



Neighborhood-Level Redlining and Lending Bias Are Associated with Breast Cancer Mortality in a Large and Diverse Metropolitan Area

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ABSTRACT

Background: Structural inequities have important implications for the health of marginalized groups. Neighborhood-level redlining and lending bias represent state-sponsored systems of segregation, potential drivers of adverse health outcomes. We sought to estimate the effect of redlining and lending bias on breast cancer mortality and explore differences by race.

Methods: Using Georgia Cancer Registry data, we included 4,943 non-Hispanic White (NHW) and 3,580 non-Hispanic Black (NHB) women with a first primary invasive breast cancer diagnosis in metro-Atlanta (2010–2014). Redlining and lending bias were derived for census tracts using the Home Mortgage Disclosure Act database. We calculated hazard ratios and 95% confidence intervals (CI) for the associations of redlining, lending bias on breast cancer mortality and estimated race-stratified associations.

Results: Overall, 20% of NHW and 80% of NHB women lived in redlined census tracts, and 60% of NHW and 26% of

NHB women lived in census tracts with pronounced lending bias. Living in redlined census tracts was associated with a nearly 1.60-fold increase in breast cancer mortality (hazard ratio = 1.58; 95% CI, 1.37–1.82) while residing in areas with substantial lending bias reduced the hazard of breast cancer mortality (hazard ratio = 0.86; 95% CI, 0.75–0.99). Among NHB women living in redlined census tracts, we observed a slight increase in breast cancer mortality (hazard ratio = 1.13; 95% CI, 0.90–1.42); among NHW women the association was more pronounced (hazard ratio = 1.39; 95% CI, 1.09–1.78).

Conclusions: These findings underscore the role of ecologic measures of structural racism on cancer outcomes.

Impact: Place-based measures are important contributors to health outcomes, an important unexplored area that offers potential interventions to address disparities.

Introduction

Place-based socio-ecologic inequities contribute to adverse health outcomes (1–3). Structural racism encompasses inequitable macro-level social systems—such as housing, education, employment, criminal justice, and healthcare—that interact to reinforce inequities across race and ethnic groups (4–6). These systemic inequities can lead to limited healthcare access, inadequate transportation, and fewer community resources (4, 6). Within a metropolitan area, neighborhood composition varies substantially. The presence of disadvantaged neighborhoods often have an increased burden of adverse health outcomes, not only for the residents of those areas, but the larger metropolitan area as well (7). A holistic approach to uncovering health

inequities is an important consideration in epidemiology; it may further our understanding of the structural and policy changes that can be implemented to reduce disease burden in a population—providing a broader range of intervention targets beyond the individual.

Two neighborhood-level factors that reflect systemic inequities include redlining—defined as the systematic denial of mortgages based on place, and lending bias—the systematic denial of mortgages based on a person's race or ethnicity. Historically, redlining emerged in the 1930s as part of a “state-sponsored system of segregation,” inhibiting the ability of predominately African American communities to successfully apply for mortgages (8–10). Current day redlining is a concern for disadvantaged neighborhoods because it inhibits financial security and stability for residents, which are important contributors to health and wellbeing (4). Lending bias encompasses a similar systematic denial of mortgages; however, it is specific to the applicant rather than place (11, 12). Examining the associations between redlining and lending bias and breast cancer mortality could provide new insights into how socio-contextual factors drive cancer disparities by place and race.

Persistent inequities in breast cancer outcomes between non-Hispanic black (NHB) and non-Hispanic white (NHW) women exist in the United States (13–15). Among NHB women diagnosed with breast cancer, documented disparities include those related to the initial cancer diagnosis (i.e., stage), tumor biology (i.e., molecular subtype), and first-line therapy (i.e., delays, adherence), which impact breast cancer mortality (13, 15). Although these disparities are important for understanding health outcomes, they do not fully explain inequities by race (13, 16). The recent race/ethnic disparities highlighted by the COVID-19 pandemic demonstrate that structural inequities

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have dire consequences for minority groups (17–19). Ecologic measures of structural disadvantage have been limitedly explored as potential drivers of adverse outcomes among women diagnosed with breast cancer. This study sought to evaluate the role of neighborhood-level redlining and lending bias on breast cancer mortality, and whether there were differences by race/ethnicity. Building upon the foundational work of Beyer and colleagues (20), we aimed to understand how spatial measures of structural inequity impact breast cancer mortality among women living in the metropolitan-Atlanta area—a diverse city with racial segregation, neighborhood deprivation, and pronounced race disparities in breast cancer mortality (13, 21, 22).

