextual factors can be categorized as 1) characteristics of the built environment (e.g. access to healthy food, space for exercise); 2) characteristics of the social environment (e.g. community norms regarding smoking, obesity, or treatment-seeking); and 3) direct psychosocial and physical stressors (e.g. pollution, crime). Such contextual factors may act independently of SES, they may mediate the effects of SES, and they may exhibit other complex relationships with SES and related factors such as income and education.

Contextual factors may be modifiable, and are thus an important potential target for health policy and interventions aimed at reducing health disparities. To inform the design of such interventions, is it critical to demonstrate definitively that place is important, to identify which specific contextual factors matter, and to understand the mechanisms by which they affect health. There is currently little evidence in each of these areas.

Isolating the contribution of any single environmental factor to health disparities is challenging. We have begun with a more fundamental question - to what extent does place matter in life expectancy and cardiovascular outcomes? Specifically, we sought to 1) characterize the contribution of place to life

expectancy, by identifying geographic disparities in life expectancy that persist after adjusting for individual SES and race; 2) measure the effect of place – using neighborhood-level SES as a proxy – on outcomes after acute myocardial infarction (AMI); and 3) measure the relative effects of individual SES and place on delays to seeking treatment for AMI.

A proposed conceptual model for these relationships is given below. We hypothesize that SES and place exhibit complex interactions. For example, the effect of a person's SES on health may be modified by the context in which they live. Conversely, a person's SES may modify any effects of place on health. There are a wide range of potential mechanisms for the effects of SES and place on health, which we summarize as being related to 1) direct environmental exposures (e.g. pollution, crime); 2) healthcare access and quality; and 3) health-related behaviors. Together, these factors would mediate the effect of SES and place on health outcomes and, subsequently, life expectancy.



To thoroughly test this model would require a complete characterization of contextual exposures, which is outside the scope of this study. We instead limit our focus to shaded items in the diagram above. We first establish the plausibility of such a model by characterizing the association of SES and other contextual factors (i.e. place) with life expectancy. We then use acute myocardial infarction (AMI) as a model condition for measuring the contribution of SES and place to health-related behaviors and health outcomes. Our health-related behavior of interest is delay to hospital presentation in the setting of AMI. Our outcomes of interest include mortality, rehospitalization, and angina symptoms after AMI.

In summary, our study aims include the following:

1) To characterize the contribution of place to life expectancy, by identifying geographic disparities in life expectancy that persist after adjusting for individual SES and race
2) To measure the effect of place - using neighborhood SES as a proxy - on outcomes after AMI
3) To measure the relative effects of individual SES and place on delays to seeking treatment for AMI

Aim 1: Characterizing the contribution of place to life expectancy

We began at the macro-level, with the objective of understanding the reasons behind variation in life expectancy across the United States. This variation has been previously described, and previous studies have shown that SES is significantly associated with life expectancy at a regional level. Ours is the first study to quantify the degree to which differences in SES can account for geographic disparities in longevity nationwide. Using county as the unit of analysis, our results show that we find that SES does explain many of the striking geographic differences in life expectancy in the United States. This is consistent with traditional conceptions of health disparities as being primarily driven by socioeconomic factors.

Yet despite the prevailing influence of SES, our results also reveal significant exceptions in which regional variation persists, or increases, after adjusting for SES. In particular, we identify several comparisons of areas which are virtually identical in terms of racial and SES composition, yet differ dramatically in terms of life expectancy. Based on such comparisons, along with the observation that disparities in life expectancy persist after controlling for SES, we conclude that contextual factors are important contributors to health disparities.

In a secondary analysis, we applied the concept of "deviance" to identify places in which life expectancy is significantly higher or lower than what would be expected based on the race and SES composition of the population. Our results identified counties of significant positive and negative deviance. We conclude that the existence of these positive deviance areas – many of which have low SES, high minority populations - demonstrates that the disadvantages of SES are not insurmountable with respect to health outcomes. We further conclude that in-depth investigation of these positive deviance areas – and comparison with negative deviance areas of similar (race and SES) composition - may reveal characteristics of their environments that drive health disparities.

Aim 2: Measuring the effect of place on outcomes after AMI

Our second objective was to measure the independent contribution of place to outcomes after acute myocardial infarction (AMI). We employed neighborhood SES in an individual's area of residence as a proxy for place. Neighborhood SES was measured as a composite of median household income and five other factors related to wealth, education, and occupation. Neighborhood SES has been previously linked with a range of cardiovascular risk factors and outcomes, including incidence of coronary heart disease. Importantly, these associations have been shown to persist after simultaneously adjusting for person-level SES (e.g. personal income, education, insurance status, and/or occupation). This suggests that neighborhood SES is not merely a proxy for individual-level SES, and that where one lives has an effect on cardiovascular health beyond that of one's own resources.

Using this framework, we performed an analysis among patients in the nationwide PREMIER registry, which includes 2321 patients with AMI from 19 US hospitals. Our results show that neighborhood SES is independently associated with the prevalence of angina and risk of rehospitalization in the 12 months after AMI. This association persists after accounting for individual SES variables, again demonstrating that context matters independent of a patient's personal socioeconomic circumstances. The magnitude of this association is comparable to that of individual SES with outcomes. From this we conclude that context may be as important as personal resources in driving health disparities.

Aim 3: Measuring the relative effects of individual SES and place on prehospital delays in AMI

Having demonstrated an influence of neighborhood context on outcomes, there is a need for further studies to identify mechanisms underlying the effect of neighborhood on health. Such mechanisms may represent targets for public policy and interventions to reduce health disparities. These are summarized in the conceptual model above as involving 1) poorer health-related behaviors; 2) poorer healthcare access; or 3) the direct influence of psychosocial and environmental stressors on health. We focus on the first category, noting that features of both the physical environment (e.g. proximity to healthy food sources and space for exercise) and social environment (e.g. local norms and attitudes toward healthcare) may have a significant impact on health-related behaviors such as smoking, obesity, physical activity, and treatment-seeking, all of which could explain our above findings related to AMI outcomes.

Specifically, our objective is to investigate whether place – again using neighborhood SES as a proxy – is related to delays in seeking treatment ("prehospital delays") for AMI among patients in VIRGO, a nationwide AMI registry. Longer prehospital delays are associated with delayed revascularization, and thus can contribute to worse outcomes after AMI. Moreover, prehospital delays in AMI can be viewed as a marker for an individual's propensity to seek medical care when in need, and as such serve as a proxy for overall healthcare-seeking behavior.

VIRGO includes a high proportion of young and female patients with significant racial diversity. This diversity allows us to further investigate possible differences in the importance of neighborhood and person-level SES by race and sex. Our results show that both low neighborhood SES and low individual income are independently associated with delays of greater than 2 hours. Based on this observed relationship between neighborhood SES and delays, we conclude that context affects treatment-seeking in the setting of AMI. This association could in part mediate our observed effect of neighborhood on outcomes after AMI. Moreover, we find differential effects of SES variables according to race. Specifically, for black patients only individual-level SES, and not neighborhood SES, is a significant predictor of delays. Conversely, only neighborhood SES is a significant predictor of delays among non-blacks. From these observations, we conclude that different demographics have varying sensitivity to the influence of place on health-related behaviors.

A. Geographic disparities in life expectancy

Introduction

Geographic disparities in life expectancy across the United States are well-documented, with evidence of widening gaps over time.[1] Attempts to explain these health disparities typically focus on the role of income, education, and other disadvantages related to socioeconomic status (SES). A comparison of counties at the extremes in terms of life expectancy reinforces this explanation. Those in the top 10 are uniformly wealthy and suburban, while the bottom ten are in poor, rural parts of Appalachia.[1] In eight out of ten selected states, SES is significantly associated with cross-county differentials in life expectancy.[2-4] Race is also a significant predictor of life expectancy, and this effect is not fully attributable to racial disparities in income, education, and other socioeconomic factors.[5]

These observations reinforce the contribution of race and socioeconomic disadvantages to disparities in health and longevity. Yet in each instance, significant residual geographic variation persists after adjusting for the racial and socioeconomic composition of the population. With race and SES effectively held constant, this *composition-independent* variation is likely the result of *contextual* differences; that is, community-level factors such as access to healthcare, social norms regarding health-related behaviors (e.g. smoking, diet), or environmental exposures.

Identifying the effect of such contextual factors is an important objective in health disparities research. Unlike race and SES, contextual factors are potentially modifiable and thus a potential target of health policy and interventions. Given that race, income, and contextual advantages (e.g. healthcare access, community norms) are highly correlated, disentangling their relative contributions to health is analytically challenging. This task is further complicated by the fact that race, SES, and contextual factors exhibit many interactions. As shown in the conceptual model above, context may have composition-independent effects, and may also serve to mediate or modify any effects of race, income, insurance status, and other socioeconomic factors on health outcomes.

In this study, we apply this concept of composition-independent variation to elucidate the contribution of contextual factors to variations in county-level life expectancy across the US. We describe geographic patterns of life expectancy in the United States that persist after adjustment for race and socioeconomic characteristics. This approach allows us to isolate the effect of contextual factors on life expectancy by adjusting away the effect of counties' varying composition – at least along dimensions of race and SES. We present "excess life expectancy" – the difference between the actual life expectancy and what would be predicted based on race and SES based on multivariate analyses– for all counties in the US. In doing so, we confirm whether familiar geographic patterns in life expectancy can be explained by race and SES differences, and describe new patterns that emerge after race and SES adjustment.

We also pinpoint examples of both positive and negative *deviance*, in which life expectancy differs significantly from what would be expected based on their income and racial composition. Identifying these will allow us and other researchers to pursue in-depth investigations into what makes these counties unique. Examination of positive deviance areas may yield insights into the community-level determinants of higher life expectancy, while negative deviance areas may share contextual traits that lead to poor health.

In particular, this positive deviance approach will highlight counties that achieve relatively high life expectancy despite lower SES or larger minority populations. These counties may offer a feasible model for lower-performing counties of similar race and SES composition, prompting policies and interventions that could be translated across communities. The top counties in crude life expectancy – predominantly wealthy, white, and suburban – may not provide such a model. Their health advantages may be inextricably tied to their higher SES, making translation to lower SES settings impractical.

In this study we also explore the contribution of race and SES to geographic patterns in the *change* of life expectancy over time. The gap between the healthiest and least healthy counties has increased steadily in the last two decades, largely due to increasing disparities in mortality from lung cancer, chronic obstructive pulmonary disease, and diabetes.[6] It is important to understand whether this widening gap can be explained by concurrent changes in SES and racial composition.

When disparities in life expectancy and their change over time are not explained by race and SES, this implicates other contextual factors as responsible. The findings presented here could prompt further research to identify these underlying factors, which may be modifiable through health policy and interventions. The "excess life expectancy" measures presented here can also offer public health managers insight into how a particular area compares to others of similar race and SES, while allowing for fair comparisons across regions of differing composition.

In summary, our primary aim is **to characterize the contribution of place to life expectancy, by identifying geographic disparities in life expectancy that persist after adjusting for individual SES and race**

Methods

Data

We adopted estimates on annual life expectancy by gender for all counties in the years 2009 and 1989 from Wang et al (2013).[1] This study calculates life expectancy based on county-specific mortality rates, using a model-based approach that accounts for the county-specific age distribution of the population. Life expectancy estimates based on annual mortality rates are sensitive to random variation, particularly in smaller areas. However, this study uses a Bayesian estimator that incorporates mortality rates in prior

years and neighboring counties, along with race and income characteristics, to produce robust maximum likelihood estimates of life expectancy over time.

Independent covariates in our analysis include variables related to race, educational attainment, and income in each county, for both 1989 and 2009. We obtained data on racial composition in each county from the US Decennial Census. Race data from 1990 and 2010 were used as proxies for counties' racial composition in 1989 and 2009, respectively. Similarly, data from the 1990 census was used to characterize educational attainment in 1989. Educational attainment in 2009 for each county was based on 5-year aggregated data from the American Community Survey for the years 2007 to 2011. For income variables, we used annual county level estimates from the Small Area Income and Poverty Estimates (SAIPE) project. The SAIPE income estimates are model-based, incorporating data from multiple sources over multiple years to produce robust annual estimates.

Analytic Plan

In descriptive analyses, we classify counties into quartiles by life expectancy and estimate the univariate associations of race and SES variables with life expectancy quartile using the Spearman rank correlation coefficient. To determine the contributions of race and SES to life expectancy, we fit linear models with gender-specific life expectancy as the dependent variable and county as the unit of analysis. Separate models were fit for female and male life expectancy, using the same set of independent variables related to race, income, and education. Independent variables related to race included 1) percentage of black race, 2) percentage of Hispanic race, and 3) percentage of other minority race, which includes all who do not identify as white, black, or Hispanic. Median household income in both 2009 and 1999 were included as separate independent variables, with 1999 income adjusted for inflation and expressed in 2009 dollars. This was intended to capture both current and lagged effects of income on life expectancy. Variables related to education included 1) percentage of college graduates and 2) percentage of high school graduates (inclusive of college graduates) in the county.

We fit linear models for females and males separately with the change in county–level life expectancy from 1989 to 2009 as the dependent variable. Independent variables included the concurrent changes in 1) percentage of black race 2) percentage of Hispanic race 3) percentage of other minority race 4) median household income 5) percentage of high school graduates and 6) percentage of college graduates. Median household income in 1989 was adjusted for inflation and expressed in 2009 dollars.

Separately for males and females, we calculated "excess life expectancy" for each county by subtracting its life expectancy from the life expectancy predicted based on its race and SES characteristics. We calculated "excess change in life expectancy" for each county as the residual of the regression of county-level life expectancy against variables related to the concurrent change in racial composition and SES.

For the ten highest performing counties by excess life expectancy, we identified counties which have similar race and SES characteristics – defined as those which differ by no more than 0.5 standard deviations in each race, education, and current income variables. Among these, we identified the single county that had the lowest life expectancy. We performed a similar analysis for the ten lowest performing counties by excess life expectancy, identifying for each the similar county that had the highest life expectancy.

We represent these results in map form, with counties color-coded by excess life expectancy (Figure A.1) and excess change in life expectancy (Figure A.2). We use these maps to identify overall regional patterns.

Results

Life expectancy estimates and data on SES and race were available for 3132 counties and county-equivalents and all were included in our cross-sectional analyses. Data on income or life expectancy from 1989 were unavailable for 64 of these counties. Accordingly, analyses related to the change in life expectancy between 1989 and 2009 included only 3068 counties.

County-level life expectancy in 2009 varied from 72.6 years to 84.6 years for females (IQR: 78.2 – 80.9) and 63.2 years to 82.1 years for males (IQR: 72.8 - 76.4). We grouped the counties into quartiles by life expectancy and found that all variables related to education, income, and race were significantly associated with life expectancy for both females and males (Table A.1). For females, counties in the lowest-performing quartile had on average 21% blacks, 78% high school graduates, 20% college graduates, and a median household income of $34,829. In comparison, counties in the highest-performing quartile had on average 3% blacks, 89% high school graduates, 35% college graduates, and a median household income of $51,178. A similar pattern was seen for males.

