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Methodologic implications of social inequalities for analyzing health disparities in large spatiotemporal data sets: An example using breast cancer incidence data (Northern and Southern California, 1988–2002)

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SUMMARY

Efforts to monitor, investigate, and ultimately eliminate health disparities across racial/ethnic and socioeconomic groups can benefit greatly from spatiotemporal models that enable exploration of spatial and temporal variation in health. Hierarchical Bayes methods are well-established tools in the statistical literature for fitting such models, as they permit smoothing of unstable small-area rates. However, issues presented by ‘real-life’ surveillance data can be a barrier to routine use of these models by epidemiologists. These include (1) shifting of regional boundaries over time, (2) social inequalities in racial/ethnic residential segregation, which imply differential spatial structuring across different racial/ethnic groups, and (3) heavy computational burdens for large spatiotemporal data sets. Using data from a study of changing socioeconomic gradients in female breast cancer incidence in two population-based cancer registries covering the San Francisco Bay Area and Los Angeles County, CA (1988–2002), we illustrate a two-stage approach to modeling health disparities and census tract (CT) variation in incidence over time. In the first stage, we fit race- and year-specific spatial models using CT boundaries normalized to the U.S. Census 2000. In stage 2, temporal patterns in the race- and year-specific estimates of racial/ethnic and socioeconomic effects are explored using a variety of methods. Our approach provides a straightforward means of fitting spatiotemporal models in large data sets, while highlighting differences in spatial patterning across racial/ethnic population and across time.

Keywords

breast cancer; race/ethnicity; socioeconomic; health disparities; spatiotemporal analysis; CAR model; disease mapping; multilevel model

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1. INTRODUCTION

Increasing research points to the persistence, and even widening, of health disparities in the United States across racial/ethnic and socioeconomic groups and across communities in space [1]. National, state, and local reports on health inequities, however, typically have focused on racial/ethnic disparities, in part due to the lack of routinely collected socioeconomic measures in public health surveillance data, other than birth and death certificates [2,3]. Although specialized surveys, such as the National Health Interview Survey and the Behavioral Risk Factor Surveillance system, do collect socioeconomic data, the majority of surveillance and administrative data systems do not [3]. The net effect is to obscure socioeconomic gradients in health and the contribution of economic deprivation to racial/ethnic and geographic inequalities in health, at the national, state, and local levels [4,5].

Geocoding and linking health records to area-based socioeconomic measures has become increasingly popular as a method for addressing this problem [6–8]. Briefly, the residential addresses of cases are geocoded so that cases are identified with their residential area. Drawing on population counts and socioeconomic characteristics of the corresponding areas, both cases (numerators) and population at risk (denominators) may be classified by area-based socioeconomic characteristics, thereby permitting calculation of rates stratified by those socioeconomic measures.

Previous work by our Public Health Disparities Geocoding Project [8–13] has investigated which area-based socioeconomic measures, at which geographical level (e.g. census block group, census tract (CT), or ZIP code (ZC)) would be most suitable for monitoring the U.S. socioeconomic inequalities in health, bearing in mind that routine surveillance should be based on a readily interpretable and easily calculated socioeconomic measure that reliably detects expected socioeconomic gradients in health across a wide variety of health outcomes and population subgroups. Our key finding was that CT poverty level is the most apt measure for monitoring socioeconomic disparities, as it yields maximal geocoding (compared with census block group or ZIP code data), reliably detects expected socioeconomic gradients, and is readily interpretable. Since making our initial recommendations [10,11], this methodology has been adopted by a variety of state and local health departments and cancer registries, as well as individual researchers [14–20].

The geocoding methodology described above uses spatial data only insofar as it provides a means to assign each case to a socioeconomic ‘exposure.’ Once that assignment has occurred, cases and denominators are aggregated across space into socioeconomic strata—we term this the ‘aggregation’ method, and note that it is the standard practice in public health surveillance for computing and reporting disease rates stratified by age, gender, or race. Recent interest in the analysis of spatial data, spurred in part by computational advances, has resulted in a finer appreciation of spatial correlation and its effects on estimates of covariate effects [21,22]. Much of the spatial epidemiologic literature, and related multilevel literature, implicitly focus on using the spatial residual structure to try to account for unmeasured confounding in which the confounding variable is spatially correlated [23]. A typical approach, for example, is to fit a mixed effects regression model for disease counts, which includes a spatial residual term to account for variability that is spatially correlated [22,23]. How this spatial residual term is treated depends on the conceptual framework employed. Investigators posing multilevel hypotheses typically treat the random effects as drawn from multiple independent random normal distributions (e.g. census block groups nested within tracts nested with counties nested within states) [24,25]. Studies that posit underlying spatial variation in the risk surface are inclined to treat spatial correlation between two regions as varying as a function of the distance between the two regions [21,22]. A popular approach to the latter is to specify a conditional (intrinsic) autoregressive (CAR) model based on adjacency of areas [26]. Options for fitting

the multilevel approach are now readily available in standard software (e.g. PROC GLMMIX in SAS and MLwiN) [27,28]. Software for the CAR model is less readily available, but such models may be specified and fit in S+SpatialStats [22] and using Bayesian methods in WinBUGS [29].

Surveillance of health disparities over time adds an additional dimension to the problem. Bernardinelli *et al.* [30] proposed a fully Bayesian model in which both area-specific intercept and trend are modeled as random effects, with both spatial and temporal correlations allowed. Waller *et al.* [31] considered an extension of this model in which spatial effects are nested within time and applied this model to an analysis of annual lung cancer mortality rates for counties in Ohio, U.S.A. This model, with independent time and space effects, is appealing in part due to the ease of interpretation, as the spatial random effects offer area-specific adjustments to the overall relative risks in each time period [32]. Xia and Carlin enhanced this model to include age standardization and errors in covariates [33].

However, in many surveillance contexts, including investigation of racial/ethnic and socioeconomic health disparities in the United States, there are additional complexities that make straightforward application of existing methods rather more difficult. These issues include (1) regional boundaries shifting over time in longitudinal studies of disease, (2) patterns of racial/ethnic and socioeconomic segregation, which can lead to sparse disease counts for racial/ethnic groups in different areas and population differences in spatial variation, and (3) computational difficulties due to the sheer sizes of the data sets.

In this paper, we illustrate some of these ‘real-life’ data complexities that arise in a study of changing socioeconomic gradients over time in female breast cancer rates across different racial/ethnic groups. In particular, we argue that social inequality and patterns of racial/ethnic residential segregation in the U.S. imply that it is inappropriate to assume a common spatial correlation structure across racial/ethnic groups. We present a two-stage modeling procedure that makes use of spatiotemporal data ‘normalized’ to a set of area boundaries that are constant over years. Our data are drawn from 15 years (1988–2002) of breast cancer surveillance data from two U.S. population-based registries in the San Francisco Bay Area and Los Angeles, CA. In Section 2, we describe the Breast Cancer Incidence Project from which our data derive. Section 3 provides a brief review of spatial and spatiotemporal modeling strategies. Section 4 describes each of the three methodologic issues in detail. In Section 5, we present a two-stage procedure and presents results from the application of this procedure to the Breast Cancer Incidence Project data. A discussion of the substantive and methodologic results is presented in Section 6.

2. CHANGING SOCIOECONOMIC PATTERNS OF BREAST CANCER INCIDENCE

Motivating this paper is a project we undertook, using the methods of the Public Health Disparities Geocoding Project, to quantify secular changes in socioeconomic gradients over the past three decades (NCI 5R01 CA095983, PI: Krieger) in relation to area-based socioeconomic measures [34]. Our hypothesis was that the socioeconomic gradient reported for much of the 20th century (whereby incidence rates are highest among more affluent women) is decreasing over time, due to secular declines in the socioeconomic gradient for key breast cancer risk factors (e.g. age at menarche, parity, age at first birth). We further hypothesized that the smallest socioeconomic disparities in breast cancer incidence would occur in the racial/ethnic groups with the highest incidence rates.

