

Monitoring Socioeconomic Determinants for Healthcare Disparities

Tools From the Public Health Disparities Geocoding Project

Nancy Krieger, PhD, Pamela D. Waterman, MPH,
Jarvis T. Chen, SCD, S. V. Subramanian, PhD,
and David H. Rehkopf, SCD

INTRODUCTION

Adding insult to injury. This well-worn phrase redounds with new significance when considering healthcare disparities in the context of social inequalities in health. The very same social groups at greatest risk of being subjected to inadequate access to and unequal treatment in healthcare also endure the greatest risk of poor health status and premature mortality, reflecting the daily toll of discrimination, economic deprivation, political marginalization, and prioritization of economic gain over human needs (1-3). Greater need and lesser care nefariously combine to create even more onerous burdens of preventable suffering, for it is within the very same bodies that these injuries and insults are integrated and embodied (4).

To right these health wrongs, and to hold accountable the institutions, policies, and priorities that routinely permit or actively benefit from the everyday health inequities so evident within and across countries, data are essential. Information is needed on the magnitude of the problem, on who is most burdened by poor health and healthcare, and whether the disparities are shrinking or expanding. Not that these data can by themselves change anything. Rather, in the hands of those working for health equity, evidence of disparities in health status and healthcare is required to identify who is most harmed, who gains, and what actions need to be taken, by which groups, to make a change for the better.

The connections between social determinants of health, health status inequities, and healthcare disparities would seem obvious. After all, our

bodies readily make the connections each and every day (4–6). Yet, in the United States, we confront a major obstacle to counting for accountability: the lack of routinely available good data on the magnitude of socioeconomic inequities in health status and healthcare, overall and in relation to diverse forms of social inequality variously involving racism, gender, sexuality, age, nativity, and immigration status (7–10).

Although hospital records and public health data systems almost always include data on age and sex (typically construed as biological variables only), numerous reports have documented the poor quality and spottiness of data on race/ethnicity, the paucity if not total absence of socioeconomic information, and the invisibility of data on immigrant status and sexuality (7–10). These gaps in the data are not accidental, even if they might not be willful. Instead, they reflect the priorities and frameworks (conscious and unconscious) of the groups who design and implement the data systems (7,11–14). Often these data gaps can be explained by the time-disgraced ruse of “no data, no problem;” however, also at play are the vulnerabilities of those who may be targeted for discrimination if they provide information on aspects of their subjugated social position (10,13–14).

In this chapter, our focus on the lack of socioeconomic data in most US medical records and public health surveillance systems (7–10) in no way discounts the importance of discrimination—whether in relation to race/ethnicity, gender, sexuality, age, immigrant status, and so on, and within and across socioeconomic strata—in shaping population health (4,15). However, in a context of an all-too-long misguided legacy of interpreting health disparities in these other dimensions as a function of allegedly innate biology, rather than social inequity (1–4,11–17), it is essential to show the extent to which socioeconomic resources (themselves reflecting the impact of past and present discrimination) are associated with health status and healthcare disparities *within and between* these different social groups, as well as within the population as a whole. Bringing socioeconomic position into the picture is thus one of several critical steps needed to confront naïve causal narratives of “health differences” premised on biological or cultural determinism. The challenge is both conceptual and empirical. It is in this spirit that the ideas and tools of the *Public Health Disparities Geocoding Project* are presented (Table 1) (18–29).

PUBLIC HEALTH DISPARITIES GEOCODING PROJECT: PURPOSE, PERSPECTIVE, AND CONTEXT

We undertook our project because of an important problem: the lack of socioeconomic data in most US public health surveillance systems (7). This is why 72% of the 74 tables on “Health status and determinants” in the major federal report, *Health United States, 2005* include no socioeconomic data,