The change in life expectancy between 1989 and 2009 varied from -3.2 years to +6.4 years among females (IQR: 0.4 – 2.0) and -2.0 years to +12.9 years among males (IQR: 2.4 – 4.1) (Table A.2). Changes in education, income, and the percentages of Hispanic and other minority race were significantly associated with change in life expectancy over this time period for both females and males. Counties in the highest quartile by life expectancy change had an average increase of $2,613 in household income over this period, compared to $1,099 in the lowest quartile.

In multivariate linear regression, all race and education variables were significantly associated with life expectancy for both genders ($p < 0.001$ for all associations). Educational attainment and the percentage of Hispanics were associated with higher life expectancy, with negative associations for the percentages of blacks and other minorities. For males, increases of $10,000 in current and lagged income are both associated with 0.2 year increases in life expectancy ($p < 0.01$ for both associations). For females, current income, but not lagged income, showed a significant association. The estimated regression coefficients are shown in Table A.3. Overall, race and SES variables explain 63% and 68% of the variation in life expectancy across counties for females and males, respectively, as determined by the R-squared statistic.

Multivariate analysis with the change in life expectancy (from 1989 to 2009) as the outcome variable is presented in Table A.4. The change in median household income was independently associated with changes in life expectancy over time, with each $10,000 increase producing 0.3 year and 0.2 year increases in life expectancy for males and females, respectively. Significant associations were also seen for both education variables, black race, and Hispanic race. Overall, changes in racial composition and SES explained 18% (for females) and 24% (for males) of the differences across counties in the change in life expectancy between 1989 and 2009, as determined by the R-squared statistic.

“Excess life expectancy” and “excess change in life expectancy” are presented in map form for both females (Figure A.1a, A.2a) and males (Figure A.1b, A.2b).

Those counties with the highest and lowest adjusted life expectancy are presented with associated SES and race characteristics in Table A.5. For each of these high and low performing counties, we identified the similar county with lowest and highest life expectancy, respectively. The counties with the highest and lowest excess change in life expectancy are presented with associated SES and race characteristics in Table A.6.

Legend (Figures A.1-A.2)

Denotes excess life expectancy (in years) associated with each color

Figure A.1a: Excess life expectancy by county (females)

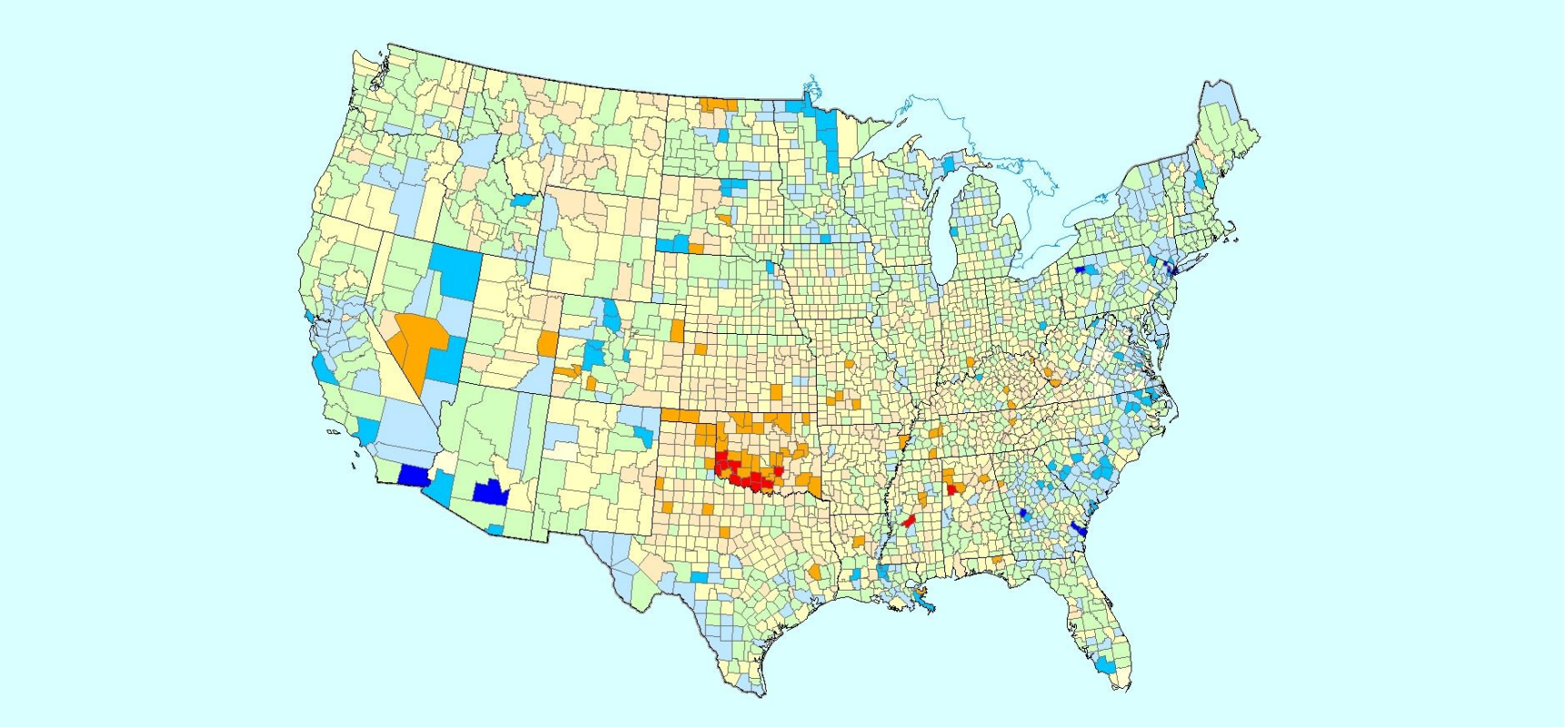


Figure A.1b: Excess life expectancy by county (males)

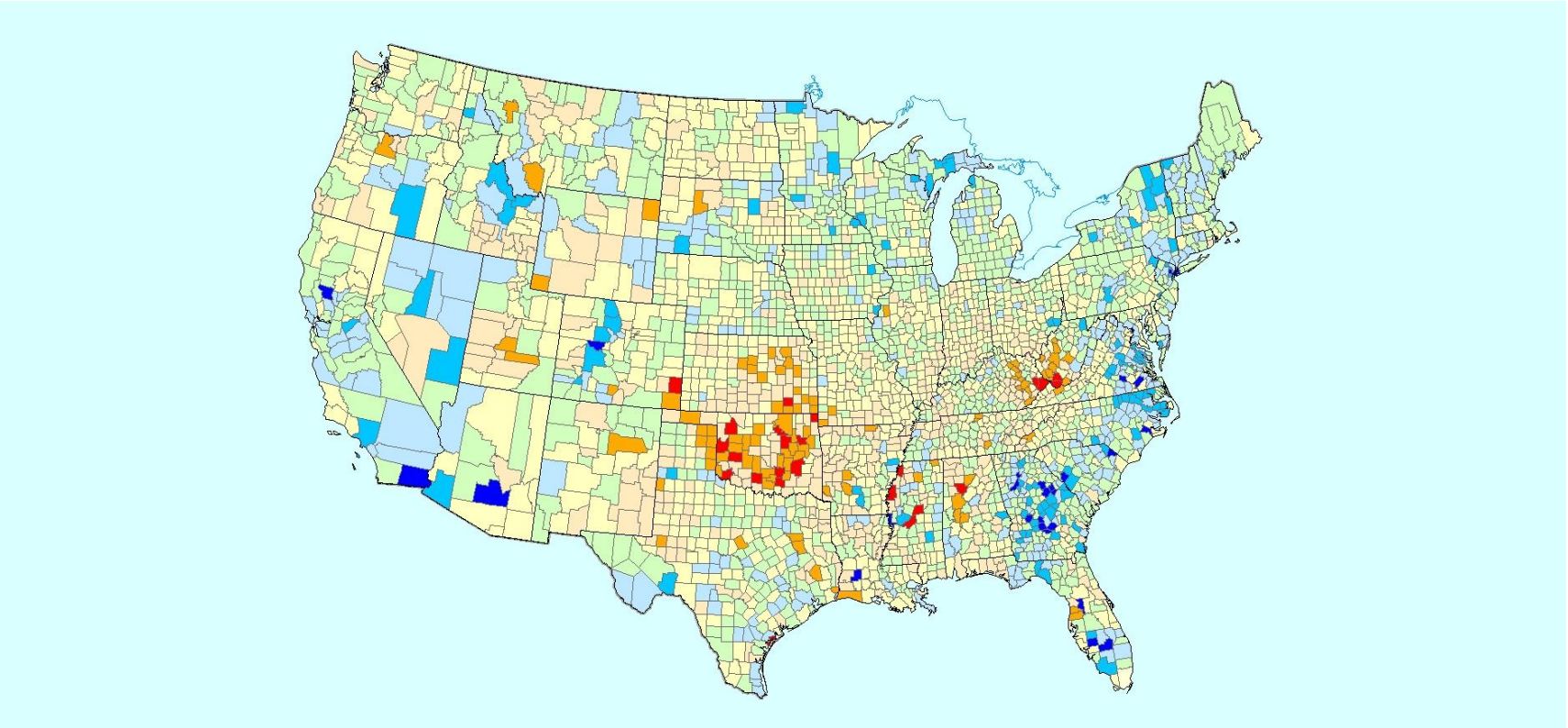


Figure A.2a: Excess change in life expectancy by county (females)

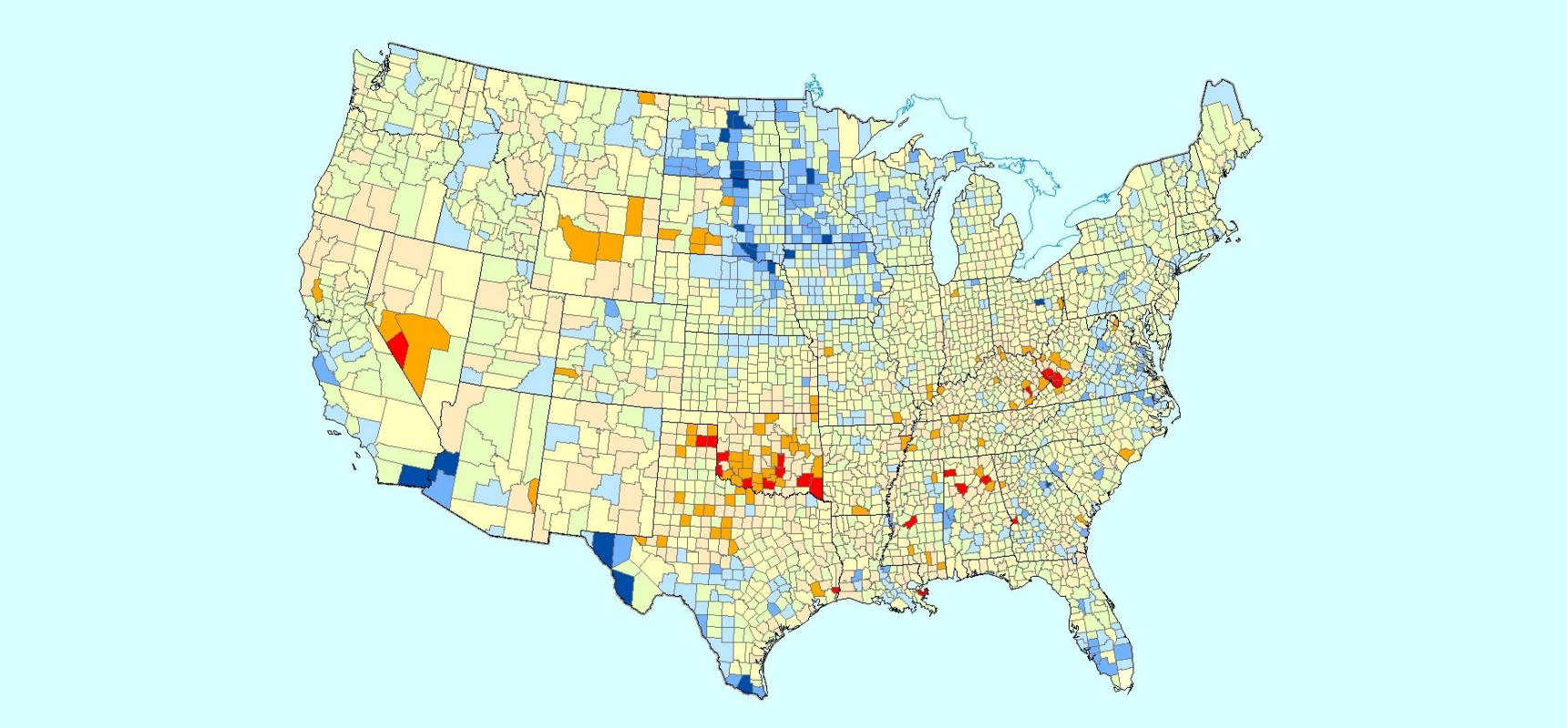


Figure A.2b: Excess change in life expectancy by county (males)

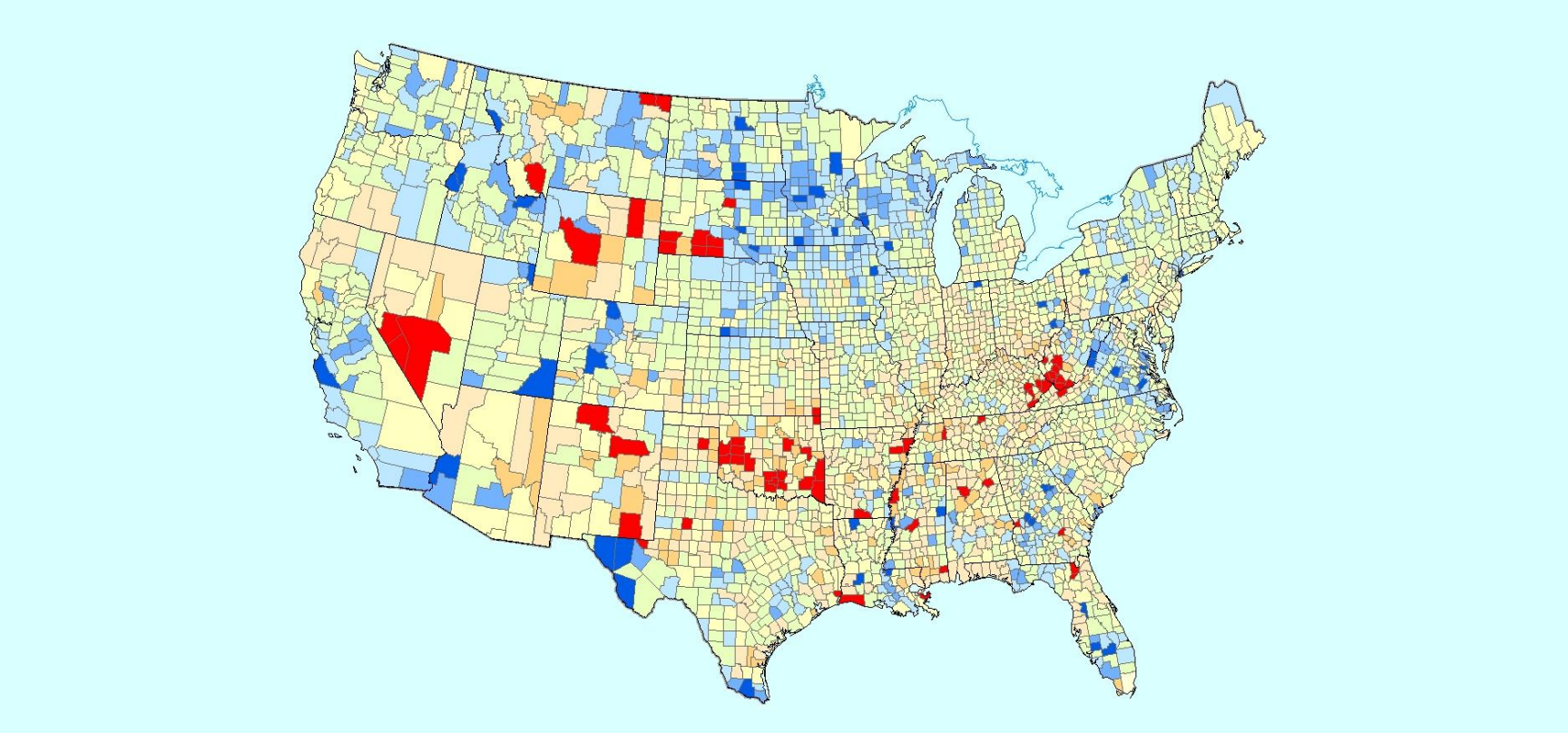


Table A.1a: Race and socioeconomic characteristics of counties by life expectancy quartile (females)

