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After the Maps: Assessing Longitudinal Neighborhood Change After Historical Redlining with Present-Day Breast Cancer Survival

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Abstract Historical redlining is a 1930s residential segregation policy that graded neighborhoods according to race, class, and land-use and has been linked to worse breast cancer outcomes today. Since redlining grades were determined by socioeconomic and environmental attributes, evaluating neighborhood change presents a unique opportunity to study the relative contributions of socioeconomic and physical environment to breast cancer. We evaluated whether longitudinal neighborhood change, specifically gentrification and disinvestment, is associated with survival among breast cancer cases today. We used historical redlining grade and labor class census data from 1940 to 2010 to create neighborhood change typologies: stable high neighborhood socioeconomic status (NSES), disinvested, gentrified, and stable low NSES; additional criteria were used for a second, stricter definition of stable types ("truly stable"). Typologies were linked to 43,023 breast cancer cases diagnosed 2008–2018 from New York State. Cox models estimated hazard ratios (HR) associated with neighborhood change types, using both stable high NSES and stable low NSES as referents in separate models. We found significant survival differences according to neighborhood change type. All neighborhood change

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typologies had higher mortality risks compared to stable high NSES, regardless of how stable NSES was defined. This was consistent in models using stable low NSES as the referent when stable NSES was defined broadly, where only stable high NSES was associated with higher survival (HR = 0.73, 95% CI 0.67–0.80) and gentrification and disinvestment did not show differential mortality risks. However, when stable NSES is defined conservatively (truly stable NSES), we found evidence of survival benefits for disinvestment (HR = 0.76, 95% CI 0.65, 0.89) and gentrification (HR = 0.76, 95% CI 0.67, 0.87) compared to truly stable low NSES neighborhoods, and the survival benefit for truly stable high NSES was strengthened (HR = 0.43, 95% CI 0.35, 0.52), though sample size is reduced in the truly stable NSES models. Our results suggest survival is always highest among consistently high NSES neighborhoods but that gentrification and disinvestment may offer buffers compared to redlined neighborhoods with consistently low NSES. This study demonstrates the complexity of neighborhood change and suggests contemporary socioeconomic conditions and underlying physical environment may both be significant domains for breast cancer outcomes.

Keywords Breast cancer · Survival · Historical redlining · Neighborhood change · Gentrification · Disinvestment

Introduction

There are major disparities in breast cancer across the cancer continuum, with differences according to race/ethnicity, income, and geography [1]. Evidence suggests disparities are derived in part from structural drivers that determine socioeconomic opportunities, environmental exposures, and access to health resources [2–5]. One such factor includes historical redlining, which has been associated with worse breast cancer endpoints, including more aggressive subtype, later stage at diagnosis, and shorter survival [6–12].

Historical redlining refers to a 1930s-era US residential segregation policy. In response to the Great Depression and housing crisis, the US federal government created the Home Owners' Loan Corporation (HOLC) to appraise neighborhoods for mortgage security in effort to expand homeownership [13]. HOLC graded neighborhoods explicitly on the basis of racial, ethnic, and class composition as well as land use (e.g., residential vs industrial) [14]. HOLC grades ranged from A ("best") to D ("hazardous"); D-graded neighborhoods were colored in red on maps, thus "redlined." Though historical redlining was outlawed through the 1968Fair Housing Act, it helped perpetuate residential segregation and is associated with current-day socioeconomic and environmental profiles of neighborhoods [15, 16].

Historical redlining may be uniquely well-suited for understanding breast cancer disparities, given that the grades encompass socioeconomic and environmental properties, features that are significant for breast cancer risk and prognosis [1, 17–19]. This is further supported by studies showing redlining is associated with cumulative clustering of breast cancer risk factors and the breast tumor epigenome [20, 21]. However, it is unclear what the relative contributions of socioeconomic features versus environmental features are in the production of current-day breast cancer neighborhood disparities.

While links between historical redlining and breast cancer have been consistently shown, there is little research on neighborhood change over time, despite the policy being nearly a century old. Three studies on historical redlining and breast cancer have considered current-day neighborhood socioeconomic status (NSES), but results are mixed [9–11]. Notably, each of these studies only considered two time points—HOLC grades and current-day NSES.

Literature on neighborhood change and health generally is mixed, with many approaches to define and measure neighborhood change (i.e., gentrification and disinvestment) [22]. Gentrification is defined as a transition of a neighborhood's demographic and socioeconomic conditions from a disadvantaged class

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to privileged class [22, 23]. Though gentrification results in material improvements of neighborhoods, the health of original residents may suffer and thus lead to health consequences and the production of health disparities [22, 24]. In contrast, neighborhood disinvestment—which we define as a transition from privileged to disadvantaged—may lead to deterioration of the physical environment and fewer socioeconomic and health resources. There is evidence to suggest that NSES decline is associated with particularly poor health, often with worse outcomes than stable low NSES [25, 26].

To improve breast cancer survival and reduce disparities, it is crucial to understand whether interventions should focus on improving the socioeconomic environment or physical environment. That HOLC grades were explicitly defined by neighborhoods' socioeconomic features and their land use provides a unique opportunity to longitudinally follow NSES. We have previously shown that HOLC grades are associated with lower overall survival among women with breast cancer in New York State (NYS) [12]. Here, we used nine time points, including HOLC grades and eight decennial censuses, to develop neighborhood change typologies for NYS, with a specific interest in stable high/low NSES, gentrification, and disinvestment. We then evaluated 5-year all-cause survival among a population-based cohort of NYS breast cancer cases according to these typologies. Comparing gentrification and disinvestment to their stable NSES counterparts enables us to characterize the relative contribution of socioeconomic changes and underlying physical environment to survival. Specifically, we used HOLC grades as a surrogate for underlying physical conditions. We hypothesize survival is highest in stable high NSES neighborhoods and lowest in disinvested neighborhoods, while survival in gentrified neighborhoods is similar to stable low NSES neighborhoods.

Methods

Study Design and Sample

This population-based cohort study included cases from the New York State Cancer Registry (NYSCR). Eligibility criteria included female-only invasive first primary breast cancer cases, aged ≥ 20 years, residential census tract at diagnosis in a HOLC-graded neighborhood, and diagnosis during 2008–2018. There were 60,773 total breast cancer cases from 2,509 HOLC-graded neighborhoods (census tracts) during this period.

Neighborhood Methodology

There were 18 cities with HOLC maps that span across NY (Supplemental Fig. 2) [14]. We used the Historic Redlining Score (HRS) dataset, in which census tracts were assigned an area-weighted average HOLC grade; details have been published elsewhere [27–29]. Census tracts with < 20% of area covered by a historical redlining grade were not assigned a score. Neighborhoods were eligible for initial inclusion in the sample if they had a HOLC score.