Materials and Methods

Study population

The Georgia Cancer Registry (GCR) is a statewide population-based registry that has collected nearly all cancer cases diagnosed among Georgia residents since January 1, 1995. Using this registry, we identified NHB and NHW women diagnosed with a first primary stage I–IV breast cancer diagnosis [International Statistical Classification of Diseases and Related Health Problems 10th revision (ICD-10) ICD-O-3 = C50] occurring between January 1, 2010, and December 31, 2014. Women were included if they resided in the metropolitan Atlanta area at the time of diagnosis, which included Cobb, Clayton, DeKalb, Fulton, and Gwinnett counties. All other diagnoses were excluded, including those among other race/ethnic groups, patients ages <18 years, male patients, patients with a previous history of cancer or any secondary tumor diagnoses, and patients with *in situ* disease. Patients were also excluded if diagnosed solely by death certificate or if stage was missing in the registry. The GCR captures the address at the time of diagnosis for each cancer patient and geocodes all addresses to the census tract level. Census tracts generally encompass between 3,000 and 8,000 individuals and were originally designed to be relatively homogeneous units with respect to population characteristics, economic status, and living conditions (23). This study was approved by Emory IRB (#00099875) and the Georgia Department of Public Health (#190805) and was conducted in accordance of the Declaration of Helsinki.

Exposure assessment

Redlining and lending bias

We define redlining as a systematic denial of mortgage based on location. Neighborhoods are often defined on the basis of the population characteristic or socioeconomic makeup of the geographical unit; thus, redlining is more specific to the neighborhood where the applicant intends to reside, rather than their race/ethnicity. We define lending bias as the systematic denial of mortgages to NHB applicants compared with NHW applicants in areas where they intend to reside, regardless of their current residence.

Redlining and lending bias were calculated on the basis of a previously published methodologic approach by Beyer and colleagues (20). Briefly, data were abstracted from the national database established as part of the Housing Mortgage Disclosure Act (HMDA) for the years 2010 to 2014 (24, 25). The HMDA was passed in 1975 as part of an effort to address mortgage discrimination. The database collects information on mortgage lending practices, including location for which a mortgage was being requested (census tract); loan approval/denial; loan type (purchase/refinance) and amount; owner-occupancy; and the applicant's race, sex, and income.

The redlining index was estimated as the odds of denial of a mortgage application for a residence inside the census tract compared with those outside of the census tract. In this way, the redlining index identifies areas that are less likely to receive mortgages compared with others within the metropolitan Atlanta area. The index centers around a value of one, which corresponds to an area that receives the same rate of mortgage approvals when compared with other areas in metropolitan Atlanta (Fig. 1A). A value less than one means that applicants in the area are less likely to be denied, whereas a value greater than one means that applicants in the neighborhood are more likely to be denied mortgage applications than applicants in other areas.

Lending bias was similarly estimated as the odds of denial of a mortgage application from a NHB applicant compared with denial of a NHW applicant desiring to move in the same census tract, controlling for applicant sex and the ratio of the loan amount to applicants reported annual income (i.e., debt to income ratio). A value of one would indicate that NHB and NHW applicant have equal probability of being denied a mortgage application in the census tract of interest. The distribution of lending bias in the metropolitan Atlanta area had a median value of 3 (used as the cut point for high vs. low lending bias), which reflects a three-fold increase in the odds of mortgage denial for NHB applicants compared with NHW applicants. The odds ratios for redlining and lending bias were calculated using logistic regression with an adaptive spatial filter based on tract level data from the HMDA (Fig. 1A and B). The centroid of the adaptive filter was then assigned as the value of redlining and lending bias to census tracts in the metropolitan-Atlanta area. Using the patient's address at diagnosis, we then assigned the area level measures for redlining and lending bias to the patients residing in those census tracts.

