Research Article

Cancer Epidemiology, Biomarkers & Prevention

The Impact of Neighborhood Economic and Racial Inequalities on the Spatial Variation of Breast Cancer Survival in New Jersey

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Abstract

Background: Mapping breast cancer survival can help cancer control programs prioritize efforts with limited resources. We used Bayesian spatial models to identify whether breast cancer survival among patients in New Jersey (NJ) varies spatially after adjusting for key individual (age, stage at diagnosis, molecular subtype, race/ethnicity, marital status, and insurance) and neighborhood measures of poverty and economic inequality [index of concentration at the extremes (ICE)].

Methods: Survival time was calculated for all NJ women diagnosed with invasive breast cancer between 2010 and 2014 and followed to December 31, 2015 ($N = 27{,}078$). Nonlinear geoadditive Bayesian models were used to estimate spatial variation in hazard rates and identify geographic areas of higher risk of death from breast cancer.

Results: Significant geographic differences in breast cancer survival were found in NJ. The geographic variation of hazard rates statewide ranged from 0.71 to 1.42 after adjustment for age and stage, and were attenuated after adjustment for additional individual-level factors (0.87–1.15) and neighborhood measures, including poverty (0.9–1.11) and ICE (0.92–1.09). Neighborhood measures were independently associated with breast cancer survival, but we detected slightly stronger associations between breast cancer survival, and the ICE compared to poverty.

Conclusions: The spatial models indicated breast cancer survival disparities are a result of combined individual-level and neighborhood socioeconomic factors. More research is needed to understand the moderating pathways in which neighborhood socioeconomic status influences breast cancer survival.

Impact: More effective health interventions aimed at improving breast cancer survival could be developed if geographic variation were examined more routinely in the context of neighborhood socioeconomic inequalities in addition to individual characteristics.

Introduction

Improvements in breast cancer survival can be attributed to advances in screening, early detection, clinical treatments, and targeted interventions based on clinical risk factors, such as earlier age at diagnosis, lower grade tumors, hormone receptor status, and known modifiable lifestyle behaviors, including alcohol consumption (1–4). In addition to the growing population of breast cancer survivors, there is a growing population of patients with breast cancer diagnosed with metastatic, or stage IV, disease who are also living longer (5). Thus, continued understanding of factors contributing to breast cancer survival is increasingly relevant.

Despite improvements in breast cancer survival, disparities persist, and are multilevel and complex (6, 7). Demographic factors including Black race, low socioeconomic status (SES) and education (8, 9), lack of health insurance (10–12), and not being married (9, 13) are associated with lower breast cancer survival. Studies have reported that in addition to patient-level demographics, breast cancer survival is influenced by neighborhood-based characteristics, or the social, physical, and economic conditions of a patient's environment. Studies have indicated that women living in low-SES neighborhoods had worse survival than women living in high-SES neighborhoods did, regardless of race/ethnicity (8, 14–16). Neighborhood SES (n-SES) has also been found to be among the most influential factors associated with racial disparities in breast cancer mortality (17), particularly for non-Hispanic Blacks (NHB) and Hispanics (18, 19). Other studies report strong combined effects of individual SES and n-SES on breast cancer survival (20, 21). Racial segregation was also found to be an important factor in breast cancer mortality in several studies (22–25). Krieger and colleagues (26) found that a joint local income and race/ethnicity-based residential segregation measure was associated with the breast cancer estrogen receptor (ER) status, which is related to breast cancer survival. They defined economically segregated areas along a continuum from concentrated poverty to concentrated affluence, using the index of

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concentration at the extremes or ICE (26). They posit that the ICE, in contrast to a poverty measure, keeps visible both the most and least privileged groups, and better represents social polarization (18).

Examining differences in survival using measures of n-SES (e.g., low poverty vs. high poverty) is important for documenting disparities and implementing interventions in specific populations. However, knowing whether survival varies geographically, and specifically where significant disparities are spatially distributed, is also important. This is because mapping places with poor cancer survival can help cancer control programs prioritize efforts with limited resources. Three main spatial statistical methods have been used for mapping geographic variation in cancer survival: spatial scan statistics (27–29); adaptive spatial filtering (25, 30, 31); and Bayesian spatial regression models (32–34).

To date, only two studies have utilized spatial statistical approaches to examine geographic variation in breast cancer survival in the United States. Carroll and colleagues (34) found geographic variation in breast cancer survival among residents in Louisiana and that these differences could not be explained solely by individual-level characteristics, such as grade and ER or progesterone receptor (PR) status. They concluded that observed spatial differences were most likely related to n-SES and access to care and quality of care. Schootman and colleagues (29), using spatial scan statistics, conducted a multilevel analysis examining geographic disparities (GD) in breast cancer survival among five Surveillance, Epidemiology, and End Results (SEER) Program regions in the United States. Along with stage at diagnosis, census tract (CT) poverty levels were identified as the most important factor, explaining the presence of short survival clusters across the regions. Other studies have shown that including n-SES and segregation measures in multilevel modeling contributes to defining target groups and areas with lower survival rates associated with racial disparities (25, 35, 36).