Our first approach to testing this hypothesis used the ‘aggregate’ method. The study base consisted of all cases of primary, invasive incident breast cancer in women for three U.S.

population-based cancer registries covering: Los Angeles County, CA (1978–1982, 1988–1992, 1998–2002; $n=68762$ cases), the San Francisco Bay Area, CA (1978–1982, 1988–1992, 1998–2002; $n=37210$ cases) and Massachusetts (1988–1992, 1998–2002; $n=48111$ cases), and the population for each registry's catchment area. For these analyses, we linked the cases and population at risk to CT area-based socioeconomic measures, and, for each socioeconomic stratum, we computed average annual breast cancer incidence rates for the 5-year period straddling the 1980, 1990, and 2000 census, overall and by race/ethnicity. Our findings indicated that the socioeconomic gradient in breast cancer incidence is (a) relatively small (incidence rate ratio for most *versus* least deprived at most 1.2) and stable among the U.S. white non-Hispanic and black women, (b) sharper and generally increasing among Hispanic and Asian and Pacific Islander American women, and (c) cannot be meaningfully analyzed without considering effect modification by race/ethnicity and immigration. These results indicate that secular changes in the U.S. socioeconomic gradients in breast cancer incidence exist and vary by race/ethnicity.

2.1. Data sources

2.1.1. Cancer cases—In this paper, we extend our initial analyses by employing spatiotemporal models that take into account spatial and temporal structures. We restrict our data set to data from Los Angeles (LA) County and the San Francisco Bay Area (SF Bay Area: consisting of Alameda, Contra Costa, Marin, San Francisco, and Oakland Counties), for the period 1988–2002, and focus on modeling rates for white non-Hispanic, black, Asian Pacific Islander (API), and Hispanic women. Both the Los Angeles Cancer Surveillance Program (LA CSP) and the Northern California Cancer Center (NCCC) have excellent track records regarding completeness (estimated at >98 per cent), timeliness, and accuracy of registering cancer cases [35,36]. Use of these data for our investigation was approved by the institutional review boards of the LACSP, NCCC, and Harvard School of Public Health.

In our original study, we had all cases geocoded by a commercial geocoding company, whose accuracy we had previously tested and found to be high (96 per cent) [37], and compared the results with in-house geocoding done by the LACSP and NCCC. To maximize geocoding, we (a) used the geocoding company geocode (93.2 per cent of total cases) if both the geocoding company and registry codes were high precision (assigned based on exact street address or ZIP +4 code), (b) used the registry geocode if it was high precision and the geocoding company's was not (0.8 per cent of total cases), and (c) categorized the case as 'ungeocodable' (5 per cent of total cases) if neither the registry nor the geocoding company was of high precision.

2.1.2. Population counts—We obtained population counts stratified by age, gender, and race/ethnicity at the CT level from the 1990 Summary Tape File 2 (STF2) and 2000 Summary File 2 (SF2) of the U.S. Census [38]. Age-specific counts were categorized as <1, 1–4, 5–9, 10–14, 15–19, 20–24, 30–34, 35–39, 40–44, 45–49, 50–54, 55–59, 60–64, 65–69, 70–74, 80–84, 85+ years old, matching the age categorizes used by the National Cancer Institute's SEER system [39].

Although the U.S. Census publishes intercensal population estimates at the county level, no such reliable estimates exist at the CT level. Therefore, we used linear interpolation to estimate age-specific counts in each CT for years between 1990 and 2000. Estimates for 1988–1989 and 2001–2002 were obtained by extrapolating backwards or forward using the 1990–1991 and 1999–2000 slopes, respectively. The choice of a consistent spatial unit for interpolation is non-trivial, and we address it in greater detail in Section 4.

To compute the expected cancer counts by race/ethnicity, we obtained the U.S. age-specific breast cancer rates from SEER for 2003. We multiplied the age-specific rates by the age-

specific population counts and summed over age to obtain an expected count for each CT in each year [21].

2.1.3. Census-derived area-based socioeconomic measures—For these analyses, we use CT median household income as our primary socioeconomic measure. We chose this measure because it covers the whole range of the socioeconomic spectrum from poor to affluent, and, as a continuous variable, can be efficiently modeled as a linear term. To account for inflation, we adjusted the 1990 CT median household income values by the Consumer Price Index [40] so that they would be comparable to 2000 values. As with the population counts, we used linear interpolation and extrapolation as necessary to obtain yearly CT median household income values, which we modeled in these analyses in increments of \$10 000.

3. REVIEW OF SPATIOTEMPORAL MODELING

In this section, we review the generalized linear mixed model (GLMM) approach to spatiotemporal modeling of areal count data [21,22,41,42]. Areal count data, also termed 'lattice' data, arise when information on disease occurrences are available as areal-level aggregations, as is typical from routine surveillance sources. Interestingly, although geocoding of surveillance data may in fact permit identification of exact point locations for the cases, population *denominators* are available only at the areal level. Over the past 30 years, a vast statistical literature has accumulated on spatial modeling of count data—we do not attempt to summarize it all here, but refer the reader to Banerjee *et al.* for a more thorough treatment of this material [22].

3.1. Spatial model for areal count data

Let Y_{ij} and N_{ij} represent the number of cases and the number of individuals at risk in age stratum j , $j = 1, \dots, J$, and area i , $i = 1, \dots, n$. A Poisson model for the count data typically assumes that

$$Y_{ij} \sim \text{Poisson}(N_{ij}p_{ij})$$

where p_{ij} is the rate in stratum j , area i . In practice, the data will often be too sparse to obtain robust estimates of the age-specific quantities. Instead, the data are often indirectly standardized, so that we model

$$Y_i \sim \text{Poisson}(E_i\psi_i)$$

where $Y_i = \sum_j Y_{ij}$ and $E_i = \sum_j N_{ij}p_j^*$ denotes the expected number of cases in area i based on stratum-specific reference rates p_j^* . The reference rates may be obtained from an external standard, or, where such a standard is unavailable, internal standardization may be employed using $p_j^* = \sum_{ij} y_{ijt} / \sum_{ij} n_{ijt}$. The MLE $\hat{\psi}_i = Y_i/N_i$ corresponds to the standardized incidence ratio (SIR). Indirect standardization makes an assumption of proportionality such that the effect of being in area i is to multiply each of the age-specific rates by the common incidence rate ratio $\hat{\psi}_i$ for that area [41]. This has the appealing effect of reducing the dimensionality of the model, but also precludes explicit modeling of the effect of age. It also means that summary relative risks may be inappropriate if the proportionality assumption is violated [43].

Under the Poisson mixed model, we specify a log-linear model for the relative risk as a function of observed covariates, $\mathbf{X}_i$, and area-specific effects, η_i ,

$$\log(\phi_i) = \alpha + \mathbf{X}_i^T \beta + \eta_i \quad (1)$$

Besag *et al.* proposed decomposing the random effects η_i into independent unstructured heterogeneity (θ_i) and spatial structural (ϕ_i) components, which they term a convolution prior [44].