Table 1
Synopsis of The Public Health Disparities Geocoding Project

Background	Despite longstanding evidence on intimate links between neighborhood poverty and neighborhood health, most US public health surveillance systems lack socioeconomic data, thus precluding routine monitoring of socioeconomic disparities in health and their contribution to US urban health inequities
Methods	To address this problem, <i>The Public Health Disparities Geocoding Project</i> geocoded and linked public health surveillance data from Massachusetts and Rhode Island to 1990 census-derived ABSMs to determine which ABSMs, at which geographic level (census BG, CT, and ZC) could validly be used to monitor socioeconomic inequalities in health. Outcomes included: birth, childhood lead poisoning, sexually transmitted infections, tuberculosis, nonfatal weapons-related injuries, cancer incidence, and mortality
Results	In both the total population and diverse racial/ethnic-gender groups, measures of economic deprivation proved most sensitive to expected socioeconomic gradients in health, with CT ABSMs yielding the most consistent results and maximal geocoding across outcomes, and the CT poverty measure performing as well as more complex composite measures
Implications	Geocoding and use of the CT poverty measure permits routine monitoring and mapping of US socioeconomic inequalities in health, using a common and accessible metric

ABSMs, area-based socioeconomic measures; BG, block group; CT, census tract; ZC, zip code.

See refs. 18–29.

even as they are stratified by race/ethnicity and gender (30). It is also why 70% of the 467 *Healthy People 2010* objectives lack socioeconomic targets (31). Clearly, without data on social class, one can neither monitor progress—or setbacks—in eliminating socioeconomic inequalities in health, let alone ascertain their contribution to racial/ethnic disparities in health.

Our study accordingly systematically investigated a possible solution, drawing on an approach used eclectically in US health research for over 75 yr: that of using geocoding and area-based socioeconomic measures (ABSMs) (19,32,33). The basic method is to characterize both cases and the population from which they arise by the socioeconomic characteristics of their residential areas, using US census data. This in turn permits calculating rates stratified by the ABSMs—which, because they are census-derived, can be used in any region in the United States.

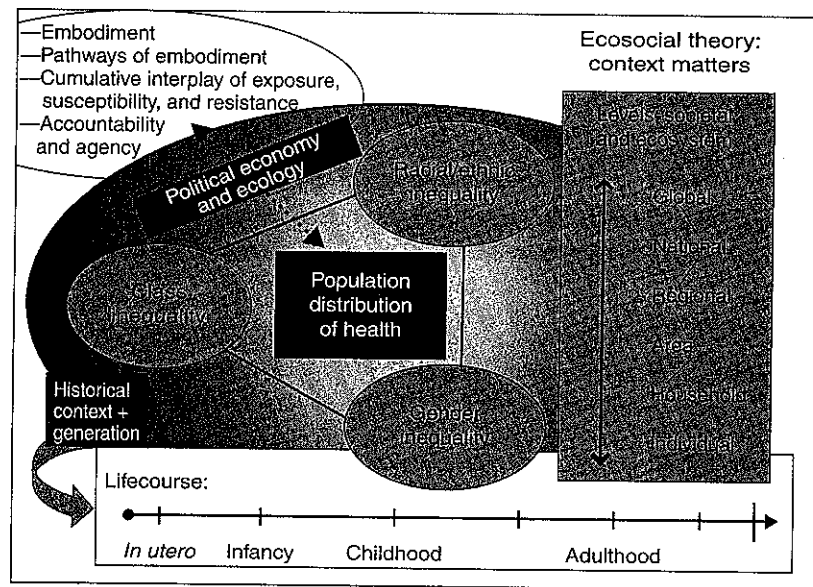


Fig. 1. Ecosocial theory (34–36).

However, one major problem is that, before our *Project*, there existed no consensus about which ABSMs should be used, and at which geographic level. Owing to absence of a common methodology, monitoring is impossible, because results cannot be compared across regions or over time. Accordingly, the key question we sought to answer was: does choice of ABSM and geographic level matter? The answer, in brief, is “yes,” as the rest of this chapter explains.

Informing our *Project* was the theoretical perspective of ecosocial theory, a theory of disease distribution guided by the question “*Who and what drives current and changing patterns of social inequalities in health?*” (Fig. 1) (4,34–36). Its four core constructs, described in detail elsewhere (4,34–36), pertain to: (1) “embodiment,” referring to how we literally embody, biologically, our lived experience thereby creating population patterns of health and disease; (2) “pathways of embodiment,” referring to how there are often multiple pathways to a given outcome, through diverse physical, chemical, biological, and social exposures, and involving gene expression, not just gene frequency; (3) “cumulative interplay of exposure, susceptibility, and resistance across the lifecourse,” because all three matter; and (4) “accountability and agency,” both for social inequalities in health and for ways they are—or are not—analyzed and addressed. In the case of our *Project*, the intent was to increase accountability for and understanding of pathways of embodiment

leading to socioeconomic health inequities by doing the kind of research that lies squarely within the domain of responsibilities of health researchers: developing a methodology to overcome the absence of socioeconomic data in most US public health surveillance systems (7). The express intent was to rectify a gap that removes class inequities in health from public view and hence from the policy and action agenda to eliminate health disparities.