In this study, we sought to improve our understanding of the impact of economic and racial inequality on breast cancer survival from a geospatial perspective. We used Bayesian spatial models to identify whether breast cancer survival among patients in New Jersey (NJ) varies spatially after adjusting for key individual and neighborhood factors. We examined four n-SES measures, including CT-Poverty and the ICE measure. Our purpose in conducting this study was to better understand breast cancer survival disparities in NJ and demonstrate how Bayesian spatial models can complement traditional nonspatial statistical approaches to identify GD in breast cancer survival for planning future interventions.

Materials and Methods

Study population

Female breast cancer cases were obtained from the New Jersey State Cancer Registry (NJSCR). The NJSCR is a population-based cancer registry established in October 1978 to monitor cancer among the more than 8.9 million residents of NJ (https://www.state.nj.us/health/ces/reporting-entities/njscr/). The NJSCR has consistently received recognition from the Centers for Disease Control and Prevention (CDC), the National Cancer Institute (NCI), and the North American Association of Central Cancer Registries (NAACCR) for its high quality and timely submission of data.

The study population includes all female NJ residents 18 years and older with histologically confirmed, first primary, invasive breast cancer according to the International Classification of Diseases for Oncology, 3rd Edition (ICD-O3 C500-C509; excluding histology codes 9590–9989; ref. 37) diagnosed between January 1, 2010 and December 31, 2014 ($N = 36{,}309$). Cases with *in situ* ($n = 8{,}240$) and unknown stage ($n = 851$), unknown age ($n = 4$), negative or zero survival time ($n = 118$), or missing addresses ($n = 17$) were excluded. A total of 27,078 cases were used in the analysis.

Individual-level demographic measures

Individual-level measures were obtained from the NJSCR, and included age at diagnosis, race [White, Black, Asian or Pacific Islander (API), other], ethnicity (Hispanic, non-Hispanic), date of diagnosis, primary insurance payer (self-pay, private, Medicaid, Medicare, military, uninsured), and stage at diagnosis (*in situ*, local, regional direct extension, regional lymph nodes only, regional extension and nodes, distant), marital status (married, single never married, divorced, widowed, unmarried/domestic partner, unknown), and breast cancer subtype. Breast cancer subtype was defined using a summary variable (SSF16) that uses $ER^{+/-}$, $PR^{+/-}$, and $HER2^{+/-}$ values to classify breast cancer into four categories: Luminal A (ER^+ and/or $PR^+/HER2^-$), Luminal B (ER^+ and/or $PR^+/HER2^+$), HER2 ($ER^-/PR^-/HER2^+$), and triple negative (TNBC, $ER^-/PR^-/HER2^-$). Cases for which ER, PR, and HER2 status are unknown were classified as unknown breast cancer subtype.

NJSCR is linked with state and national death files, hospital discharge files, Medicare and Medicaid files, Social Security Administration Services for Epidemiologic Researchers, and motor vehicle registration files, allowing annual updates to vital status. Patients were followed until their deaths or until December 31, 2015. Deaths attributed to breast cancer were abstracted from death certificates and identified according to ICD-10 code C50.

Neighborhood measures

Cases were geocoded by the NJSCR to the residential address at the time of diagnosis and assigned a 2010 CT. CT or neighborhood measures of poverty have proved useful for comparing health outcomes in populations with more versus less socioeconomic resources, but they do not summarize the full range of concentrations of groups at the extremes of high and low deprivation. Recently, Krieger and colleagues reintroduced the ICE (26, 38, 39), which was developed in 2001 by Douglas Massey (40) to quantify how rising income and wealth inequalities were leading to growing spatial and social economic polarization. The ICE measure ranges from -1 (concentrated poverty) to $+1$ (concentrated affluence), and is more informative than are the Gini Index for income inequality and the index for dissimilarity for segregation, because it can be "meaningfully used at lower as well as at higher levels of geography" (38). In this study, we included four neighborhood-based measures: (i) percentage of the population 18 years and older living below the Federal poverty level; (ii) income-based ICE (I-ICE), (iii) income-and-race/ethnicity-based ICE for NHB ($\text{I-ICE}_{\text{NHB}}$), and (iv) income-and-race/ethnicity-based ICE for Hispanics (I-ICE_{H}). Neighborhood-measures assigned to the cases are based on the 2010 U.S. Census and the American Community Survey (ACS) 2011–2015. We used Massey's (40) formula for the calculation of the I-ICE while following methods from Krieger and colleagues (26) for

the integration of a racial/ethnic component, which compares the most privileged or affluent race/ethnic group (White, non-Hispanics) to Blacks or Hispanics, respectively.

