Psychological Science OnlineFirst, published on August 24, 2016 as doi:10.1177/0956797616658450

Research Article

Psychological Science
1–13

DOI: 10.1177/0956797616658450
pss.sagepub.com

Blacks' Death Rate Due to Circulatory Diseases Is Positively Related to Whites' Explicit Racial Bias: A Nationwide Investigation Using Project Implicit

Jordan B. Leitner[1], Eric Hehman[2], Ozlem Ayduk[1], and Rodolfo Mendoza-Denton[1]
[1]Department of Psychology, University of California, Berkeley, and [2]Department of Psychology, Ryerson University

Abstract
Perceptions of racial bias have been linked to poorer circulatory health among Blacks compared with Whites. However, little is known about whether Whites' actual racial bias contributes to this racial disparity in health. We compiled racial-bias data from 1,391,632 Whites and examined whether racial bias in a given county predicted Black-White disparities in circulatory-disease risk (access to health care, diagnosis of a circulatory disease; Study 1) and circulatory-disease-related death rate (Study 2) in the same county. Results revealed that in counties where Whites reported greater racial bias, Blacks (but not Whites) reported decreased access to health care (Study 1). Furthermore, in counties where Whites reported greater racial bias, both Blacks and Whites showed increased death rates due to circulatory diseases, but this relationship was stronger for Blacks than for Whites (Study 2). These results indicate that racial disparities in risk of circulatory disease and in circulatory-disease-related death rate are more pronounced in communities where Whites harbor more explicit racial bias.

Keywords
racial and ethnic attitudes and relations, prejudice, health, sociocultural factors, open data, open materials

Received 11/30/15; Revision accepted 6/16/16

Blacks die at a higher rate than Whites from circulatory-related diseases (e.g., heart disease; U.S. Department of Health and Human Services, 2014). Prominent theories have suggested that one cause of this disparity is that Blacks experience more discrimination, which leads to stress, which in turn has negative health consequences (Clark, Anderson, Clark, & Williams, 1999; Hatzenbuehler, Phelan, & Link, 2013; Major, Mendes, & Dovidio, 2013). Studies supporting this view have found that the perception of discrimination is associated with anxiety, cardiovascular threat response, hypertension, and mortality (Barnes et al., 2008; Mendoza-Denton, Downey, Purdie, Davis, & Pietrzak, 2002; Pascoe & Richman, 2009; Sawyer, Major, Casad, Townsend, & Mendes, 2012; Williams & Mohammed, 2009).

Although this previous work suggests that perceived racial bias contributes to disparities between Blacks' and Whites' health, less is known about whether the *actual* racial bias of Whites contributes to these disparities. A deeper understanding of links between Whites' racial bias and racial health disparities could help identify communities in greatest need of prejudice-prevention and health-promotion interventions. Therefore, the aim of the current research was to establish whether Black-White disparities in risk of circulatory disease and in circulatory-disease-related death rate are greater in communities where Whites harbor more racial bias.

Corresponding Author:
Jordan B. Leitner, University of California, Berkeley–Psychology, 3210 Tolman Hall, Berkeley, CA 94720
E-mail: jleitner@berkeley.edu

Whites' Racial Biases and Health Disparities

Previous research has contrasted two forms of racial bias: explicit and implicit bias. Explicit bias refers to deliberate, consciously controlled biases, whereas implicit bias refers to more automatic biases that are difficult to control (Greenwald, Poehlman, Uhlmann, & Banaji, 2009). Explicit and implicit racial biases are positively correlated, though research suggests that they are relatively independent constructs (Hofmann, Gawronski, Gschwendner, Le, & Schmitt, 2005). The distinction between explicit and implicit biases is supported by research showing that explicit bias predicts intentional behaviors, whereas implicit bias predicts relatively unintentional behaviors (Dovidio, Kawakami, & Gaertner, 2002).

Both explicit and implicit racial biases might contribute to racial health disparities. For instance, Whites' explicit or implicit racial bias may hinder Blacks' access to health care and thus decrease the likelihood that Blacks will receive diagnosis of and treatment for health problems. Additionally, Whites' explicit or implicit bias may contribute to hostile community environments that evoke psychological stress in Blacks, and stress has been linked to circulatory disease (Black & Garbutt, 2002). Studies consistent with these possibilities have demonstrated that Blacks show increased death rates in regions where population-level measures (i.e., survey responses from multiracial samples) reveal more explicit anti-Black attitudes (Kennedy, Kawachi, Lochner, Jones, & Prothrow-Stith, 1997; Lee, Kawachi, Muennig, & Hatzenbuehler, 2015). Similarly, Blacks die at a higher rate in regions where more racist Internet searches are conducted (Chae et al., 2015), and sexual minorities have shorter life expectancies in regions where population-level measures reveal more antigay attitudes (Hatzenbuehler, Bellatorre, et al., 2014).

Though these studies provide evidence for the pervasive effects of explicit bias, several important questions remain. First, is there a relationship between the dominant group's (e.g., Whites') negative attitudes toward a targeted group (e.g., Blacks) and the targeted group's health? Addressing this question would be important, as previous research has not disaggregated the bias of targeted and nontargeted groups. For instance, Lee et al. (2015) examined the effects of population-level anti-Black attitudes that were aggregated across all respondents (including Blacks). Similarly, Hatzenbuehler, Bellatorre, et al. (2014) examined the effects of population-level antigay attitudes that were aggregated across straight and gay respondents. Accordingly, these studies leave open the possibility that effects of population-level bias on the target group's health are driven by that group's bias against itself (e.g., Blacks' anti-Black attitudes), as opposed to nontargeted groups' bias against the target group (e.g., Whites' anti-Black attitudes).

Second, does explicit or implicit bias play a stronger role in predicting Black-White health disparities? Given that explicit and implicit biases are positively correlated (Hofmann et al., 2005), it would be important to determine whether they independently predict health disparities. Indeed, understanding the independent relationships between the various forms of bias and health could provide insight into whether explicit or implicit bias should be the target of interventions aimed at reducing health disparities.

Finally, would a relationship between racial bias and health emerge across a large number of small geographic areas? Previous research has examined relationships between bias and health outcomes in a relatively limited number of large geographic areas (Chae et al., 2015: n = 196; Hatzenbuehler, Bellatorre, et al., 2014: n = 170; Kennedy et al., 1997: n = 39; Lee et al., 2015: n = 100). Given that bias might vary within geographic units (e.g., county-to-county variation within a state), examining the effects of bias across smaller geographic areas may provide a more sensitive analysis.

To address these issues, we examined whether Black-White disparities in risk of circulatory disease (Study 1) and in rate of death due to circulatory disease (Study 2) were more pronounced in counties where Whites harbored more racial bias. We pitted explicit and implicit biases against one another to determine the stronger predictor of health outcomes.