		Life expectancy quartile (female)					
	Total	1st (lowest)	2nd	3rd	4th	Spearman rank correlation coefficient	p-value for association
Range in life expectancy	72.59 - 84.63	72.59 - 78.20	78.20 - 79.64	79.64 - 80.85	80.85 - 84.63		
Race							
% black	8.9%	21.0%	8.0%	3.9%	2.8%	-0.44	<0.001
% hispanic	8.3%	5.4%	10.4%	8.2%	9.1%	0.12	<0.001
% other minorities	4.6%	4.0%	4.1%	5.0%	5.1%	0.19	<0.001
SES							
Median household income	42913	34829	41188	44423	51178	0.59	<0.001
% HS graduate	84%	77%	82%	86%	89%	0.69	<0.001
% college graduate	27%	20%	24%	28%	35%	0.65	<0.001

Table A.1b: Race and socioeconomic characteristics of counties by life expectancy quartile (males)

		Life expectancy quartile (male)					
	Total	1st (lowest)	2nd	3rd	4th	Spearman rank correlation coefficient	p-value for association
Range in life expectancy	63.22 - 82.12	63.22 - 72.79	72.79 - 74.82	74.82 - 76.37	76.37 - 82.12		
Race							
% black	8.9%	20.6%	8.6%	3.7%	2.7%	-0.43	<0.001
% hispanic	8.3%	5.3%	10.4%	9.1%	8.4%	0.15	<0.001
% other minorities	4.6%	4.6%	3.5%	5.4%	4.8%	0.22	<0.001
SES							
Median household income	42913	34249	41105	44876	51439	0.63	<0.001
% HS graduate	84%	77%	82%	86%	89%	0.71	<0.001
% college graduate	27%	20%	24%	28%	35%	0.66	<0.001

Table A.2a: Race and socioeconomic characteristics of counties by change in life expectancy quartile (females)

		Change in life expectancy quartile (females)					
	Total	1st (lowest)	2nd	3rd	4th	Spearman rank correlation coefficient	p-value for association
Range in change in life expectancy	-3.21 - 6.37	-3.21 - 0.41	0.41 - 1.20	1.20 - 1.98	1.98 - 6.37		
Race							
Δ % black	0.3%	0.2%	0.4%	0.5%	0.2%	0.11	<0.001
Δ % hispanic	3.9%	4.0%	3.5%	3.5%	4.6%	0.08	<0.001
Δ % other minorities	2.2%	2.1%	1.7%	2.2%	2.7%	0.20	<0.001
SES							
Δ Median household income	1537	1099	1108	1327	2613	0.10	<0.001
Δ % HS graduate	15%	17%	16%	15%	14%	-0.28	<0.001
Δ % college graduate	12%	10%	11%	12%	14%	0.39	<0.001

Table A.2b: Race and socioeconomic characteristics of counties by change in life expectancy quartile (males)

		Change in life expectancy quartile (males)					
	Total	1st (lowest)	2nd	3rd	4th	Spearman rank correlation coefficient	p-value for association
Range in change in life expectancy	-1.96 - 12.87	-1.96 - 2.43	2.43 - 3.27	3.27 - 4.05	4.05 - 12.87		
Race							
Δ % black	0.3%	0.4%	0.5%	0.5%	-0.1%	0.03	0.16
Δ % hispanic	3.9%	3.6%	3.2%	3.9%	4.8%	0.14	<0.001
Δ % other minorities	2.2%	2.0%	1.9%	2.1%	2.6%	0.17	<0.001
SES							
Δ Median household income	1537	842	1138	1240	2929	0.15	<0.001
Δ % HS graduate	15%	16%	15%	15%	14%	-0.14	<0.001
Δ % college graduate	12%	10%	11%	12%	14%	0.30	<0.001

Table A.3: Associations of county-level life expectancy with race and socioeconomic variables in ordinary least squares regression

	Females		Males	
	Coefficient	p-value	Coefficient	p-value
Intercept	69.60	<0.01	60.22	<0.01
Race				
% black	-0.038	<0.01	-0.051	<0.01
% hispanic	0.029	<0.01	0.041	<0.01
% other minorities	-0.009	<0.01	-0.016	<0.01
SES				
Median household income, current (in 10,000s of dollars)	0.15	0.01	0.24	<0.01
Median household income, lagged (in 10,000s of dollars)	0.06	0.33	0.21	<0.01
% HS graduate	0.092	<0.01	0.131	<0.01
% college graduate	0.055	<0.01	0.059	<0.01

Table A.4: Associations of change in county-level life expectancy (1989 to 2009) with race and socioeconomic variables in ordinary least squares regression

	Females		Males	
	Coefficient	p-value	Coefficient	p-value
Intercept	0.82	<0.01	2.17	<0.01
Race				
Δ % black	-0.022	<0.01	-0.044	<0.01
Δ % hispanic	-0.001	0.81	0.039	<0.01
Δ % other minorities	0.003	0.71	0.024	0.02
SES				
Δ Median household income (in 10,000s of dollars)	0.24	<0.01	0.33	<0.01
Δ % HS graduate	-0.055	<0.01	-0.017	<0.01
Δ % college graduate	0.103	<0.01	0.098	<0.01

Table A.5a: Top 10 counties by excess life expectancy (females)

County	actual life expectancy	Adjusted life expectancy	% black	% hispanic	% other minorities	Median household income (current)	Median household income (lagged)	% HS graduate	% college graduate	Similar county with lowest life expectancy
MCPHERSON SOUTH DAKOTA	82.4	83.7	0%	1%	1%	31945	31475	73%	23%	PERRY KENTUCKY (73.37743)
BUFFALO SOUTH DAKOTA	81.4	83.6	0%	2%	83%	18860	19988	78%	17%	none
BENSON NORTH DAKOTA	82.5	83.5	0%	1%	56%	32815	32069	81%	24%	MELLETTE SOUTH DAKOTA (76.383)
HUDSPETH TEXAS	82.0	83.5	1%	80%	1%	27053	27247	53%	14%	LA SALLE TEXAS (79.99853)
HOLMES OHIO	80.0	83.2	0%	1%	1%	42757	45773	56%	14%	none
TALIAFERRO GEORGIA	77.6	83.2	60%	2%	2%	25293	29556	60%	13%	none
LA PAZ ARIZONA	82.2	83.2	1%	23%	13%	30939	32116	75%	15%	none
SHERIDAN NORTH DAKOTA	82.5	83.1	0%	1%	2%	32729	31762	82%	20%	FAYETTE WEST VIRGINIA (75.91113)
MCINTOSH NORTH DAKOTA	81.7	83.1	0%	1%	1%	32492	33610	72%	23%	JACKSON ALABAMA (76.21941)
QUEENS NEW YORK	83.4	83.0	19%	28%	27%	54671	48122	80%	37%	none

Table A.5b: Top 10 counties by excess life expectancy (males)

County	actual life expectancy	Adjusted life expectancy	% black	% hispanic	% other minorities	Median household income (current)	Median household income (lagged)	% HS graduate	% college graduate	Similar county with lowest life expectancy
ISSAQUENA MISSISSIPPI	71.8	80.7	64%	1%	1%	24850	25726	60%	7%	none
WADE HAMPTON ALASKA	75.4	79.8	0%	0%	97%	30238	32396	75%	9%	none
HOLMES OHIO	75.2	79.6	0%	1%	1%	42757	45773	56%	14%	none
BUFFALO SOUTH DAKOTA	75.4	79.2	0%	2%	83%	18860	19988	78%	17%	none
LA PAZ ARIZONA	77.7	79.1	1%	23%	13%	30939	32116	75%	15%	none
HUDSPETH TEXAS	76.9	79.1	1%	80%	1%	27053	27247	53%	14%	LA SALLE TEXAS (73.64238)
PRESIDIO TEXAS	77.2	78.9	1%	83%	2%	28636	25429	54%	19%	HUDSPETH TEXAS (76.8935)
TALIAFERRO GEORGIA	71.0	78.9	60%	2%	2%	25293	29556	60%	13%	none
MCPHERSON SOUTH DAKOTA	76.8	78.8	0%	1%	1%	31945	31475	73%	23%	PERRY KENTUCKY (66.61608)
DE SOTO FLORIDA	76.4	78.8	13%	30%	2%	33791	36287	69%	15%	OKEECHOBEE FLORIDA (73.25385)

Table A.5c: Bottom 10 counties by excess life expectancy (females)

County	actual life expectancy	Adjusted life expectancy	% black	% hispanic	% other minorities	Median household income (current)	Median household income (lagged)	% HS graduate	% college graduate	Similar county with lowest life expectancy
CARTER OKLAHOMA	74.4	74.8	7%	5%	16%	37352	37001	84%	23%	CLEARWATER MINNESOTA (81.21248)
MADISON MISSISSIPPI	75.9	75.1	38%	3%	3%	55490	56205	89%	51%	none
PERRY KENTUCKY	73.4	75.2	2%	1%	2%	29660	30308	70%	18%	MCPHERSON SOUTH DAKOTA (82.41029)
ROBERTS TEXAS	77.3	75.2	0%	8%	2%	63082	53162	93%	39%	GRAND COLORADO (83.07765)
MINGO WEST VIRGINIA	73.7	75.7	2%	0%	1%	29102	29535	70%	15%	PATRICK VIRGINIA (80.02758)
LOGAN WEST VIRGINIA	74.4	75.8	2%	1%	1%	34596	31398	76%	16%	LOGAN NORTH DAKOTA (81.74673)
BECKHAM OKLAHOMA	75.5	75.8	4%	12%	5%	44634	35019	81%	22%	LOUISA IOWA (81.75346)
WALKER ALABAMA	74.5	75.8	6%	2%	2%	36582	37384	76%	17%	LOGAN NORTH DAKOTA (81.74673)
PONTOTOC OKLAHOMA	76.0	75.9	2%	4%	24%	36196	34762	85%	31%	MACKINAC MICHIGAN (80.88956)
ETOWAH ALABAMA	75.2	76.0	15%	3%	2%	38575	38609	82%	23%	BEDFORD CITY VIRGINIA (80.59589)

Table A.5d: Bottom 10 counties by excess life expectancy (males)

County	actual life expectancy	Adjusted life expectancy	% black	% hispanic	% other minorities	Median household income (current)	Median household income (lagged)	% HS graduate	% college graduate	Similar county with lowest life expectancy
CUSTER SOUTH DAKOTA	68.5	66.5	0%	2%	5%	46441	44839	93%	39%	STEARNS MINNESOTA (79.75548)
RIO ARRIBA NEW MEXICO	69.2	67.8	1%	71%	16%	39723	36133	78%	23%	none
FALL RIVER SOUTH DAKOTA	68.5	67.8	1%	2%	10%	34464	37592	90%	30%	MARSHALL SOUTH DAKOTA (77.27036)
MCDOWELL WEST VIRGINIA	63.2	68.2	10%	0%	1%	22222	23142	60%	9%	CLAY KENTUCKY (68.68736)
FLOYD KENTUCKY	66.2	69.0	1%	1%	1%	29725	29291	69%	17%	ADAIR KENTUCKY (73.36455)
WALKER ALABAMA	67.4	69.2	6%	2%	2%	36582	37384	76%	17%	LOGAN NORTH DAKOTA (76.27959)
PERRY KENTUCKY	66.6	69.2	2%	1%	2%	29660	30308	70%	18%	MCPHERSON SOUTH DAKOTA (76.79811)
JACKSON SOUTH DAKOTA	68.7	69.7	0%	1%	56%	30375	30362	86%	26%	none
MINGO WEST VIRGINIA	67.1	69.9	2%	0%	1%	29102	29535	70%	15%	PATRICK VIRGINIA (75.01547)
PIKE KENTUCKY	67.5	70.0	1%	1%	1%	32258	32848	71%	17%	PATRICK VIRGINIA (75.01547)

Table A.6a: Top 10 counties by "excess change in life expectancy" (females)

County	actual change in life expectancy	predicted change in life expectancy	excess change in life expectancy	Life expectancy (2009)	Life expectancy (1989)
BRONX NEW YORK	6.1	1.4	4.7	80.6	74.6
KINGS NEW YORK	6.4	2.2	4.2	81.9	75.5
ESSEX NEW JERSEY	5.2	1.7	3.5	79.9	74.7
LONG GEORGIA	4.2	0.8	3.4	79.4	75.2
IMPERIAL CALIFORNIA	4.2	0.9	3.4	82.8	78.6
QUEENS NEW YORK	5.5	2.1	3.3	83.4	78.0
PINAL ARIZONA	4.9	1.7	3.2	81.7	76.8
MCINTOSH GEORGIA	4.2	1.0	3.2	79.4	75.2
PASSAIC NEW JERSEY	4.5	1.3	3.2	81.8	77.4
HUDSON NEW JERSEY	5.3	2.2	3.1	81.7	76.3

Table A.6b: Top 10 counties by "excess change in life expectancy" (males)

County	actual change in life expectancy	predicted change in life expectancy	excess change in life expectancy	Life expectancy (2009)	Life expectancy (1989)
BRONX NEW YORK	11.1	3.7	7.4	74.6	63.5
NEW YORK NEW YORK	12.9	5.8	7.1	78.7	65.8
SAN FRANCISCO CALIFORNIA	12.0	5.4	6.6	78.3	66.3
KINGS NEW YORK	10.8	4.4	6.4	76.8	66.0
DISTRICT OF COLUMBIA	10.8	6.0	4.8	72.3	61.5
PINAL ARIZONA	8.3	3.8	4.5	77.9	69.6
ESSEX NEW JERSEY	8.4	4.0	4.4	74.9	66.5
IMPERIAL CALIFORNIA	7.4	3.3	4.1	77.2	69.7
EDGEFIELD SOUTH CAROLINA	7.5	3.7	3.8	74.5	67.0
ISSAQUENA MISSISSIPPI	5.2	1.4	3.8	71.8	66.6