Statistical analysis

Survival time was calculated as the difference in months between the date of breast cancer diagnosis and either the date of death from breast cancer or the date of the last contact. Patients who died of other causes were censored at the time of death for analyses of breast cancer–specific survival. Patients alive at the study end date (December 31, 2015) were censored at this time or at date of last follow-up (i.e., last known contact). Bayesian geoadditive models were applied to survival time as an extension of conventional Cox regression survival models. In conventional survival analysis, T_i typically denotes the observed survival time for patient i, and C_i denotes the right censoring time. Therefore, a patient's observed time is defined as $t_i = \min(T_i, C_i)$, and δ_i is used to denote whether the patient is censored or not (e.g., 1 = death, 0 = censored). $x_1 \ldots x_n$ are the covariate vectors (i.e., explanatory variables) for the patients. The Cox proportional hazard model is defined as: $\log[h(t_i,\ \delta_i, x_i)] = \log[h_0(t_i)] + x_i\beta$ where $\log[h(t_i,\ \delta_i, x_i)]$ is the log-baseline function. We use a an extension of this model described by Kneib and Fahrmeir (41) that includes s_i, which represents the geographic location of the patients CT at the time of diagnosis, while $f_{spat}(s_i)$ denotes the spatial function, used to estimate the spatial effect. Our final Cox regression–based model was established as:

$$\text{Model: } \log[h(t_i,\delta_i,\ x_i,\ s_i)] = \log[h_0(t_i)] + x_i\beta + f_{spat}(s_i)$$

The spatial function allows us to estimate the geographic variation in the hazard rate (HRate; i.e., risk of death from breast cancer) after controlling for various covariates (individual and neighborhood variables; ref. 42). The HRate measures the instantaneous event rate or the probability that an individual would experience an event (breast cancer death) at a particular time point after diagnosis. The spatial function is based on stationary Gaussian random fields (bivariate penalized splines). P-spline smoothed spatial effects were incorporated into the model based on an adjacency matrix of geographic neighbors by CTs (weights based on rook's case; refs. 43, 44). In case of high spatial heterogeneity or small numbers, no smoothing is applied (45). The HRate for each tract is the smoothed rate for the CT based on those living in that CT at time of diagnosis.

We first established a null model and a baseline model that included both age and stage (model 1). We also ran separate models that in addition to age and stage were adjusted for each of the individual level (subtype, race/ethnicity, marital status, primary payer/health insurance) and neighborhood measures (CT-Poverty, I-ICE, I-ICE_{NHB}, I-ICE_H; models S3–S10, see Supplementary Tables S1 and S2). We then developed a model that included only the individual-level variables (full individual-level, model 2). Finally, we developed models that included all individual-level variables and each of the following neighborhood measures defined as categorical variables: CT-Poverty (model 3), I-ICE (model 4), I-ICE_{NHB} (Supplementary Tables S1 and S2; model S11), I-ICE_H (Supplementary Tables S1 and S2; model S12). Associations with neighborhood measures were further tested in *post hoc* analysis, in which we included continuous variables in the models and found similar results.

Estimation of regression models is based on Markov chain Monte Carlo simulation techniques, corresponding to full Bayesian inference, obtained by specifying prior distributions for all unknown parameters. For each model, 12,000 iterations were run, with the first 2,000 samples used as a burn-in. Every 20th sample from the remaining 10,000 samples was saved, and used to construct the posterior distribution for each of the parameter estimates in the model. The 95% credible intervals (CI) were calculated on the basis of the posterior distribution of the 1,000 samples to identify significant HRs and the CTs with significantly higher or lower hazard rates. All models were implemented with R using BayesX (42), BayesXsrc (46), and R2BayesX (47) packages.

HRs with 95% CIs were calculated for each of the individual and neighborhood measures from the models. The exponentiated spatial effects of each CT from the models were mapped to visualize the HRates. In addition, we compared model fit using the deviance information criterion (DIC), where lower values of DIC indicate a better fit, as well as a method originally proposed by Chien and colleagues (33) to estimate the GD percentage. It is calculated as the square root of the spatial variance. Areas with statistically significant higher and lower HRates were also mapped and the case characteristics in these areas were summarized.

Results

Table 1 summarizes the study population (n = 27,078) by individual-level factors. Patients were diagnosed between the ages of 18 and 103 (mean 60.3). Approximately 89% of the study population were alive at the end of follow-up (December 31, 2015). The average survival time in the sample was 36.9 months. Of all cases, 63.9% were diagnosed at the localized stage, 29.7% at the regional stage, and 6.4% at the distant stage. Among the breast cancer subtypes, Luminal A accounts for nearly 68% of all cases, followed by TNBC (10.1%), Luminal B (9.8%), and HER2 (4.2%). Eight percent of all breast cancer cases were categorized as Unknown breast cancer subtype. Around three quarters of the study population were non-Hispanic White (NHW), 11.7% NHB, 10% Hispanic origin (any race), and 5.7% API. Fifty-five percent of women had private insurance and 33.5% had Medicare. Approximately one third of patients with breast cancer were living in areas with a poverty rate as low as 2.6%, while 16.14% were residents in high-poverty areas (up to 73.4%). The distribution of all other n-SES measures follows similar patterns, with approximately 15%–17% living in areas of concentrated affluence and 32% living in neighborhoods of concentrated poverty.