We used census data to characterize longitudinal neighborhood change after historical redlining. We joined the 1940–2014 census tract data to their corresponding geographies [30]. Historical census tracts were separately geolinked to the HRS dataset using spatial join with the 'center in' link; this enabled us to link all historical census data to 2010 census tracts. After these linkages, there were 1,828 census tracts with a HOLC score and census data throughout 1940–2014. Neighborhoods with historical redlining score and historical NSES data were finally linked to breast cancer cases through 2010 census tracts. After restricting to cases with a residential census tract at diagnosis that had historical NSES data, our final sample included 43,023 breast cancer cases. Supplemental Fig. 3 provides a graphical representation of the sample selection.

Exposure

Our exposure of interest was neighborhood change after historical redlining. We operationalized this change using both HOLC grade data and NSES data for subsequent decades. Figure 1 is a graphical representation of the steps described here. First, neighborhoods were assigned area-weighted HOLC grades, ranging A to D [29]. Then, neighborhoods were assigned NSES for each decade during 1940–2010. NSES was represented by quartile of labor class index of concentrations at the extremes (labor class-ICE),

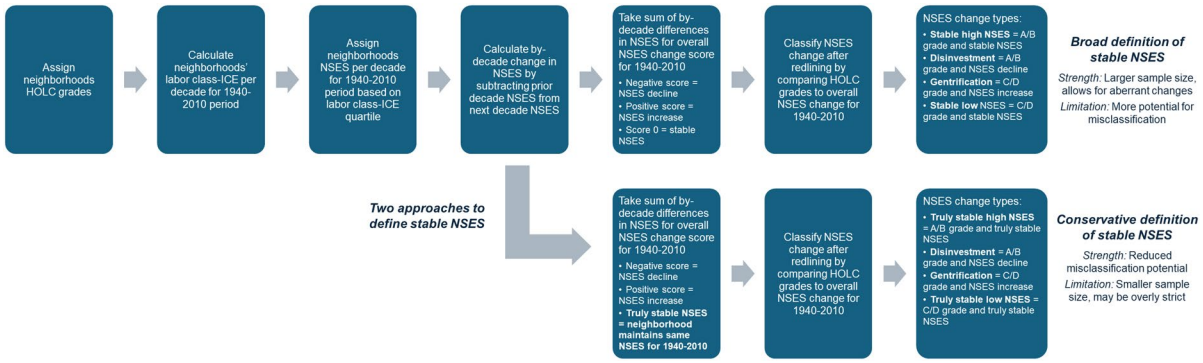


Fig. 1 Flowchart for defining neighborhood change types

which is a neighborhood-level measure of class segregation [31]. ICE ranges from −1 to 1 and is calculated as

$$\mathrm{ICE} = \left(A_i - P_i\right)/T_i$$

where for every i^{th} census tract, A_i = number of professional-class residents; P_i = number of working-class residents; and T_i = total population. For example, a labor class-ICE = −1 means the neighborhood is 100% working class; a labor class-ICE = 1 means the neighborhood is 100% professional class; labor class-ICE = 0 means there is complete balance in working class and professional class residents. Labor class-ICE was calculated for each decade for 1940–2014 using the decennial census (1940–2000) and the American Community Survey (ACS; 2010–2014) data. Supplemental Table 1 provides more detail on class-ICE. Quartile 1 (Q1) represented the highest NSES (i.e., majority professional class) and quartile 4 (Q4) represented the lowest NSES (i.e., majority working class).

To operationalize NSES change, we took the difference in NSES quartiles for each decade, subtracting the prior decade from the next decade (e.g., 1940 NSES–1950 NSES). A positive difference reflects an increase in NSES (i.e., increased proportion of professional class), while a negative difference reflects a decrease in NSES (i.e., increased proportion of working class). We then summed these differences across 1940–2010 for an overall change in NSES, which ranged −3 to 3. Neighborhoods with an overall change score of 0 were considered to be stable; neighborhoods with an overall change score < 0 were considered to experience NSES decline; neighborhoods with an overall change score > 0 were considered to experience NSES increase.

The NSES trajectory for 1940–2010 was then compared to HOLC grades to define neighborhood change. A- and B-graded neighborhoods with stable NSES over time were defined as stable high NSES. A- and B-graded neighborhoods that displayed NSES decline (i.e., negative overall change score) were defined as disinvested. C- and D-graded neighborhoods with stable NSES over time were defined as stable low NSES, while neighborhoods that showed NSES increase (i.e., positive overall change score) were defined as gentrified. Finally, we found some neighborhoods had contrasting HOLC grades and early NSES, which we labeled as "mixed." A- and B-graded neighborhoods with middle/low NSES in the 1940s that increased over time were classified as A/B-grade mixed NSES. C- and D-graded neighborhoods with middle/high NSES in the 1940s that declined over time were classified as C/D-grade mixed NSES. Supplemental Table 2 provides a table version of this classification.

As sensitivity analysis to more accurately classify stable neighborhoods, we further defined truly stable neighborhoods as those that maintained the same NSES quartile position for 1940–2010. Similar to before, truly stable high NSES neighborhoods were defined as those that were A- or B-grade and that maintained NSES Q1 or Q2 throughout time; truly stable low neighborhoods were defined as C- or D-grade that maintained NSES Q3 or Q4 throughout time. We used both approaches for defining stable NSES given there are strengths and limitations to

each approach: the broad definition of stable NSES provides a larger sample size and allows for aberrant changes in NSES but may have larger misclassification potential; the conservative definition of stable NSES likely reduces misclassification but may be overly conservative and reduces the sample size.

Outcome

Five-year all-cause mortality was the outcome of interest. Follow-up lasted from January 1, 2008, to December 31, 2021. To allow equal follow-up for the cohort, we right-truncated data at 60 months, with an event defined as death within 5 years of diagnosis, using presumed months alive as the survival time variable [32]. Cases that were diagnosed after 2016 were censored if alive at the end of the follow-up period.

Covariates

Our covariates included age, year at diagnosis, and city of residence at diagnosis, first course treatments (radiation, chemotherapy, hormone therapy, and surgery), health insurance, and stage at diagnosis. First course treatments were each categorized as yes (referent) or no/unknown. Health insurance was categorized as employer-sponsored (referent), Medicare, Medicaid, dual insurance, uninsured, or unknown. Stage at diagnosis was categorized as local (referent), regional, distant, and unknown.