Outcome assessment

Underlying cause of death was determined directly from death certificates using ICD-10 codes. The GCR was linked to the Georgia vital statistics registry annually to identify deaths and causes of death from the preceding year. In addition, the GCR was also linked to the US National Death Index each year to identify deaths that occurred outside of Georgia. In this study, we included only breast cancer-related deaths (ICD-10 = C50) recorded through December 31, 2016.

Covariates of Interest

Neighborhood characteristics

Neighborhood characteristics were derived using publicly available data from the American Community Survey (ACS) and calculated at the census tract level using 5-year estimates centered on 2012 (26). Characteristics included: proportion of the population identified as Black, percent of the population living below the federal poverty level, percent of population age 25 and older without a high school diploma, and median household income.

Patient characteristics

We considered different patient demographic characteristics at the time of diagnosis that may relate to redlining, lending bias, and breast cancer mortality. Race and ethnicity were obtained from documentation in medical records using classifications similar to the 2010 Decennial Census (27). When medical record data were not available, Hispanic ethnicity was determined by the North American Association of Central Cancer Registries Hispanic Identification Algorithm (28), which uses a combination of variables routinely captured by registries (e.g., birthplace, race, and names) in addition to Hispanic surname lists from the US Census to classify women as Hispanic or

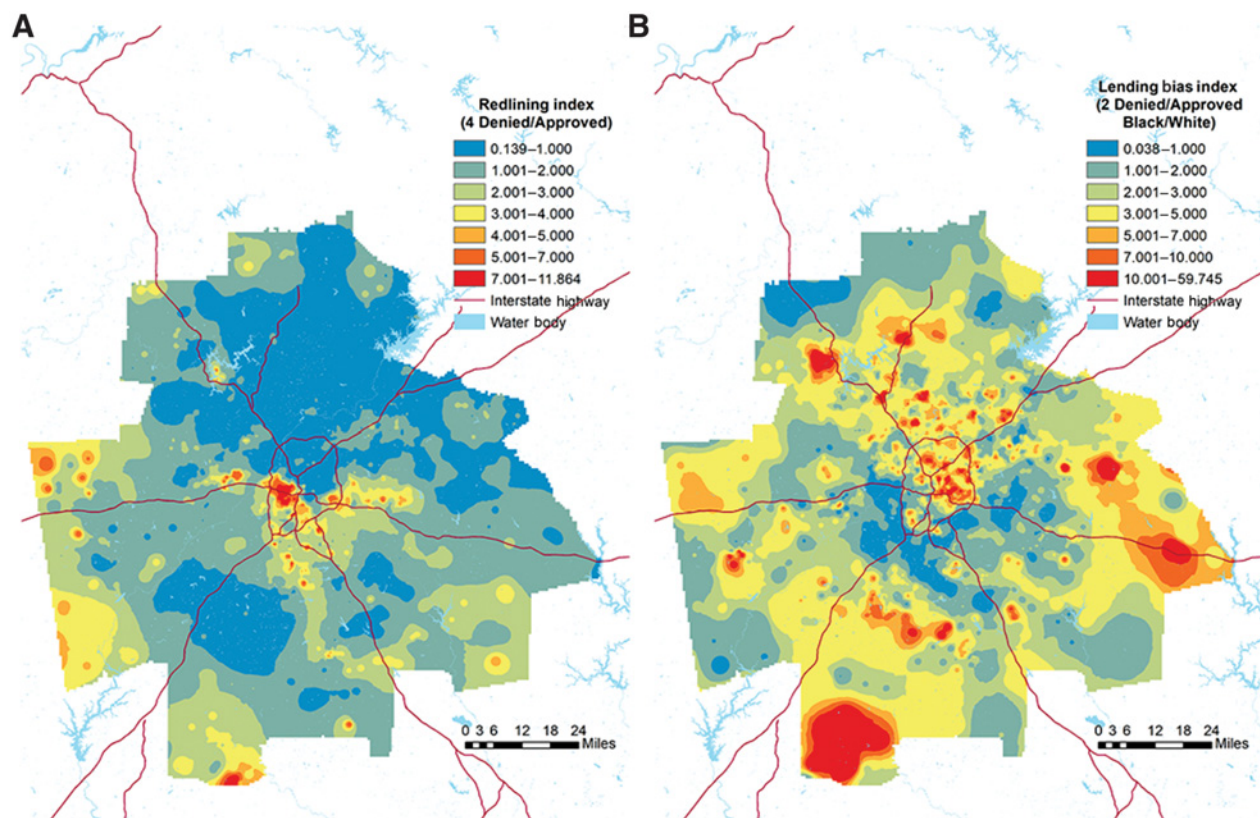


Figure 1. Distribution of redlining and lending bias in the metropolitan Atlanta area. Figure illustrates the distribution of redlining (A) and lending bias (B) indices modeled using adaptive spatial filters in the metropolitan Atlanta area (2010–2014).