Study 1

Data sources

Racial bias. To assess explicit and implicit racial bias, we compiled data from Project Implicit (Xu, Nosek, & Greenwald, 2014), an initiative that has measured racial bias from millions of respondents over the Internet since 2002. Project Implicit has generated the largest known repository of data on explicit and implicit bias. Though respondents are self-selected, a major strength of the data set is that their general geographic locations can be ascertained from their Internet protocol (IP) addresses.

At the time when we obtained the Project Implicit data set, it included responses made from 2002 through 2013, though only five responses (0.0001%) were from 2002. Because we examined changes in bias over time and sought reliable estimates of bias in each year, we omitted 2002 responses. Thus, our analyses included responses in the time window from 2003 through 2013. Respondents completed measures of both explicit and implicit racial bias. For the measure of explicit racial bias, community

members rated how warm they felt toward European Americans and toward African Americans, on scales from 0 (*coldest feelings*) to 10 (*warmest feelings*). We computed the difference between these responses (warmth toward European Americans minus warmth toward African Americans) and operationalized pro-White explicit bias as more reported warmth toward European Americans compared with African Americans.

The measure of implicit racial bias was an Implicit Association Test (IAT), a speeded dual-categorization task in which respondents categorized social targets (e.g., Black and White faces) and verbal targets (e.g., words referring to "good" and "bad" things) by key press. Faster responses when White faces and "good" things (and Black faces and "bad" things) required the same key press, as compared with the inverse pairing, reflect pro-White implicit attitudes (Greenwald et al., 2009). The IAT was scored according to the *D* measure (Greenwald, Nosek, & Banaji, 2003). Explicit and implicit bias at the county level were positively related, $r = .25$, $p < .0001$.

Within the Project Implicit data set, we identified White respondents for whom the county where they completed the measures was known: 1,391,632 responses from 1,836 counties met these inclusion criteria (M = 759.57 responses per county, SD = 1,766.10). Counties were defined according to the February 2013 Federal Information Processing Standard (FIPS) county codes of the U.S. Census Bureau's (2013) Metropolitan and Micropolitan Delineation Files.

A limitation of the Project Implicit data set is that it was obtained with convenience sampling, and thus the sample for a given county may not be representative of all individuals in that county. One dimension on which the Project Implicit sample was likely nonrepresentative was age: Whereas the median age for all Project Implicit respondents was 23, the national median age was 37, according to the Median Age by Sex report from the U.S. Census Bureau's 2009–2013 American Community Survey (ACS).[1] Estimating the racial bias of older nonrespondents would be important, given that racial bias is significantly greater among older individuals (Gonsalkorale, Sherman, & Klauer, 2009). Accordingly, we used poststratification weights that assigned greater weight to respondents the more representative they were of the age distribution of their community's population (cf. Lohr, 2009). We employed the following poststratification weighting scheme. First, separately for explicit and implicit bias, we computed average racial-bias scores for five age groups in each county: 15–24, 25–34, 35–54, 55–75, and 75+. Second, we determined the population count of Whites in each of these age groups in each county using the Sex by Age (White Only) reports from the U.S. Census Bureau's 2005–2009 and 2009–2013 ACSs. Third, for each county, we computed estimates for explicit and implicit racial bias that were weighted by the White population count in each age group in that county. The result of this weighting scheme was that respondents were assigned a greater weight when they belonged to an age group that was more populous in their county. We report findings obtained using this weighting scheme, but our conclusions were identical when we used unweighted county averages (see the Supplemental Material available online).

Although the racial-bias measure was limited to an 11-year window, we believe that it served as a reasonable proxy for prejudice before and after this time period. Supporting this notion, fixed-effects models revealed that year (treated as a factor) accounted for only 1% of the variance in explicit bias and 2% of the variance in implicit bias. In contrast, county (treated as a factor) accounted for 42% of the variance in explicit bias and 27% of the variance in implicit bias. Thus, year-to-year change in bias was minimal, whereas counties differed considerably in their levels of bias. Moreover, previous work has demonstrated that racial bias is highly stable over time, even following a historic event (i.e., Barack Obama's rise to the presidency; Schmidt & Nosek, 2010).

Accordingly, we included racial-bias estimates from 2013, even though data from the previous year were used to calculate our outcome measures of risk of circulatory disease (see the next section). The advantage of including racial-bias responses from 2013 was that it maximized the sample (i.e., 8% of all responses in the data set were from 2013), thereby increasing the reliability of the racial-bias estimates. Nevertheless, when we used racial-bias data from 2003 through 2012 only, the pattern of findings was extremely similar to what we report here (see the Supplemental Material).

Risk of circulatory disease. To estimate risk of circulatory disease, we compiled data from the 2012 Selected Metropolitan/Micropolitan Area Risk Trends (SMART) of the Behavioral Risk Factor Surveillance System survey, a telephone survey in which participants were asked about their health risk factors (Centers for Disease Control and Prevention, CDC, 2013). We targeted two factors related to circulatory-disease risk.

First, we examined participants' response to the question, "Was there a time in the past 12 months when you needed to see a doctor but could not because of cost?" We coded "yes" responses as 0 and "no" responses as 1. Thus, when aggregated at the county level, responses to this question provided an estimate of the percentage of county residents who had access to affordable health care.

Second, to determine the percentage of respondents who had been diagnosed with circulatory diseases, we examined responses to two questions: "Has a doctor, nurse, or other health professional ever told you that you

had a heart attack, also called a myocardial infarction?" and "Has a doctor, nurse, or other health professional ever told you that you had angina or coronary heart disease?" We coded "yes" responses as 1 and "no" responses as 0. Responses to these items were strongly related for both Blacks, $r = .66$, $p < .0001$, and Whites, $r = .77$, $p < .0001$. For parsimony, we averaged responses to these two items. When aggregated at the county level, these averages provided an estimate of the percentage of county residents who had received these diagnoses.

In total, 23,522 Blacks from 208 counties and 175,637 Whites from 210 counties completed the health survey (White responses per county: $M = 836.37$, $SD = 591.07$; Black responses per county: $M = 113.09$, $SD = 193.83$). We aggregated responses by race and county to arrive at separate point estimates for the percentages of Whites and Blacks with access to health care and with circulatory-disease diagnoses. Figure 1a shows the location of the 205 counties for which we had estimates of Whites' racial bias and SMART-survey responses from both Blacks and Whites.

Race. Participants reported their race on the SMART survey. Race was coded as 0 for Black and 1 for White.

Covariates

Sex and age. Participants reported their sex and age (in years) on the SMART survey. Sex was coded as −1 for male and 1 for female.

Population. Population estimates by race and county were derived from the modified counts for 2010 from the following U.S. Census Bureau report: Annual Estimates of the Resident Population by Sex, Race Alone or in Combination, and Hispanic Origin for the United States, States, and Counties: April 1, 2010 to July 1, 2013. From these data, we computed the *total population* (the sum of Blacks and Whites) and the *Black-to-White ratio* of the population for each county in 2010. To produce unstandardized regression coefficients that were interpretable, we log-transformed the total-population estimates (but not the Black-to-White ratios).