We evaluated race/ethnicity and subtype descriptively. Hormone receptor status was categorized as positive, negative or unknown based on estrogen receptor (ER) and progesterone receptor (PR) status. Triple negative breast cancer (TNBC) status was defined as TNBC, non-TNBC, or unknown using ER, PR, and HER2 data when available. HER2 status was not routinely collected by NYSCR before 2010, resulting in a large sample with unknown TNBC status.

Statistical Analysis

Descriptive statistics were calculated according to neighborhood change. While we report descriptive statistics for all six neighborhood change types, we focused analyses on stable high NSES, disinvestment, gentrification, and stable low NSES. Kaplan–Meier curves estimated survival probability according to neighborhood change.

Cox proportional hazard models estimated hazard ratios (HRs) for 5-year survival associated with neighborhood change. The proportional hazards assumption was tested through evaluation of weighted Schoenfeld residuals across time. Age at diagnosis violated the proportional hazard assumption and was included categorically as a stratification variable to allow baseline hazards to vary. Using a relational approach[33, 34], we ran all Cox models twice. The first set of Cox models used stable high NSES as the referent group; in the second set of Cox models, stable low NSES was used as the referent group. Using these two referent groups allows us to control for underlying physical environment (proxied by HOLC grade) and model the effect of socioeconomic change on survival and thus easier interpretation of results. Specifically, disinvestment vs stable high NSES controls for A/B-grade (good physical environment) and identifies the effect of NSES decline; gentrification vs stable low NSES controls for C/D-grade (poor physical environment) and identifies the effect of NSES increase. We re-ran analyses using truly stable NSES types as a sensitivity check to determine whether the definition of stable NSES influences results.

Our main models adjusted for city-level clustered standard errors using robust sandwich covariance matrix, age (continuous), year at diagnosis, and city fixed-effects. We additionally adjusted for health insurance and first course treatment. Finally, we further adjusted for stage at diagnosis. We hypothesize that gentrified neighborhoods may have greater access to healthcare resources, including screening and treatment; thus we adjusted for healthcare factors and stage to test this hypothesis. We ran a sensitivity analysis adjusting for case race/ethnicity. While the focus of this study is on the four primary neighborhood change types (i.e., stable high NSES, disinvestment, gentrification, and stable low NSES), we ran Cox models for all six neighborhood change types as a supplementary analysis. Statistical analyses were conducted using SAS 9.4 (SAS, Cary, NC). Figures were created using SankeyMATIC, R 4.2.1, and ArcGIS Pro 10.8 (ESRI, Redlands, CA).

Results

Among the 43,023 breast cancer cases in this cohort, 9.8% (4224) lived in a stable high NSES neighborhood at diagnosis, 9.9% (4240) lived in a disinvested neighborhood, 29.8% (12,837) lived in a gentrified neighborhood, 23.9% (10,293) lived in stable low NSES neighborhood, 1.6% (668) lived in an A/B-grade mixed neighborhood, and 25.0% (10,761) lived in a C/D-grade mixed neighborhood, as shown in Table 1.

Figure 2 shows cases according to their neighborhoods' HOLC grade and neighborhood change type. Panel (A) reveals most A-grade neighborhoods maintained high NSES throughout time, while roughly half of B-grade neighborhoods underwent disinvestment. C-grade neighborhoods transitioned to gentrified, stable low NSES, and mixed NSES neighborhoods in roughly equal proportions. Notably, we found most D-grade neighborhoods were gentrified. Panel (B) shows the complexity of how neighborhoods change over time, in which many neighborhoods vacillate across NSES quartiles. Supplemental Fig.3 shows stable high NSES and gentrified neighborhoods have a higher concentration of White residents and White professional class residents, while disinvested and stable low NSES neighborhoods are more heterogeneous for race ICE and racialized economic ICE. Supplemental Fig. 4 shows how labor class ICE changed over 1940–2010 by HOLC grade.

We found differences in case characteristics according to neighborhood change type (Table 1). Gentrified neighborhoods had the highest proportion of cases under 50 years. Disinvested neighborhoods had the highest proportion of non-Hispanic Black cases (35.9%) whereas stable high NSES neighborhoods had the highest proportion of non-Hispanic White cases (71.9%). Local-stage cases were most prevalent among stable high NSES neighborhoods (66.1%), while distant-stage cases were most prevalent among disinvested and gentrified neighborhoods (7.6% and 7.2%, respectively). The distribution of cases by hormone receptor status followed a similar pattern; HR+/HER2-breast cancer was most common among stable high NSES neighborhoods, while TNBC was most common in disinvested neighborhoods.

The Kaplan–Meier survival curves by the four primary neighborhood change types are shown in Fig. 3. Survival significantly differed according to neighborhood change, with stable high NSES having the highest survival. Disinvestment had the lowest survival, and gentrification and stable low NSES had similar survival probabilities (logrank $P < 0.0001$).

Table 2 (top panel) shows the associations between neighborhood change and 5-year survival, with stable NSES types defined broadly. Compared to stable high NSES, disinvestment is associated with 42% higher mortality risk (HR = 1.42, 95% CI 1.25, 1.62), gentrification is associated with 48% higher mortality risk (HR = 1.48, 95% CI 1.23, 1.77), and stable low NSES is associated with 37% higher mortality risk (HR = 1.37, 95% CI 1.25, 1.50). Adjustment for first course treatments, health insurance, and stage each attenuated the associations, though all neighborhood change types maintained a significantly higher mortality risk compared to stable high NSES. When using stable low NSES as the referent, we confirmed that stable high NSES is protective (HR = 0.76. 95% CI 0.67, 0.80), but we did not find that mortality risk is associated with disinvestment (HR = 1.04, 95% CI 0.91, 1.19) or gentrification (HR = 1.08, 95% CI 0.93, 1.26).