non-Hispanic. In addition, we included type of health insurance (uninsured, private, Medicaid, and Medicare), age at diagnosis (<40, 40–49, 50–65, >65 years), and marital status (married, single, divorced/widowed/separated), which are standard variables collected by the GCR.

Tumor characteristics

Tumor characteristics used in this analysis included: cancer stage at diagnosis; tumor grade; expression of the estrogen receptor (ER), progesterone receptor (PR), HER2, and extrapolated molecular subtype. Cancer stage at diagnosis was a derived variable based on the American Joint Committee on Cancer (AJCC) Staging Manual Seventh Edition using combined clinical and pathological information. Tumor grade was categorized as 1, 2, or 3+ with priority coding for Nottingham or Bloom-Richardson scores/grades. Hormone receptor (HR) expression was classified as positive or negative based on the expression of ER ($\geq 1\%$), PR ($\geq 1\%$), or both. HER2 expression was similarly classified as positive or negative through standard reporting to the GCR, based on summary of results from IHC (3+), FISH, or chromogenic in situ hybridization test results, and has been routinely collected by the GCR since 2010. Derived molecular subtype was based on the joint expression of HR and HER2: luminal A (HR+/HER2–), luminal B (HR+/HER2+), HER2 overexpressing (HR–/HER2+), and triple negative (TNBC), which corresponds to a lack of expression of either tumor biomarker (HR–/HER2–).

Statistical methods

Descriptive statistics were calculated for covariates across categorizations of redlining (≥ 1 vs. < 1) and lending bias (≥ 3 vs. < 3) as median values with interquartile range, or frequency and proportion within categories. We categorized redlining and lending bias as the approximate mean (1 and 3, respectively) based on the distribution observed in the study population for the purposes of the analysis (Supplementary Figs. S1 and S2). Follow-up was defined as time in months, from the date of diagnosis until the first of (i) mortality event, (ii) last date of contact in the registry, or (iii) December 31, 2016. We used age-adjusted and multivariable-adjusted Cox proportional hazard models to calculate the hazard ratios and 95% confidence intervals (CI) for the association between neighborhood level redlining or lending bias and breast cancer mortality. We also calculated race-specific effects to explore potential differences in these associations by race (NHB and NHW), through inclusion of an interaction term and the common referent approach to calculate the departure from additivity based on the relative excess risk due to interaction (RERI). The 95%CI for the RERI was calculated using the variance-covariance estimates and the delta method. Potential confounders were determined *a priori*, based on previous literature and graphical-based methods (29). Our graphical assessment of potential confounders showed that all covariates of interest were on the causal path between redlining and breast cancer mortality (Supplementary Fig. S3). These models were thus adjusted for age (continuous). We additionally report model results including age and stage adjustment. Final models for the association between

lending bias and breast cancer-specific mortality included age and stage based on graphical assessment (Supplementary Fig. S4). All analyses were carried out using R version 3.6 and SAS version 9.4.

Results

We identified 8,523 (3,580 NHB and 4,943 NHW) women diagnosed with a first primary breast cancer between 2010 and 2014 in the Metropolitan-Atlanta area (Table 1). On average, women were followed for 3.5 years, ranging 0 to 7 years. We observed 488 breast cancer deaths among NHB women and 319 breast cancer deaths among NHW women (Supplementary Table S1). In our study population, 3,871 (45%) and 3,843 (45%) patients resided at diagnosis in areas of redlining and high lending bias, respectively.