Historical Context of the Project

However, before jumping in the methodological details it is important to put our *Project* in conceptual and historical context. The first point, perhaps obvious, is that awareness of what is now referred to as social inequalities in health, or health inequities, is not exactly new. In fact, it is a bit hard to miss the injurious effects of destitution, degradation, and hard work on health, and descriptions can be found in documents dating back to the earliest known medical texts. One, from around 2000 BCE in Egypt, during the time of the prosperous Middle Kingdom, recounted (37):

“... I have seen the metal worker at this task at the mouth of his furnace. His fingers were like the hide of crocodiles The barber shaves till late in the evening ... He strains his arms to fill his belly and works as indefatigably as a bee The weaver in the workshop is worse off than the women (who must always sit in the house) He bribes the doorkeeper with bread that he may see the light ...”

The Hippocratic treatise, *On Diet*, likely written in the fourth century BCE, likewise observed that only a small minority of the Greek population—their vaunted citizens—had the wherewithal to lead a healthy life. The vast majority—upward of 75% of the population—could not, described as “the mass of people” who “are obliged to work,” “who drink and eat what they happen to get,” and so “who cannot, neglecting all, take care of their health”(38).

These kinds of comments, however, were comments were chiefly asides. What these early texts mainly provided was advice on how to live well, directed to those who could afford to live leisured lives precisely because others did the hard labor allowing them this leisure. Indeed, it would not be for another 2000 years, in the 16th century CE, that the question of how work affects health would first attain sustained treatment in European medical texts (39,40). It was not until the early 19th century that studies systematically began to explore links between poverty and health and between slavery and health, and not until the later 19th century that research began seriously to investigate the impact of women’s work—whether at home or in the paid labor force—on women’s health (15,16,39–41). Interest in the 20th century in social inequalities in health, moreover, has waxed and waned (16,40,41), though of late it has been on the increase, such that in the

United States, the elimination of social disparities in health is now one of the two overarching goals of *Healthy People 2010* (31).

The neglect of what may seem obvious leads to a second point: that social inequality can shape the very picture people draw of social inequalities in health (4,13,14). At issue are both description and explanation. In other words, social inequality can influence: what is seen—or ignored—by whom; how these patterns are—or are not—explained; and what sorts of remedies are—or are not—proposed. One implication is social inequalities in health—however real—can be ignored and rendered invisible if the data to document them are not collected, whether by conscious design or unconscious neglect. A second implication is that even if the data are collected, and no one disputes the reality of the disparate health status between the groups at issue, there can still be major controversies over *why* these disparities exist and *who* should do *what* about them.

Consider only centuries of debate in the United States over the poor health of black Americans. In the 1830s and 1840s, contrary schools of thought asked: was it because blacks are intrinsically inferior to whites?—the majority view, or because they were enslaved and economically impoverished?—as argued by, among others, James McCune Smith (1811–1865) and James S. Rock (1825–1866), two of the country's first credentialed African American physicians (42). The fundamental tension, then and now, is between individualistic vs contextualized theories, in other words, theories that seek causes of social inequalities in health in innate vs imposed, and individual vs societal, characteristics. Highly relevant to these debates is whether even data are available on the extent and contours of health inequities.

Also worth emphasizing is that during the early 19th century research indicated the utility of using neighborhood socioeconomic data to understand population health. For example, in the mid 1820s, research conducted by Louis René Villermé (1782–1863) in France broke new ground by showing that mortality rates in Parisian districts could be meaningfully ordered by a measure of neighborhood assets, whereby mortality rates were highest among areas whose residents paid the least in “untaxed rents,” a type of tax paid only by the wealthy (43,44). Whereas such data are not surprising now, in the early 1800s, they were astounding. This is because the dominant mode of thought, until this time, had followed Hippocratic doctrine in assuming that the “natural environment”—that is, “air, water, places”—was what drove population patterns of health. Thus, before producing this table, Villermé had valiantly tried, without success, to find correlations between Parisian neighborhood mortality rates and various environmental features predicted by Hippocratic reasoning, including exposure to sunlight (or lack thereof), proximity to the Seine, wind patterns, and presence of trees and parks (43,44).