The average statewide poverty level based on 2010 U.S. Census data was 10.5% (0%–73.4%). Mean I-ICE was 0.15, ranging from −0.7 (concentrated poverty) to 0.8 (concentrated affluence). Race/ethnicity and income-based ICE indicated that NJ's population is slightly more segregated among poor NHB ($\text{I-ICE}_{NHB} = 0.62$) than among poor Hispanics ($\text{I-ICE}_H = 0.61$) in comparison with affluent NHW.

Fixed effects: individual-level and neighborhood factors

Table 2 describes HRs and 95% CIs for each individual and n-SES measure adjusted for age and stage and the multivariable adjusted models. The effect sizes for age, stage, and breast cancer subtype were consistent across models. However, for many of the individual variables, HRs were attenuated in the multivariable models, but remained statistically significant, where NHB women had a 50% a higher risk of death from breast cancer compared

Table 1. NJ female breast cancer patient characteristics ($N = 27,078$)

Characteristics	Mean	Range
Age at diagnosis, mean years (SD)	60.3 (13.7)	18–103
Survival time, mean months (SD)	36.9 (18.3)	1–71
	N	%
Vital status		
Alive	24,184	89.3
BC-related deaths	2,894	10.7
Stage at diagnosis		
Localized	1,7293	63.9
Regional, direct extension only	464	1.7
Regional, regional lymph nodes only	6,676	24.6
Regional, direct extension and regional lymph nodes	922	3.4
Distant	1,723	6.4
BC subtype		
Luminal A	18,343	67.7
Luminal B	2,641	9.8
HER2	1,139	4.2
TNBC	2,729	10.1
Unknown	2,226	8.2
Race/ethnicity		
NHW	19,485	72.0
NHB	3,171	11.7
Hispanic (of any race)	2,714	10.0
NH API	1,553	5.7
NH Other	155	0.6
Marital status		
Single (previously married)	6,201	22.9
Single (never married)	4,052	15.0
Married	14,270	52.7
Unknown	2,555	9.4
Primary payer at diagnosis		
Not insured	667	2.5
Private/self-pay	15,019	55.5
Medicaid/military	1,109	4.1
Medicare	9,068	33.5
Unknown	1,215	4.5
Census tract poverty (quartiles)		
1 < 2.6%	8,463	31.3
2 < 5.0%	7,916	29.2
3 < 7.4%	6,325	23.4
4 7.4%–73.4%	4,370	16.1
Census tract ICE income (quartiles)		
1 Concentrated affluence	4,635	17.1
2	6,166	22.8
3	7,485	27.6
4 Concentrated poverty	8,787	32.5
Census tract ICE income + NHB (quartiles)		
1 Concentrated affluence of NHW	4,288	15.8
2	6,564	24.2
3	7,519	27.8
4 Concentrated poverty of NHB	8,702	32.1
Census tract ICE income + Hispanics (quartiles)		
1 Concentrated affluence of NHW	4,185	15.5
2	6,616	24.4
3	7,566	28.0
4 Concentrated poverty of Hispanics	8,706	32.2

Abbreviation: NHW, non-Hispanic White.

with NHW (HR = 1.49; 95% CI, 1.42–1.57). Hispanic and API women, on the other hand, had a lower risk of death from breast cancer than NHWs did (Hispanic HR = 0.9; 95% CI, 0.84–0.97; API HR = 0.9; 95% CI, 0.81–0.99).

Women with breast cancer who were single (previously married or never married), uninsured, or Medicaid or Medicare insured were all at a higher risk of death from breast cancer compared with married or privately insured women, respectively. After adding neighborhood measures to the full individual-level model, our final model found that women, who live in less affluent, more economically segregated areas had a significantly higher risk of death from breast cancer (HR = 1.29; 95% CI, 1.21–1.37) compared with women in more affluent, less economically segregated areas (Table 2).

Geographic clustering and spatial effects

Figure 1 shows the spatial variation of HRates in NJ. The top panel shows the results of the baseline (model 1) and full individual-level models (model 2), while the bottom panel shows the results based on the fully adjusted model with CT-Poverty and the ICE measures. After controlling for age and stage, the baseline model shows several clusters where the HRates are significantly higher and lower than 1. The majority of significant clusters with a higher risk of death from breast cancer are located in or around the metropolitan area of Newark, NJ in the northeast, and in parts of southern NJ. After adjusting for relevant clinical and demographic characteristics in the full individual-level model, the areas with significantly lower risk of death from breast cancer were eliminated; however, an area with a significantly higher risk of death from breast cancer persisted in one location. In the multivariable models, adding CT-Poverty, I-ICE, or the $\text{I-ICE}_{\text{NHB}}$ measures to the full individual-level model resulted in the complete elimination of areas with significantly higher or lower risk of death from breast cancer. The lone exception was in the I-ICE_{H} model S12 (Supplementary Fig. S1), which shows an area with significantly lower risk of death from breast cancer in Northeast NJ.