Table 2 (bottom panel) reports the associations between neighborhood change and 5-year survival, with stable NSES types defined conservatively (i.e., "truly stable"). Using a more restricted referent group resulted in stronger associations for both truly stable high NSES and truly stable low NSES referent models. Compared to truly stable high NSES neighborhoods, we found a significantly higher hazard risk associated with disinvestment (HR = 1.77, 95% CI 1.59, 1.97), gentrification (HR = 1.78, 95% CI 1.60, 1.97), and truly stable low NSES (HR = 2.33, 95% CI 1.91, 2.85). Similarly, adjustment for healthcare factors and stage attenuated HRs, but all neighborhood change types continued to be associated with significantly higher mortality. In contrast to our original models, using truly stable low NSES as a referent revealed all neighborhood change types are associated with significantly lower mortality risk in main models. Specifically, we found lower mortality with disinvestment (HR = 0.76, 95% CI 0.65, 0.89) and gentrification (HR = 0.76, 95% CI 0.67, 0.87). After adjustment for healthcare factors and stage, we found a significant protect effect persisted for all neighborhood change types, though the effect for gentrification attenuated slightly more than for

Table 1 Descriptive statistics of breast cancer cohort according to neighborhood change after historical redlining

Characteristic	Total	Neighborhood change types					
		Stable high NSES	*Disinvested*	*Gentrified*	*Stable low NSES*	*Mixed—A/B*	*Mixed—C/D*
	N = 43,023	4224 (9.8%)	4240 (9.9%)	12,837 (29.8%)	10,293 (23.9%)	668 (1.6%)	10,761 (25.0%)
Survived < 5 years	7147 (16.6%)	534 (12.6%)	775 (18.3%)	2157 (16.8%)	1700 (16.5%)	90 (13.5%)	1891 (17.6%)
Age at diagnosis							
< 40	3207 (7.5%)	277 (6.6%)	301 (7.1%)	1048 (8.2%)	779 (7.6%)	45 (6.7%)	757 (7.0%)
40–49	7893 (18.3%)	725 (17.2%)	733 (17.3%)	2495 (19.4%)	1781 (17.3%)	108 (16.2%)	2051 (19.1%)
50–64	16,066 (37.3%)	1457 (34.5%)	1711 (40.4%)	4595 (35.8%)	3841 (37.3%)	259 (38.8%)	4203 (39.1%)
65–74	8945 (20.8%)	986 (23.3%)	862 (20.3%)	2601 (20.3%)	2213 (21.5%)	149 (22.3%)	2134 (19.8%)
75 +	6912 (16.1%)	779 (18.4%)	633 (14.9%)	2098 (16.3%)	1679 (16.3%)	107 (16.0%)	1616 (15.0%)
Race/ethnicity							
Hispanic	8522 (19.8%)	404 (9.6%)	915 (21.6%)	2103 (16.4%)	2154 (20.9%)	71 (10.6%)	2875 (26.7%)
Non-Hispanic Black	11,760 (27.3%)	407 (9.6%)	1522 (35.9%)	3472 (27.0%)	2838 (27.6%)	120 (18.0%)	3401 (31.6%)
Non-Hispanic White	17,529 (40.7%)	3035 (71.9%)	1452 (34.2%)	5948 (46.3%)	4191 (40.7%)	404 (60.5%)	2499 (23.2%)
Non-Hispanic other*	4874 (11.3%)	345 (8.2%)	325 (7.7%)	1213 (9.4%)	1027 (10.0%)	NA	1898 (17.6%)
Non-Hispanic, unknown race	338 (0.8%)	33 (0.8%)	26 (0.6%)	101 (0.8%)	83 (0.8%)	NA	88 (0.8%)
Stage at diagnosis							
Local	25,772 (59.9%)	2794 (66.1%)	2438 (57.5%)	7647 (59.6%)	6179 (60.0%)	414 (62.0%)	6300 (58.5%)
Regional	13,068 (30.4%)	1074 (25.4%)	1364 (32.2%)	3870 (30.1%)	3175 (30.8%)	198 (29.6%)	3387 (31.5%)
Distant	2949 (6.9%)	244 (5.8%)	323 (7.6%)	923 (7.2%)	680 (6.6%)	36 (5.4%)	743 (6.9%)
Unknown	1234 (2.9%)	112 (2.7%)	115 (2.7%)	397 (3.1%)	259 (2.5%)	20 (3.0%)	331 (3.1%)
Hormone receptor status							
HR + /HER-	22,146 (69.0%)	2383 (76.5%)	2064 (65.7%)	6595 (69.6%)	5364 (68.9%)	354 (73.6%)	5386 (66.4%)
HR + / HER2 +	3934 (12.3%)	339 (10.9%)	424 (13.5%)	1139 (12.0%)	941 (12.1%)	54 (11.2%)	1037 (12.8%)
HR-/HER2 +	1728 (5.4%)	120 (3.9%)	170 (5.4%)	494 (5.2%)	434 (5.6%)	23 (4.8%)	487 (6.0%)
TNBC	4297 (13.4%)	273 (8.8%)	482 (15.4%)	1243 (13.1%)	1051 (13.5%)	50 (10.4%)	1198 (14.8%)
Insurance status							
Employer-insured**	18,936 (44.0%)	2191 (51.9%)	1679 (39.6%)	6136 (47.8%)	4539 (44.1%)	349 (52.2%)	4042 (37.6%)
Medicaid	9209 (21.4%)	409 (9.7%)	1043 (24.6%)	2325 (18.1%)	2155 (20.9%)	95 (14.2%)	3182 (29.6%)
Medicare**	6804 (15.8%)	896 (21.2%)	653 (15.4%)	2020 (15.7%)	1708 (16.6%)	116 (17.4%)	1411 (13.1%)
Dual eligibility	6160 (14.3%)	543 (12.9%)	655 (15.4%)	1778 (13.9%)	1484 (14.4%)	85 (12.7%)	1615 (15.0%)
Uninsured	763 (1.8%)	57 (1.3%)	97 (2.3%)	223 (1.7%)	173 (1.7%)	NA	205 (1.9%)
Unknown	1151 (2.7%)	128 (3.0%)	113 (2.7%)	355 (2.8%)	234 (2.3%)	NA	306 (2.8%)
Metropolitan area size							

Table 1 (continued)

Characteristic	Total	Neighborhood change types					
		Stable high NSES	*Disinvested*	*Gentrified*	*Stable low NSES*	*Mixed—A/B*	*Mixed—C/D*
NYC borough	39,127 (90.9%)	3539 (83.8%)	3395 (80.1%)	12,186 (94.9%)	9159 (89.0%)	644 (96.4%)	10,204 (94.8%)
Large metropolitan area	3219 (7.5%)	514 (12.2%)	686 (16.2%)	604 (4.7%)	989 (9.6%)	NA	426 (4.0%)
Medium metropolitan area	677 (1.6%)	171 (4.1%)	159 (3.8%)	47 (0.4%)	145 (1.4%)	24 (3.6%)	131 (1.2%)

Statistical significance estimated using chi-square tests. Reported percent is column percent. Stable high = neighborhood was A/B grade and high NSES throughout. Stable low = neighborhood was C/D grade and low NSES throughout. Disinvested = neighborhood was A/B grade and NSES declined during the period. Gentrified = neighborhood was C/D grade and NSES increased during the period. Mixed—A/B = neighborhood was A/B grade with low NSES that increased over time. Mixed—C/D = neighborhood was C/D grade with high NSES that declined over time

*Non-Hispanic other group combined non-Hispanic Asian/Pacific Islander and American Indian/Alaskan Native

**The following insurance types were grouped with Medicare due to a small sample size: Military, Veterans Affairs, Indian/Public Health Service. TRICARE was classified as employer-sponsored insurance

disinvestment ($HR_{gentrification} = 0.88$, 95% CI 0.78, 1.00; $HR_{disinvestment} = 0.82$, 95% CI 0.70, 0.98).