One typically assumes an exchangeable prior for the unstructured heterogeneity component, i.e. $\theta_i \sim N(0, \sigma_\theta^2)$. A popular distributional model for ϕ_i is the intrinsic Gaussian autoregression prior [44] given by

$$\phi_i | \phi_{j \neq i} \sim N(\bar{\phi}_i, \sigma_\phi^2)$$

where

$$\bar{\phi}_i = \frac{\sum_{j \neq i} w_{ij} \phi_j}{\sum_{j \neq i} w_{ij}} \quad \text{and} \quad \sigma_\phi^2 = \frac{1}{\lambda \sum_{j \neq i} w_{ij}}$$

We take $w_{ij} = 1$ if areas i and j are adjacent and $w_{ij} = 0$ otherwise, so that the conditional mean of the spatially structured effect is simply the average over the adjacent areas. Bernardinelli *et al.* [30] motivate the convolution prior by noting that ‘a cluster size bigger than the area size leads to a [spatially structured] clustering model, while a cluster size smaller than the area size leads to a heterogeneity model.’

The relative magnitude of the heterogeneity and clustering effects is controlled by the two-scale parameters, $\tau = 1/\sigma_\theta^2$ and λ , which require proper prior specifications in the Bayesian setting. As is well recognized in the literature, considerable care must be taken when specifying hyperpriors. Kelsall and Wakefield suggested a diffuse gamma(0.5, 0.0005) prior for the scale parameters [45]. Alternatively, Bernardinelli *et al.* noted that the *conditional* scale parameter λ has a relationship with the *empirical marginal* variability of ϕ_i that depends on the pattern of adjacencies between areas and provide guidelines for scaling the prior distributions on τ and λ [46].

3.2. Spatiotemporal extensions

Let ψ_{it} describe the relative risk in area i at time t . Bernardinelli *et al.* [30] proposed a fully Bayesian model in which both area-specific intercept and trend are modeled as random effects with allowance for correlation among them [30]. Waller *et al.* [31] considered an extension to equation (1) from above, nesting spatial effects within time, so that we model

$$\log(\psi_{it}) = \alpha + \mathbf{X}_i^T \beta + \delta t + \theta_{it} + \phi_{it} \quad (2)$$

where δ is the fixed time effect and the unstructured and structured spatial effects are nested within time. Note that the fixed covariate effects do not interact with space or time in this particular model, although it would be easy to extend the model in this direction. Multiple authors have considered variations of this basic framework, including extensions for multiple health outcomes [47] and spatial clustering [48], among others.

4. PROBLEMS ENCOUNTERED IN MODELING HEALTH DISPARITIES SURVEILLANCE DATA

4.1. Boundary changes over time

Spatiotemporal models that assess longitudinal changes in disease rates over time while accounting for spatial correlation among nearby CTs typically assume that the tracts are well defined throughout the course of the study. However, when the area boundaries shift during the period between census years, this approach becomes problematic. Changes in tract boundary definitions present an additional problem for our analysis in that we also do not have a consistent set of areal units for interpolating intercensal population estimates and area-based socioeconomic measures.

In the United States, CT boundaries are updated prior to each decennial census to reflect changes in population. To understand this, we recall that the primary purpose of the census is enumeration of the population for the purposes of determining taxation and representation. Consequently, the census redefines CT boundaries as necessary to maintain an average population of 3000–4000 that is socioeconomically homogeneous [49]. For example, an area that undergoes development and population growth between censuses may be split for a subsequent census, while multiple adjacent areas that experience population loss may be merged for a subsequent census. Table I presents sociodemographic changes in the SF Bay Area and Los Angeles between 1990 and 2000. This period saw considerable population growth overall, with dramatic changes in racial/ethnic composition.

Figure 1 shows some of the ways in which CT boundaries may be re-defined over time. In Figure 1(a), a single hypothetical CT in 1990 is split into two CTs in 2000. This relationship is sometimes reflected in the CT code itself, for example, tract 0101.00 becomes 0101.01 and 0101.02. (Note that this coding relationship is not always useful for identifying split tracts, as if in a subsequent census 0101.02 splits further, it may end up as 0101.03 and 0101.04.) In Figure 1(b), two CTs in 1990 (0102.04 and 0102.05) are merged into a single CT (0102.04). Figure 1(c) displays a more complicated set of boundary re-definitions, in which tract 0103.02 has absorbed a large chunk of tract 0104.01 and a small chunk of 0104.02.

4.1.1. Supertract approach—If boundary changes represent simple splits or merges of existing tracts, then a potential solution might be to aggregate tracts that split or merge across two censuses into ‘supertracts’ [50] that are then common across multiple census occasions. However, in the applications we have encountered, boundary changes are rarely this simple. The U.S. Census publishes a CT relationship file that tracks changes in tract boundaries from one census to another [51]. Using this resource, we calculated the number of CTs in the SF Bay Area that underwent simple splits, simple merges, and more complex redefinitions from 1990 to 2000 (Table II). In both the SF Bay Area and Los Angeles, almost 60 per cent of 2000 CTs had undergone some change from 1990 definitions. Of the 873 CTs in the SF Bay Area, only 5.4 per cent were the product of a simple split or merge; 52.3 per cent underwent a more complex redefinition. In Los Angeles, 19.8 per cent were the product of a split or merge, with 38.3 per cent deriving from more complex redefinitions. We note, too, that while the number of CTs in the SF Bay Area increased by 5 per cent from 1990 to 2000, the number of CTs in Los Angeles increased 25 per cent.

As a result of the complex relationships between multiple tracts from one census to another, the ‘supertract’ approach can result in a highly unbalanced spatial data set, wherein single tracts with relatively small populations coexist with supertracts that are ‘agglomerations’ of neighboring tracts (and in which potentially disparate populations are now forced to have the same ‘supertract’ random effect). Figure 2 presents an extreme example of from Los Angeles

County, in which small boundary changes involving multiple tracts result in a sort of ‘snowballing’ effect across a whole swathe of Los Angeles. Aggregation of disease data over such a large area would clearly result in loss of resolution of spatial variation. Even if aggregating in this way were appropriate, one would still need to decide how to combine the socioeconomic information from the original CTs to obtain a summary socioeconomic measure for each supertract. Thus, although this approach may lead to simpler methods for modeling, overall it is *ad hoc*.

4.1.2. Normalized boundary data set—A preferable strategy is to use commercial GIS software [52] that ‘normalizes’ census boundaries to a reference year. This normalization is achieved by redistributing census blocks into the CT boundaries from the reference year [53]. For sociodemo-graphic variables from the 1990 U.S. Census, normalized values based on 2000 geography are calculated by weighting and converting 1990 block group data to 2000 areas, as this is the smallest area for which 1990 U.S. Census long form data are available. For our analyses, we used these data to define the 1990 population in terms of 2000 boundaries and proceeded with interpolation of intercensal denominators and CT median household income values as described above.

4.2. Racial/ethnic residential segregation in the United States

The persistence of racial/ethnic segregation in the United States is well documented in the sociological literature, and a growing body of public health research suggests that links exist between patterns of racial/ethnic residential segregation and population health [54,55]. Figure 3 presents two maps of CT-level racial–ethnic composition for Los Angeles in 2000. Figure 3 (a) shows the CT per cent white composition, and 3(b) the CT per cent black composition. We can see starkly that these are mirror images of one another, and that, in the extreme, there are CTs where there is no black population in residence, and conversely CTs where there are very few white population in residence. These patterns of racial/ethnic segregation result in sparse racial/ethnic-specific populations at risk in some CTs and contribute to rate instability.