Education. County-level education was assessed by averaging the high school graduation rates for Blacks and Whites (data taken from the U.S. Census Bureau's 2009–2013 ACS: report titled Sex by Educational Attainment for the Population 25 Years and Over).

Income, unemployment, and poverty. County-level income, unemployment, and poverty were assessed by compiling data for Whites and Blacks from the 2005–2009 and 2009–2013 ACSs (income data were taken from the reports titled Median Household Income in the Past 12 Months (Householder), unemployment data were taken from the reports titled Employment Status, and poverty data were taken from the reports titled Poverty Status in the Past 12 Months by Sex and Age). County-level income was estimated by averaging the median household income for Whites and Blacks. County-level unemployment was estimated by averaging the unemployment rates for Whites and Blacks. County-level poverty was estimated by averaging the poverty rates for Whites and Blacks. So that unstandardized coefficients would be interpretable, we divided income values by 10,000.

Segregation. County-level racial segregation was indexed via dissimilarity, an estimate of the percentage of non-Hispanic Whites who would have to move to another census tract within the same county in order to achieve racial integration with non-Hispanic Blacks. Dissimilarity indices at the county level were provided by J. Dewitt (personal communication, December 15, 2015) and were based on methods described in Frey and Meyers (2005). We averaged dissimilarities from 2000 and 2010, so that each county had one value of dissimilarity.

Geographic mobility. A relationship between racial bias and Black-White health disparities could be driven by social selection forces. Specifically, rather than reflecting an effect of racial bias, health disparities could be due to more healthy Blacks selecting to live in environments with lower bias or to sick Blacks selecting to live in high-bias environments. Accordingly, we accounted for geographic mobility, as has been done in previous work (Hatzenbuehler, Jun, Corliss, & Austin, 2014). The U.S. Census Bureau's 2005–2009 and 2009–2013 ACSs provided estimates of the percentage of Blacks in each county who moved into that county during the previous year (a) from a different county in the same state, (b) from a different state, and (c) from abroad (data taken from the reports titled Geographic Mobility by Selected Characteristics in the United States). For each county, we summed these three percentages in each time window and then averaged the two sums to obtain a single index of *geographic mobility*.

Housing density. To capture where each county fell on the continuum from rural to urban, we assessed housing density, the number of housing units per square mile. For each county, we averaged housing-density values across the U.S. Census Bureau's 2000 and 2010 Population, Housing Units, Area, and Density reports.

Age bias. To examine whether any effects were specific to racial bias, or generalized to bias on nonracial dimensions, we used Project Implicit's age-bias data from 2003 through 2013. Project Implicit's indices of age bias

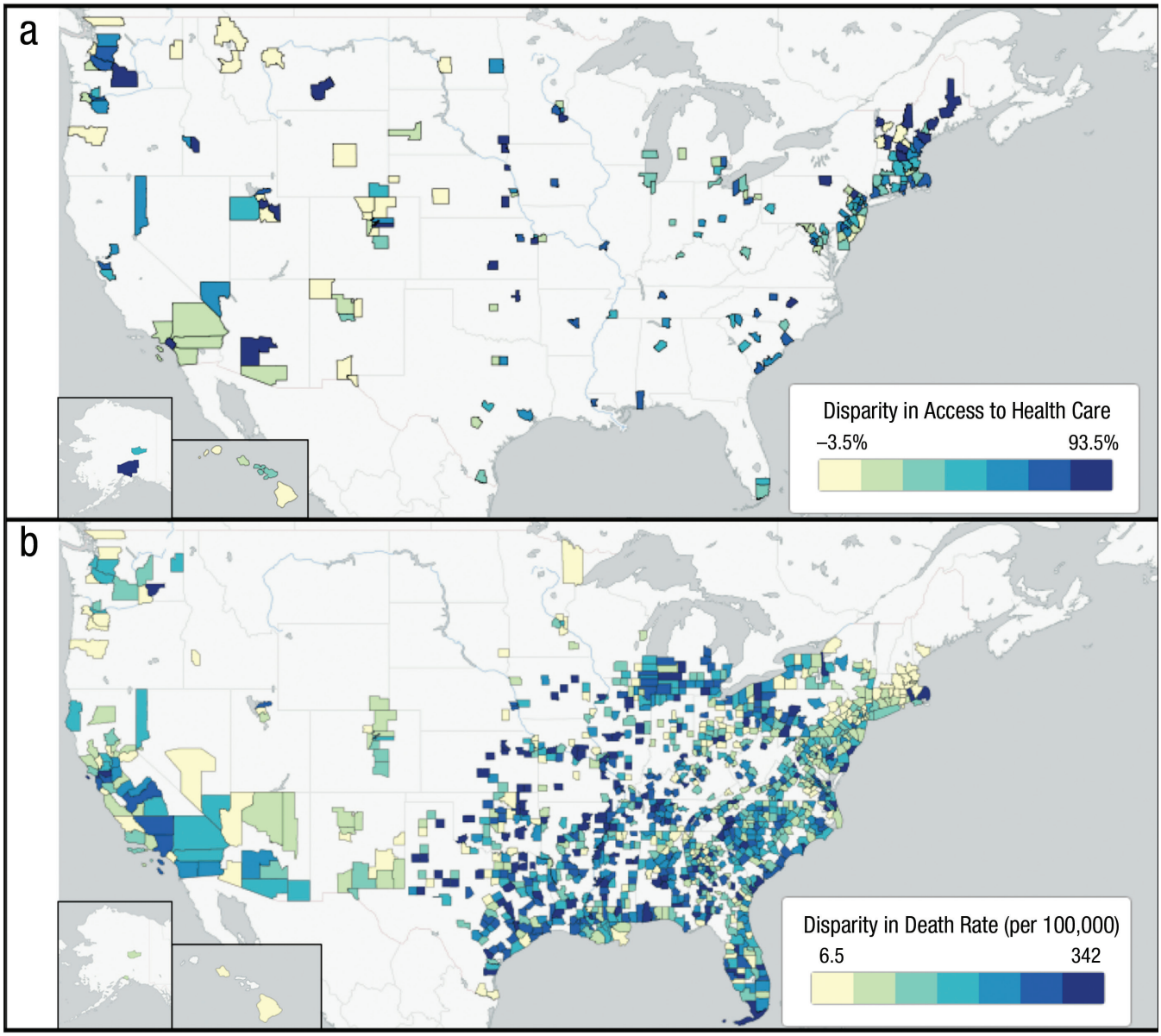

Fig. 1. Results for racial disparities in (a) access to affordable health care (Study 1) and (b) death rate (per 100,000) due to circulatory diseases (Study 2). In (a), darker colors indicate counties where Whites reported greater access to health care than Blacks; in (b), darker colors indicate counties where Blacks died from circulatory diseases at a higher rate than Whites did. For interactive versions of these maps, visit www.jordanbleitner.com/maps.

paralleled those for race bias. Implicit age bias was indexed with an IAT (respondents categorized young and old faces and "good" and "bad" words), and explicit age bias was indexed with feeling thermometers for young and old people (explicit age bias was computed as warmth toward young people minus warmth toward old people). This data set contained 585,242 geo-coded responses from 1,850 counties (M = 316.35 responses per county, SD = 777.29). We estimated county-level implicit age bias and explicit age bias following the same procedures used to compute race bias.