Supplemental Table 3 reports results after adjusting for race/ethnicity in models. Results were largely similar to healthcare-adjusted results shown in Table 2. Adjustment for race/ethnicity resulted in disinvestment and gentrification becoming marginally non-significant when compared to truly stable low NSES neighborhoods (disinvestment HR = 0.82, 95% CI 0.62, 1.07; gentrification HR = 0.83, 95% CI 0.68, 1.02). Supplemental Table 4 shows results using all six neighborhood change types. The HR for A/B-grade mixed NSES is similar to that for disinvestment, and the HR for C/D-grade mixed NSES is similar to that for gentrification. In other words, effects for these mixed types seem to follow HOLC grade patterns rather than subsequent NSES change.

Discussion

We found that a neighborhood's HOLC grade and subsequent long-term socioeconomic pattern is associated with survival in a contemporary cohort of breast cancer cases. Using a longitudinal neighborhood approach that used original HOLC grades and 80 years of census data on labor class segregation, we identified six overall neighborhood change typologies in this NY-based cohort, including four primary typologies: stable high and low NSES, disinvestment, and gentrification. The largest and most consistent survival disparity relates to whether a neighborhood had stable high NSES or not, where stable high NSES was associated with the highest survival. We also found gentrification and disinvestment were associated with higher survival than stable low NSES when stable low NSES was defined conservatively.

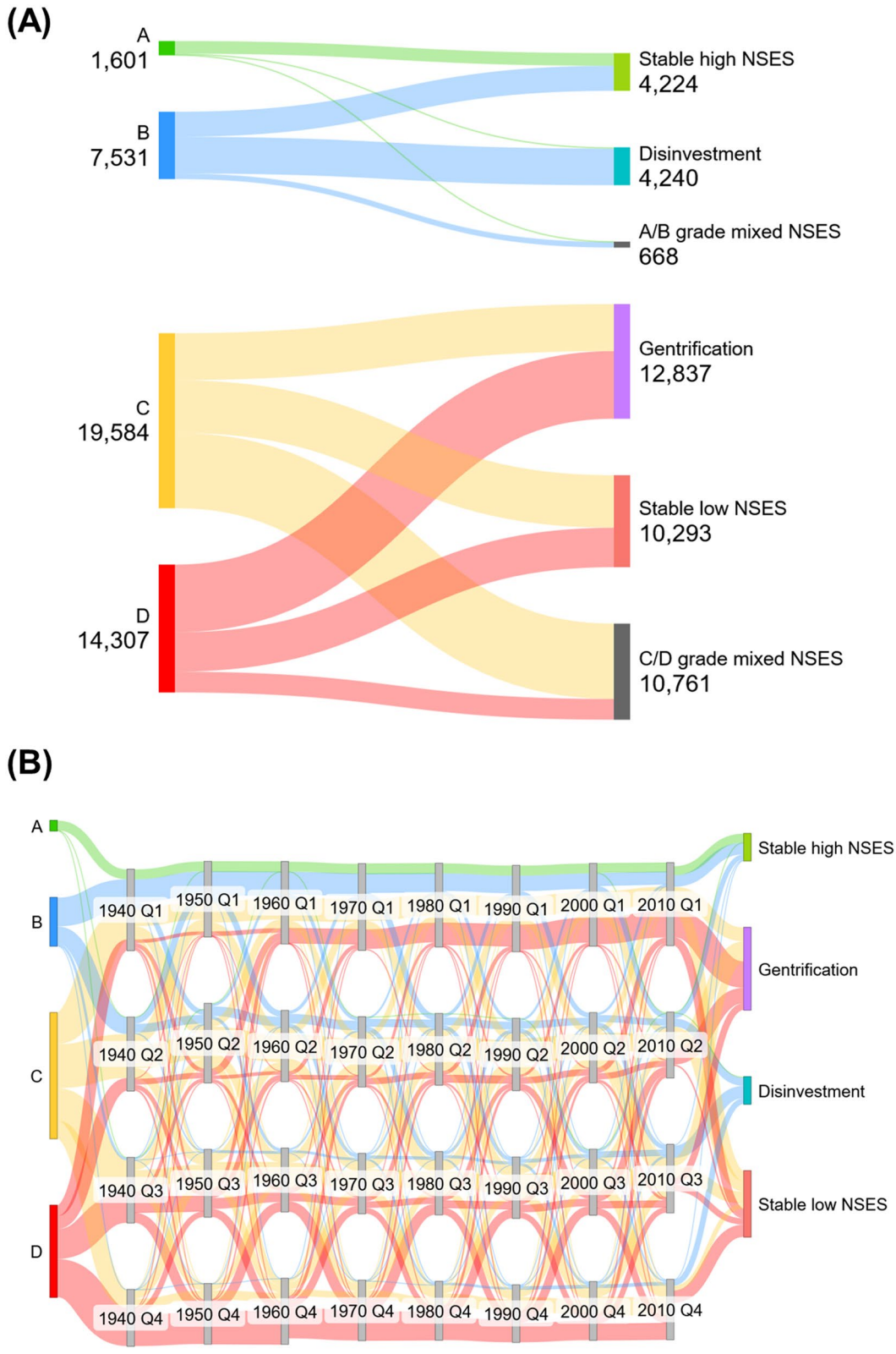
The results provide important information on neighborhood determinants of breast cancer survival and potential pathways by which HOLC grades may continue to be influential. HOLC appraised neighborhoods on their race and class composition as well as the land use. D-grade neighborhoods, specifically, were often near industrial sites, which may continue to present environmental hazards [14, 35–38]. Text-based analyses of HOLC grades provide evidence that environmental features of neighborhoods were influential in grade assignment, such that polluted areas were assigned worse grades [39]. Further, HOLC grades may have informed highway construction and industrial siting, as D-graded neighborhoods have a higher density and closer proximity to highways and oil and gas wells [36, 40]. Given this evidence, we argue that HOLC grades encompass both environmental and socioeconomic profiles and informed urban development through the twentieth century. Creating neighborhood change types dependent on HOLC grades allows us to partially disentangle the

effects of underlying physical environment from socioeconomic changes in their contribution to redlining-based survival disparities observed today. While we hypothesized disinvested neighborhoods would have the lowest survival due to their socioeconomic decline, our results suggest disinvested neighborhoods may have a beneficial physical environment due to their historical A/B grade that could provide a health buffer. Consistent with our hypothesis, we found gentrified neighborhoods do not have the same survival benefits as stable high NSES neighborhoods despite their socioeconomic increase. We believe this may be due to a poor underlying physical environment from their C/D grade and presumed increased exposure to noxious factors, such as proximity to historical industrial sites [36, 39]. This interpretation is further supported by our supplementary results that used all six neighborhood change types, in which the mixed NSES types seem to follow a HOLC gradient rather than a subsequent NSES change gradient (i.e., despite a decreasing NSES over time, C/D-grade mixed neighborhoods had similar HRs as gentrified neighborhoods).