Patterns of racial/ethnic segregation also highlight the fact that the social realities of racialized experience mean that it may be inappropriate to assume a common spatial effect across racial/ethnic groups. We highlight two lines of reasoning for this assertion. Firstly, we note that the random effects in spatial models can be thought of to some extent as capturing variation due to unmeasured covariates (both spatially structured and unstructured) [41]. We might imagine that the populations of different racial/ethnic identification who reside in the same geographic space may nevertheless be quite different in terms of both individual covariates (‘composition’) and their experience of the area-based social context. This implies a different constellation of unmeasured covariates for each group and would suggest that we need to explore modeling separate racial/ethnic-specific spatial effects. Secondly, we note that the random effects may *also* be interpreted as accounting for data anomalies [41]. Given the evidence of racial/ethnic and socioeconomic disparities in access to health care (affecting numerators) and historic patterns of minority undercount in the U.S. Census (affecting denominators), we can conjecture that this, too, would imply differences in the racial/ethnic-specific spatial structure. This was borne out for us in early attempts to fit models to our data with a common spatial effects across all four racial/ethnic groups, when these models exhibited Markov chains with poor mixing properties, as well as poor model fit.

4.3. Computational issues

We note that much of the published work using Bayesian methods to fit spatiotemporal models have involved much fewer areas than those seen in our study. For example, the Ohio cancer mortality data set analyzed by Waller *et al.* involved 88 counties over 10 years, i.e. 880 data points [31], whereas the Sardinian diabetes mellitus data analyzed by Bernardinelli *et al.* [30]

involved 366 communes over 4 nine-year time periods, or 1464 data points. In contrast, our two data sets consist of data from 873 (SF Bay Area) and 2056 (Los Angeles) CTs over 15 years. If, as we suggest above, it is appropriate to model the spatial structure separately for four different racial/ethnic groups, this yields between 52 380 and 123 360 data points. When we attempted to fit the full spatiotemporal model from (2) to incidence data from Los Angeles for a single racial/ethnic group, the WinBUGS program ran for two days before crashing due to memory errors.

As an alternative, one might consider approximate maximum likelihood estimation to fit the model, for example, using penalized quasilielihood (PQL) [42] as implemented in SAS PROC GLIMMIX. However, in such existing implementation of PQL, almost all of the correlation structures provided as part of PROC GLIMMIX apply strictly to geostatistical (point referenced) spatial data. To our knowledge, packages for the analysis of spatial data in the popular R software also apply only to point referenced data. Conceivably, one could still use PQL and apply spatial correlations functions for point-referenced data to the centroids of the administrative areas of interest, but this is not optimal when areas are of irregular size and shape [21]. These considerations lead us to the two-stage approach outlined in the following section.

5. A TWO-STAGE APPROACH

5.1. Model specification

As the full spatiotemporal model over all the years was computationally unwieldy for our data, we reasoned that a two-stage approach would preserve the essential character of the ‘nested’ spatiotemporal model of Waller *et al.* [31] and enable proper modeling of the spatial structure within each year. As we also anticipated that patterns of racial/ethnic segregation in our two study areas would mean that we could anticipate different spatial patterns by race/ethnicity, in stage 1 we fit models separately for each of the four racial/ethnic groups in our study as

$$\begin{aligned} y_{irt} &\sim \text{Poisson}(E_{irt}\psi_{irt}) \\ \log(\psi_{irt}) &= \alpha_{rt} + \beta_{rt}x + \theta_{irt} + \phi_{irt} \end{aligned} \quad (3)$$

where r represents racial/ethnic group and x is the CT median household income as an area-based socioeconomic indicator. We note that, although in (2) the fixed covariate effects do not interact with time or space, in (3), they are allowed to vary across racial/ethnic groups and time, as α and β are estimated separately in each year of data for each racial/ethnic group. We computed expected counts using breast cancer incidence rates for white non-Hispanic across the SEER registries in 2000–2003 [39].

Model fitting via WinBUGS of the 60 separate stage 1 models for a single catchment area yields posterior means and 95 per cent credible intervals for α_{rt} and β_{rt} (as well as the spatial effects $\eta_{rt} = \theta_{rt} + \phi_{rt}$ and the hyperparameters τ_{rt} and λ_{rt}). For notational convenience, we denote the posterior mean of a parameter ω from the stage 1 model as $\hat{\omega}$. In stage 2, we explore temporal patterns in these terms using three approaches. Firstly, we plot $\hat{\alpha}_{rt}$ and $\hat{\beta}_{rt}$ against time to visualize the temporal trend. Secondly, to assess possible non-linearities in these temporal trends, we smooth $\hat{\alpha}_{rt}$ and $\hat{\beta}_{rt}$ over time using penalized regression splines in an additive model [56], with each coefficient weighted by the inverse variance estimate from the first stage of the model. We fit these models using the `gam()` function in the `mgcv` package in R, which uses generalized cross validation as the default for smoothing parameter selection [56]. We then formally assess the linearity of the temporal trends using the approximate F -test provided as part of the model output.

Thirdly, where a linear fit is supported by the GAM model, we fit a weighted least-squares (WLS) model to summarize the time trend, with weights again being the inverse variance estimates from the first stage of the model. For example,

$$E(\hat{\alpha}_{rt}) = \gamma_{r0}^{\alpha} + \gamma_{r1}^{\alpha} t$$

where t is the time. We center the time covariate t at the midpoint of the years, $t=7$, so that $\hat{\gamma}_0$ is interpretable as the average value over all the years.

To test formally for racial/ethnic differences in the time trends, we fit a WLS regression model to the full set of race- and time-specific parameter estimates in terms of a full set of race/ethnicity dummy variables, time, and the interaction of race/ethnicity and time.

5.2. Prior specifications and computing details

As required when using the intrinsic CAR prior in WinBUGS, we place a flat improper prior on α_{rt} [29]. We assumed a proper Normal(0,1000) prior on β_{rt} . We initially tried gamma (0.5,0.0005) priors for τ_{rt} and λ_{rt} , but found poor convergence. Alternatively, we followed Xia and Carlin [33] in setting $\tau_{rt} \sim \text{gamma}(1,100)$ and $\lambda_{rt} \sim \text{gamma}(1,7)$ and found that the resulting Markov chains had better mixing properties.

We ran models using WinBUGS via an R [57] interface using R2WinBUGS [58]. For each model, we ran a chain of 10 000 iterations with a 5000 iteration burn-in. To keep the size of the resulting simulation arrays manageable, we thinned the chains by 2; even so, the coda file produced by WinBUGS for a typical spatial model for a single year with 2056*2 spatial effects was ≥ 150 Mb. A typical model run for a year of Los Angeles data took 2.5 h.

We used the CODA package to handle posterior samples [59] and evaluated model convergence by examining sample traces of the fixed effects and variance components and the autocorrelation function. These diagnostics supported convergence once we adopted the gamma(1,100) and gamma(1,7) priors for τ_{rt} and λ_{rt} , respectively.

5.3. Results

Table III(a) and (b) presents estimates and 95 per cent credible intervals of the racial/ethnic disparity and socioeconomic gradient from race/ethnicity- and year-specific spatial models of breast cancer incidence in Northern California and Los Angeles, from 1988 to 2002. These are derived from the posterior means and 2.5th and 95th quantiles of the α_{rt} and β_{rt} parameters from the stage 1 models. In the table, we present these on the exponentiated scale, so that $\exp(\hat{\alpha}_{rt})$ can be interpreted as the SIR for each racial/ethnic group relative to the external rate standard (i.e. among white non-Hispanic women across all the SEER registries in 2003). Similarly, we present the socioeconomic gradient in terms of $\exp(7*\hat{\beta}_{rt})$, that is, for a CT median household income difference of \$70 000. As shown in Table I, this corresponds to the average CT median household income in the most affluent and most impoverished CTs as categorized by the composite poverty/high income measure reported in our earlier publication [34].