Results

To determine whether Whites' explicit or implicit racial bias (as measured by Project Implicit) independently predicted health risk for Blacks and Whites, we employed generalized estimating equations (GEEs). We analyzed the data using GEEs with robust standard errors in light of the minimal distributional assumptions they require and their robustness to misspecification in large samples (Hubbard et al., 2010). Our conclusions do not depend on the decision to use GEEs; effects for all analyses were

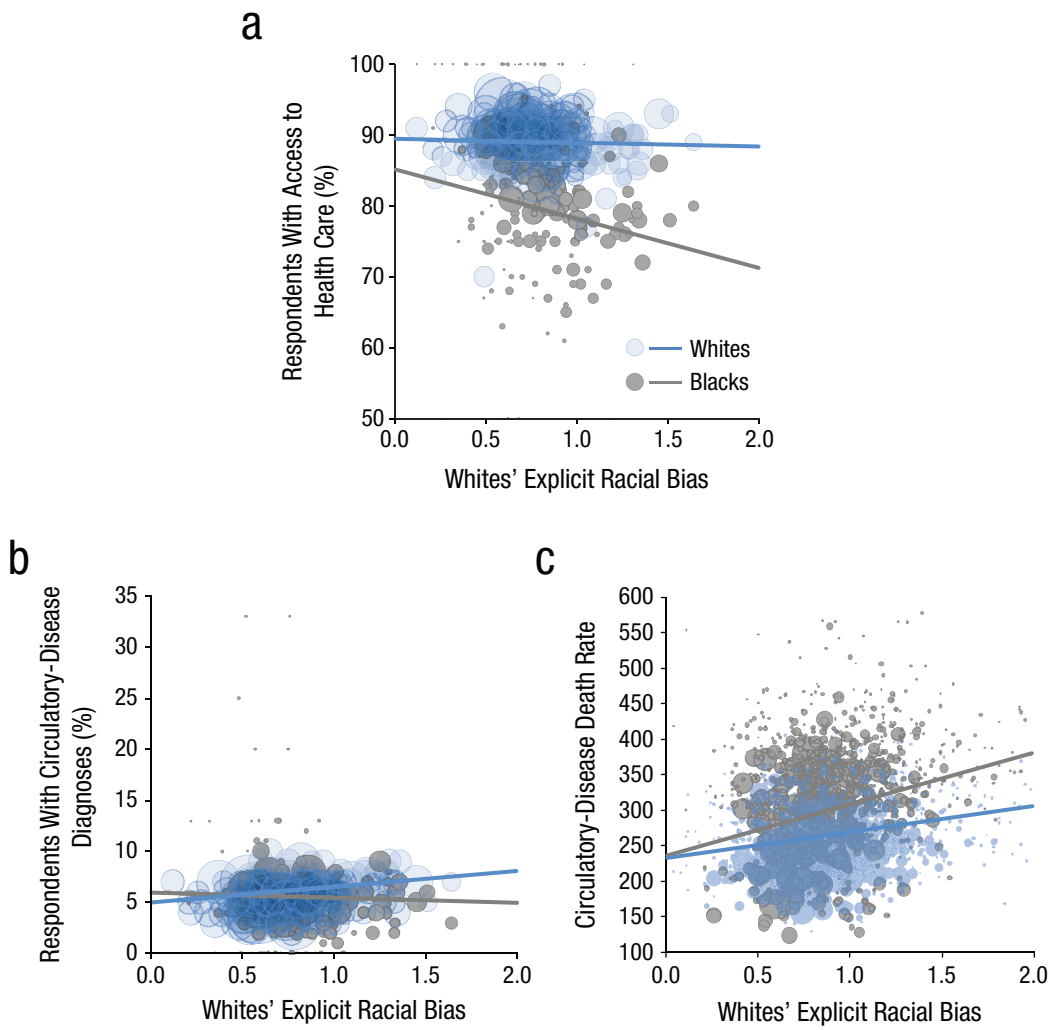

Fig. 2. Bubble plots showing the county-level relationships between average explicit racial bias of White respondents and (a) the percentage of respondents with access to affordable health care (Study 1), (b) the percentage of respondents with diagnoses of circulatory disease (Study 1), and (c) the age-adjusted rate of death due to circulatory diseases (deaths per 100,000; Study 2). The size of each plotted circle is proportionate to the number of respondents in that county. The lines are the best-fitting regression lines before covariates were entered in the model. For visualization purposes only, counties with values that deviated from the mean by more than 2.5 *SD* are not shown in the graphs in (a) and (c) (2% of counties, but see the Supplemental Material for plots that include these counties), and the graph in (c) does not show counties that had fewer than 50 responses on the racial-bias measure (the bubbles would be too small to visualize).

similar when estimated with mixed linear models. All predictors were mean-centered unless otherwise noted. The number of responses on the health survey varied across counties, and we conjectured that our county-level health estimates were more accurate in counties where more participants completed the survey. Therefore, we weighted counties by the number of responses on the health survey. To isolate the effects of race and bias, we controlled for age, sex, and all the county-level covariates described in the Method section (total population, Black-to-White ratio of the population, education, income, unemployment, poverty, segregation, geographic mobility, housing density explicit age bias, and implicit age bias).

Access to health care. Figure 2a shows the relationship between Whites' explicit racial bias and Whites' and Blacks' access to affordable health care before accounting for covariates. To test whether Black-White disparities in access to health care were more pronounced in counties where White respondents showed more racial bias, even after controlling for county-level covariates, we

Table 1. Results of the Generalized Estimating Equation Analysis Predicting Access to Affordable Health Care in Study 1