Table A.6c: Bottom 10 counties by “excess change in life expectancy” (females)

County	actual change in life expectancy	predicted change in life expectancy	excess change in life expectancy	Life expectancy (2009)	Life expectancy (1989)
HARMON OKLAHOMA	-2.7	1.3	-4.0	75.5	78.2
CARTER OKLAHOMA	-2.9	1.0	-4.0	74.4	77.3
FAYETTE ALABAMA	-3.2	0.6	-3.8	76.0	79.2
PONTOTOC OKLAHOMA	-2.2	1.5	-3.8	76.0	78.3
BECKHAM OKLAHOMA	-2.7	1.1	-3.8	75.5	78.2
MADISON MISSISSIPPI	-1.0	2.6	-3.6	75.9	76.9
COTTON OKLAHOMA	-2.6	1.0	-3.6	76.2	78.8
TILLMAN OKLAHOMA	-2.6	0.9	-3.5	76.2	78.8
STEPHENS OKLAHOMA	-2.6	0.7	-3.4	76.8	79.4
KIOWA OKLAHOMA	-2.2	1.1	-3.3	76.7	78.9

Table A.6c: Bottom 10 counties by “excess change in life expectancy” (males)

County	actual change in life expectancy	predicted change in life expectancy	excess change in life expectancy	Life expectancy (2009)	Life expectancy (1989)
FLOYD KENTUCKY	-2.0	2.6	-4.6	66.2	68.1
CREEK OKLAHOMA	-1.0	3.1	-4.1	70.9	71.9
MCDOWELL WEST VIRGINIA	-1.5	2.4	-3.9	63.2	64.8
PIKE KENTUCKY	-1.0	2.7	-3.7	67.5	68.5
PAWNEE OKLAHOMA	-0.4	3.4	-3.7	72.0	72.3
ROGER MILLS OKLAHOMA	0.4	4.1	-3.7	71.5	71.1
ATTALA MISSISSIPPI	-0.5	3.1	-3.6	68.2	68.7
WYOMING WEST VIRGINIA	-0.9	2.6	-3.5	68.1	69.0
STEPHENS OKLAHOMA	-0.5	2.9	-3.4	72.2	72.7
BOLIVAR MISSISSIPPI	-0.4	3.0	-3.4	65.0	65.5

Discussion

Our findings confirm that differences in race and SES explain most of the geographic variation in life expectancy across the United States. All race, income, and education variables included in our analysis were significant predictors of life expectancy. We find that a $10,000 increase in current and lagged median household income is associated with a life expectancy increase of 0.45 years among males, but only 0.21 years among females. Effect sizes for race and education variables were also slightly greater for males. Of note, the proportion of Hispanics in a county shows a large positive association for both genders, consistent with prior findings of a "Hispanic paradox".[65]

Overall regional patterns

Males and females exhibit similar regional patterns in excess life expectancy. For both genders, some familiar geographic disparities are mostly explained by differences in race and SES. In particular, most of the Southeastern US – including much of Georgia, Alabama, and Mississippi – falls near the average in terms of excess life expectancy. Many counties in this region actually perform significantly above average after adjustment for race and SES. This suggests that racial composition and lower SES explain the low crude life expectancy observed across this region. Similarly, we note that the relatively high life expectancy in the northeast and west coast is largely explained by higher income and education levels in these areas.

Other regional disparities persist after controlling for race and SES. Notable among these is the poor life expectancy seen in parts of West Virginia and eastern Kentucky. While income and education levels here are significantly below the national average, we find that these disadvantages do not account for poor longevity in this area. Even after race and SES adjustment, three of the bottom ten counties in the US are in this region, for both males and females. While Appalachia is an often cited exemplar of domestic health disparities, Oklahoma is rarely presented in the same light. However, Oklahoma actually performs worse than Appalachia after adjustment for race and SES, comprising 12 of the bottom 30 counties in terms of excess female life expectancy.

The Northland region previously described by Murray et al. (2006) – including much of North Dakota, South Dakota, Nebraska, Minnesota, and Iowa – retains a significant life expectancy advantage after race and SES adjustment. This confirms prior reports in their "Eight Americas" work that the Northland - Appalachia disparity cannot be explained by socioeconomic differences.[66] This suggests that there are factors unrelated to SES that are responsible for variation in health between these two regions.

Some high-performing regions become apparent only after adjusting for race and SES. Parts of the southwestern US, particularly lower income counties on the US-Mexico border, exhibit significantly better than predicted life expectancy. This is true even in multivariate models adjusting for their high Hispanic populations. This suggests that there may be contextual advantages of this region in particular – beyond those related to ethnicity – that confer better health. Other concentrated areas of high excess life expectancy are seen in Virginia and Southern Florida.

While urban areas typically underperform surrounding suburbs in terms of crude life expectancy, the opposite pattern emerges after race and SES adjustment. Urban counties representing Los Angeles, Bronx, Queens, and Brooklyn, for instance, all rank among the top 10% in excess life expectancy for both males and females. This mortality advantage in urban areas has been previously described, and has been attributed to differences in education, poverty, and health insurance.[67] Urban counties in the southeast exhibit the opposite trend, as the counties representing Baltimore, Washington D.C., and Atlanta are all in the bottom 20% in excess life expectancy for both males and females. Together these findings indicate significant disparities in health across cities that are not explained by race and SES. This suggests a contribution of contextual factors, perhaps related to healthcare quality or the physical and social environment.

Accounting for changes in life expectancy over time

We find that only a small proportion (18-24%) of the change in counties' life expectancy over the last two decades can be explained by concurrent changes in income and racial composition. On average, each $10,000 increase in median household income (inflation adjusted, in 2009 dollars) over this span was associated with 0.33 year and 0.24 year increases in life expectancy for males and females, respectively. Associations between income and health are subject to confounding; whether they reflect an effect of income itself on health, as opposed to effect of unmeasured factors correlated with income, is unclear. However, by focusing on within-county changes in life expectancy over time, our "difference-in-difference" model removes the influence of non-time varying confounders. As a result, our measured association represents a reasonable estimate of the effect of income on life expectancy.

While race and SES explained changes in life expectancy on aggregate, there are clusters of counties for which race and SES do not account for observed changes in life expectancy. One such cluster is in Oklahoma. While income increased on pace with the rest of the country, over three quarters of the counties in the state experienced a decline in female life expectancy. Appalachia performs less poorly

than Oklahoma after race and SES adjustment, as its declines in life expectancy are partly explained by concurrent declines in real income.

Meanwhile, much of the US Southeast – including North Carolina, South Carolina, Georgia, and Florida - experienced an increase in life expectancy significantly greater than predicted. Many urban counties also experienced much higher than expected increases in longevity over the last two decades. The counties which comprise Oakland, Boston, Washington DC, Los Angeles, San Francisco, and New York were all in the top 5% by this metric for males and females, each experiencing substantial increases in longevity which are not explained by changes in racial composition or SES. These examples reflect the importance of contextual factors in shaping life expectancy. Improvements in the physical and social environment in these cities – including reductions in crime and drug use – likely had a direct impact on health over the last two decades.

Examples of positive deviance

Examples of positive deviance are diverse in both geographic and sociodemographic terms. There is significant overlap across genders, with 5 counties appearing in the top 10 of excess life expectancy for both males and females. This indicates that the county-level determinants of health may be similar across genders. The regional patterns described above are apparent. For instance, three of the 15 positive deviance counties are near the US-Mexico border and have high Hispanic populations. Six of the 15 are in North Dakota and South Dakota. This includes two counties (Buffalo and Benson) with high Native American populations (82% and 48%, respectively), suggesting that the contextual advantage in "Northland" is not limited to whites.

Many of these Northland counties can be matched to similar (in terms of race and SES) counties in Appalachia in which life expectancy is 6 to 10 years lower. For example, McPherson, South Dakota differs by less than 0.5 standard deviations in all race and SES characteristics from Perry, Kentucky, but differs by more than nine years in life expectancy for both males and females. Similar contrasts are also evident between counties in the same region. For instance, Benson (North Dakota), De Soto (Florida), and Gunnison (Colorado) have comparable nearby counties that differ by 3-6 years in life expectancy. By effectively holding race and SES constant, such comparisons highlight the role of contextual factors in determining life expectancy.

Other examples of positive deviance are unique in their demographic and socioeconomic composition. This includes Holmes, Ohio – with a 42% Amish population, Wade Hampton, Alaska – with a 93%

Native Alaskan population, and Queens, New York – with 47% of the population foreign-born. Given the lack of comparable counties in terms of race, ethnicity, and SES, it is unclear whether their higher-than-expected performance reflects the role of compositional or contextual factors.

Examples of negative deviance

Some examples of negative deviance reflect the regional disparities described above. Of the 18 counties among the bottom 10 in excess life expectancy for males and females, 3 are in Oklahoma, 5 are in Appalachia, and 3 are in the Southeast (Georgia, Alabama, Mississippi). Of note, three of the five in Appalachia (Floyd, McDowell, and Mingo) are similar in race and SES composition to other counties in the same region in which life expectancy is 4 to 6 years higher. Even within this largely poor-performing region, there is significant variation in life expectancy that cannot be explained by differing race and SES. Other negative deviance counties illustrate similar within-region heterogeneity. Three (Jackson, Fall River, and Custer) are in the otherwise high-performing Northland region, and are similar in race and SES to positive deviance counties in that area. Two are predominantly Hispanic counties in the otherwise high-performing southwestern US (San Miguel and Rio Arriba). Together, these examples indicate that there is significant heterogeneity even within neighboring areas in the contextual determinants of health.

Limitations

As described previously, our county-level estimates of life expectancy are subject to uncertainty. This is a limitation in any research on geographic disparities, particularly that which involves comparisons of infrequent events – such as mortality - across small areas.[68] In deriving the life expectancy estimates used in this study, Wang et al. (2013) employ a Bayesian maximum likelihood estimator to minimize the influence of random variations.[1] However, counties of smaller population size will still be subject to the greatest margin of error. This requires interpreting examples of positive or negative deviance with caution, particularly when such outliers represent a small population in isolation.

We apply commonly used measures of income and education to represent county-level SES. However, SES is a complex multidimensional construct with other components, such as those related to occupational prestige, employment, or fixed resources (e.g. savings, home ownership).[69] Some studies have utilized more complex SES measures that incorporate these components. However, given that these SES measures are all highly correlated, we determined that income and education alone would capture meaningful area-level differences in SES, and thus utilized a more parsimonious model. It is possible that

unmeasured aspects of SES are contributing to some of the observed differences in excess life expectancy, but we maintain that this contribution will be small relative to other factors.

As with SES, there are also many possible ways to represent racial composition of counties in multivariate models. Given that poorer health and life expectancy have been noted consistently among blacks, independent of SES, we determined that the percentage of blacks warranted inclusion in the model.[70] Similarly, the percentage of Hispanics warranted inclusion given the well-established "Hispanic paradox".

We also considered inclusion of separate variables for other race groups, such as the percentage of Asians or Native Americans in a county. However, the degree to which these groups differ, after accounting for SES, has not been established. Moreover, each of these groups encompasses persons from a wide variety of ethnic backgrounds and health-related traits. Thus it is unclear what, if any, prognostic information would be contained with a "% Asian" or "% Native American" variable. For this reason, these race groups were aggregated into a "% other minority" variable, acknowledging that the interpretation of its association with life expectancy is unclear. Similarly, white, black, and Hispanic groups are not homogenous. The experiences of blacks in the north and south – and associated health outcomes – differ substantially enough to warrant their distinction into two separate "Americas" by Murray et al. (2006).[66] With race modeled as a single parameter, our model may not capture this heterogeneity.

Race and SES also interact in a complex manner which our multivariate model fails to capture.[71] For example, prior studies have suggested a "diminishing returns" phenomenon, whereby blacks accrue less health benefit with increasing education than whites.[72] We tested for such an interaction by inclusion of a "% race" times "median income" parameter (not shown) and find that it is not significant, so this interaction term was left out of our final model. However, the true interaction between race and SES may is likely more complex than what is represented in this interaction term.

Interpretation

Understanding the causes of geographic disparities in health represents a major challenge in public health research. To date, the predominant focus has been on the contribution of population composition – including race and SES – to these disparities. Race and SES-based disparities in health are themselves a cause for alarm and an urgent topic for further research.

Leading explanations for these race- and SES-based disparities cite both material disadvantages – such as lacking resources to pay for nutritious food and healthcare – and psychosocial disadvantages – such as stress and dissatisfaction resulting from low social standing – associated with low SES. Such SES-based disadvantages are likely to be the primary drivers of health disparities. Contextual influences on health – ranging from healthcare quality and access, to social norms, to environmental exposures – may each have smaller and more variable influences than race- and SES-related factors. As a result, the influence of such contextual factors is not readily apparent when examining geographic patterns in crude life expectancy.

In this paper, we focus on those geographic disparities that are not the result of differences in race or SES. The intent of such a focus is not to diminish the importance of race- and SES-based disparities, or to imply that these disparities are somehow "warranted". Instead, we present our race- and SES- adjusted "excess life expectancy" metric as an analytical tool that may be useful for understanding the other underlying causes of geographic health disparities. Patterns in "excess life expectancy" may offer greater insight into the importance of contextual factors.

While we confirm familiar associations between race, SES, and longevity, a key finding in our analysis is that the contribution of race and SES to disparities is not uniform. We identify significant regional disparities that persist after race and SES adjustment, while other regional disparities disappear after accounting for race and SES. Overall, these findings suggest significant heterogeneity in the etiology of geographic health disparities. Race, SES, and related factors are the key drivers of life expectancy in some areas, but factors unrelated to SES are responsible for other geographic patterns in life expectancy.

The finding of significant diversity among the highest-performing counties – in terms of "excess life expectancy" - is notable. Rather than pointing to any single ideal health environment, it suggests that outstanding population health is achievable in a diverse array of settings, and in spite of perceived disadvantages. Some of the positive deviance counties we identify outperform peers despite remoteness and low proximity to and concentration of specialized healthcare providers. Other positive deviance counties succeed despite the perceived disadvantages of an ethnically diverse, economically challenged urban population. In-depth examination of these positive deviance counties might provide insights into the community-level determinants of better population health, which could provide lessons for both rural and urban areas with varying SES and racial composition.

Our findings are largely descriptive, and we offer limited insight here into the etiology of our observed patterns in excess life expectancy. The principal aim in this paper is to illustrate the value of this

framework and provide tools for ongoing research on the causes of geographic health disparities. Analytical approaches may be employed to quantify the contribution of specific community-level factors to excess life expectancy. Alternatively, in-depth "case studies" may provide insight into what distinguishes certain positive deviance counties and regions from peers of similar race and SES composition.

Overall, our findings serve as a reminder – both to researchers and public health officials – that economics is not destiny when it comes to health, and that contextual factors matter. This acknowledgement should spur researchers to identify those contextual factors responsible for health disparities and prompt policy and interventions to target such contextual factors.

B. Neighborhood SES and outcomes after AMI

Introduction

To further understand the contribution of SES and contextual factors to health, we focus on outcomes in the setting of acute myocardial infarction (AMI). We hypothesize that contextual factors will be particularly important in AMI, given that socioeconomic disparities in cardiovascular disease (CVD) are well-established, with low socioeconomic status (SES) linked with greater CVD incidence[7-11] and with poorer quality of care[9,12-16], adherence to therapy[17-19], and outcomes[8,9,20-28] related to CVD.