To aid with visualization of the temporal trend, we present plots of the year-by-year estimates of $\hat{\alpha}_{rt}$ and $\hat{\beta}_{rt}$ in Figures 4(a) and (b). As some ‘noisiness’ in the year-by-year estimates is apparent, we also present smoothed plots of $\hat{\alpha}_{rt}$ and $\hat{\beta}_{rt}$ from generalized additive model fits to the data. Table IV summarizes the temporal trends in $\hat{\alpha}_{rt}$ and $\hat{\beta}_{rt}$, along with formal tests for comparing the black, API, and Hispanic socioeconomic time trends with those of white non-Hispanic women.

We first note, from Table IV, that there is some evidence of non-linearity in the time trends for $\hat{\alpha}_{rt}$ for all racial/ethnic groups, with the exception of black women in Los Angeles. This means that estimates from the linear WLS regressions for these terms must be interpreted with caution. In contrast, although there is some evidence of non-linearity in the socioeconomic gradient for white non-Hispanic and API women in the SF Bay Area, we can have greater confidence in the validity of the simple linear trends for the socioeconomic parameters for the other racial/ethnic groups and for the Los Angeles data.

With this in mind, we turn to the pattern of racial/ethnic disparities in breast cancer incidence and find that our results match patterns previously reported in annual SEER incidence data, whereby rates are highest among white non-Hispanic women, lower among black women, and lowest among Asian Pacific Islander and Hispanic women. As we used an external set of age-specific rates to calculate expected counts, the estimates of $\exp(\hat{\gamma}_0^\alpha)$ for white non-Hispanic women show that these women in the SF Bay Area and Los Angeles consistently experienced higher incidence rates compared with white non-Hispanic women across all the SEER registries. The second-stage linear models suggest that rates among Hispanic women decreased significantly over time (SF Bay Area: -3.4 per cent annually; Los Angeles: -1.5 per cent annually); however, in light of the significant non-linearity, closer inspection of the smoothed plots reveals (a) in the SF Bay Area, a pattern of decreasing rates until 1997, at which point rates began to increase and (b) in Los Angeles, a sharp decline in rates between 1992 and 1995, followed by increases in rates for Hispanic women. Meanwhile, the rates among API women increased significantly over time (SF Bay Area: +1.5 per cent annually; Los Angeles, +1.8 per cent annually). Incidence rates among black women in the SF Bay Area decreased over time, while remaining flat in Los Angeles.

With respect to the year-by-year estimates of the socioeconomic gradient from stage 1, a modest and significant socioeconomic gradient was evident among white non-Hispanic women in many, but not all years, hovering between 1.1 and 1.2. Among the smaller black, Asian Pacific Islander, and Hispanic populations, the estimated socioeconomic gradients show more variability from year to year. These gradients were almost always non-significant for black women and tended to be larger among API and Hispanic women, particularly in Los Angeles, although the 95 per cent credible limits tend to be wide.

The second-stage models in Table IV provide a quantitative summary of these patterns. Looking first at the $\hat{\gamma}_0$ estimates, a positive socioeconomic gradient by CT median household income can be seen in all racial/ethnic groups. The magnitude of this gradient tends to be modest among white non-Hispanic women (SF Bay Area: $\exp(\hat{\gamma}_0) = 1.13$, 1.12–1.13; Los Angeles: $\exp(\hat{\gamma}_0) = 1.11$, 1.11–1.12). Black women experience a similar socioeconomic gradient in the SF Bay Area ($\exp(\hat{\gamma}_0) = 1.13$, 1.12–1.14), with a steeper socioeconomic gradient seen in Los Angeles ($\exp(\hat{\gamma}_0) = 1.26$, 1.25–1.27). Although the gradient among white non-Hispanic women in the SF Bay Area appears to be increasing slowly with time, the smoothed trend flattens out in later years and matches the flat trend for white non-Hispanic women in Los Angeles and black women in both areas. In contrast, the average socioeconomic gradients for API and Hispanic women are larger. Only the Hispanic women in the SF Bay Area appear to experience a significant decrease in the socioeconomic gradient over time, although the magnitude of the gradient remains large relative to that of the white non-Hispanic and black women.

In Figures 5(a) and (b), we present smoothed plots of the posterior medians of λ_{rt} and τ_{rt} over time. Inspection of these plots can give us information on changes in spatial variation over time, with increases in λ_{rt} corresponding to increasing spatial similarity and increases in τ_{rt} corresponding to *decreasing* heterogeneity (noting that τ_{rt} is the precision in the mean 0 prior for $\hat{\theta}_{rt}$) [31]. With this in mind, we note that, in Figure 5, the posterior medians of λ_{rt} for white

non-Hispanics are larger than those of other groups, reflecting more spatial similarity in the CT rates for these women in San Francisco, while the posterior medians of λ_{rt} for black women decreases over time and is relatively flat for the other groups. In Los Angeles, there appears to be a sharp increase for white non-Hispanic and a decrease for black women, with flatter trends for the other two groups.

We also note that the posterior medians of τ_{rt} are close to the prior mean of 100, suggesting relatively little excess heterogeneity in CT rates, above and beyond the CAR structure. This is also reflected in the posterior medians of ϕ_{rt} , which are close to zero for most areas. Non-linear trends in λ_{rt} and τ_{rt} must be interpreted with caution, given uncertainty in the estimates, and further investigation, coupled with local knowledge of the SF Bay Area and Los Angeles, is needed to understand the significance of observed changes in these parameters.

In Figures 6(a) and (b), we present pairwise scatterplots of the posterior mean values $\hat{\eta}_{irt} = \hat{\theta}_{irt} + \hat{\phi}_{irt}$ for the racial/ethnic groups (all years together). Owing to the presence of a small number of extreme outliers (<1 per cent of areas), we constrain the x - and y -limits on the plots to the 1–99th percentiles of the distribution of $\hat{\eta}_{irt}$. The diagonal of the scatterplot matrix, which plots the spatial effects for a racial/ethnic group against themselves, shows what we would expect to see if any of the pairwise sets of estimates exhibited evidence of a common CT effect for both racial/ethnic groups. The off-diagonal plots show that there is little evidence of this in both the SF Bay Area and Los Angeles.

6. DISCUSSION

6.1. Substantive results

With respect to the substantive research question of the Breast Cancer Incidence Project, these two-stage spatiotemporal models support our *a priori* hypothesis that the smallest socioeconomic gradients would be detected in populations with the highest breast cancer incidence rates (white non-Hispanic and black women) and generally agree with the results of our previous work [34] that aggregated disease counts over space, stratified by area-based socioeconomic measure. Our results also confirm that socioeconomic gradients among white non-Hispanic and black women are relatively stable across the time period. In contrast, for the smaller API and Hispanic populations, the socioeconomic gradient tends to be of larger magnitude but is also more unstable. Although no significant temporal trend in the socioeconomic gradient is discernable for API women in both registries, the socioeconomic gradient does appear to decrease over time among Hispanic women in the SF Bay Area. This latter trend varies slightly from our previous results, although we note that a temporal model with 15 years of data affords better resolution of the temporal trend than the aggregated data around three time points reported in our previous paper.

6.2. Methodologic implications and future directions

The two-stage spatiotemporal approach we have presented is a simple and straightforward solution for dealing with the computational burden of a fully Bayesian approach to fitting spatiotemporal models in large data sets. Our approach retains the essential character of the spatiotemporal model of Waller *et al.* [31], i.e. the nesting of spatial effects within time. However, instead of modeling all the longitudinal data together, we fit a series of spatial models to each year of data and then proceed with an analysis of temporal trends in the parameter estimates from each year. This two-stage approach treats the year-specific estimates as independent, effectively ignoring temporal autocorrelation. If there is strong temporal correlation in incidence over time, the resulting p -values will be only approximations to those one would obtain using a spatiotemporal model applied to data from all years jointly. However,

this limitation is greatly outweighed by the gains we achieve in computational efficiency from using the two-stage approach.