The spatial pattern of redlining and lending bias in Atlanta are illustrated in Fig. 1A and B. Redlining is most prevalent in the southwest portion of the city inside the perimeter highway. On the other hand, racial lending bias is more prevalent in the northern and eastern parts of the metro area both inside and outside the perimeter highway as well as in the far southwestern and eastern regions of the metro area. Areas of redlining were more likely to be predominately Black neighborhoods (76% vs. 2.1%), with a larger percent poverty (49% vs. 7.9%), and a larger portion of the population without high school education (25% vs. 2.7%; Table 1). Conversely, areas of high lending bias were more likely to have a low percent Black population (12% vs. 55%), low poverty (18% vs. 36%), and low proportion of the population without a high school level educational achievement (14% vs. 28%).

Table 1. Patient demographic and clinicopathologic characteristics among 8,523 NHW and NHB women diagnosed with stage I to IV breast cancer in the metropolitan Atlanta area between 2010 and 2014 and registered with the GCR.

Neighborhood characteristics	Redlining				Lending bias			
	<1		≥1		<3		≥3	
	N	%	N	%	N	%	N	%
Percent Black								
≥50%	99	2.1	2,948	76	2,574	55	473	12
<50%	4,553	98	923	24	2,106	45	3,370	88
Percent poverty								
≥20%	369	7.9	1,957	49	1,672	36	693	18
<20%	4,283	92	1,914	51	2,969	64	3,189	82
Percent less than high school education								
≥20%	124	2.7	911	26	1,323	29	530	14
<20%	4,528	97	2,960	74	3,318	71	3,352	86
Medium household income								
<\$44,311	213	4.6	1,915	49	1,502	32	587	15
\$44,311–<\$61,403	774	17	1,355	35	1,424	30	705	18
\$61,403–<\$84,497	1,578	34	544	14	1,157	25	1,004	26
≥\$84,497	2,087	45	57	1.5	597	13	1,547	40
Patient characteristics								
	Median	IQR	Median	IQR	Median	IQR	Median	IQR
Age at diagnosis (years)	58	49, 68	58	49, 67	58	49, 66	59	49, 68
Length of follow-up (months)	44	30, 62	43	28, 61	44	28, 61	44	29, 62
Time to event (months)	23	12, 37	21	11, 33	21	12, 33	23	10, 36
	N	%	N	%	N	%	N	%
Breast cancer-specific death	314	3.7	493	5.8	486	5.7	321	3.8
Race/ethnicity								
NHB	721	16	2,859	75	2,668	57	912	24
NHW	3,931	85	1,012	26	2,012	43	2,931	76
Stage								
I	2,496	54	1,628	42	2,093	45	2,031	53
II	1,483	32	1,395	36	1,654	35	1,224	32
III	427	9.2	522	13	586	13	363	9.4
IV	246	5.3	326	8.4	347	7.4	225	5.9
Molecular subtype								
HR+/HER2– (luminal A)	3,260	75	2,325	64	2,936	67	2,649	74
HR+/HER2+ (luminal B)	496	11	461	13	553	13	404	11
HR–/HER2+ (HER2 overexpressing)	175	4.1	182	5.0	205	4.7	152	4.3
HR–/HER2– (triple negative)	395	9.1	652	18	683	16	364	10
Unknown	326		251		303		274	
Insurance type								
Uninsured	70	1.5	131	3.4	126	2.7	75	2.0
Private	3,004	65	2,050	53	2,686	57	2,368	62
Medicaid	186	4	469	12	453	9.7	202	5.3
Medicare	1,295	28	1,094	28	1,266	27	1,123	29
Military/other/unknown ^a	97	2.5	127	3.3	149	3.1	75	1.9

^aMostly military; N = 8 other among NHB; N = 0 other among NHW.

Breast cancer characteristics also varied within neighborhood-level redlining and lending bias measures. Patients with breast cancer residing in areas of high redlining at the time of diagnosis were more likely to have a stage IV diagnosis (8.4% vs. 5.3%) and TNBC (18% vs. 9.1%) compared with women residing in areas with low redlining (**Table 1**). In contrast, women residing in communities with high lending bias were more likely to have a stage I diagnosis (53% vs. 45%) and luminal A subtype (74% vs. 67%) compared with women living in neighborhoods with low lending bias.