Table 3 presents the sociodemographic characteristics of the breast cancer cases and the NJ population with the statistically significantly geographic clusters of higher (HRate>1) or lower risk of death from breast cancer (HRate<1). Compared with the low-risk clusters, the high-risk clusters have a larger proportion of NHB (34.5% vs. 4.3%) and Hispanic cases (19.1% vs. 8.1%), and a lower proportion of NHW cases (42.2% vs. 79.1%). High-risk clusters also have a higher proportion of patients living below the Federal poverty level (12.9%) compared with the low-risk clusters (3.7%) and NJ overall (6.9%). A summary of the clusters using population data also indicates more minorities and impoverishment in the high-risk clusters compared with low-risk clusters.

Geographic variation in HRates

Compared with the baseline model (HRates 0.71–1.42), the statewide range of HRates describing the risk of death from breast cancer attenuated after adjusting for the individual factors (HRates 0.87–1.15) and further attenuated after adding the neighborhood measures (CT-Poverty, HRates 0.9–1.11; I-ICE, HRates 0.92–1.09; Fig. 1; Table 4).

Table 4 summarizes the model fit (DIC), statewide range of HRates, and GD percentage for each of the spatial models. The model with individual-level factors plus I-ICE had the lowest DIC, best fit compared with the other neighborhood factors. The GD percentage based on the spatial variance decreased from 83% in the baseline model to 24.7% in full individual-level model. The GD percentage was further reduced to 19.26% after including CT-Poverty and was the lowest for (I-ICE) at 15.3% (Table 4). The GD percentage for the variable race/ethnicity when added to the model adjusted for age and stage was slightly lower compared with CT-Poverty (32.4%) and lower than the other individual-level factors including subtype (GD 59.9%), marital status (GD

Table 2. HRs and 95% credible intervals from age- and stage-adjusted models and multivariable models

	Variables	Age and stage adjusted HR (95% CI)	Multivariable model (model 2)[a] HR (95% CI)
Age	Age	1.03 (1.03–1.03)	1.03 (1.03–1.03)
Stage	Localized	Ref.	Ref.
	Regional, direct extension	4.58 (4.13–5.09)	4.48 (4.06–4.95)
	Regional, lymph nodes	2.74 (2.6–2.88)	2.72 (2.59–2.86)
	Regional, direct extension and regional lymph nodes	7.42 (6.91–7.98)	7.02 (6.54–7.55)
	Distant	24.31 (23.16–25.51)	23.44 (22.32–24.61)
Subtype	Luminal A	Ref.	Ref.
	Luminal B	0.96 (0.9–1.03)	0.94 (0.88–1)
	HER 2	1.46 (1.34–1.59)	1.42 (1.31–1.54)
	Triple negative	2.8 (2.66–2.95)	2.66 (2.53–2.8)
	Unknown	1.55 (1.46–1.64)	1.48 (1.39–1.57)
Race/ethnicity	NHW	Ref.	Ref.
	NHB	1.8 (1.71–1.9)	1.49 (1.42–1.57)
	Hispanic (any race)	1.03 (0.96–1.1)	0.9 (0.84–0.97)
	Asian and Pacific Islander	0.87 (0.79–0.97)	0.9 (0.81–0.99)
Marital status	Married	Ref.	Ref.
	Single (previously married)	1.59 (1.51–1.68)	1.41 (1.34–1.48)
	Single (never married)	1.36 (1.29–1.42)	1.26 (1.21–1.32)
	Unknown	1.27 (1.19–1.36)	1.16 (1.09–1.25)
Insurance	Private/self-pay	Ref.	Ref.
	Not insured	1.58 (1.41–1.76)	1.41 (1.34–1.48)
	Medicaid/military	1.85 (1.7–2.02)	1.26 (1.21–1.32)
	Medicare	1.28 (1.21–1.35)	1.16 (1.09–1.25)
	Unknown	1.57 (1.43–1.71)	1.51 (1.38–1.64)
	Neighborhood CT measures	**Age and stage adjusted + CT measures HR (95% CI)**	**Multivariable model (models 3 and 4)[b] HR (95% CI)**
Poverty	1QT (lowest proportion)	Ref.	Ref.
	2QT	1.13 (1.08–1.19)	1.09 (1.04–1.15)
	3QT	1.24 (1.17–1.3)	1.14 (1.08–1.2)
	4QT (highest proportion)	1.62 (1.53–1.72)	1.30 (1.23–1.38)
I-ICE (income)	1QT (concentrated affluence)	Ref.	Ref.
	2QT	1.09 (1.03–1.15)	1.04 (0.99–1.09)
	3QT	1.24 (1.17–1.32)	1.12 (1.06–1.18)
	4QT (concentrated poverty)	1.64 (1.54–1.74)	1.29 (1.21–1.37)

Abbreviation: HR, hazard ratio.
[a]Multivariable model adjusted for age, stage at diagnosis, subtype, race/ethnicity, marital status, insurance, and spatial effect (full individual-level model).
[b]Multivariable models adjusted for age, stage at diagnosis, subtype, race/ethnicity marital status, and insurance, neighborhood measures, and spatial effect.

52.1%), insurance (GD 58.9%; Table 4). Summary values for all models examined in this study are found in Supplementary Table S2.