The underlying causes of these disparities are not precisely understood. Traditionally, emphasis is placed on the health impact of *personal* socioeconomic factors, such as individual income, education, and health insurance status. The contribution of contextual factors is less well established.

Neighborhood SES is a composite of contextual factors reflecting an individual's immediate surroundings. It is often used as a surrogate for personal SES in studies where individual-level socioeconomic data are unavailable. However, there is growing evidence that where one lives is relevant to health outcomes independent of an individual's SES. For instance, even after adjusting for individual SES, neighborhood SES is associated with coronary heart disease incidence[7,10,11], all-cause mortality[29], and several cardiovascular risk factors, including smoking[30], poor diet[31], impaired physical fitness[32], and hypertension[33]. These observations suggest an independent effect of neighborhood-level SES on cardiovascular health, but there is a need for larger, more definitive studies to test this effect.

Neighborhood may be particularly important among patients after acute myocardial infarction (AMI). There are several plausible mechanisms for such an effect. Geographic variation in the quality and proximity of healthcare providers may affect one's access to timely revascularization or cardiac rehabilitation. Features of a neighborhood's physical environment, such as walkability and healthy food access, may influence health behaviors relevant to recovery post-AMI. The spread of smoking, obesity, and alcohol use exhibit social network dynamics, suggesting that neighborhood social norms may also influence health behaviors.[34-36]

Given the many ways by which contextual factors may shape AMI outcomes, AMI is an ideal condition for understanding the broader impacts of neighborhood on health. Yet there is scarce evidence to date on the effects of neighborhood after AMI. While SES is often studied in the context of AMI and is a reliable predictor of outcomes,[8,9,21,27,28] most studies lack information on both individual and neighborhood-level SES and thus cannot disentangle their effects. This has been done in few studies, all based on non-US cohorts. For example in one cohort from Central Israel, low neighborhood SES was independently associated with mortality and recurrent coronary events.[37,38] Whether this observed neighborhood effect extends to broader settings and other health outcomes after AMI is unknown.

The current study aims to address these gaps in knowledge. We use data from the PREMIER study,[39] which includes a detailed profile of individual-level SES, clinical factors, and outcomes for patients with AMI from 19 US hospitals, in order to investigate the relationship between neighborhood SES and mortality, rehospitalization, and angina symptoms after AMI. This research to distinguish the effect of neighborhood from that of individual-level traits will help clarify the utility of health policy and interventions that target contextual factors.

In summary, our primary aim is **to measure the effect of place – using neighborhood SES as a proxy – on outcomes after AMI.**

Methods

Study Design

We utilized data from the previously described PREMIER study, which enrolled 2438 patients from 19 US medical centers between January 1, 2003, and June 28, 2004.[39] Patients presented with AMI confirmed by both elevated biomarkers of myocardial injury (troponin level or creatine kinase MB fraction (CK-MB)) and supporting evidence (>20 minutes of ischemic signs and symptoms and/or

electrocardiographic ST changes). Patients aged less than 18 years, those admitted from penal facilities, and those with elevated troponins or CK-MB secondary to percutaneous coronary intervention were excluded.

A patient interview was administered within 24 to 72 hours of admission, eliciting data on sociodemographics, use of the medical system, and baseline health status. Detailed information on patient presentation, comorbidities, treatments during hospitalization, complications, and discharge medications was obtained via chart review. Follow-up interviews were conducted at 1, 6, and 12 months, and obtained details of follow-up care and intermittent hospitalizations.

Informed consent was obtained from each patient, and institutional research board approval was obtained at each institution.

Neighborhood socioeconomic measures

Census-block groups were used as proxies for neighborhoods. These are contiguous areas containing an average of 1000 people, designed to have stable boundaries and relatively homogeneous demographic and economic characteristics.[61] Neighborhood of residence was identified by geocoding each patient's residential address at the time of enrollment using ArcGIS™ ArcMap™ versions 9.3.1 and 10.0 (ESRI®, Redlands, CA; See Appendix 1 for further details). We successfully geocoded addresses for 2321 (95%) of the patients in the parent study. The remainder could not be linked to a block group, mainly because of incomplete or ambiguous address fields.

As a measure of neighborhood SES, we adopted a summary score defined in Diez Roux et al (2001). This score incorporates six block group-level datapoints from the American Community Survey (2005-2009): 1) log of the median household income 2) log of the median value of housing units 3) percentage of households receiving interest, dividend, or net rental income 4) percentage of adults ≥ 25 years who completed high school 5) percentage of adults ≥ 25 years who completed college 6) percentage of employed persons ≥ 16 years in executive, managerial, or professional specialty occupations.

Each variable was standardized and the resulting z-scores were summed to construct the neighborhood SES summary score, with increasing scores indicative of higher SES. For ease of interpretation, quintiles of the neighborhood SES score were used in the analysis.

Individual socioeconomic measures

Measures of individual SES included household income, collected as a categorical variable, educational attainment, and current employment status. To more thoroughly characterize an individual's economic circumstances, we included subjective measures of financial stress, financial barriers to healthcare, and the perceived burden of healthcare costs.

Financial stress was assessed with the question "In general, how do your finances usually work out at the end of the month? Do you find you usually end up with…" followed by these response choices: "some money left"; "just enough to make ends meet"; and "not enough to make ends meet". Financial barriers to healthcare were assessed with two questions. First, "In the past year, have you avoided obtaining health care services because of cost?", with answer choices of "yes" or "no". Second, "In the past year, how often have you not taken medication that your doctor prescribed because of cost?", with answer choices on a 5-point Likert scale ranging from "never" to "always". Burden of healthcare costs was captured with five answer choices ranging from "severe burden" to "not a burden at all".

The above measures were divided into separate domains of "General SES" – including income, education, employment, and subjective financial strain - and "Healthcare-related SES" – including financial barriers to healthcare, burden of healthcare costs, and patient's health insurance status.

Outcome Variables

Outcomes of interest included presence of angina symptoms, readmission, and mortality.

Angina symptoms were assessed at one year after the index hospitalization using the Seattle Angina Questionnaire (SAQ). The SAQ is a validated 19-item instrument assessing patients' perspectives of the impact of ischemic disease.[62] We used a specific component of the SAQ that quantifies angina frequency (SAQ AF) on a scale of 0 to 100, with an SAQ AF score of 100 representing no angina symptoms. For the purposes of analysis, the SAQ AF score was transformed into a binary variable representing the presence of any angina symptoms (i.e. SAQ AF < 100).

We determined readmission due to any cause within twelve months of index hospitalization via phone interview. Mortality at the 4 year timepoint was determined by cross referencing patients' Social Security numbers with the Social Security Death Master File.[63]

Analytic Plan

All analyses were performed using SAS software version 9.1 (SAS Institute Inc, Cary, NC). We defined significance as a 2-sided *P* value of < .05. Patient-level demographic and socioeconomic were compared across quintiles of neighborhood SES using the χ^2 or Fisher's exact test for categorical variables and ANOVA for continuous variables.

We used logistic regression with generalized estimating equations (GEE) to measure the association between neighborhood SES and the presence of angina. We used Cox proportional hazards models to compare mortality and rehospitalization across neighborhood SES quintiles.

In multivariable models, we evaluated the association between neighborhood SES and each outcome variable in a stepwise fashion, adding blocks of covariates one at a time. The first set of models included only age, sex, and marital status (model 1); subsequent models added race (model 2) and 'individual SES' (model 3). In all models, we considered patients in high SES neighborhoods as the referent group.

We used the single imputation technique for covariates with missing values. Demographic data (age, sex, race, marital status) were each available for ≥98% of subjects. Among SES-related covariates, individual income had the highest rate of missing values (29.8%), while insurance status and other individual SES items were missing in ≤4% of subjects. SF-12 and SAQ scores were complete in 74% and 76% of participants, respectively.

Results

The baseline characteristics across neighborhood SES quintiles are presented in Table B.1.

Patients living in more affluent neighborhoods were older and more likely to be male, white, employed, and married. As expected, patients' income and education levels were higher in more affluent neighborhoods. Patients from low SES neighborhoods were more likely to be uninsured. Subjective measures of financial strain, avoidance of healthcare due to cost, and burden of healthcare costs were also significantly greater in the lowest SES neighborhoods. (P<0.0001 for all comparisons)

Neighborhood SES and mortality

Four-year survival was 75%, 79%, 83%, 84%, and 85% in the lowest through highest quintiles (Figure B.1). Adjusted for demographics, including race, mortality risk was 30% greater in the lowest compared to highest SES tertiles, though this difference did not reach significance (adjusted HR: 1.31; 95% CI 0.96

– 1.78; Figure B.2). This increased risk was fully attenuated after adjustment for individual SES (adjusted HR: 1.01; CI 0.72 – 1.41); of note, this result did not change when subjective indicators of individual SES were excluded from the model, leaving only individual income, education, employment, and insurance status.

Neighborhood SES and rehospitalization

Rehospitalization within one year occurred in 40% of the patients, and this ranged from 47% in the lowest neighborhood SES quintile to 34% in the highest SES quintile (Figure B.3). Increased risk was observed for low-SES compared to high-SES neighborhoods both before (HR 1.39; CI 1.12 – 1.73) and after adjustment for patient demographics, including race (HR 1.37; CI 1.09 – 1.73; Figure B.4). This association was attenuated by adjustment for individual SES, as fully-adjusted models showed a 20% increased risk of rehospitalization in low-SES neighborhoods, though this did not reach statistical significance (HR 1.22; CI 0.95 – 1.57).

Neighborhood SES and angina

At 12 month follow-up interview, 360 (20%) of 1836 patients reported experiencing any angina symptoms. This varied significantly by neighborhood SES, with angina frequency of 29%, 24%, 18%, 16%, and 14% in the lowest through highest SES quintiles (Figure B.5).

After adjustment for patient demographics including race, patients in low-SES neighborhoods were significantly more likely to report angina symptoms (OR 2.03; CI 1.45 – 2.83; Figure B.6). The association between neighborhood SES and angina remained significant in the final model (OR 1.56; CI 1.09 – 2.24), with modest attenuation after adjustment for individual SES.