It was only by linking data on mortality and socioeconomic resources, derived from the newly amassed and unprecedented Parisian census that Villermé could make sense of Parisian mortality data. In doing so, he empirically demonstrated—for the first time anywhere—that variations in mortality rates across neighborhoods were neither a result of solely chance or the natural environment, but instead were profoundly patterned by poverty and wealth (13,41,43,44). The net effect was to introduce a whole new realm—societal conditions—into the lexicon of determinants of health, as well as to make socioeconomic inequalities in health a visible topic of research, monitoring, and action. Regarding the cause of these health inequalities and relevant remedies: well, the debate was fierce, with some arguing moral sloth was the underlying cause of both poverty and poor health, and others pointing to destitution resulting from low wages and high rents.

Taking these arguments a step further, in 1844 Friedrich Engels (1820–1895) published the now classic text *The Condition of the Working Class in England* (45). To Engels and other radical investigators, the evidence at hand led them to argue that the poor health and immiseration of the urban working class and poor was routinely and inherently produced by the heightened imperative and capacity to accumulate capital, producing great wealth for the few and poverty for the many (2,3,39–41,45). Fabulous fortunes and novel consumer goods were but the other side of a coin minted by an economic system whose deadly “dark satanic mills,” in Blake’s famous phrase (46), destroyed health through both horrendous working conditions and starvation wages.

Importantly attuned to how class matters for not only workplace conditions but also standard of living at the individual, household, and neighborhood level, Engels highlighted evidence of higher mortality among poor households in poor compared with improved streets (45). Notably, it has only been in the past decade that this type of contextual effect has again begun to receive serious attention in contemporary research (47–49).

The basic point, then, is that issues of social inequalities in health and use of area-based socioeconomic data are not new. Conceptual frameworks and the ability to generate empirical evidence to address these issues have existed for over 150 years.

PUBLIC HEALTH DISPARITIES GEOCODING PROJECT: STUDY DESIGN AND KEY RESULTS

Given this background, the methodological purpose of this empirical investigation was to determine which ABSMs, at which geographic level, would be most appropriate for public health monitoring (18–29), while at the same time availing ourselves of recent advances in computer technology

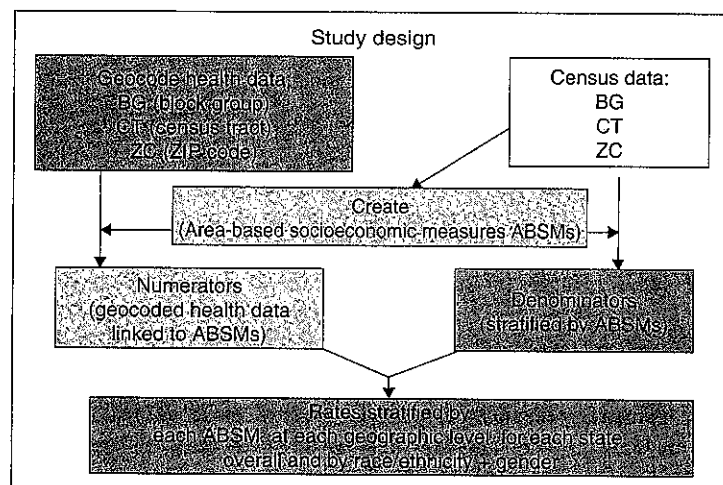


Fig. 2. Public Health Disparities Geocoding Project: study design (19–23).

and software, geographic information systems, statistical methods, and ease of accessing public health surveillance data and US census data (12,50). Our goal was to come up with valid, robust, easy to construct, and easy to interpret ABSMs that could readily be used by any US state health department or health researcher, for any health outcome—from birth to death, for women and men, young and old alike, among any racial/ethnic group. Guided by ecosocial theory, we anticipated that different ABSMs might function differently for diverse outcomes. Thus, our outcomes spanned the gamut and included: low birthweight, childhood lead poisoning, sexually transmitted infections, tuberculosis, nonfatal weapons-related injuries, cancer incidence (all-sites and site-specific), and mortality (all-cause and cause-specific).