Comparing and contrasting results according to neighborhood change type may inform intervention points to improve survival. For instance, our finding that disinvestment and gentrification are associated with higher survival compared to stable low NSES neighborhoods suggests that these transformations may confer protection. Disinvested neighborhoods that were previously A/B-grade may benefit from the underlying physical environment, whereas the NSES increase in gentrified neighborhoods may provide health buffer against the C/D-grade adverse underlying environment. Adjustment for healthcare factors and stage attenuated the protective effects of gentrification more so than disinvestment. This could be due to gentrified neighborhoods deriving benefits from increased access to health resources over time. If replicated, these findings could have important implications for interventions to remove residual effects of historical redlining. Overall, our results suggest investment in neighborhoods—whether socioeconomic or environmental—may confer health advantages, including to women with breast cancer.

To our knowledge, this is the first study to use the full period spanning the development of HOLC maps to current day to characterize neighborhood change and subsequent health outcomes. Our study is thematically similar to prior work investigating historical redlining with contemporary socioeconomic neighborhood characteristics, along with applied geography studies that have classified longitudinal neighborhood transitions [7, 9–11, 41–44]. Previous studies on historical redlining and breast cancer that considered neighborhood change have used only contemporary neighborhood characteristics to operationalize changes (i.e., two time points). Results have been inconsistent. Some have found only persistent disadvantage is associated with adverse outcomes [7, 11], while others have found only socioeconomic changes are associated with adverse endpoints [9, 10]. Findings from an investigation on historical redlining and life expectancy suggest declines in property value would have stronger effects among A-graded neighborhoods than D-graded (i.e., similar to our definition of disinvestment), while urban renewal projects (i.e., gentrification) explain little of the disparity [44]. We build upon this literature, and longitudinal neighborhood trajectory studies [41–43], by utilizing a larger time window to characterize neighborhood change. Further, we show that associations for gentrification and disinvestment with survival differ based on how stable NSES is defined, highlighting the complicated nature of studying neighborhood trajectories.

The effects we detected associated with gentrification and disinvestment could be related to multiple pathways. Gentrification has been linked to both positive and negative health effects [24, 45]. Positive health effects may come through economic development, increases in health-protective resources, and improvement of the built environment and neighborhood greening [22]. However, these place-based resource improvements may provide health benefits to the incoming demographic groups (typically younger White professionals) but may not outweigh the consequences faced by original demographic groups (typically older Black and/or Hispanic working-class residents) [23]. Gentrification has also been associated with reduced social networks and social cohesion and increased psychosocial stress. We posit that the initial protective effect from gentrification compared to stable low NSES we found is due higher access to health resources, such as screening, health insurance, and treatment. While gentrification may involve improvements to the environmental conditions, we assume that this does not necessarily include remediation of industrial toxic sites or re-routing/removal


(A)
A
1,601
B
7,531
C
19,584
D
14,307
Stable high NSES
4,224
Disinvestment
4,240
A/B grade mixed NSES
668
Gentrification
12,837
Stable low NSES
10,293
C/D grade mixed NSES
10,761
(B)
A
B
C
D
1940 Q1
1950 Q1
1960 Q1
1970 Q1
1980 Q1
1990 Q1
2000 Q1
2010 Q1
1940 Q2
1950 Q2
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2010 Q3
1940 Q4
1950 Q4
1960 Q4
1970 Q4
1980 Q4
1990 Q4
2000 Q4
2010 Q4
Stable high NSES
Gentrification
Disinvestment
Stable low NSES

◂**Fig. 2** Breakdown of cases according to HOLC grade and neighborhood change type. **A** Simplified depiction of HOLC grade (left) to neighborhood change (right), with sample size. **B** Cases according to HOLC grade (left), NSES quartile (Q1–Q4) by decade for 1940–2010 (middle), and neighborhood change type (right). Beginning node (left) and flows are colored according to HOLC grade; end node (right) are colored according to neighborhood change type

of highway systems, which were often placed in the C/D-graded neighborhoods [45–47]. Thus, we suspect this may contribute to worse survival associated with gentrification (compared to stable high NSES). The higher survival associated with gentrification compared to stable low NSES could be due to differences in populations and baseline mortality risk, as adjustment for race/ethnicity led to gentrification becoming marginally non-significant in our sensitivity analysis. However, given the large effect size after adjustment (HR = 0.83) and that we observed similar patterns with disinvested neighborhoods, we believe the lower mortality risk associated with gentrification is not solely due to population differences. Neighborhood disinvestment may impact health outcomes through deterioration of physical environment, increased psychosocial stress, and reduced access to health resources [48]. NSES declines have been associated with numerous adverse health outcomes, lower health-related quality of life, colorectal cancer risk, late-stage breast cancer, and breast cancer mortality [25, 26, 49].

A specific complexity of assessing neighborhood change is the timing of neighborhood transformations versus the latency of breast cancer mortality and intermediate pathways. Consistent with prior work [50], our data suggest neighborhood transformations occurred during the 1960s–1980s. This period coincides with the introduction and widespread use of mammography, which may be a temporally related pathway that could influence mortality [51]. Fundamental cause theory would suggest the highest-advantage areas would likely be the first populations to gain screening access [52]. Given we observe non-redlined neighborhoods transition to disinvestment during this period, it is possible these neighborhoods did not have the same screening investment as stable high NSES neighborhoods from the beginning and thus had reduced screening long-term. Long-term erosion of social capital and social networks in gentrified and disinvested neighborhoods could have contemporaneous influences on healthcare engagement [53]. Furthermore, these neighborhood transformations may impact the diet of residents both positively, through increases in quality supermarkets, or negatively, through increases in non-nutritious and ultra-processed foods from food swamps, which have been linked to cancer mortality [54, 55]. Finally, chronic exposure to pollutants has been associated with breast cancer mortality [56]. Moreover, there is evidence that environmental toxins and pollution can lead to transgenerational epigenetic modifications [57, 58]; this pathway may allow for historical exposures to persist and influence present-day health and mortality.