Redlining and breast cancer mortality

In the age-adjusted model, for each 1-unit increase in the redlining metric, we observed a 1.19-fold increase in the estimated mortality rate (hazard ratio = 1.19; 95% CI, 1.15–1.24; **Table 2**). Comparing patients who resided in areas of redlining with those who did not (≥ 1 vs. < 1), we observed a two-fold increase in the estimated breast cancer mortality rate (hazard ratio = 1.97; 95% CI, 1.71–2.27). In models that additionally adjusted for stage, we observed similar, although attenuated, estimates of association (hazard ratio = 1.58; 95% CI, 1.37–1.82). The association between redlining and breast cancer mortality differed by race/ethnicity. Among NHB women, each 1-unit increase in the redlining metric did not increase the estimated breast cancer mortality rate (hazard ratio = 1.03; 95% CI, 0.97–1.08). Results were similar using a dichotomous classification of redlining (hazard ratio = 1.08; 95% CI, 0.86–1.36; **Table 3**). However, among NHW women, each 1-unit increase in the redlining metric was associated with 1.28 times the estimated breast cancer mortality rate (hazard ratio = 1.28; 95% CI, 1.14–1.44). Among NHW women, those who resided in areas of redlining had 1.6 times the estimated rate of breast cancer mortality (hazard ratio = 1.60; 95% CI, 1.26–2.04) compared with women who did not reside in redlined areas (≥ 1 vs. < 1).

Lending bias and breast cancer mortality

In the age-adjusted models, for each additional increase in unit of the lending bias metric, we observed a slight decrease in the estimated rate of breast cancer mortality (hazard ratio = 0.93; 95% CI, 0.90–0.97), which was similar to the multivariable-adjusted model (hazard ratio =

0.95; 95% CI, 0.92–0.99; **Table 2**). Women who lived in neighborhoods of high lending bias (≥ 3 vs. < 3) had 0.86 times the estimated rate of breast cancer mortality compared with those who did not (hazard ratio = 0.86; 95% CI, 0.75–0.99). In the race-stratified models, there was no association between neighborhood lending bias and breast cancer mortality among NHB women (hazard ratio = 1.00; 95% CI, 0.96–1.04; **Table 3**). Similarly, among NHW women, we observed a near null association for each unit increase in lending bias measure on breast cancer mortality (hazard ratio = 0.96; 95% CI, 0.90–1.02).

Discussion

This study reiterates established racial disparities in neighborhood measures of structural inequity, and relates these measures of structural inequities to their impact to breast cancer mortality. In our study, we observed that areas with current redlining had increased rates of breast cancer mortality, and areas with lending bias was associated with a decrease in the estimated rate of breast cancer mortality.

In the race-stratified models, the association between redlining and breast cancer mortality was more pronounced among NHW women compared with NHB women, and both estimates were lower than the estimate observed among all patients with breast cancer. This is likely due to a combination of two factors. First, NHB women represent approximately 42% of the study population, yet of the 3,871 women who resided in redlined neighborhoods 2,859 (74%) were NHB women (Supplementary Table S1). Similarly, there were proportionately fewer NHW women living in redlined census tracts compared with NHB women (20% vs. 80%, respectively). As such, redlining is a common exposure among NHB women, but a rare exposure among NHW. In addition, breast cancer deaths are more common among NHB women. The combination of these two prevalence estimates for exposure and outcome leads to ratios that are lower than the combined, but a higher estimated rate ratio among NHW women. Among the total study population, lending bias was associated with a slight reduction in breast cancer mortality; however, in the race-stratified models, this association did not persist among women living in areas with high

Table 2. Hazard ratio and 95% CI for breast cancer–specific death according to census tract redlining and lending bias indices among NHW and NHB women diagnosed with breast cancer in the metropolitan Atlanta area, 2010 to 2014, and registered with the GCR.

	Deaths N	Adjusted ^a hazard ratio (95% CI)	Adjusted ^b hazard ratio (95% CI)
Redlining index			
Continuous			
Overall	807	1.19 (1.15–1.24)	1.13 (1.08–1.17)
NHB	488	1.03 (0.97–1.08)	1.03 (0.97–1.08)
NHW	319	1.28 (1.14–1.44)	1.23 (1.08–1.41)
Dichotomous			
≥ 1	493	1.97 (1.71–2.27)	1.58 (1.37–1.82)
< 1	314	Referent	Referent
Lending bias index			
Continuous			
Overall	807	0.93 (0.90–0.97)	0.95 (0.92–0.99)
NHB	488	1.03 (0.99–1.07)	1.00 (0.96–1.04)
NHW	319	0.93 (0.88–0.99)	0.96 (0.90–1.02)
Dichotomous			
≥ 3	476	0.77 (0.66–0.88)	0.86 (0.75–0.99)
< 3	331	Referent	Referent

^aAge adjusted.