The study design of the *Public Health Disparities Geocoding Project* is provided in Fig. 2. Briefly stated, each public health surveillance data set was first geocoded to three different geographic levels: the census block group (BG), the census tract (CT), and the ZIP code® (ZC). Geocoding entails assigning a record, based on its geographic location (in this case, the residential address), the relevant geographic codes used for this location by the US census (for the census BG and CT) and also the US post office (for the ZC). To carry out the geocoding, we used a geocoding firm whose accuracy we verified to be high (96%) (25). Additionally, for each of the three chosen geographic levels, we created diverse ABSMs as described below. We then linked the health records and the ABSMs thereby allowing us to compute rates stratified by these ABSMs. Numerators consisted of the cases and denominators of the population (ascertained in the 1990 census) living in areas

at the specified socioeconomic level. The methodological details of how we carried out each of these steps is provided, at no cost, at the *Project's* website (18) (<http://www.hsph.harvard.edu/thegeocodingproject>), as are downloadable pdf files of our *Project's* published scientific articles (18–27).

For the analyses, we computed, for each health outcome, rates stratified by the ABSMs at each level of geography and did so first for the total population of each state and then also stratified by race/ethnicity and gender. We then compared estimates of socioeconomic gradients for each outcome, within each level of ABSM, and also, for each ABSM, across levels. Before conducting these comparisons, we delineated four *a priori* criteria for evaluating the ABSMs (18–22):

1. *External validity*: did we detect the expected socioeconomic gradient, in magnitude and direction, based on what has been reported in the literature?
2. *Robustness*: did the ABSM perform well across diverse outcomes, among both women and men, overall and by race/ethnicity?
3. *Completeness*: was the ABSM affected by relatively little missing data?
4. *User-friendliness*: could the ABSM be easily understood by health department staff and the general public, as opposed to by only health professionals or other researchers?

Here we emphasize that our goal was to choose an ABSM that would be appropriate for routine monitoring of socioeconomic inequities in health across many health outcomes, which is distinct from the objective of choosing, for any given health outcome, the ABSM that might be most etiologically relevant.

Study Base and ABSMs

Regarding the units of geography, Fig. 3 illustrates the relationship of the census-defined units (26,51). The basic census-building block is literally the census block, with an average population of approx 85 persons. It is nested within the census block, with an average population of approx 85 persons. It is nested within the next unit, the census BG, which on average contains 1000 persons and is the smallest census unit for which estimates of socioeconomic characteristics are released. Census BGs in turn are nested within CTs, which typically include 4000 people and are defined by the US census to be a “small, relatively permanent statistical subdivision of a county ... designed to be relatively homogeneous with respect to population characteristics, economic status, and living conditions” (51). Underscoring the real-life relevance of CTs for their residents, CT data are used to determine eligibility of areas for diverse programs, including “Urban Empowerment Zones,” “Medically Underserved Areas,” and “Qualified Census Tracts” for the low-income housing credit (19,52,53). ZCs are not shown because they are not defined by the US census; instead, they are virtual overlapping geographic areas designed to facilitate the delivery of mail and typically contain at least 10,000 people (24,54).