Effect	*b*	*SE*	*z*	*p*
Race (Black = 0, White = 1)	0.057	0.008	7.479	< .0001
Explicit racial bias	–0.064	0.025	2.563	.0103
Implicit racial bias	0.237	0.153	1.546	.1220
Race × Explicit Racial Bias	0.061	0.023	2.668	.0076
Race × Implicit Racial Bias	–0.148	0.140	1.058	.2909
Sex (male = −1, female = 1)	–0.010	0.003	3.211	.0013
Age	0.006	0.001	5.256	< .0001
Total population	–0.012	0.014	0.894	.3711
Black-to-white ratio	–0.037	0.036	1.025	.3066
Education	–0.164	0.161	1.020	.3078
Income	0.018	0.007	2.458	.0140
Segregation	0.051	0.056	0.906	.3657
Geographic mobility	0.001	0.002	0.436	.6637
Unemployment	–0.001	0.002	0.387	.6989
Poverty	–0.002	0.002	0.860	.3899
Housing density	< 0.001	< 0.001	1.249	.2117
Explicit age bias	–0.023	0.030	0.762	.4456
Implicit age bias	0.103	0.112	0.922	.3575
Race × Sex	–0.004	0.003	1.245	.2139
Race × Age	–0.002	0.001	1.939	.0524
Race × Total Population	0.003	0.014	0.224	.8197
Race × Black-to-White Ratio	0.028	0.033	0.860	.3912
Race × Education	0.322	0.158	2.042	.0411
Race × Income	< 0.001	< 0.001	< 0.001	.9661
Race × Segregation	–0.057	0.051	1.122	.2609
Race × Geographic Mobility	–0.001	0.002	0.735	.4624
Race × Unemployment	–0.001	0.002	0.520	.6033
Race × Poverty	0.005	0.002	2.648	.0081
Race × Housing Density	< 0.001	< 0.001	< 0.001	.9952
Race × Explicit Age Bias	0.047	0.028	1.688	.0916
Race × Implicit Age Bias	–0.032	0.110	0.300	.7691

Note: Data from 204 counties were included in the analysis. Pseudo-R^2 for the model was .62.

regressed the percentage of respondents who had access to affordable health care on race, explicit racial bias, implicit racial bias, the Race × Explicit Racial Bias interaction, the Race × Implicit Racial Bias interaction, all covariates, and the interactions between the covariates and race (Table 1). The significant effect of explicit racial bias was qualified by the Race × Explicit Racial Bias interaction. Simple-slopes analyses indicated that increased explicit racial bias predicted decreased access to health care for Blacks, $b = -0.064$, $SE = 0.025$, $z = 2.563$, $p = .0103$, but this relationship was not significant for Whites, $b = -0.003$, $SE = 0.011$, $z = 0.300$, $p = .7587$. With all covariates included in the analysis, in counties with high (1 *SD* above the mean) explicit racial bias, Blacks were 8% less likely than Whites to report access to affordable health care. In contrast, in counties with low (1 *SD* below the mean) explicit racial bias, Blacks were 3% less likely than Whites to report access to affordable health care.

Notably, these analyses controlled for multiple socioeconomic indices, so socioeconomic status did not appear to account for the link between explicit racial bias and the racial disparity in access to health care. In contrast to explicit racial bias, implicit racial bias was unrelated to access to health care. Furthermore, given that the effects of age bias were not significant, the results suggest that racial bias specifically predicted Black-White disparities in access to health care. We report simple slopes for the significant interactions with covariates in the Supplemental Material. Sex did not further moderate the Race × Explicit Race Bias interaction, $p = .4964$.

Circulatory-disease diagnoses. Figure 2b shows the relationship between Whites' explicit racial bias and Blacks' and Whites' rate of self-reported circulatory diseases before accounting for covariates. To test whether, after accounting for covariates, Black-White disparities in diagnoses of circulatory diseases were more pronounced in counties where White respondents showed more racial bias, we regressed the percentage of participants in each county who reported receiving such diagnoses on the same predictors as in the model for access to health care (Table 2). The model with all covariates included showed that Blacks, compared with Whites, were more likely to receive diagnoses of circulatory diseases. However, neither explicit nor implicit racial bias was significantly related to the percentage of respondents with diagnoses of circulatory diseases. Moreover, neither the Race × Explicit Racial Bias interaction nor the Race × Implicit Racial Bias interaction was significant. Thus, even though greater explicit racial bias corresponded with increased Black-White disparities in access to affordable health care, greater explicit racial bias was not related to increased Black-White disparities in diagnoses of circulatory diseases.

Discussion

The Black-White disparity in access to affordable health care was more pronounced in counties where Whites harbored more explicit racial bias. However, explicit racial bias did not predict racial disparities in the percentage of respondents with circulatory-disease diagnoses. One potential explanation for this null effect is that Blacks in more biased counties

Table 2. Results of the Generalized Estimating Equation Analysis Predicting Circulatory-Disease Diagnoses in Study 1

Effect	*b*	*SE*	*z*	*p*
Race (Black = 0, White = 1)	–0.008	0.003	2.890	.0038
Explicit racial bias	–0.003	0.007	0.436	.6642
Implicit racial bias	0.023	0.038	0.592	.5534
Race × Explicit Racial Bias	0.010	0.007	1.327	.1847
Race × Implicit Racial Bias	–0.019	0.040	0.480	.6314
Sex (male = –1, female = 1)	–0.006	0.001	4.157	< .0001
Age	0.003	< 0.001	9.501	< .0001
Total population	0.002	0.004	0.346	.7248
Black-to-White ratio	0.004	0.009	0.412	.6772
Education	–0.001	0.052	< 0.001	.9899
Income	–0.004	0.002	2.345	.0190
Segregation	0.015	0.014	1.072	.2830
Geographic mobility	0.001	< 0.001	1.817	.0693
Unemployment	< 0.001	0.001	0.346	.7324
Poverty	< 0.001	0.001	0.693	.4896
Housing density	< 0.001	< 0.001	1.400	.1615
Explicit age bias	0.007	0.007	0.964	.3356
Implicit age bias	–0.022	0.036	0.600	.5467
Race × Sex	–0.015	0.002	9.221	< .0001
Race × Age	< 0.001	< 0.001	0.917	.3600
Race × Total Population	–0.008	0.005	1.775	.0761
Race × Black-to-White Ratio	0.004	0.012	0.300	.7609
Race × Education	–0.065	0.052	1.249	.2115
Race × Income	0.001	0.002	0.520	.6051
Race × Segregation	–0.014	0.014	1.005	.3145
Race × Geographic Mobility	–0.001	< 0.001	2.406	.0161
Race × Unemployment	< 0.001	0.001	< 0.001	.9708
Race × Poverty	–0.001	0.001	1.459	.1444
Race × Housing Density	< 0.001	< 0.001	0.300	.7661
Race × Explicit Age Bias	–0.008	0.008	1.077	.2810
Race × Implicit Age Bias	0.036	0.041	0.872	.3821

Note: Data from 204 counties were included in the analysis. Pseudo-R^2 for the model was .73.

were less likely to see a health-care provider even if they were sick. If this were the case, it is possible that Blacks would have a higher death rate due to circulatory diseases in communities where Whites harbored more explicit racial bias. We tested this possibility in Study 2.

Study 2

In Study 2, we examined whether the Black-White disparity in rate of death due to circulatory diseases was more pronounced in counties where Whites harbored more racial bias.

Data sources

Racial bias. Explicit and implicit racial biases were estimated with the methods described for Study 1.