^bAge and stage adjusted.

Table 3. Hazard ratio and 95% CI for breast cancer-specific death according to census tract redlining and lending bias indices by NHB and NHB women diagnosed with breast cancer in the metropolitan Atlanta area, 2010 to 2014, and registered with the GCR.

	Deaths, <i>n</i>	Common referent hazard ratio (95% CI)		RERI (95% CI)	Stratified effects ^a hazard ratio (95% CI)	Stratified effects ^b hazard ratio (95% CI)
Redlining index	<1 ≥1					
NHB	89 399	2.48 (1.93–3.17)	2.68 (2.28–3.16)	–0.40 (–1.08–0.29)	1.08 (0.86–1.36)	1.13 (0.90–1.42)
NHW	225 94	Reference	1.60 (1.26–2.04)	Reference	1.60 (1.26–2.04)	1.39 (1.09–1.78)
Lending bias	<3 ≥3					
NHB	141 178	1.62 (1.33–1.97)	1.75 (1.39–2.22)	0.21 (–0.82–1.24)	1.18 (0.97–1.43)	1.08 (0.89–1.32)
NHW	345 143	Reference	0.93 (0.74–1.16)	Reference	0.86 (0.69–1.07)	0.93 (0.74–1.16)

^aAge adjusted.^bAge and stage adjusted.

lending bias. This again may reflect the large proportion of NHB women living in areas with high lending bias (60%) compared with NHB women (40%).

Previous research suggests that discriminatory practices, such as racial bias by financial institutions, manifest biologically through stress pathways (1). This stress may lead to epigenetic perturbations that adversely impact health outcomes, representing one mechanism via which structural inequities above the skin translate below (30, 31). In addition, residential segregation limits access to educational opportunities, greenspace (32), healthy foods (33), and healthcare, while increasing exposure to violence (34) and environmental injustice (35), potentially augmenting differences by SES (36). We observed differences in the role of redlining on breast cancer mortality between NHB and NHB women. The more pronounced association between redlining and breast cancer mortality among NHB women may be suggestive of resilience among NHB women (37), or a protective community effect (38, 39). Importantly, it reiterates that race is a social construct, as NHB women exposed to equivalent economic, spatial, and social deprivation experience similarly poor outcomes. We observed lower estimated rates of breast cancer mortality with an increase in the lending bias metric. Communities with high lending bias are likely to have greater economic advantage, robust education and healthcare infrastructures, which would improve health outcomes for the women residing in those communities. Collectively, these factors influence discriminatory housing practices—facilitating residential segregation, a concentration of people of color in disadvantaged neighborhoods, and the eventual downstream adverse breast cancer outcomes among women residing in those areas (40, 41). These discriminatory housing practices do not exist only at the individual level and place, but are also built into institution mortgage lending practices. For example, documentation of biases in algorithms used to determine an applicant's mortgage eligibility and interest rate have been widely reported, although there are efforts to ameliorate their use (42, 43).

In this study, a disproportionate number of NHB women lived in neighborhoods with high levels of structural racism. Descriptively, neighborhoods with higher redlining indices and lower lending bias tended to also be those with a larger proportion of the population living in poverty and with lower rates of high school level education. The confluence of these attributes contributes to adverse health outcomes. Neighborhood not only influences mortality but can also influence access to primary care, which increases the chance of early detection of a breast cancer via screening. We examined the stage distribution among census tracts contributing NHB versus NHB cases only to explore if differences in breast cancer mortality were driven by stage at diagnosis, which would reflect barriers in access to

screening rather than a direct association with breast cancer mortality. The stage distribution of census tracts where only NHB breast cancer cases were diagnosed had nearly the same stage distribution as NHB women from the larger cohort (Supplementary Table S2). However, the stage distribution among census tracts with only NHB breast cancer diagnoses had a slightly higher percentage of stage I diagnoses than from the larger cohort (58% vs. 55%). The similar stage distributions suggest that the associations observed in this study are not due to differential screening access leading to later-stage diagnoses among women residing in segregated census tracts. Future studies may benefit from further exploration of the neighborhood attributes to identify modifiable targets for intervention to improve breast cancer outcomes.