Figure B.1: Kaplan-Meier plot of 4-year mortality by SES quintile

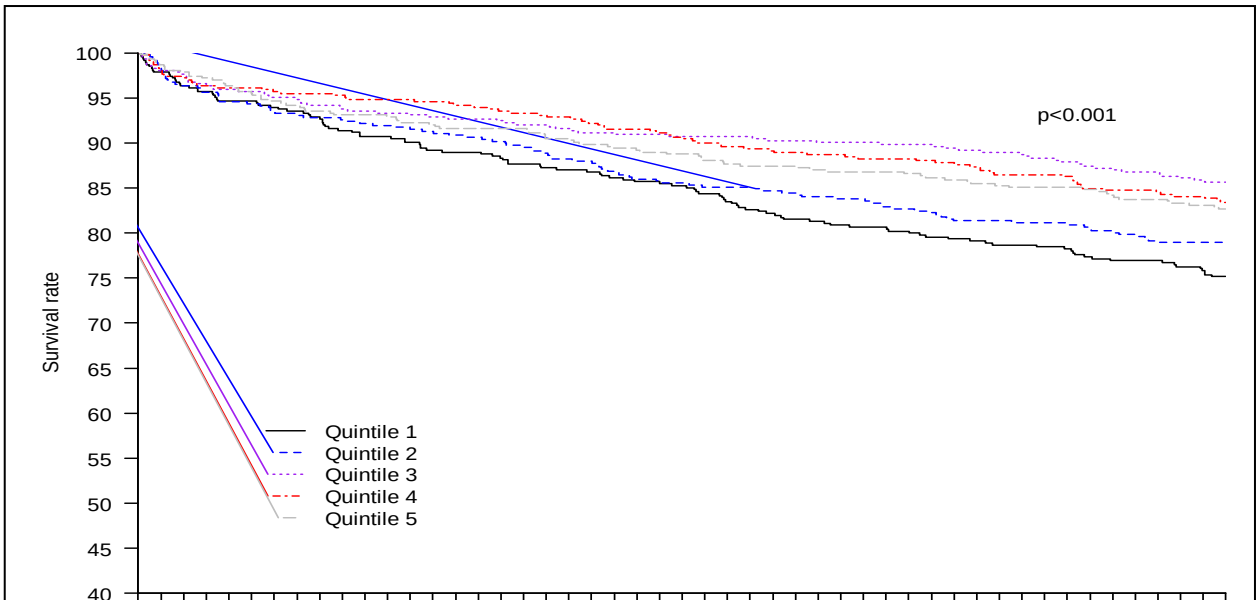


Figure B.2: Forest plot of mortality hazard ratios

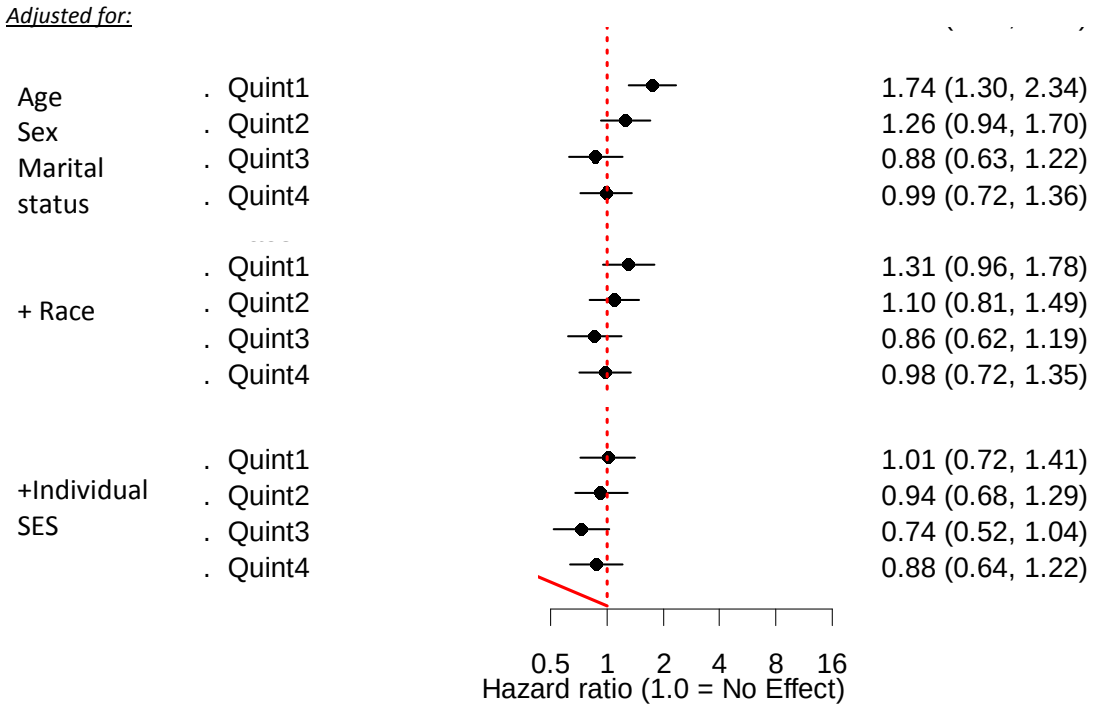


Figure B.3: Kaplan-Meier plot of 1-year rehospitalization by SES quintile

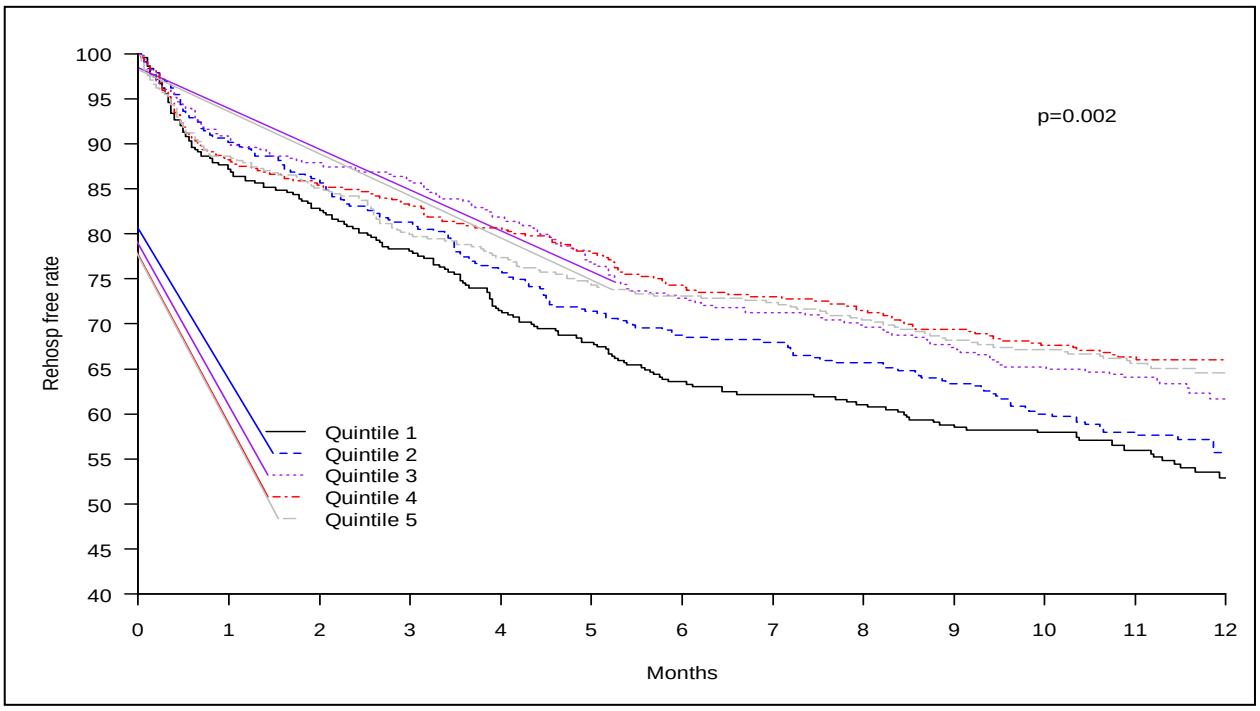


Figure B.4: Forest plot of rehospitalization hazard ratios

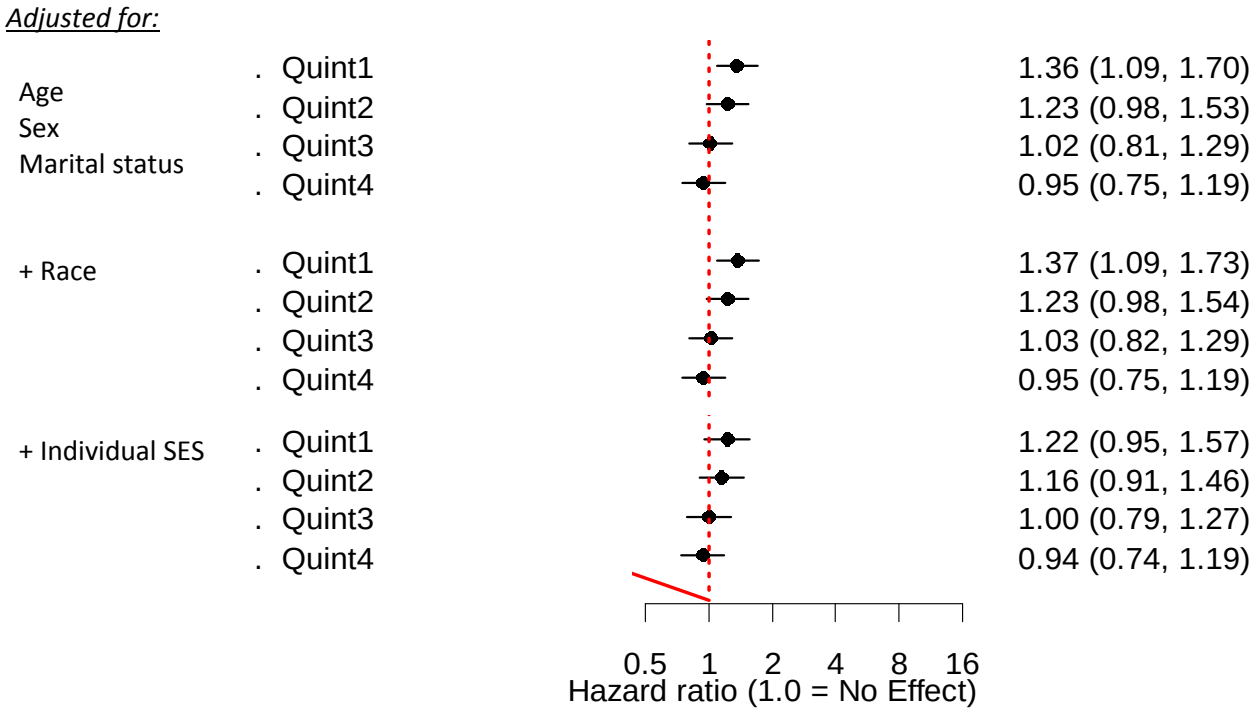


Figure B.5: Presence of any angina symptoms at 12 months by SES quintile

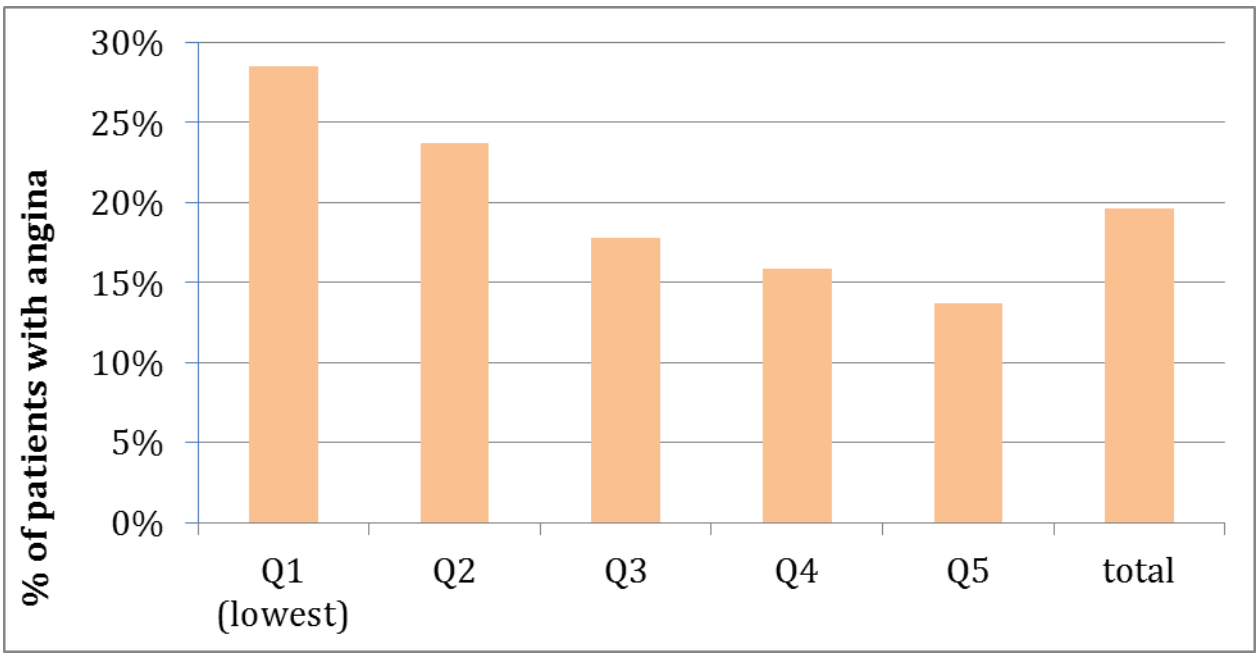


Figure B.6: Forest plot of angina odds ratios

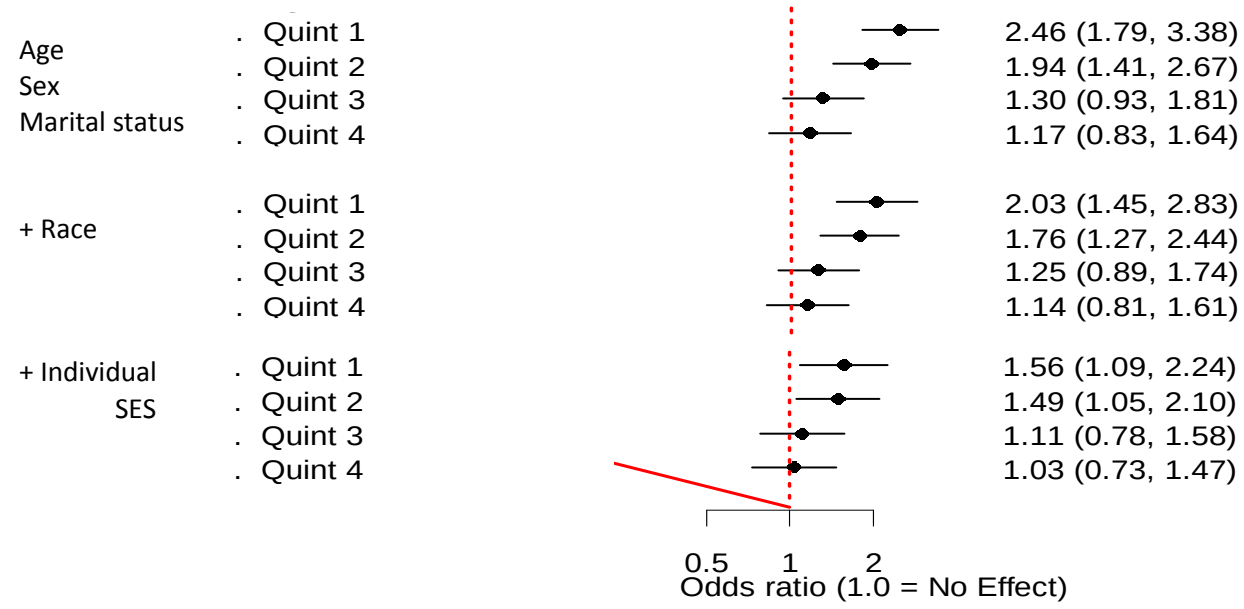


Table B.1: Baseline characteristics across neighborhood SES tertiles (PREMIER)

	Neighborhood SES quintile					Total	
	Quint1 n = 464	Quint2 n = 463	Quint3 n = 464	Quint4 n = 464	Quint5 n = 466	n = 2321	P-Value
Age	58.5 ± 12.7	60.9 ± 13.5	60.3 ± 12.7	62.0 ± 12.9	63.3 ± 12.9	61.0 ± 13.0	< 0.001
Sex							< 0.001
(1) Male	287 (61.9%)	292 (63.1%)	314 (67.7%)	324 (69.8%)	344 (73.8%)	1561 (67.3%)	
(2) Female	177 (38.1%)	171 (36.9%)	150 (32.3%)	140 (30.2%)	122 (26.2%)	760 (32.7%)	
Race Category							< 0.001
(1) White/Caucasian	209 (45.2%)	315 (68.2%)	369 (80.0%)	401 (87.0%)	421 (91.3%)		
(2) Black/African American	216 (46.8%)	123 (26.6%)	69 (15.0%)	50 (10.8%)	32 (6.9%)		
(3) Other	37 (8.0%)	24 (5.2%)	23 (5.0%)	10 (2.2%)	8 (1.7%)		
Missing (.)	2	1	3	3	5		
Marital Status							< 0.001
(1) Married	228 (50.2%)	257 (56.5%)	274 (59.6%)	306 (67.4%)	320 (69.7%)	1385 (60.7%)	
(2) Divorced/separated	102 (22.5%)	86 (18.9%)	75 (16.3%)	68 (15.0%)	56 (12.2%)	387 (17.0%)	
(3) Widowed	64 (14.1%)	67 (14.7%)	62 (13.5%)	54 (11.9%)	49 (10.7%)	296 (13.0%)	
(4) Single	60 (13.2%)	45 (9.9%)	49 (10.7%)	26 (5.7%)	34 (7.4%)	214 (9.4%)	
Missing (.)	10	8	4	10	7	39	