Death rate. Death records for Blacks and Whites were obtained from the CDC (2014). Specifically, we examined rates (per 100,000) of death from circulatory diseases (e.g., heart disease; Internal Statistical Classification of Diseases and Related Health Problems codes I00–I99) in 2003 through 2013. Circulatory diseases are the leading cause of death in the United States and have shown pervasive racial disparities in prevalence over time (U.S. Department of Health and Human Services, 2014). To account for potential age differences between counties and racial groups and allow for more meaningful comparisons, we used age-adjusted death rates. To derive these age-adjusted rates, we used the default 2000 U.S. standard population detailed in Anderson and Rosenberg (1998).

We aggregated the data across males and females, given that sex did not moderate the effects of bias in Study 1, and aggregation minimized missing data (i.e., aggregated data were less likely to be suppressed by the CDC than were separated data for males and females). We were able to obtain death rates for Whites in 3,110 counties and death rates for Blacks in 1,490 counties. Data were unavailable for counties recording fewer than 10 deaths for a given group. Figure 1b shows the location of the 1,149 counties for which we obtained racial-bias data and death-rate data for both Blacks and Whites.

To determine whether racial bias predicted Black-White disparities in deaths from causes other than circulatory diseases, we used the CDC (2014) data set to compile county-level data on age-adjusted rates of death due to neoplasm (e.g., cancer) for 2003 through 2013. We focused on death due to neoplasm because neoplasms are the second most prevalent cause of death in the United States (U.S. Department of Health and Human Services, 2014).

To isolate effects of interest, we incorporated the same set of county-level covariates used in Study 1, except for sex (because death rates were aggregated across males and females) and age (because death rates were already age adjusted).

Results

As in Study 1, we used GEEs to estimate all effects. Data from a given county were weighted in the analyses by the number of respondents who completed the racial-bias measure in that county. As in Study 1, race was coded as 0 for Black and 1 for White, and all other predictors were mean-centered.

Figure 2c shows the relationship between Whites' explicit racial bias and Blacks' and Whites' death rates due to circulatory diseases before accounting for covariates. To test whether racial disparities in death rate due to circulatory diseases were more pronounced in counties where White respondents showed greater racial bias, even after controlling for a set of county-level covariates, we regressed circulatory-disease-related death rate on race, explicit racial bias, implicit racial bias, the Race × Explicit Racial Bias interaction, the Race × Implicit Racial Bias interaction, all covariates, and the interactions between race and the covariates (Table 3). The effect of explicit racial bias was qualified by the Race × Explicit Racial Bias interaction. Simple-slopes analyses indicated that the relationship between explicit racial bias and rate of death due to circulatory diseases was positive for both Blacks and Whites, but stronger for Blacks, $b = 43.200$, $SE = 12.100$, $z = 3.559$, $p = .0004$, than for Whites, $b = 13.900$, $SE = 4.970$, $z = 2.795$, $p = .0052$. As in Study 1, the Race × Explicit Racial Bias interaction was significant over and above the effects of age bias, which suggests that racial bias specifically was related to Black-White disparities in death rate. Neither the main effect for implicit racial bias nor the Race × Implicit Racial Bias interaction was significant.

With all covariates included in the model, in counties with high (1 *SD* above the mean) explicit racial bias, the difference between Blacks' and Whites' death rates was 62 deaths per 100,000. In contrast, in counties with low (1 *SD* below the mean) explicit bias, the difference was 35 deaths per 100,000. Furthermore, adjusting for all covariates, we estimated how many more Blacks died of circulatory-related diseases annually in counties that were high (1 *SD* above the mean), rather than low (1 *SD* below the mean), in explicit racial bias. We made this estimate at the average Black population level in counties for which we had death-rate data for Blacks (average Black population = 28,598); 11 more Blacks per county were predicted to die annually in high-explicit-bias counties (95 deaths) than in low-explicit-bias counties (84 deaths).

To determine whether similar effects would emerge for death rate not due to circulatory diseases, we regressed

Table 3. Results of the Generalized Estimating Equation Analysis Predicting Death Rate Due to Circulatory Diseases in Study 2

Effect	*b*	*SE*	*z*	*p*
Race (Black = 0, White = 1)	–48.400	7.000	6.917	< .0001
Explicit racial bias	43.200	12.100	3.559	.0004
Implicit racial bias	64.400	56.100	1.149	.2513
Race × Explicit Racial Bias	–29.300	11.700	2.500	.0124
Race × Implicit Racial Bias	–3.810	54.800	0.000	.9445
Total population	–9.390	10.300	0.917	.3602
Black-to-White Ratio	92.300	25.400	3.632	.0003
Education	–176.000	99.700	1.769	.0769
Income	–8.200	4.140	1.982	.0475
Segregation	19.000	12.700	1.493	.1350
Geographic mobility	–2.500	0.485	5.146	< .0001
Unemployment	2.140	1.180	1.817	.0695
Poverty	1.570	0.935	1.676	.0934
Housing density	< 0.001	< 0.001	< 0.001	.9762
Explicit age bias	–16.400	8.870	1.849	.0645
Implicit age bias	24.600	47.000	0.520	.6005
Race × Total Population	–2.560	8.560	0.300	.7647
Race × Black-to-White Ratio	–63.900	32.700	1.954	.0506
Race × Education	–17.600	88.700	0.200	.8431
Race × Income	0.313	4.140	0.100	.9397
Race × Segregation	–6.610	11.700	0.566	.5730
Race × Geographic Mobility	2.020	0.462	4.374	< .0001
Race × Unemployment	–0.852	1.130	0.755	.4518
Race × Poverty	–2.180	0.868	2.508	.0122
Race × Housing Density	< 0.001	0.001	0.583	.5580
Race × Explicit Age Bias	–1.170	8.480	0.141	.8903
Race × Implicit Age Bias	34.000	40.000	0.849	.3955

Note: Data from 1,776 counties were included in the analysis. Pseudo-R^2 for the model was .42.

rate of death due to neoplasm on the same predictors as in our analyses of deaths due to circulatory diseases. Neither the main effect of explicit racial bias nor the Race × Explicit Racial Bias interaction was significant, *p*s > .14. Moreover, when we modeled neoplasm death rate as a covariate in the model predicting death rate due to circulatory diseases, the Race × Explicit Racial Bias interaction remained significant, $b = -21.100$, $SE = 9.240$, $z = 2.283$, $p = .0224$. These findings suggest that that the relationship between explicit racial bias and death rate was specific to circulatory-related, and not neoplasm-related, disease. (See the Supplemental Material for additional analyses.)

Discussion

In counties where White respondents harbored more explicit racial bias, the rate of death from circulatory disease was increased for both Whites and Blacks. However, Whites' explicit racial bias predicted this death rate more strongly for Blacks than for Whites. As in Study 1, explicit racial bias, compared with implicit racial bias, was a stronger predictor of Black-White health disparity.

General Discussion

In counties where White Project Implicit respondents harbored more explicit racial bias, Black-White disparities in access to affordable health care (Study 1) and rate of death due to circulatory diseases (Study 2) were more pronounced. The robustness of these findings was evidenced by the replication of the same pattern across two independent data sets that both included a large number of counties. Although the effects could have been driven by an unmeasured third variable, the fact that racial bias was a significant predictor in models with a large set of covariates supports the notion of a direct relationship between Whites' racial bias and Black-White health disparities.