Discussion

In this study, we used Bayesian spatial models to assess the impact of CT-Poverty and economic inequality measured using the ICE on the spatial distribution of breast cancer survival in NJ. We found several geographic areas (i.e., clusters) of significantly higher risk of death from breast cancer that were not explained by age and stage at diagnosis, and remained partially unexplained by other key individual-level factors including molecular subtype, race/ethnicity, and primary insurance payer. Each of the n-SES measures examined were independently associated with breast cancer survival after adjustment for several individual-level factors. The spatial models also indicated that the n-SES measures were influential in reducing the GD percentage in breast cancer survival statewide. Our study is among the first to use Bayesian spatial models to summarize the statewide GD percentage in breast cancer survival before and after adjusting for important individual-level and n-SES, and to show that the ICE measure is associated with female breast cancer survival.

A central finding of our study is that when comparing the n-SES measures, we detected slightly stronger associations between breast cancer survival, and the ICE compared with CT-Poverty. Previous studies by Krieger and colleagues (26, 38, 39) also suggested that I-ICE is more strongly associated with breast cancer survival. In our study, associations between breast cancer survival and poverty and I-ICE were similar based on HRate ranges, but the I-ICE appeared more influential than CT-Poverty in explaining more of the GD in breast cancer survival (i.e., explaining the spatial variation; 74% compared with 70%). While the ICE and poverty measures are correlated, the ICE measure accounts for economic variation and extremes within a neighborhood and captures social polarization (26, 40). Capturing socioeconomic polarization using the I-ICE and the alternative ICE measures that capture racialized economic segregation may account for potential economic stressors that can impact breast cancer survival, and thus, this measure may be slightly more informative than neighborhood-level poverty alone.

While individual-level factors were important in reducing NJ's GD in breast cancer survival, models with both neighborhood (e.g., I-ICE) and individual-level factors explained more of the GD than models with individual-level factors alone. At the individual level, consistent with previous studies, we found that race/ethnicity (18, 48, 49); molecular subtype of tumor (50, 51); marital

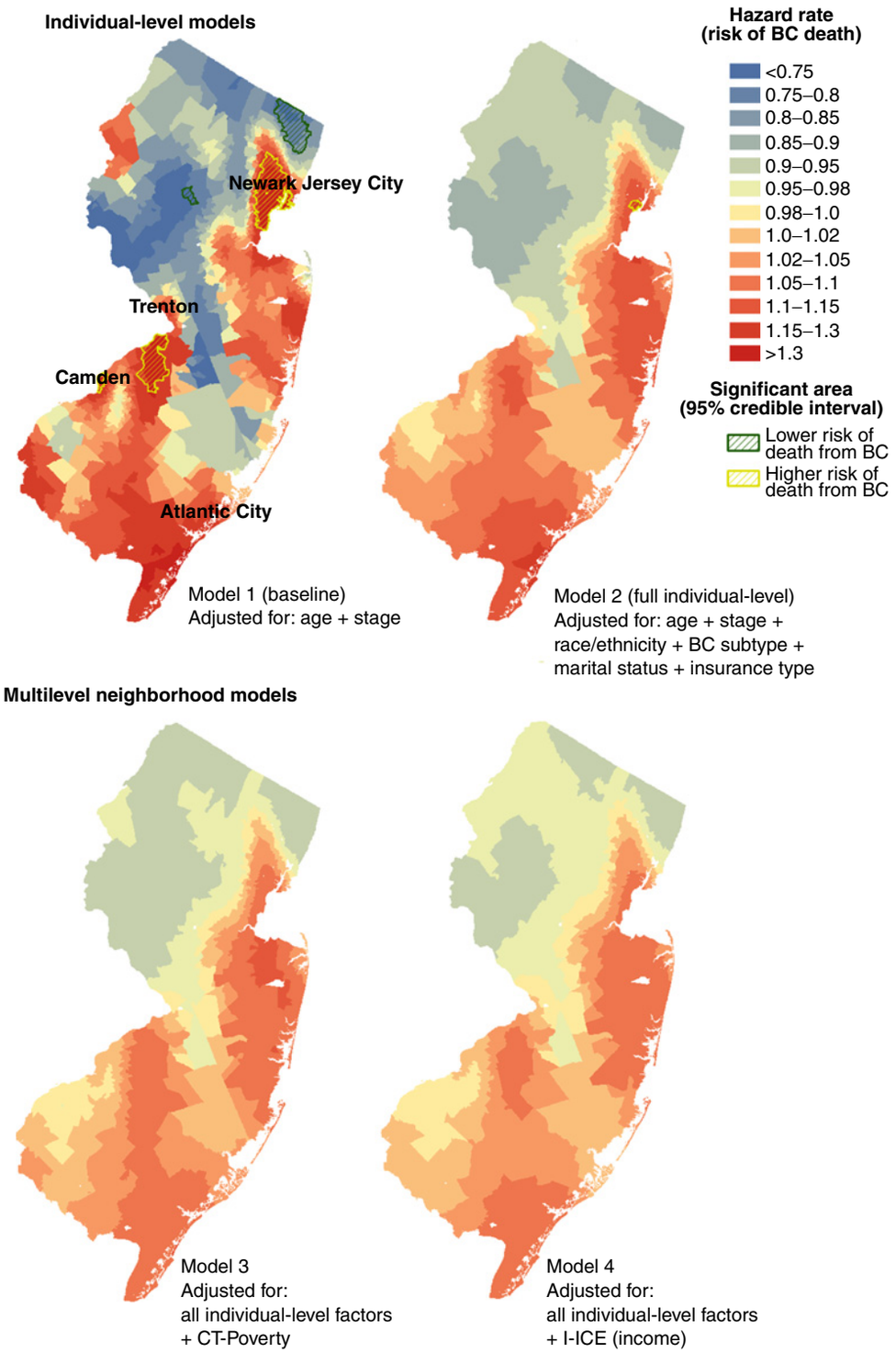

Figure 1.