	Neighborhood SES quintile					Total	
	Quint1 n = 464	Quint2 n = 463	Quint3 n = 464	Quint4 n = 464	Quint5 n = 466	n = 2321	P-Value
Educational Attainment							< 0.001
(1) Did not finish high school	175 (38.7%)	120 (26.7%)	89 (19.6%)	60 (13.2%)	28 (6.1%)	472 (20.8%)	
(2) Completed high school	150 (33.2%)	149 (33.1%)	158 (34.7%)	133 (29.2%)	96 (20.8%)	686 (30.2%)	
(3) Some college/vocational school	94 (20.8%)	120 (26.7%)	130 (28.6%)	139 (30.5%)	127 (27.5%)	610 (26.8%)	
(4) Graduated from college	20 (4.4%)	42 (9.3%)	54 (11.9%)	78 (17.1%)	109 (23.6%)	303 (13.3%)	
(5) Post-graduate degree	13 (2.9%)	19 (4.2%)	24 (5.3%)	46 (10.1%)	101 (21.9%)	203 (8.9%)	
Missing (.)	12	13	9	8	5	47	
Currently working for pay							< 0.001
(1) Yes, I work full time	112 (24.6%)	146 (31.9%)	191 (41.6%)	185 (40.7%)	191 (41.5%)	825 (36.1%)	
(2) Yes, I work parttime for pay	41 (9.0%)	32 (7.0%)	29 (6.3%)	34 (7.5%)	51 (11.1%)	187 (8.2%)	
(3) No, I don't currently work for pay	303 (66.4%)	279 (61.1%)	239 (52.1%)	236 (51.9%)	218 (47.4%)	1275 (55.7%)	
Missing (.)	8	6	5	9	6	34	
Household Income							< 0.001
(1) <$10,000	92 (33.3%)	65 (21.3%)	55 (15.8%)	44 (12.5%)	25 (7.2%)	281 (17.2%)	
(2) $10,000-$29,999	105 (38.0%)	118 (38.7%)	110 (31.5%)	82 (23.2%)	61 (17.6%)	476 (29.2%)	
(3) $30,000-$49,999	45 (16.3%)	60 (19.7%)	95 (27.2%)	76 (21.5%)	66 (19.1%)	342 (21.0%)	
(4) $50,000-$69,999	17 (6.2%)	35 (11.5%)	43 (12.3%)	58 (16.4%)	40 (11.6%)	193 (11.8%)	
(5) >=$70,000	17 (6.2%)	27 (8.9%)	46 (13.2%)	93 (26.3%)	154 (44.5%)	337 (20.7%)	
Missing (.)	188	158	115	111	120	692	
Uninsured /Self-Pay	70 (16.3%)	67 (15.3%)	58 (13.2%)	36 (8.1%)	36 (8.1%)	267 (12.2%)	< 0.001
Missing (.)	5	1	8	5	6	25	
(.U) Unknown	30	24	15	17	13	99	
Monthly financial situation							< 0.001
(1) Some money left over	152 (34.5%)	209 (47.4%)	241 (53.8%)	273 (61.9%)	303 (67.6%)	1178 (53.1%)	
(2) Just enough to make ends meet	174 (39.5%)	158 (35.8%)	151 (33.7%)	116 (26.3%)	106 (23.7%)	705 (31.8%)	
(3) Not enough to make ends meet	114 (25.9%)	74 (16.8%)	56 (12.5%)	52 (11.8%)	39 (8.7%)	335 (15.1%)	
Missing (.)	24	22	16	23	18	103	
Avoided getting health care due to cost	118 (26.1%)	96 (21.3%)	88 (19.3%)	54 (12.0%)	45 (9.8%)	401 (17.7%)	< 0.001
Missing (.)	12	12	8	14	9	55	
Not taken medication due to cost							< 0.001
(1) Always	12 (2.6%)	10 (2.2%)	9 (2.0%)	7 (1.5%)	5 (1.1%)	43 (1.9%)	
(2) Frequently	37 (8.1%)	22 (4.8%)	13 (2.9%)	11 (2.4%)	5 (1.1%)	88 (3.9%)	
(3) Occasionally	46 (10.1%)	34 (7.5%)	33 (7.2%)	21 (4.6%)	20 (4.4%)	154 (6.8%)	
(4) Rarely	35 (7.7%)	27 (5.9%)	22 (4.8%)	22 (4.8%)	13 (2.9%)	119 (5.2%)	
(5) Never	327 (71.6%)	363 (79.6%)	379 (83.1%)	397 (86.7%)	411 (90.5%)	1877 (82.3%)	
Missing (.)	7	7	8	6	12	40	
Medical costs have been an economic burden							< 0.001
(1) Severe burden	67 (14.6%)	60 (13.3%)	49 (10.8%)	36 (7.9%)	28 (6.1%)	240 (10.5%)	
(2) Moderate burden	62 (13.5%)	35 (7.7%)	43 (9.5%)	37 (8.1%)	28 (6.1%)	205 (9.0%)	
(3) Somewhat burden	49 (10.7%)	47 (10.4%)	37 (8.1%)	44 (9.6%)	26 (5.7%)	203 (8.9%)	
(4) A little	32 (7.0%)	27 (6.0%)	40 (8.8%)	31 (6.8%)	37 (8.1%)	167 (7.3%)	
(5) No burden at all	248 (54.1%)	283 (62.6%)	286 (62.9%)	309 (67.6%)	340 (74.1%)	1466 (64.3%)	
Missing (.)	6	11	9	7	7	40	

Continuous variables compared using one-way analysis of variance.
Categorical variables compared using chi-square or Fisher's exact test.

Discussion

Our study demonstrates higher rates of angina and all-cause rehospitalization after AMI among patients in low-SES neighborhoods. The associations of low neighborhood SES with rehospitalization and angina are comparable in magnitude to those of low individual income, suggesting that neighborhood context may be as influential as personal resources. We find that mortality also differs significantly across neighborhood SES quintiles; however, this association does not persist after adjustment for individual SES.

Taken together, our results suggest that the mechanisms by which neighborhood SES affects AMI may vary by outcome. Disease morbidity, as reflected in rehospitalization and angina symptoms at one-year post-AMI, appears to be influenced by contextual factors captured in the neighborhood SES variable. However, neighborhood-level disparities in four-year mortality are fully mediated by individual SES.

Our study complements earlier evidence that neighborhood contributes to cardiovascular risk throughout a person's life course, conferring, for instance, increased risk of incident CVD. The magnitude of this effect – comparable to that of individual SES - lends strong evidence to the joint importance of person-level disadvantages and neighborhood context in shaping health outcomes.

Comparison with prior studies

Multiple studies have demonstrated an independent association between neighborhood SES and the incidence of CHD and AMI. Demonstrating such an effect requires adjustment for individual socioeconomic characteristics. This adjustment is done in our study and only three prior AMI cohorts.

One such cohort enrolled patients in 1992-93 at eight sites in Central Israel. In this cohort, *Koren et al.* (2012) report an increased risk of recurrent coronary events after AMI due to low neighborhood SES.[38] This finding parallels our observed association of neighborhood SES with angina and rehospitalization, together suggesting that the contribution of neighborhood to morbidity after AMI is robust across time and geographic context.

In the same cohort, *Gerber et al. (2010)* report an increased risk of long-term mortality in low SES neighborhoods, adjusting for baseline clinical risk factors and individual SES.[37] In contrast, we find no such association. This divergence may reflect differences in the populations or health systems studied, implying that the influence of neighborhood varies by context. Our study enrollment also took place over

a decade later; it is possible that the effect of neighborhood on mortality has diminished over time, with increasing adoption of disease-modifying interventions in previously neglected populations. Another important difference is length of follow-up, which is four years in our study compared to a median of thirteen years in *Gerber et al. (2010).* While our findings suggest a short-term effect on morbidity – as reflected in one-year angina and rehospitalization - the effect of neighborhood on mortality after AMI may be delayed over several years, and as such would be unobservable in our cohort.

Two additional studies point to an independent link between neighborhood SES and mortality related to CHD. Among patients with incident CHD in Sweden, *Winkleby et al. (2007)* report increased 1-year case-fatality associated with low neighborhood SES.[73] *Gerber et al (2008)* also show such a link among patients in Olmsted County, Minnesota after a median of 13 months follow-up. This study controlled for individual education but no other individual SES variables (e.g. income), so neighborhood was potentially a proxy for unmeasured individual socioeconomic characteristics.[27]

Possible mechanisms

In our study, neighborhood SES is likely a proxy for multiple characteristics of a neighborhood's physical and social environment. Little is known regarding which are most important, and which are responsible for the relationship between neighborhood SES and outcomes after AMI. These potential mechanisms may involve:

Access to quality care: Patients of lower SES are less likely to receive invasive revascularization procedures and evidence-based medical therapies (i.e. aspirin, statins, and β-blockers), which would predispose them to angina.[74-76] This may represent an adverse effect of their neighborhood of residence, reflecting lack of access to high-quality providers and hospitals with PCI capability.

Adherence to secondary prevention: Low SES patients have lower attendance at cardiac rehabilitation programs, which may result from lack of facilities near their place of residence.[18,19,77] Poor adherence to postdischarge medications is also associated with low SES; this may stem from neighborhood-level factors such as social support and community attitudes toward healthcare.[17]

Lifestyle modifications: Features of a neighborhood's physical environment, such as availability of open space, clean air, or healthy food outlets, may influence diet or physical activity levels. Neighborhood social norms may also impact a patient's ability to employ lifestyle changes after AMI. In support of this

hypothesis, higher neighborhood SES is associated with greater physical activity after AMI, even after adjusting for individual SES and other patient characteristics.[78]

Community-level stressors: Patients in low SES neighborhoods are exposed to greater levels of both psychological (e.g. crime, residential instability) and physical (e.g. air pollution) stressors. Stress may have direct physiological consequences exacerbating CHD.[79,80] It may also contribute to the development of anxiety and depression, both of which are associated with poorer CHD outcomes.[80-83]

An alternative explanation for our findings is that neighborhood SES is merely capturing unobserved dimensions of individual SES. This is unlikely, given the extensive array of both objective and subjective individual socioeconomic variables adjusted for in our analysis.

Strengths and Limitations

To the best of our knowledge, our study is the first to measure the association between neighborhood SES and outcomes after AMI in a US cohort while controlling for individual SES.

There is extensive geographic and demographic variation in our PREMIER cohort, with residential neighborhoods ranging from urban to very rural. Study sites varied by size and degree of specialization.[39] This diversity contributes to the generalizability of our results.

Block group level socioeconomic data from ACS were first made available in 2010; hence our study is among the first in this field to employ block group as the geographic unit of analysis.[84] Comparable prior studies have instead used census tracts, which are four times the size of block groups.[85] We believe that block group level data allows for a more precise characterization of a patient's environment.

Some limitations of this study warrant consideration. First, neighborhood of residence was only ascertained at baseline. Patients may have changed their place of residence during the follow-up period, leading to some misclassification of exposures. Second, our PREMIER cohort is limited to those patients well enough to consent to participation in the study; as such, our findings may not generalize to a more clinically severe AMI population.

Finally, while demographic, and neighborhood SES variables were available for the vast majority of participants, data on individual income was missing for 30% of participants. However, for most

participants with missing income data, we were able to capture individual SES through several other variables including education and subjective financial strain.

Interpretation

Traditional explanations for socioeconomic disparities in health focus on the role of individual-level disadvantages, such as low education or income, with neighborhood SES often treated as a proxy for these individual traits in the health literature. This motivates a focus on policy and interventions targeting individual-level disadvantages, for instance, by increasing health literacy or insurance coverage among the poor. However, our study adds to a growing body of evidence that socioeconomic disparities in health reflect the disadvantages of not just individuals, but also of the places where they live.

From a research standpoint, this should prompt a more nuanced characterization of SES in order to disentangle individual and contextual factors and understand the root causes of socioeconomic disparities in health. Researchers who employ neighborhood-level measures to represent an individual's SES should acknowledge that such measures also capture the impact of an array of contextual factors.

From a policy standpoint, this body of evidence implies that reversing health disparities requires attention to contextual factors. Further research is needed to characterize which contextual factors underlie the association of neighborhood SES with outcomes after AMI, and with broader health outcomes. Once identified, such contextual factors will represent effective targets for public policy and interventions aimed at reducing socioeconomic disparities in health.

C. Neighborhood SES and prehospital delays in AMI

Introduction

We proceed to investigate precisely how contextual factors might impact outcomes after AMI. Such mechanisms would represent targets for public policy and interventions to reduce socioeconomic health disparities. Several explanations have been suggested, and can be categorized as related to 1) poorer health-related behaviors; 2) poorer healthcare quality and access; or 3) the direct influence of psychosocial and environmental stressors on health among individuals in low SES neighborhoods. We focus on the first category, noting that features of the social environment (e.g. local norms and attitudes toward healthcare) may have a significant impact on treatment-seeking behavior in the setting of AMI.

In particular, we hypothesize that contextual factors – as captured by neighborhood SES – influence a patient's delay to seeking treatment in the setting of AMI. The clinical importance of such a delay is well established. Both infarct size and mortality are significantly associated with total ischemic time.[40] Accordingly, quality of care efforts have succeeded in substantially reducing the time between presentation at hospital and treatment ("door-to-balloon" time) over the past several years. [41]

However, *prehospital* delays - between symptom onset and presentation - have remained constant over the same time period. [42] Over half of patients with AMI delay more than two hours before seeking treatment, and more than a quarter wait more than six hours. [43] Efforts to reduce prehospital delays through community intervention have demonstrated little efficacy. [44,45] To better target future efforts, it is important to identify groups at highest risk of prehospital delay.

Minorities may be one such risk group, though the evidence is mixed; studies have estimated greater delays, [46-50] smaller delays, [51,52] and no difference in delays [53,54] among non-whites. Similarly, multiple studies have linked low socioeconomic status (SES) with delayed treatment seeking after AMI, with highly varied effect sizes. [46,55-57] The variability in results across studies may reflect the impact of other contextual variables that vary by locale; where urban hospitals are located in lower SES neighborhoods, for instance, shorter travel times may offset other disadvantages. The largest of these studies (n=102,339) did find significant associations for both race and SES; poor white males, non-poor black males, and poor black males were 12%, 22%, and 33% more likely than non-poor white males to present >6 hours after symptom onset, respectively.[46]

Women are another such risk group. Twenty-four studies have demonstrated higher delays among women than men, while 14 showed no significant difference.[42] In the largest of these (n=482,327), women had a mean delay of 142 minutes between symptom onset and presentation, compared with 115 minutes for men.[43] To some extent, this reflects the fact that women tend to carry more of the clinical factors shown to be associated with greater delays, including atypical AMI symptoms (e.g. lack of chest pain), and comorbidities (e.g. hypertension, diabetes). [58] Delays among some women may stem from the perception that AMI is a "male disease", making them less likely to attribute acute symptoms to AMI and seek timely treatment. Studies have suggested other psychosocial factors – the tendency to live alone and utilize self-reliant coping mechanisms, for instance – that might contribute to delays in female and older patients.[59]

Surely, none of these psychosocial factors act in isolation. There is a complex interplay of clinical, psychosocial, and socioeconomic factors that drives the decision to seek treatment. For example, women commonly cite social demands and familial responsibilities, including care of grandchildren or aging parents, as reasons for ignoring symptoms.[60] These demands would likely be pronounced in a low SES setting. Similarly, the misconception of AMI as a "male disease", while surmountable through education by peers or physicians, may be particularly influential in a low SES neighborhood with limited access to primary care. In short, it is plausible that low SES potentiates the psychosocial factors that contribute to longer delays to presentation among female and older patients.

Our study focuses on the role of neighborhood context – as captured in neighborhood SES – in contributing to prehospital delays among patients with AMI. As noted above, SES may potentiate the effect of gender- and race-related factors. We have a unique opportunity to understand these interactions between gender, race, and SES by studying patients from VIRGO, a nationwide cohort which includes a large proportion of young and female patients. No prior studies have had the sample size or composition necessary to profile the effect of SES on prehospital delays in younger females; our study is the first.

In summary, our primary aim is **to measure the relative effects of individual SES and place on delays to seeking treatment for AMI.**

Methods

Patients

We utilized data from the previously described VIRGO study, which included 2985 patients enrolled at 103 US medical centers over a three-year period between 2010 and 2012.[64] We successfully performed geocoding for 95% (n= 2826) of these patients, linking each to a specific block group. The remainder (n = 159) were excluded from our analysis. We excluded additional patients according to the following criteria:

- Time of symptom onset or presentation was missing or recorded imprecisely (n = 752)
- Reported time of symptom onset was after hospital presentation (n = 22)
- Reported time of symptom onset was more than 3 days before hospital presentation (n = 42)

The above exclusion criteria left a total of 2010 patients. Of these, 35 were excluded due to missing values for other explanatory variables, leaving a total of 1975 included in our analyses.

Data

For each patient in VIRGO, we created a composite neighborhood SES score based on data from the latest American Community Survey, collected from 2005-2009, as described above. This neighborhood score reflects characteristics at the census block group level. Neighborhood SES (nSES) was defined using a single block group-level composite measure derived from census data, as described above, and represented in tertiles of low, medium, and high nSES. Having geocoded the locations of all patient addresses and presenting hospitals, we calculated the driving time between the two using Google Maps.

Other covariates included individual-level SES variables, including education and income characteristics. Educational attainment and individual income were obtained through self-report, with "low income" defined as less than $30,000 per year.