To our knowledge, this is the first research to show that racial bias from a dominant group (e.g., Whites) predicts negative health outcomes more strongly for the target group (e.g., Blacks) than for the dominant group. These results are consistent with research that has shown that population-level bias (i.e., antigay attitudes), when aggregated across targeted and nontargeted groups, predicts negative health outcomes more strongly for the targeted than the nontargeted group (Hatzenbuehler, Bellatorre, et al., 2014). However, the current results extend this previous work, which did not directly address the issue of whether the effects were driven by the dominant group's stigmatization of the targeted group or the targeted group's self-stigmatization. Furthermore, by demonstrating a relationship between Whites' racial biases and health outcomes of Blacks in the same community, these results support previous findings that Blacks' subjective perceptions of racism are linked to their own health (Pascoe & Richman, 2009; Williams & Mohammed, 2009). However, because perceptions of racism can be shaped by race-based rejection sensitivity (Mendoza-Denton et al., 2002), we extended this previous work by measuring racial bias directly from Whites.

Additionally, to our knowledge, this is the first research to use geo-coded data on implicit bias to examine whether racial health disparities are more pronounced in communities where Whites show more implicit bias. Notably, when implicit bias was modeled without explicit bias, it showed patterns similar to those for explicit bias (see Tables S4 and S6 in the Supplemental Material), but when explicit and implicit biases were modeled together, only explicit bias predicted health outcomes. The null effects of implicit bias are informative, as research is increasingly focusing on the predictive utility of implicit bias in medical contexts (e.g., Hall et al., 2015), and it is important to identify the outcomes that are more strongly related to explicit than to implicit bias. One potential explanation for why Whites' explicit bias was a stronger predictor than their implicit bias in the current work is that explicit bias has historically exerted stronger effects on the structural factors (e.g., regulation of environmental pollution) and psychological factors (e.g., overtly negative interracial interactions) that ultimately shape health outcomes.

One limitation of this research is that the respondents who completed Project Implicit's racial-bias measures might not have been representative of their counties on all dimensions. For instance, Project Implicit respondents might not reflect racial biases of older community members. Though we employed a poststratification weighting scheme designed to circumvent this limitation, no amount of poststratification weighting can make a sample truly representative on all dimensions. Thus, future research should examine whether the observed effects remain when bias is measured with full probability sampling.

Another limitation is that we did not have data on the geographic mobility of specific individuals for whom we assessed health outcomes. It is possible that the deceased in Study 2 had moved to their communities soon before their deaths and had died before the racial bias of their communities had any effect on their health. However, two lines of evidence suggest that this scenario occurs relatively infrequently. First, 95% of the people who died from circulatory-disease-related causes were over age 55 (CDC, 2014), and the median duration of residency for people in this age group is more than 11 years (Mateyka & Marlay, 2011). Second, when people of this age do move, they are more likely to move to another residence within the same county than to a different county (data from the U.S. Census Bureau's 2009–2013 ACS: report titled Geographic Mobility by Selected Characteristics in the United States). Together, this evidence suggests that many people are geographically stable in the years leading to their death. Nevertheless, future research might further examine the role of geographic mobility in the relationship between racial bias and health.

The finding that Whites' circulatory-disease-related death rate was increased in counties where White respondents harbored greater explicit bias is consistent with research showing that racial bias is linked to negative health outcomes for Whites (Kennedy et al., 1997; Lee et al., 2015; Mendes, Gray, Mendoza-Denton, Major, & Epel, 2007). One explanation for this finding, suggested by recent research (Lee et al., 2015), is that highly biased communities have decreased social capital (i.e., trust and bonding between community members), which in turn predicts negative health outcomes.

Though the current research does not establish that White respondents' racial bias caused the observed health disparities between Whites and Blacks, the relationships between Whites' racial bias and Black-White health disparities were independent of a large set of county-level socio-demographic characteristics. Thus, our findings raise compelling questions about the mechanisms through which Whites' racial bias can be related to health outcomes. On the basis of existing theoretical frameworks (Clark et al., 1999; Hatzenbuehler et al., 2013; Major et al., 2013), we posit that multiple causal pathways might account for this relationship. These pathways might include structural (e.g., discrimination in health care), interpersonal (e.g., hostile interactions), emotional (e.g., stress), and behavioral (e.g., maladaptive coping) processes that catalyze biological systems that increase disease risk. We hope that the current work serves to generate future research examining why there is a relationship between racial bias and health.

Action Editor

Jamin Halberstadt served as action editor for this article.

Author Contributions

J. B. Leitner, E. Hehman, and R. Mendoza-Denton developed the theoretical framework. J. B. Leitner conducted the analyses and drafted the manuscript. All the authors provided critical revisions and approved the final version of the manuscript.

Acknowledgments

We are grateful to Doc Edge for providing insight into our statistical analyses.

Declaration of Conflicting Interests

The authors declared that they had no conflicts of interest with respect to their authorship or the publication of this article.

Funding

This research was supported by the National Science Foundation under Award Numbers 1306709 (to R. Mendoza-Denton and O. Ayduk) and 1514510 (to O. Ayduk and J. B. Leitner), and by a Social Sciences and Humanities Research Council Institutional Grant (to E. Hehman).

Supplemental Material

Additional supporting information can be found at http://pss.sagepub.com/content/by/supplemental-data

Open Practices

All data and materials have been made publicly available via the Open Science Framework and can be accessed at https://osf.io/5ybhd/. The complete Open Practices Disclosure for this article can be found at http://pss.sagepub.com/content/by/supplemental-data. This article has received badges for Open Data and Open Materials. More information about the Open Practices badges can be found at https://osf.io/tvyxz/wiki/1.%20View%20the%20Badges/ and http://pss.sagepub.com/content/25/1/3.full.

Note

1. Unless otherwise noted, all data from the U.S. Census Bureau were downloaded from factfinder.census.gov.

References

Anderson, R. N., & Rosenberg, H. M. (1998). Age standardization of death rates: Implementation of the year 2000 standard. *National Vital Statistics Reports*, *47*(3), 1–17.

Barnes, L. L., Mendes De Leon, C. F., Lewis, T. T., Bienias, J. L., Wilson, R. S., & Evans, D. A. (2008). Perceived discrimination and mortality in a population-based study of older adults. *American Journal of Public Health*, *98*, 1241–1247. doi:10.2105/AJPH.2007.114397

Black, P. H., & Garbutt, L. D. (2002). Stress, inflammation and cardiovascular disease. *Journal of Psychosomatic Research*, *52*, 1–23. doi:10.1016/S0022-3999(01)00302-6

Centers for Disease Control and Prevention. (2013). *Behavioral Risk Factor Surveillance System survey data*. Atlanta, GA: U.S. Department of Health and Human Services, Centers for Disease Control and Prevention.