Spatial distribution of HRates in NJ. HRates > 1 indicate an elevated risk of death from breast cancer. Green boundaries indicate significant clusters of lower risk of death from breast cancer. Yellow boundaries indicate significant clusters of higher risk of death from breast cancer.

Table 3. Sociodemographic characteristics of the statistically significant geographic clusters of risk of death from breast cancer based on the Bayesian spatial model adjusted for age and stage at diagnosis (model 1)

Sociodemographic characteristics	% Within clusters with statistically significant lower risk of BC death		% Within clusters with statistically significant higher risk of BC death		% Outside the clusters		% Statewide	
Total cases	***N* = 1,083**		***N* = 3,423**		***N* = 22,572**		***N* = 27,078**	
	Cases	**Area (census)**	**Cases**	**Area (census)**	**Cases**	**Area (census)**	**Cases**	**Area (census)**
NHW	79.13	68.0	42.19	26.89	76.13	62.80	71.96	56.49
NHB	4.34	5.1	34.5	38.72	8.61	9.32	11.71	14.39
Hispanic	8.13	12.5	19.11	26.90	8.74	17.10	10.02	18.75
Non-Hispanic Asian	8.03	12.6	3.53	4.71	5.96	8.73	5.74	8.16
Below poverty	3.67	4.4	12.92	16.88	6.9	9.25	7.53	10.47
Median household income[a]	106,475	103,722	59,279	50,471	81,079	73,852	79,340	70,604
Poverty by quartiles	Cases only (%)		Cases only (%)		Cases only (%)		Cases only (%)	
1 Low	63.16		12.95		32.50		31.26	
2	21.42		19.50		31.09		29.24	
3	13.39		28.35		23.08		23.36	
4 High	2.03		39.20		13.32		16.14	
ICE by quartiles								
1 Low income	1.85		42.50		14.01		17.12	
2	5.45		26.89		22.98		22.78	
3	20.50		19.15		29.28		27.65	
4 Affluence	72.21		11.46		33.73		32.46	
ICE income and NHB by quartiles								
1 Low income and NHB	2.03		50.16		11.3		15.84	
2	14.22		32.01		23.55		24.25	
3	21.33		10.76		30.66		27.77	
4 Affluence and NHW	62.42		7.07		34.49		32.14	
ICE income and Hispanics by quartiles								
1 Low income and Hispanics	2.03		50.22		10.83		15.46	
2	15.33		30.02		24.03		24.44	
3	21.51		12.98		30.52		27.95	
4 Affluence and NHW	61.13		6.78		34.61		32.16	
Patients' stage at diagnosis								
Localized	67.77		58.08		64.56		63.87	
Regional, direct extension	1.94		1.52		1.73		1.71	
Regional, lymph nodes	23.27		29.52		23.98		24.65	
Regional, direct extension and regional lymph nodes	2.59		3.54		3.43		3.41	
Distant	4.43		7.34		6.31		6.36	
Patients' insurance								
Not insured	1.29		4.27		2.25		2.46	
Private/self-pay	60.20		52.59		55.68		55.47	
Medicaid/military	1.85		7.10		3.75		4.10	
Medicare	33.33		29.99		34.02		33.48	
Unknown	3.32		6.05		4.30		4.48	
Patients' marital status								
Single (never married)	10.71		26.75		13.38		22.90	
Married	64.64		41.39		53.84		52.70	
Single (prev. married)	21.98		24.52		22.70		14.96	
Unknown	2.68		7.34		10.08		9.43	
Patients' BC subtype								
Luminal A	68.88		62.96		68.41		67.74	
Luminal B	9.70		10.23		9.69		9.76	
HER2	4.34		4.71		4.12		4.20	
Triple negative	8.49		11.55		9.93		10.08	
Unknown	8.59		10.55		7.85		8.22	

[a]*P* = 0.05.

status (13, 48); and insurance type (11, 52) were all significantly associated with breast cancer survival, after accounting for age and stage at diagnosis. In our study, it is noteworthy that race/ethnicity explained more of the GD percentage than the other individual factors did and was similar to neighborhood SES. This is likely related to NHBs having a higher proportion of the individual risk factors associated with worse survival and their concentration in impoverished communities. Worse survival among NHBs compared with other race/ethnicity groups could be related to unmeasured factors, including a higher prevalence of obesity and comorbidities, as well as delays in accessing care and follow-up care after treatment. A study of NJ women (53) found that Blacks experienced delays in initiating adjuvant chemotherapy more frequently than Whites did. They also noted that these differences were observed in a population with similar socioeconomic status and insurance access, implying that there might be specific cultural and psychosocial factors contributing to the observed differences (53). Thus, findings using individual-level data suggest that