Although the two-stage approach we consider here represents a simple solution to the problem of heavy computational burden, future research on computationally efficient algorithms for both exact Bayesian approaches and approximations would be a welcome addition to the literature. Along these lines, Guha and Ryan proposed a computationally efficient PQL strategy based on the Gauss–Seidel algorithm [60] for enormous spatiotemporal disease count data sets. However, this approach is based on a relatively simple temporal structure, allowing for a common area-specific random intercept over all the years in the study. It would be of interest to extend these results to more flexible models, such as the ones considered by Waller *et al.* [31].

To address changes in CT boundaries over time, we made use of the commercial GIS software that normalizes 1990 CT population estimates and sociodemographic data to 2000 CT boundaries, thereby yielding a consistent set of areas to model [52,53]. Aside from concerns about potential bias arising from using non-aggregation-consistent boundaries (sometimes termed the ‘modifiable areal unit problem’) [61,62], we also need a consistent set of boundaries to use in imputing intercensal denominator estimates.

Another concern of using 1990 Census data normalized to 2000 boundaries is that the 2000 boundaries may not reflect meaningful spatial units (with respect to health) in 1990. For example, we note that the number of CTs in Los Angeles increases by 25 per cent, and that when 1990 populations are re-sorted into 2000 boundaries, CT-specific populations for the earlier year can be quite small. On the other hand, if the 1990 CT structure is truly driving spatial patterns in rates over several adjacent tracts according to 2000 boundaries, we imagine that this may be picked up in our model by the λ_{rt} parameters, which control the ‘coarseness’ of the clustering across CTs.

We do note that one could view this problem as a problem of spatial misalignment [63] over time. In this light, a more sophisticated strategy would be to adapt a geostatistical approach to modeling spatial variation in disease risk [62,64,65], whereby the observed areal-level risk is generated from an underlying continuous risk surface. Because this latent surface risk is continuous and thus free of a specific boundary structure, it does not break down when boundaries change over time. This geostatistical approach is also likely to have non-trivial computational cost, as most of these methods rely on Bayesian formulations of the underlying continuous risk surface.

We also note a limitation of our analysis in our reliance on linearly interpolated estimates of the population at risk in the intercensal years. Although the U.S. Census provides intercensal population estimates at the county level based on demographic models [66], such estimates are currently not available at the CT level (although they will be available from the American Community Survey based on rolling averages, starting in 2010) [67]. Methods for dealing with inaccuracies in case counts (numerators) and population denominators, including Bayesian models that apportion intercensal population estimates from higher levels of aggregation, are discussed by Best and Wakefield [68].

The posterior samples from the Bayesian model-fitting process can be fruitfully used to explore further aspects of the spatial structure and for disease mapping. In the previous work, we have proposed model-based age-standardized rates and population attributable fractions that can be easily mapped at the CT level, have intuitive appeal, and for which 95 per cent credible intervals can be easily calculated from the posterior samples [69]. In this paper, we have used the posterior estimates of the race/ethnicity-specific area effects η_{irt} to show that there is relatively little correlation between CT-specific effects across racial/ethnic groups. We note that the area

effects are derived from models with covariate adjustment for race/ethnicity and CT median household income, so that they are conditional on the common effect of race/ethnicity and area-based socioeconomic position. Our results confirm our conceptual argument that an assumption of common spatial effects across all racial/ethnic groups may not be appropriate in many settings, given what is known about patterns of racial/ethnic segregation and experiences of social inequality. This has important implications for studies of spatial variation in racial/ethnic health disparities and suggests that investigators should at least evaluate the possibility of needing to model population-specific spatial structure before proceeding with the assumption of common spatial effects across groups defined by social inequalities.

GLMMs are powerful tools for investigating spatial variation and temporal trends in health disparities. As these tools become more accessible and easily implemented by social epidemiologists, we hope that researchers will continue to be thoughtful about how to design models that truly capture the realities of socially patterned experiences of inequality for different populations.

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Figure 1.

Examples of possible changes to census tract boundaries from one census to the next. (a) Simple split: tract 1001.01 is split into tracts 1001.00 and 1001.01; (b) simple merge: tracts 1002.00 and 1003.01 are merged into a single tract 1002.00; (c) complex changes: parts of tracts 1001.00, 1002.00, and 1003.02 have been combined with the entirety of tract 1003.01.

Figure 2.

A single, large supertract resulting from aggregation of multiple census tracts that experience complex boundary changes from 1990 to 2000, Los Angeles, CA (U.S. Census 1990 and 2000).

Figure 3. Maps of census tract racial/ethnic composition (per cent white and per cent black) showing patterns of racial/ethnic residential segregation in Los Angeles (U.S. Census 2000).

Figure 4.

(a) Estimated α (annual and smoothed) from racial/ethnic- and year-specific models for breast cancer incidence in the San Francisco Bay Area and Los Angeles, 1988–2002. α is interpretable as $\log(\text{SIR})$ relative to the external standard (white non-Hispanic incidence rate over all SEER registries in 2003). (b) Estimated β (annual and smoothed) from racial/ethnic- and year-specific models for breast cancer incidence in the San Francisco Bay Area and Los Angeles, 1988–2002. β is interpretable as the $\log(\text{incidence rate ratio})$ for a \$70000 increase in CT median household income.

Figure 5.

Estimated posterior medians for λ and τ *versus* year, from racial/ethnic- and year-specific models for breast cancer incidence in the San Francisco Bay Area and Los Angeles, 1988–2002. Points represent stage 1 estimates and the lines are a lowess smooth over time.

Figure 6.

(a) Scatterplot matrix of race-specific posterior means of the spatial effects ($\eta=\theta+\phi$), over all the years, from racial/ethnic- and year-specific models of breast cancer incidence in the San Francisco Bay Area, 1988–2002. (b) Scatterplot matrix of race-specific posterior means of the spatial effects ($\eta=\theta+\phi$), over all the years, from racial/ethnic- and year-specific models of breast cancer incidence in Los Angeles, 1988–2002.

Table 1

Sociodemographic changes between 1990 and 2000 in the San Francisco Bay Area and Los Angeles (2000 U.S. Census SF1 and SF3).

	SF Bay Area			Los Angeles		
	1990	2000*	Per cent change	1990	2000*	Per cent change
Total population	4 325 348	4 802 198	11.0	8 863 164	9 519 338	7.4
White non-Hispanic	2 711 347	2 573 165	-5.1	3 618 850	2 959 614	-18.2
Black	463 430	437 812	-5.5	992 974	930 957	-6.2
Hispanic	554 407	805 446	45.3	3 351 242	4 242 213	26.6
Asian Pacific Islander	604 012	825 593	36.7	954 485	1 164 553	22.0
Two or more races	—	221 575		—	469 781	
Nativity						
Per cent U.S. born	78.9	72.6	-7.9	67.3	63.8	-5.3
Area-based socioeconomic measures						
CT median household income—mean (std)	\$56 245 (1 553 042)	\$65 806 (1 862 644)	0.2	\$47 973 (1 654 301)	\$45 670 (1 557 507)	0.0
Per cent persons living in CTs with ≥ 40 per cent college graduates	25.9	38.4	47.8	13.5	19.4	43.6
Per cent persons living in CTs with ≥ 20 per cent poverty	12.7	11.6	-9.2	28.3	38.0	34.3
Average CT median household income by composite poverty/high-income category**						
<5 per cent poverty ≥ 10 per cent high income	\$91 912	\$101 527	10.5	\$98 141	\$101 980	3.9
<5 per cent poverty <10 per cent high income	\$63 643	\$68 978	8.4	\$62 820	\$67 435	7.3
5.0–9.9 per cent poverty	\$53 905	\$62 631	16.2	\$56 452	\$60 415	7.0
10–19.9 per cent poverty	\$41 261	\$47 081	14.1	\$41 283	\$42 886	3.9
20–100 per cent poverty	\$26 518	\$29 258	10.3	\$27 133	\$27 502	1.4

* The option to check multiple races was only available on the 2000 Census. Racial/ethnic-specific counts reported here for 2000 are based on those reporting a single race, so that per cent change calculated represents the minimum (for positive change) or maximum (for negative change) population change.