This study has numerous strengths. Namely, it employs an innovative application of a method to measure redlining and lending bias measures over space and time using publicly available data from the HDMA. This study expands on the previously reported study from Milwaukee, to a new region with a large, socioeconomically diverse population. Importantly, this study measures the impact of structural racism on overall health outcomes in both NHB and NHB patients with breast cancer.

We acknowledge some important limitations of this study. First, the derived measures for redlining and lending bias were at the neighborhood-level census tract of the location where the mortgage was being sought, which we generalized to the individual. Given that we aimed to explore the role of neighborhood context on breast cancer outcomes, our approach was consistent with the study aims; although it does not account for patient mobility. Residential history may provide further insight as neighborhood-level effects can contribute to various health outcomes over the life course (22). The metropolitan Atlanta area was ranked as one of the fastest growing cities in the United States in 2016, resulting in a surge in housing cost (44), which may disproportionately impact mobility by race and SES (45). We also applied the measures to women residing in the census tracts, which implies that they either represent those who applied for and were approved for the mortgages, or that they rent in those neighborhoods. However, this does not change how the systemic denial of mortgages shapes these neighborhoods. In addition, the metropolitan Atlanta area is quickly changing. Like other city centers, people are moving away from the suburbs, closer to the city center. This leads to rapidly changing neighborhoods and gentrification. For the redlining and lending bias indices, we used HDMA data centered on the breast cancer diagnostic years (2010–2014), which is most relevant to our study population, but may not capture changes leading up to that time period, or neighborhood changes after diagnosis. We did not have

information on creditworthiness, which is likely an important indicator for mortgage denial in both the redlining and lending bias measures. Creditworthiness also has racial biases, which is separate from redlining and lending bias (46). We also did not have individual measures of SES, comorbidities at diagnosis, or menopausal status which may be contribute to adverse outcomes; however, these are likely downstream of neighborhood characteristics and would not affect our reported results. Finally, the results presented in this study are from one metropolitan area, which may not generalize to other regions. However, Atlanta is a diverse city with structural inequities that are similar to those observed in other regions throughout the United States (4, 21).

This study underscores the role of structural racism in adverse health outcomes, which are amenable to intervention. Specifically, it highlights how persistent structural biases, including those perpetuated by financial institutions, impact spatial patterns of concentrated poverty and neighborhood segregation; and how the construct of place filtered through those structural biases impacts individual and population health outcomes. Racial disparities in breast cancer mortality are often framed as an issue of race; yet, as recently highlighted through the COVID-19 pandemic, race simply reflects the systemic inequities experienced by a person across the life course (17–19). Similarly, place-based disparities are a reflection of the unequal distribution of inter-personal and structural biases that are potentially modifiable through system- and policy-change. Thus, future research in this area should not only consider person-level determinants of adverse health outcomes, but additionally characterize the social contexts in which person-level factors are experienced—facilitating interventions across levels.

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Authors' Contributions

L.J. Collin: Conceptualization, data curation, formal analysis, methodology, writing—original draft, writing—review and editing. **A.H. Gaglioti:** Conceptualization, supervision, methodology, writing—original draft, writing—review and editing. **K.M. Beyer:** Data curation, software, formal analysis, writing—review and editing. **Y. Zhou:** Data curation, software, formal analysis, visualization, writing—review and editing. **M.A. Moore:** Conceptualization, supervision, methodology, writing—review and editing. **R. Nash:** Validation, methodology, writing—review and editing. **J.M. Switchenko:** Conceptualization, supervision, methodology, writing—original draft, writing—review and editing. **J.M. Miller-Kleinhenn:** Supervision, methodology, writing—original draft, writing—review and editing. **K.C. Ward:** Data curation, software, supervision, funding acquisition, validation. **L.E. McCullough:** Conceptualization, resources, supervision, funding acquisition, methodology, writing—original draft, project administration, writing—review and editing.

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