Analytic Plan

Our outcome was "long prehospital delay" defined as two or more hours between the patient-reported time of symptom onset and recorded time of presentation to the hospital. We modeled this outcome using binary logistic regression and present odds ratios (ORs) and 95% confidence intervals (CIs).

We calculated descriptive statistics and identified univariate associations between covariates and prehospital delay using chi-square and ANOVA tests. We performed multiple logistic regression to examine associations between SES variables and prehospital delay after adjustment for demographics (age, sex, race, marital status), driving time from home to hospital, MI characteristics, and baseline medical history variables as listed in Table C.1. As above, the presence of angina symptoms at baseline was assessed using the SAQ- Angina Frequency (AF) score and represented as a binary variable (SAQ AF < 100).

We tested for varying effects of SES by race and gender by building in pairwise interaction terms between neighborhood SES tertile and each race grouping (black and non-black) and gender. We did the same for individual SES, specifically building in pairwise interaction terms between low income and each race and gender.

We fit separate regression models for each race group (blacks and non-blacks) and for four race/gender categories, namely: 1) black females 2) non-black females 3) black males 4) non-black males.

Results

Baseline characteristics of patients by time between symptom onset and presentation are given in Table C.1. In bivariate analyses, blacks, married persons, those with a history of treatment for depression, and those with ST-elevation MI are more likely to present within two hours of symptom onset ($p<0.05$ for all associations). Covariates associated with longer prehospital delay ($\geq$ 2 hours) include white race, Hispanic ethnicity, low individual income (<$30,000 per year), longer driving time, and history of diabetes ($p<0.05$ for all associations). Low neighborhood SES is also associated with longer delay, but this result does not reach statistical significance ($p = 0.08$).

Tests of pairwise interactions of the SES variables with race and gender showed a significant negative interaction between low neighborhood SES and black race. None of the other pairwise interactions were significant. Interaction terms between black race and neighborhood SES tertile were retained in the full multivariate model, while other interaction terms were discarded.

Adjusted associations between SES variables and prehospital delay are given in Table C.2. In fully-adjusted models, both low individual SES (OR: 1.24 CI: 1.00 – 1.53) and low neighborhood SES (OR: 1.90 CI: 1.14 – 3.19) were significantly associated with long prehospital delays ($\geq$ 2 hours). There was no association between prehospital delay and individual educational attainment.

Subgroup analyses divided patients by race into blacks and non-blacks. Among blacks, low individual income – but not low neighborhood SES – was associated with long prehospital delay. Among non-blacks, low neighborhood SES – but not low individual income – was associated with long prehospital delay. Further subgroup analyses divided each race group according to sex; similar associations were observed, but these did not reach statistical significance.

Table C.1. Baseline characteristics of patients by prehospital delay

	Total	Delay <2 h (n= 928)	Delay ≥ 2 h (n= 1048)	p-value
Demographic characteristics				
Age, mean	47.1	47.2	47.1	0.76
Female, %	64%	63%	65%	0.33
Married or living with partner, %	56%	59%	54%	***0.029***
Race				
White, %	17%	14%	19%	***0.0062***
Asian and Pacific Islander, %	2.4%	2.6%	2.3%	0.67
Black, %	77%	80%	75%	***0.018***
Other race, %	3.6%	3.5%	3.6%	0.83
Hispanic, %	7.6%	5.9%	9.2%	***0.0069***
Individual SES characteristics				
Less than high school	1.5%	1.3%	1.7%	0.44
Some high school	41%	40%	41%	0.70
More than high school	57%	58%	57%	0.57
Low individual income (<$30,000 / year)	40%	37%	43%	***0.006***
Neighborhood characteristics				
block group w/ SES in lowest tertile, %	33%	32%	35%	0.080
block group w/ SES in middle tertile, %	33%	34%	33%	0.50
block group w/ SES in highest tertile, %	33%	34%	32%	0.28
Driving time from residence to presenting hospital (min)	18.8	18.1	19.4	***<0.0001***
AMI Characteristics				
Killip Class 3 or 4	4.8%	5.3%	4.4%	0.36
Cardiac arrest	5.7%	6.4%	5.0%	0.18

Symptoms include chest pain	89%	90%	88%	0.44
ST elevation MI	56%	64%	49%	***<0.0001***
Baseline health factors				
Prior stroke	4.5%	4.4%	4.6%	0.86
Prior CAD	22%	23%	21%	0.35
History of hypertension	65%	63%	66%	0.27
History of hypercholesterolemia	68%	66%	70%	0.080
History of diabetes	27%	23%	31%	***<.0001***
Obesity	52%	53%	51%	0.45
Reports angina at baseline (SAQ-AF < 100)	53%	52%	53%	0.57
History of treatment for depression	38%	39%	37%	***0.047***

Table C.2. Adjusted associations between socioeconomic variables and prehospital delay (≥ 2 h) in binary logistic regression, by demographic subgroup

	All patients n=1975	All blacks n=1531	Black males n=587	Black females n=944	Non-black n=444	Non-black males n=118	Non-black females n=326
Individual SES characteristics							
No high school[1]	1.01 (0.46 - 2.22)[2]	0.85 (0.31 - 2.32)	1.04 (0.24 - 4.46)	0.7 (0.17 - 2.98)	0.8 (0.21 - 3.07)	NS	0.77 (0.19 - 3.24)
More than HS graduate	1.04 (0.86 - 1.27)	1.04 (0.83 - 1.29)	1.27 (0.87 - 1.84)	0.95 (0.72 - 1.25)	1.18 (0.77 - 1.82)	2.29 (0.84 - 6.23)	0.95 (0.57 - 1.58)
Low individual income	1.24 (1.00 - 1.53)[3]	1.29 (1.00 - 1.66)	1.3 (0.85 - 1.99)	1.33 (0.97 - 1.83)	1.12 (0.72 - 1.74)	1.36 (0.51 - 3.65)	0.99 (0.58 - 1.67)

[1] High school-only is the referent group

[2] Odds ratios given for each association, with 95% confidence intervals in parentheses

[3] Statistically significant associations shaded in table

Neighborhood characteristics							
block group w/ SES in lowest tertile, %[4]	1.90 (1.14 – 3.19)	0.87 (0.66 - 1.16)	0.87 (0.55 - 1.39)	0.82 (0.57 - 1.18)	2.17 (1.24 - 3.79)	2.63 (0.86 - 8.07)	2.42 (1.21 - 4.82)
block group w/ SES in middle tertile, %	1.29 (0.73 – 2.27)	0.93 (0.72 - 1.2)	1.02 (0.67 - 1.54)	0.85 (0.61 - 1.18)	1.34 (0.75 - 2.38)	0.68 (0.21 - 2.15)	1.93 (0.94 - 3.96)
Lowest neighborhood SES tertile * black race (interaction term)[5]	0.46 (0.26 – 0.82)	-	-	-	-	-	-
Middle neighborhood SES tertile * black race (interaction term)	0.73 (0.40 – 1.35)	-	-	-	-	-	-

Discussion

We show that both neighborhood-level and patient-level SES - as represented by individual income – are independently associated with prehospital delays among young patients with AMI. We also demonstrate differential effects of socioeconomic factors according to race. Specifically, only patient-level SES, and not neighborhood SES, is associated with prehospital delays among black individuals. In contrast, only neighborhood SES, and not patient-level SES, is associated with prehospital delays among non-blacks.

The effect of patient-level SES may reflect the extent to which one is "self-reliant"- that is, drawing on one's own resources and attitudes with regard to healthcare decision making. The effect of neighborhood SES can be interpreted as the degree to which one's treatment-seeking behavior is affected by their social context. This would reflect the extent to which an individual is influenced by their community's knowledge, attitudes towards healthcare, and collective resources. For example, living in a high SES community may confer the benefit of having neighbors who know the symptoms of a heart attack and have a favorable perception of the benefits of health care. Collective neighborhood resources may help to offset specific obstacles to prompt treatment-seeking faced by patients, such as having someone to care for their children while hospitalized, having someone to drive them to the hospital, or having a safety net to rely on when illness requires periods out of work and lost income.

[4] Highest neighborhood SES tertile is the referent group

[5] All other interaction terms were non-significant and were excluded from model

Our findings are consistent with previous reports of a differential effect of SES on delays and outcomes in AMI by patient demographic. The reasons for this differential effect in our study are unclear. One possible explanation relates to "community integration". For community-level factors to exert an effect on treatment seeking requires that patients are integrated within their community. That such an effect exists for non-blacks suggests that this group may have higher levels of community integration, and thus is able to draw on collective knowledge, attitudes, and resources. Meanwhile, the prominence of the effect of patient-level SES among blacks and absence of a neighborhood-level effect may reflect greater degrees of "self-reliance" and less community integration among this demographic.

While differences in community integration are one possible explanation, further research is needed to identify the psychosocial factors that mediate these associations and determine whether they extend to other health-seeking behaviors. This may point to demographic-specific targets for interventions aimed at reducing delays in treatment-seeking.

Strengths and Limitations

Our study improves on some methodological limitations common to prior studies. Use of geocoding to ascertain each patient's immediate neighborhood of residence represents one of these improvements. Prior studies have used zip code median income as a rough proxy for a patient's SES; the imprecision inherent in this would likely bias their estimates of the effect of SES towards the null. We instead used a block group-level SES index, composed of income, employment, and education indices. As demonstrated in prior studies, this should capture the patient's living conditions more precisely and holistically, and result in more reliable estimates of the SES effect.

Geocoding of the patient's residence and hospital allows us to calculate and control for driving time – an important mediator of time to presentation that may have confounded the effect of race and SES in prior studies which fail to adjust for distance to hospital. Many patients have onset of AMI when they are not at home; for these patients, our calculated driving distance may carry some imprecision. However, as the exact location of AMI onset could not be ascertained, our home-to-hospital calculation serves as the best feasible means of controlling for this important confounder.

Interpretation

Prehospital delay is of interest both as a mediator of outcomes in AMI and as an indicator of patients' tendency to seek healthcare when in need. The decision to seek prompt care during AMI may be a proxy

for one's overall attitudes and behaviors with regard to healthcare-seeking. As such, our observed effect of SES and neighborhood context on delays in seeking care is not relevant to only AMI, but may serve to explain broader socioeconomic disparities in health outcomes. Follow-up studies are needed to determine the degree to which variations in delays to treatment seeking mediate socioeconomic disparities in outcomes for AMI and other health conditions.

Conclusions

Our investigations have employed a variety of approaches to address the fundamental question of why social class and income are strongly associated with adverse health risk factors and poorer health outcomes. Understanding precisely how SES impacts health is a prerequisite to resolving health disparities. Establishing the importance of contextual factors in driving health disparities is especially critical, as while person-level disadvantages (e.g. low income, education) are often immutable, contextual factors may be modifiable through targeted policy and interventions.

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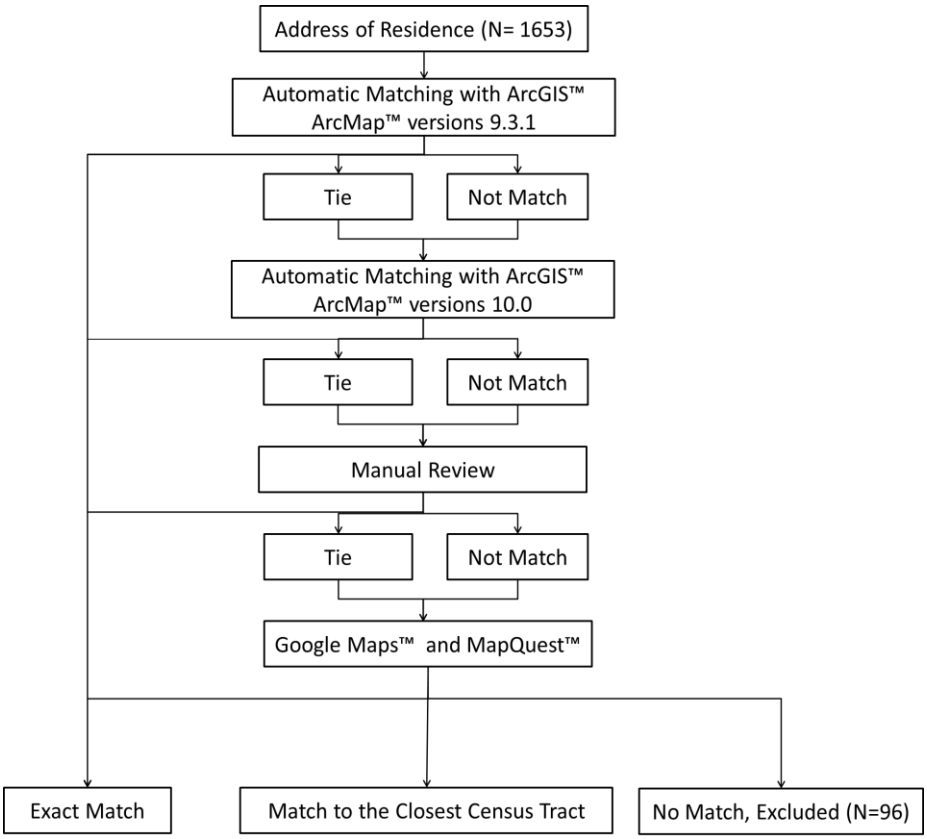
Appendix

Geocoding procedure



We used a multistep strategy for matching the geocode attributes of residences. Initially, all the residence information was entered into the automatic match process with ArcMap™ version 9.3.1. The sensitivity and specificity with which ArcMap™ suggests coordinates for entered addresses can be manually modified. Based on the automatic matching, there were three possibilities: exact match, tie; i.e. addresses for which more than one point on the map was proposed, and not-match; i.e. residence addresses for which there were no points identified in the ArcMap™ database of geocodes. We used a threshold score of ≥80 or higher (out of 100) to designate exact matches. To test the accuracy of such a cutoff, we also manually obtained the geocode coordinates for a randomly selected sample of 25 cases and received the exact coordinates as provided via the automatic matching system. Tied and unmatched addresses were entered into the automatic match process with ArcMap™ version 10.0, which includes updated information about street addresses. This process led to an incremental number of exact matches. We manually reviewed the addresses that remained tied or unmatched after two series of automatic matching.

Exact match was assigned to some of these remaining addresses after manual review, with common problems being typographic mistakes during the initial data collection leading to unrecognizable addresses in the ArcMap™ Database, and suggestion of two identical match addresses in the proposed list of ArcMap™ geocode coordinates. If the exact match could not be assigned after manual address review, we looked up the proposed residence addresses in Google Maps™ (Google Inc., Santa Clara County, CA) and MapQuest™ (MapQuest, Inc., Denver, CO) to find the exact coordinates for the residence address. If exact coordinates were not obtainable through ArcMap™, Google Maps™, or MapQuest™, attempts were made to match the address to the smallest geographical region possible, i.e. the exact geographic coordinates, block groups, or census tracts. For rare cases wherein several candidate addresses remained, we chose the candidate address that lied at the top of the ArcMap™ candidate list. If the candidate address list in ArcMap™ was blank, then we chose a candidate address in Google Maps™ or MapQuest™ that had the closest street number, and noted down its coordinates (Figure 3). Accordingly, using the derived coordinates, we determined the census tract of residence for each patient.