** Per cent high income defined as per cent of households in the CT with >400 per cent U.S. median household income.

Table II

Changes to San Francisco Bay Area and Los Angeles census tracts from 1990 to 2000.

	SF Bay Area	Los Angeles
	<i>N</i> (Per cent of total)	<i>N</i> (Per cent of total)
Total tracts in 1990	831	1642
Unchanged (compared with 2000)	369 (44.4)	859 (52.3)
Changed (compared with 2000)	462 (55.6)	783 (47.7)
Simple split	18 (2.2)	190 (11.5)
Simple merge	13 (1.6)	6 (0.4)
Other	431 (51.9)	663 (40.4)
Total tracts in 2000	873	2056
Unchanged (compared with 1990)	369 (42.3)	859 (41.8)
Changed (compared with 1990)	504 (57.7)	1197 (58.2)
Simple split	42 (4.8)	406 (19.7)
Simple merge	5 (0.6)	3 (0.1)
Complex	457 (52.3)	788 (38.3)

Table III

Estimated racial/ethnic disparity ($\exp(\hat{\alpha})$) and socioeconomic gradient ($\exp(7*\hat{\beta})^*$) in breast cancer incidence from year-by-year spatial models: (a) San Francisco Bay Area, 1988–2002 and (b) Los Angeles, 1988–2002.

	White non-Hispanics IRR (95 per cent CI)	Blacks IRR (95 per cent CI)	Asian Pacific Islanders IRR (95 per cent CI)	Hispanics IRR (95 per cent CI)
(a) $\exp(\hat{\alpha})$				
1988	1.11 (1.06,1.17)	0.96 (0.84,1.08)	0.50 (0.41,0.59)	0.78 (0.67,0.91)
1989	1.09 (1.04,1.14)	0.87 (0.76,0.99)	0.60 (0.51,0.69)	0.73 (0.61,0.85)
1990	1.11 (1.05,1.16)	0.91 (0.80,1.03)	0.66 (0.56,0.76)	0.68 (0.55,0.82)
1991	1.11 (1.06,1.17)	0.82 (0.66,0.99)	0.53 (0.45,0.62)	0.76 (0.64,0.90)
1992	1.08 (1.03,1.13)	0.82 (0.65,1.01)	0.58 (0.50,0.67)	0.67 (0.56,0.79)
1993	1.04 (0.99,1.10)	0.87 (0.72,1.04)	0.52 (0.44,0.60)	0.69 (0.58,0.81)
1994	1.09 (1.03,1.15)	0.86 (0.69,1.03)	0.57 (0.48,0.66)	0.46 (0.38,0.56)
1995	1.15 (1.09,1.21)	0.91 (0.74,1.09)	0.56 (0.49,0.64)	0.52 (0.43,0.62)
1996	1.20 (1.14,1.26)	0.90 (0.74,1.07)	0.61 (0.53,0.69)	0.45 (0.36,0.54)
1997	1.22 (1.16,1.28)	0.92 (0.74,1.10)	0.63 (0.55,0.71)	0.41 (0.34,0.50)
1998	1.23 (1.17,1.29)	0.80 (0.66,0.98)	0.65 (0.58,0.73)	0.50 (0.41,0.59)
1999	1.22 (1.17,1.28)	0.88 (0.73,1.06)	0.67 (0.60,0.75)	0.50 (0.42,0.60)
2000	1.19 (1.13,1.25)	0.89 (0.74,1.06)	0.69 (0.61,0.77)	0.58 (0.49,0.68)
2001	1.10 (1.05,1.16)	0.70 (0.57,0.87)	0.68 (0.60,0.77)	0.43 (0.36,0.52)
2002	1.06 (1.01,1.12)	0.71 (0.58,0.87)	0.62 (0.55,0.70)	0.57 (0.47,0.68)
$\exp(7*\hat{\beta})^*$				
1988	1.01 (0.86,1.18)	1.10 (0.74,1.59)	0.98 (0.56,1.63)	1.99 (1.19,3.25)
1989	0.98 (0.84,1.14)	1.34 (0.92,1.87)	1.77 (1.11,2.70)	2.05 (1.21,3.34)
1990	1.01 (0.87,1.17)	1.16 (0.80,1.66)	1.47 (0.93,2.23)	1.60 (0.92,2.71)
1991	1.03 (0.88,1.19)	1.24 (0.69,2.13)	1.96 (1.31,2.95)	0.78 (0.42,1.45)
1992	1.16 (1.01,1.33)	1.10 (0.62,2.01)	1.79 (1.20,2.63)	1.50 (0.84,2.58)
1993	1.09 (0.95,1.27)	1.26 (0.72,2.16)	1.23 (0.79,1.89)	1.20 (0.67,2.08)
1994	1.13 (0.98,1.31)	1.21 (0.70,2.05)	0.84 (0.54,1.28)	1.22 (0.61,2.28)
1995	1.24 (1.08,1.42)	1.18 (0.67,1.97)	1.18 (0.82,1.71)	0.89 (0.46,1.68)
1996	1.27 (1.12,1.43)	1.08 (0.65,1.80)	1.33 (0.92,1.89)	0.98 (0.49,1.87)
1997	1.20 (1.06,1.35)	1.32 (0.80,2.08)	1.23 (0.88,1.67)	1.73 (0.93,3.11)
1998	1.13 (1.00,1.28)	1.07 (0.61,1.80)	0.93 (0.67,1.28)	1.41 (0.80,2.44)
1999	1.26 (1.13,1.42)	0.92 (0.54,1.50)	1.19 (0.87,1.61)	1.15 (0.66,2.01)
2000	1.12 (0.99,1.25)	1.35 (0.85,2.11)	1.39 (1.05,1.78)	1.09 (0.64,1.81)
2001	1.13 (1.00,1.28)	0.76 (0.44,1.26)	1.45 (1.10,1.88)	1.02 (0.58,1.79)
2002	1.18 (1.05,1.32)	1.00 (0.62,1.62)	1.42 (1.09,1.81)	1.06 (0.64,1.67)
(b) $\exp(\hat{\alpha})$				
1988	1.23 (1.18,1.29)	0.87 (0.80,0.94)	0.54 (0.48,0.61)	0.54 (0.50,0.59)
1989	1.12 (1.07,1.18)	0.85 (0.78,0.93)	0.50 (0.44,0.57)	0.55 (0.49,0.60)
1990	1.10 (1.05,1.16)	0.87 (0.80,0.95)	0.57 (0.51,0.64)	0.57 (0.52,0.62)
1991	1.13 (1.08,1.19)	0.87 (0.76,0.98)	0.54 (0.48,0.60)	0.57 (0.52,0.63)
1992	1.11 (1.05,1.17)	0.92 (0.82,1.03)	0.56 (0.48,0.64)	0.58 (0.53,0.64)