The main strength of this study is the use of 80 years of census data to characterize neighborhood change after historical redlining across multiple cities in NY. Neighborhood studies are often limited by assessing health outcomes cross-sectionally or use a baseline measure of neighborhood to evaluate later health outcomes [59]. While we are unable to evaluate cases' residential history before or after diagnosis, which would allow us to assess neighborhoods longitudinally at the individual-level, we believe characterizing neighborhoods according to socioeconomic transitions deepens our understanding of how historical redlining influenced urban development and the pathways to contemporary health outcomes. Furthermore, operationalizing neighborhood change according to a sum of differences in NSES quartiles across time allows for neighborhoods to undergo aberrant changes without affecting their neighborhood change classification. Additionally, our large sample size provided power to evaluate according to multiple neighborhood types. Relatedly, the geographic spread of HOLC-graded cities in NY allows for robust multilevel models. Though there is skepticism about the validity of HOLC grades as deprivation proxies [60], we argue HOLC grades helped establish socio-environmental inequality in urban areas and inequitable development [16]. We believe using historical redlining grades in conjunction with socioeconomic trajectories provides a unique opportunity to contrast physical environment to socioeconomic changes in order to identify possible intervention points, similar to a natural experiment. Though further research is needed, HOLC grades provide a historical perspective of physical environment that would not be possible from NSES trajectories alone.

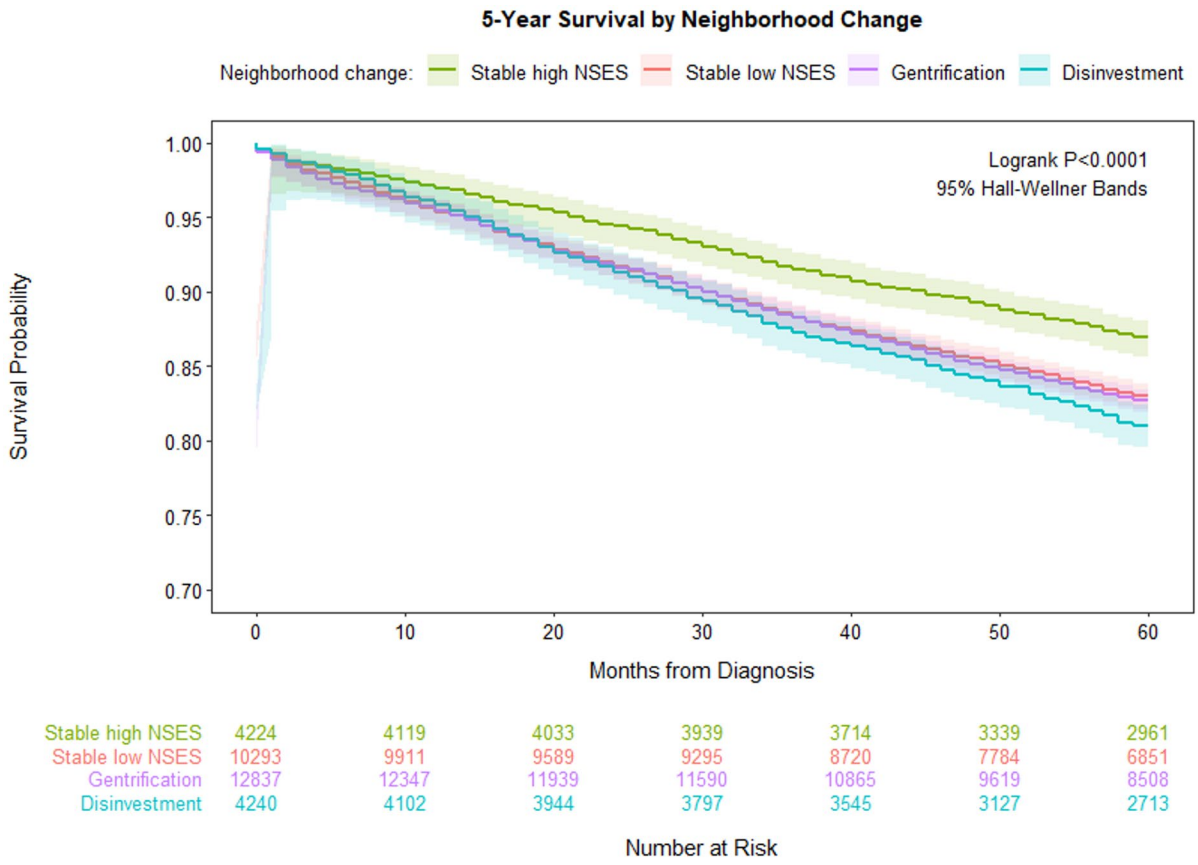


Fig. 3 Kaplan Meier curves showing 5-year survival probability according to neighborhood change

While our use of eight decades of census data to characterize neighborhood change presents important novelties, it warrants consideration of the limitations. First, the quality of US census data varies across time. Furthermore, much of the US was not covered by the census before 1980; thus, some cities with HOLC maps were not included in the present sample due to lack of earlier census data, resulting in a reduction in sample size from 60,773 eligible cases to 43,023 cases in the analytic sample. We linked historical census data to HOLC grades through spatial joins; thus, misclassification of NSES quartile and HOLC grade is possible, particularly given neighborhood boundaries change over time. We used labor class ICE to define our NSES quartiles. ICE is a measure of segregation (here, labor class segregation) and not necessarily neighborhood socioeconomic composition. However, ICE measures are more robust for small areas, such as census tracts, compared to other measures (e.g., Gini coefficient) [31]. Further, occupation is one of the few demographic features that was collected by the census throughout our study period. Additionally, our neighborhood change approach could be vulnerable to exposure misclassification. For instance, if a neighborhood changed from quartile 4 to quartile 1 and then back to quartile 4 across the 1940–2010period, this neighborhood would have a sum of differences = 0 and thus be classified as stable. We attempted to mitigate this misclassification by using a more restrictive definition of stable neighborhoods. Yet we cannot rule out exposure misclassification as a potential source of bias. Moreover, we represented socioeconomic increases and declines as gentrification and disinvestment, respectively, but both of these phenomena are sociologically and empirically difficult to define [24]. Given multiple models were used, there is a chance some findings

Table 2 Hazard ratios of 5-year all-cause mortality after breast cancer associated with neighborhood change types before and after adjustment for select covariates