Table 4. Model characteristics comparing model fit (DIC), HRates range, and unexplained GD percentage

Models[a]	Variables	DIC	ΔDIC	ΔDIC%	HRate range	GD%	ΔGD%
	Null	38,880			0.6–1.67	89.73	
	Age	38,423	457	1.18	0.66–1.77	83.33	6.4
1	Baseline model: age + stage	35,125	3,755	9.66	0.71–1.42	65.30	24.43
2	All individual-level factors: age + stage + BC subtype + race/ethnicity + marital status + insurance type	34,069	4,811	12.37	0.87–1.15	24.74	64.99
3	Individual factors + CT-Poverty	34,072	4,808	12.37	0.9–1.11	19.25	70.48
4	Individual factors + I-ICE (income)	34,054	4,826	12.41	0.92–1.09	15.31	74.42

Abbrevaitions: DIC, deviance information criterion (model fit), lower values are better fit; GD, geographic disparity: square root of the spatial variance; disparity in relation to statewide HRates average; lower number represent reduced disparities; ΔDIC, difference between the DIC for a model and DIC for the null model; ΔGD, difference between the GD for a model and GD for the Null model.
[a]Spatial effect included in all models.

increasing screening mammography and timely diagnostic follow-up can improve survival and explain GD at the community level, but not completely address geographic variations in breast cancer survival.

As we demonstrated in this study, Bayesian spatial models provide a more comprehensive approach for examining geographic disparities in cancer survival than approaches like nonspatial Cox regression because these models can incorporate a spatial effect, which provides a way to map the risk of death and summarize the magnitude of GD after adjustment for different factors. These models can also be used to identify areas with a statistically significantly higher risk of death (e.g., geographic clustering).

Several limitations should be considered. Molecular subtype could not be determined for 8.2% of cases. These records were included but coded as unknown. We also excluded records that were missing stage information (3.1%). Missing stage data were disproportional across race/ethnicity groups and neighborhood poverty ($P < 0.001$). Hispanics and blacks had a higher proportion missing stage compared with whites, and the poorest group had the highest proportion. Patients missing stage data also had survival estimates similar to patients with regional stage. This nondifferential misclassification of stage would bias estimates to the null and likely lead to an underestimate of disparities. The short follow-up time (mean 36.9 months, SD 18.3) suggests insufficient time to observe all breast cancer–attributed deaths that might occur, and the mortality from breast cancer is underestimated. Because there is a higher risk of death among those with later stage disease and lower SES, a slightly longer follow-up time would capture more deaths in these groups, which indicates our current findings are likely biased toward the null, and survival differences would be more pronounced. The neighborhood measures were based on CT data because these were the smallest geographic units available at the time the study was conducted. A change in geographic unit (from CT to block group) may result in different conclusions. Finally, we were also unable to include some factors known to impact survival, such as treatment, comorbidities, lifestyle and other neighborhood-level factors. For instance, beyond I-ICE, numerous characteristics of poor neighborhoods could impede patients' survival, such as high unemployment, poor education, health impairment, environmental exposures, substandard housing, and limited access to resources and information. Some poor neighborhoods might have limited access to grocery stores and healthy foods, which can result in poor nutrition that is associated with shorter cancer survival (54, 55); and, a higher likelihood of social disorder (i.e., high crime rates), resulting in elevated psychosocial stress, which is associated with worse survival (56, 57). Limited social networks and insufficient family support that might be more prevalent in some poor areas have also been shown to be associated with worse cancer survival (58). Further studies that are able to more comprehensively evaluate neighborhood-level effects on breast cancer survival are warranted.

Identifying geospatial variations of breast cancer survival among women diagnosed with breast cancer advanced our understanding of contributing factors to survival rates in NJ communities. Our analysis highlighted the major role that health disparities play in breast cancer survival in NJ. Mapping HRates and coupling them with health disparity–related risk factors will serve to improve the identification of target communities for cancer control efforts, who may be at risk for poor survival outcomes due to modifiable geospatial causes related to disparities; some low n-SES neighborhoods might be affected more than another because of various location-specific factors. Our study not only provides additional evidence to support widely accepted theories that breast cancer disparities are a result of combined individual-level and neighborhood sociodemographic factors including racialized economic segregation, but it also provides evidence to suggest that neighborhood economic deprivation such as poverty may be only part of the story. Future studies should continue to assess additional neighborhood factors. In this way, cancer control efforts can begin to address the full suite of modifiable factors at the area level to reduce breast cancer disparities.

Disclosure of Potential Conflicts of Interest

No potential conflicts of interest were disclosed.

Authors' Contributions

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Acquisition of data (provided animals, acquired and managed patients, provided facilities, etc.): D. Wiese, A.M. Stroup, A. Crosbie, K.A. Henry
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