	White non-Hispanics IRR (95 per cent CI)	Blacks IRR (95 per cent CI)	Asian Pacific Islanders IRR (95 per cent CI)	Hispanics IRR (95 per cent CI)
1993	1.11 (1.06,1.17)	0.82 (0.71,0.92)	0.53 (0.46,0.61)	0.53 (0.48,0.58)
1994	1.20 (1.15,1.26)	0.95 (0.85,1.05)	0.53 (0.47,0.59)	0.39 (0.35,0.44)
1995	1.21 (1.15,1.26)	0.88 (0.78,0.99)	0.61 (0.54,0.67)	0.40 (0.36,0.45)
1996	1.18 (1.12,1.24)	0.92 (0.82,1.03)	0.62 (0.54,0.69)	0.44 (0.40,0.48)
1997	1.25 (1.19,1.31)	0.89 (0.79,0.99)	0.66 (0.59,0.72)	0.46 (0.42,0.50)
1998	1.22 (1.17,1.28)	0.93 (0.83,1.03)	0.71 (0.64,0.79)	0.47 (0.43,0.51)
1999	1.27 (1.20,1.33)	0.92 (0.82,1.03)	0.67 (0.60,0.74)	0.47 (0.43,0.51)
2000	1.17 (1.11,1.22)	0.96 (0.86,1.06)	0.64 (0.59,0.70)	0.47 (0.43,0.51)
2001	1.14 (1.08,1.21)	0.80 (0.70,0.91)	0.65 (0.60,0.72)	0.51 (0.47,0.55)
2002	1.09 (1.03,1.14)	0.75 (0.67,0.84)	0.63 (0.58,0.70)	0.46 (0.42,0.50)
$\exp(7*\beta)^*$				
1988	1.14 (1.03,1.27)	1.28 (0.97,1.65)	1.08 (0.76,1.53)	1.99 (1.19,3.25)
1989	1.13 (1.01,1.27)	1.31 (1.01,1.70)	1.14 (0.78,1.64)	2.05 (1.21,3.34)
1990	1.04 (0.94,1.15)	1.04 (0.79,1.37)	0.91 (0.63,1.29)	1.60 (0.92,2.71)
1991	1.06 (0.94,1.21)	1.77 (1.20,2.54)	1.33 (0.94,1.86)	0.78 (0.42,1.45)
1992	1.07 (0.95,1.19)	1.48 (1.02,2.11)	1.54 (1.10,2.11)	1.50 (0.84,2.58)
1993	1.13 (1.01,1.26)	1.06 (0.70,1.58)	1.54 (1.10,2.10)	1.20 (0.67,2.08)
1994	1.08 (0.97,1.21)	1.49 (1.01,2.13)	1.26 (0.91,1.77)	1.22 (0.61,2.28)
1995	1.10 (0.98,1.23)	0.95 (0.63,1.40)	1.11 (0.80,1.51)	0.89 (0.46,1.68)
1996	1.15 (1.03,1.28)	1.35 (0.93,1.92)	1.41 (1.06,1.86)	0.98 (0.49,1.87)
1997	1.09 (0.99,1.21)	1.03 (0.69,1.52)	1.50 (1.14,1.96)	1.73 (0.93,3.11)
1998	1.15 (1.05,1.27)	1.74 (1.25,2.40)	1.25 (0.93,1.66)	1.41 (0.80,2.44)
1999	1.08 (0.97,1.20)	1.39 (0.96,2.00)	1.71 (1.33,2.16)	1.15 (0.66,2.01)
2000	1.23 (1.12,1.35)	1.15 (0.82,1.60)	1.38 (1.06,1.79)	1.09 (0.64,1.81)
2001	1.15 (1.04,1.27)	0.97 (0.67,1.35)	1.25 (0.95,1.59)	1.02 (0.58,1.79)
2002	1.11 (1.00,1.23)	1.23 (0.88,1.68)	1.15 (0.88,1.49)	1.06 (0.64,1.67)

* To aid interpretation, we have expressed the socioeconomic gradient as an IRR for a contrast of \$70 000 in CT median household income. This corresponds to the difference in median household income for (1) census tracts in which 20 per cent or more of the population is below the U.S. poverty line, compared with (2) census tracts in which (a) <5 per cent of the population lives below the poverty line and (b) 20 per cent or more of this population has a household income greater than 400 per cent of the U.S. median household income.

Table IV

Results of second-stage analysis: (a) test for non-linearity, (b) average value ($\hat{\gamma}_0$) of α (racial/ethnic disparity) and β (socioeconomic gradient) over time, (c) estimated linear trend ($\hat{\gamma}_1$) in α and β over time (San Francisco Bay Area and Los Angeles, 1988–2002).

	Test for non-linearity (p -value)	Average value over time exp ** ($\hat{\gamma}_0$)	95 per cent CI	Linear Time trend ($\hat{\gamma}_1$)	95 per cent CI	Test of $\hat{\gamma}_1=0$ (p - value)	Annual per cent change in IRR	Test for difference of $\hat{\gamma}_1$ from white non-Hispanic value (p - value)
<i>San Francisco Bay Area</i>								
Racial/ethnic disparity								
White non-Hispanic	<0.0001	1.14	(1.11,1.17)	0.005	(-0.001,0.011)	0.120	0.5	—
Black	0.044	0.86	(0.83,0.89)	-0.010	(-0.018,-0.003)	0.021	-1.0	0.051
Asian Pacific Islander	0.019	0.60	(0.58,0.63)	0.015	(0.006,0.024)	0.005	1.5	0.137
Hispanic	0.006	0.58	(0.54,0.62)	-0.035	(-0.052,-0.018)	0.002	-3.4	<0.0001
CT median household income gradient (per \$70000)								
White non-Hispanic	0.007	1.13	(1.09,1.17)	0.011	(0.003,0.019)	0.014	1.1	—
Black	0.241	1.13	(1.05,1.21)	-0.014	(-0.029,0.002)	0.103	-1.4	0.064
Asian Pacific Islander	0.023	1.33	(1.18,1.50)	-0.006	(-0.032,0.020)	0.659	-0.6	0.124
Hispanic	0.136	1.29	(1.14,1.47)	-0.034	(-0.062,-0.007)	0.031	-3.3	0.005
<i>Los Angeles</i>								
Racial/ethnic disparity								
White non-Hispanic	0.008	1.17	(1.14,1.20)	0.002	(-0.004,0.008)	0.560	0.2	—
Black	0.109	0.88	(0.85,0.91)	0.000	(-0.008,0.007)	0.929	0.0	0.713
Asian Pacific Islander	0.001	0.60	(0.58,0.62)	0.018	(0.011,0.025)	<0.0001	1.8	0.010
Hispanic	0.002	0.49	(0.47,0.52)	-0.015	(-0.026,-0.003)	0.030	-1.5	0.003
CT median household income gradient (per \$70000)								
White non-Hispanic	0.122	1.11	(1.09,1.14)	0.004	(-0.001,0.009)	0.122	0.4	—
Black	0.667	1.26	(1.14,1.39)	-0.005	(-0.025,0.016)	0.667	-0.5	0.391
Asian Pacific Islander	0.235	1.30	(1.19,1.41)	0.010	(-0.009,0.030)	0.322	1.0	0.554
Hispanic	0.142	1.39	(1.28,1.52)	-0.015	(-0.034,0.005)	0.167	-1.4	0.063

* From generalized additive model with penalized regression spline smooth over time.

** Average value ($\hat{\gamma}_0$) over time is presented as an IRR on the exponentiated scale for ease of interpretation.