	Cases	Deaths	Unadjusted model	Main model[1]	Healthcare-adjusted model[2]	Stage-adjusted model[3]
Neighborhood change	*N*	*N*	*HR (95% CI)*	*HR (95% CI)*	*HR (95% CI)*	*HR (95% CI)*
Stable NSES defined broadly						
Stable high NSES as ref						
Stable high NSES (ref)[a]	4224	534	1.0	1.0	1.0	1.0
Disinvestment[b]	4240	775	**1.62 (1.26, 2.08)**	**1.42 (1.25, 1.62)**	**1.21 (1.15, 1.28)**	**1.18 (1.08, 1.30)**
Gentrification[c]	12,837	2157	**1.45 (1.18, 1.78)**	**1.48 (1.23, 1.77)**	**1.31 (1.20, 1.44)**	**1.28 (1.15, 1.42)**
Stable low NSES[d]	10,293	1700	**1.41 (1.26, 1.58)**	**1.37 (1.25, 1.50)**	**1.25 (1.15, 1.36)**	**1.23 (1.13, 1.33)**
Stable low NSES as ref						
Stable high NSES[a]	4224	534	**0.71 (0.63, 0.79)**	**0.73 (0.67, 0.80)**	**0.80 (0.73, 0.87)**	**0.82 (0.75, 0.89)**
Disinvestment[b]	4240	775	1.15 (0.97, 1.36)	1.04 (0.91, 1.19)	0.97 (0.89, 1.05)	0.97 (0.90, 1.04)
Gentrification[c]	12,837	2157	1.03 (0.91, 1.17)	1.08 (0.93, 1.26)	1.05 (0.94, 1.16)	1.04 (0.96, 1.13)
Stable low NSES (ref)[d]	10,293	1700	1.0	1.0	1.0	1.0
Stable NSES defined conservatively (truly stable)						
Truly stable high NSES as ref						
Truly stable high NSES (ref)[e]	2774	299	1.0	1.0	1.0	1.0
Disinvestment[b]	4240	775	**1.96 (1.64, 2.35)**	**1.77 (1.59, 1.97)**	**1.39 (1.29, 1.49)**	**1.34 (1.22, 1.47)**
Gentrification[c]	12,837	2157	**1.76 (1.49, 2.08)**	**1.78 (1.60, 1.97)**	**1.48 (1.37, 1.59)**	**1.43 (1.32, 1.56)**
Truly stable low NSES[f]	911	202	**2.38 (1.77, 3.19)**	**2.33 (1.91, 2.85)**	**1.68 (1.45, 1.96)**	**1.63 (1.37, 1.93)**
Truly stable low NSES as ref						
Truly stable high NSES[e]	2774	299	**0.42 (0.31, 0.56)**	**0.43 (0.35, 0.52)**	**0.59 (0.51, 0.69)**	**0.61 (0.52, 0.73)**
Disinvestment[b]	4240	775	**0.82 (0.69, 0.99)**	**0.76 (0.65, 0.89)**	**0.82 (0.71, 0.96)**	**0.82 (0.70, 0.98)**
Gentrification[c]	12,837	2157	**0.74 (0.62, 0.88)**	**0.76 (0.67, 0.87)**	**0.88 (0.77, 1.00)**	0.88 (0.78, 1.00)
Truly stable low NSES (ref)[f]	911	202	1.0	1.0	1.0	1.0

Deaths are within 5 years since diagnosis

[a]Stable high NSES = A/B grade and consistently high NSES throughout 1940–2010

[b]Disinvestment = A/B grade with overall decline in NSES during 1940–2010

[c]Gentrification = C/D grade with overall increase in NSES during 1940–2010

[d]Stable low NSES = C/D grade with consistently high NSES throughout 1940–2010

[e]Truly stable high NSES = A/B grade and consistently high NSES throughout 1940–2010, defined as consistently Q1 or consistently Q2

[f]Truly stable low NSES = C/D grade with consistently high NSES throughout 1940–2010, defined as consistently Q3 or consistently Q4

[1]Adjusted for age at diagnosis (continuous), year at diagnosis (continuous), city fixed effects ($n = 17$)

[2]Adjusted for main model covariates (1) radiation (yes, no/unknown), chemotherapy (yes, no/unknown), hormone therapy (yes, no/unknown), surgery (yes, no/unknown), insurance (employer-sponsored, Medicare, Medicaid, dual, uninsured, and unknown)

[3]Adjusted for healthcare-adjusted model covariates (2) + stage (local, regional, distant, and unknown)

are false positives; future studies are needed to validate these findings. Finally, there are limitations with NYSCRdata. NYSCR collects residential neighborhood only at diagnosis; thus, we cannot account for residential mobility before or after cancer diagnosis. Further, we have no way of testing whether individuals lived in the neighborhoods during the change (i.e., experienced gentrification or disinvestment) or lived in a neighborhood after it underwent a change. Individual-level variables, such as lifestyle factors or SES, are not collected by NYSCR. Finally, first-course treatment and health insurance were collected only at diagnosis and have also been shown to differ in sensitivity by case factors [61, 62].

Neighborhood socioeconomic trajectories after historical redlining are associated with contemporary breast cancer survival. Our results indicate that the physical environment and socioeconomic resources

may interact to shape breast cancer prognosis and survival. These long-term trajectories may influence breast cancer incidence as well, which should be evaluated in the future. Future research is needed to identify potential neighborhood-level interventions to improve breast cancer survival.

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Author Contributions Sarah M. Lima: conceptualization, design, formal analysis, methodology, visualization, writing—original draft, and writing—review and editing. Tia M. Palermo: conceptualization, design, methodology, supervision, and writing—review and editing. Furrina F. Lee: data curation, methodology, and writing—review and editing. Tabassum Z. Insaf: data curation, methodology, and writing—review and editing. Jared Aldstadt: methodology and writing—review and editing. Lili Tian: methodology and writing—review and editing. Helen C. S. Meier: data curation, methodology, and writing—review and editing. Henry Louis Taylor Jr.: conceptualization and writing—review and editing. Deborah O. Erwin: writing—review and editing. Heather M. Ochs-Balcom: conceptualization, design, methodology, supervision, and writing—review and editing.

Data Availability Historical redlining score data are publicly available for download at: https://www.openicpsr.org/openicpsr/project/141121/version/V2/view. Census data are publicly available at data.cenus.gov. Breast cancer data were sourced from the NYSCR. These data cannot be shared because of privacy. Access to NYSCR data requires approval from the NYSCR. The NYSCR can be contacted at: nyscr@health.ny.gov.

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