Centers for Disease Control and Prevention. (2014). *Underlying cause of death* [Data set]. Retrieved from http://wonder.cdc.gov/ucd-icd10.html

Chae, D. H., Clouston, S., Hatzenbuehler, M. L., Kramer, M. R., Cooper, H. L. F., Wilson, S. M., . . . Link, B. G. (2015). Association between an Internet-based measure of area racism and Black mortality. *PLoS ONE*, *10*(4), Article e0122963. doi:10.1371/journal.pone.0122963

Clark, R., Anderson, N. B., Clark, V. R., & Williams, D. R. (1999). Racism as a stressor for African Americans. *American Psychologist*, *54*, 805–816.

Dovidio, J. F., Kawakami, K., & Gaertner, S. L. (2002). Implicit and explicit prejudice and interracial interaction. *Journal of Personality and Social Psychology*, *82*, 62–68. doi:10.1037/0022-3514.82.1.62

Frey, W. H., & Myers, D. (2005). *Racial segregation in U.S. metropolitan areas and cities, 1990–2000: Patterns, trends, and explanations* (Population Studies Center Research Report 05-573). Retrieved from http://www.frey-demographer.org/reports/R-2005-2_RacialSegragationTrends.pdf

Gonsalkorale, K., Sherman, J. W., & Klauer, K. C. (2009). Aging and prejudice: Diminished regulation of automatic race bias among older adults. *Journal of Experimental Social Psychology*, *45*, 410–414.

Greenwald, A. G., Nosek, B. A., & Banaji, M. R. (2003). Understanding and using the Implicit Association Test: I. An improved scoring algorithm. *Journal of Personality and Social Psychology*, *85*, 197–216. doi:10.1037/0022-3514.85.2.197

Greenwald, A. G., Poehlman, T. A., Uhlmann, E. L., & Banaji, M. R. (2009). Understanding and using the Implicit Association Test: III. Meta-analysis of predictive validity. *Journal of Personality and Social Psychology*, *97*, 17–41. doi:10.1037/a0015575

Hall, W. J., Chapman, M. V., Lee, K. M., Merino, Y. M., Thomas, T. W., Payne, B. K., . . . Coyne-Beasley, T. (2015). Implicit racial/ethnic bias among health care professionals and its influence on health care outcomes: A systematic review. *American Journal of Public Health*, *105*, e60–e76. doi:10.2105/AJPH.2015.302903

Hatzenbuehler, M. L., Bellatorre, A., Lee, Y., Finch, B., Muennig, P., & Fiscella, K. (2014). Structural stigma and all-cause mortality in sexual minority populations. *Social Science & Medicine*, *103*, 33–41.

Hatzenbuehler, M. L., Jun, H.-J., Corliss, H. L., & Austin, S. B. (2014). Structural stigma and cigarette smoking in a prospective cohort study of sexual minority and heterosexual youth. *Annals of Behavioral Medicine*, *47*, 48–56.

Hatzenbuehler, M. L., Phelan, J. C., & Link, B. G. (2013). Stigma as a fundamental cause of population health inequalities. *American Journal of Public Health*, *103*, 813–821.

Hofmann, W., Gawronski, B., Gschwendner, T., Le, H., & Schmitt, M. (2005). A meta-analysis on the correlation between the Implicit Association Test and explicit self-report measures. *Personality and Social Psychology Bulletin*, *31*, 1369–1385.

Hubbard, A. E., Ahern, J., Fleischer, N. L., Van der Laan, M., Lippman, S. A., Jewell, N., . . . Satariano, W. A. (2010). To GEE or not to GEE: Comparing population average and mixed models for estimating the associations between neighborhood risk factors and health. *Epidemiology*, *21*, 467–474.

Kennedy, B. P., Kawachi, I., Lochner, K., Jones, C., & Prothrow-Stith, D. (1997). (Dis)respect and black mortality. *Ethnicity & Disease*, *7*(3), 207–214.

Lee, Y., Kawachi, I., Muennig, P., & Hatzenbuehler, M. L. (2015). Effects of racial prejudice on the health of communities: A multilevel survival analysis. *American Journal of Public Health*, *105*, 2349–2355.

Lohr, S. (2009). *Sampling: Design and analysis*. Boston, MA: Brooks/Cole.

Major, B., Mendes, W. B., & Dovidio, J. F. (2013). Intergroup relations and health disparities: A social psychological perspective. *Health Psychology*, *32*, 514–524. doi:10.1038/nsmb.2010

Mateyka, P., & Marlay, M. (2011). *Residential duration by tenure, race, and ethnicity: 2009*. Retrieved from https://www.census.gov/content/dam/Census/library/working-papers/2011/demo/2009-Duration.pdf

Mendes, W. B., Gray, H. M., Mendoza-Denton, R., Major, B., & Epel, E. S. (2007). Why egalitarianism might be good for your health: Physiological thriving during stressful encounters. *Psychological Science*, *18*, 991–998. doi:10.1111/j.1467-9280.2007.02014.x

Mendoza-Denton, R., Downey, G., Purdie, V. J., Davis, A., & Pietrzak, J. (2002). Sensitivity to status-based rejection: Implications for African American students' college experience. *Journal of Personality and Social Psychology*, *83*, 896–918. doi:10.1037/0022-3514.83.4.896

Pascoe, E. A., & Richman, L. S. (2009). Perceived discrimination and health: A meta-analytic review. *Psychological Bulletin*, *135*, 531–554. doi:10.1037/a0016059

Sawyer, P. J., Major, B., Casad, B. J., Townsend, S. S. M., & Mendes, W. B. (2012). Discrimination and the stress response: Psychological and physiological consequences of anticipating prejudice in interethnic interactions. *American Journal of Public Health*, *102*, 1020–1026. doi:10.2105/AJPH.2011.300620

Schmidt, K., & Nosek, B. A. (2010). Implicit (and explicit) racial attitudes barely changed during Barack Obama's presidential campaign and early presidency. *Journal of Experimental Social Psychology*, *46*, 308–314. doi:10.1016/j.jesp.2009.12.003

U.S. Census Bureau. (2013). *Metropolitan and Micropolitan Delineation Files* [Data set]. Retrieved from http://www.census.gov/population/metro/data/def.html

U.S. Department of Health and Human Services, Centers for Disease Control and Prevention, National Center for Health Statistics. (2014). *Health, United States, 2014*. Retrieved from http://www.ncbi.nlm.nih.gov/books/NBK299348/pdf/Bookshelf_NBK299348.pdf

Williams, D. R., & Mohammed, S. A. (2009). Discrimination and racial disparities in health: Evidence and needed research. *Journal of Behavioral Medicine*, *32*, 20–47. doi:10.1007/s10865-008-9185-0

Xu, K., Nosek, B., & Greenwald, A. G. (2014). Data from the Race Implicit Association Test on the Project Implicit Demo Website. *Journal of Open Psychology Data*, *2*(1), Article e3. doi:10.5334/jopd.ac