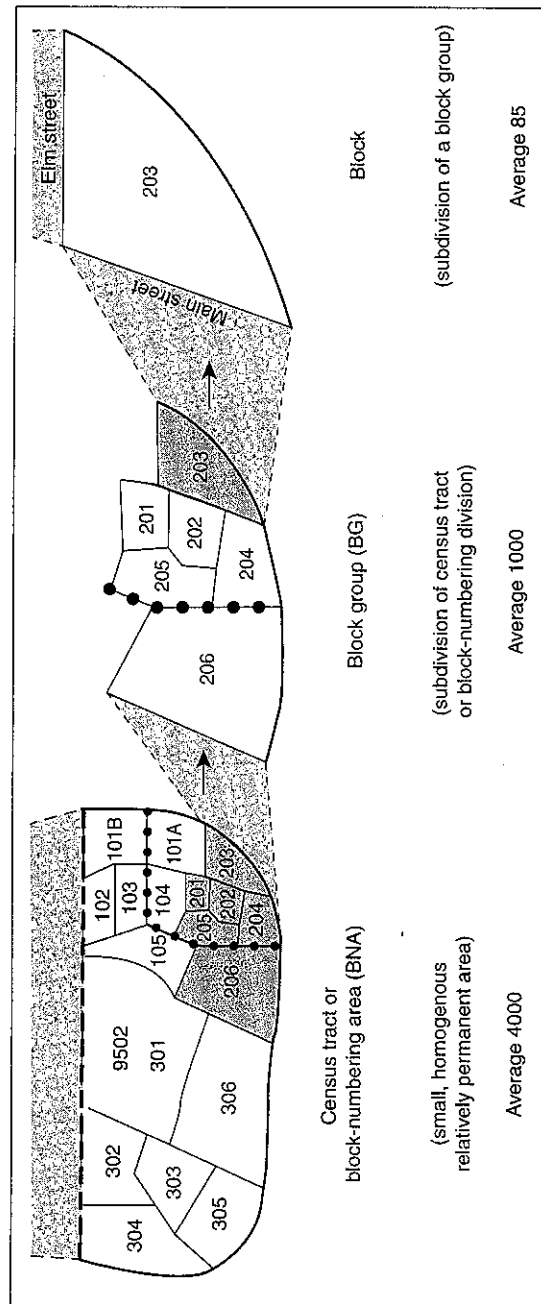


Fig. 3. US census building blocks (51).

Table 2
Public Health Disparities Geocoding Project: Study Population in Terms of Population—Massachusetts and Rhode Island, ca. 1990 US Census

	MA	RI
1990 Population	6,016,425	1,003,464
Mortality data ^a (1989–1991)	155,764	27,287
Cancer data ^b (MA: 1988–1992; RI: 1989–1992)	140,610	19,798
Birth data (MA: 1989–1991; RI: 1987–1993)	267,311	96,138
Childhood lead screening (RI only: 1994–1995)	—	62,514
STIs (MA: 1994–1998; RI: 1994–1996)	39,144	6403
TB (MA: 1993–1998; RI: 1985–1994)	1793	576
Nonfatal weapons-related injury (MA only: 1995–1997)	5517	—

MA, Massachusetts; RI, Rhode Island; STIs, Sexually Transmitted Infection; TB, Tuberculosis.

^aAll-cause plus analyses of top five causes by race/ethnicity: heart disease, malignant neoplasm, cerebrovascular disease, pneumonia and influenza, chronic obstructive pulmonary disease, unintentional injury, diabetes, HIV, and homicide and legal intervention.

^bPrimary invasive, all-site plus five key sites: breast, cervix, colon, lung, and prostate. See refs. 19–23.

Table 2 presents data on the study population, defined in terms of people. In 1990, the population of Massachusetts was approx 6 million persons and that of Rhode Island, about 1 million. The number of records obtained from each surveillance system varied by outcome, with the total equaling nearly 1 million. Table 3 in turn provides data on the study base as defined by geographic units. As expected, BGs and CTs on average contained approx 1000 and 4500 people, respectively, and the ZCs, about 13,000–14,000 people. Population size was most variable at the ZC level and least at the BG level.

Next, to generate the ABSMs, we drew on our conceptual understanding of social class and socioeconomic position (SEP) (16,55). Stated simply, “social class” refers to social groups arising from interdependent economic relationships among people. One cannot, for example, be an employee if one does not have an employer and this distinction—between employee and employer—fundamentally concerns people’s relationship to work and to others through a society’s economic structure (55). One manifest expression of the social relationship of class is thus *socioeconomic position*, an aggregate concept that includes both resource-based assets, such as income, wealth, and educational credentials, and also prestige-based measures. Given distinctions between actual assets and prestige, we use the term “socioeconomic position,” and not “socioeconomic status,” because the latter arbitrarily (if not intentionally) privileges “status” over material resources as central to the construct and lived experience of class (55).

Table 3
Public Health Disparities Geocoding Project: Study Population in Terms of Areas—Massachusetts and Rhode Island, 1990 US Census

State	Geographic level	N	Mean population size		
			N	Standard deviation	Range
MA	BG	5603	1085.40	665.20	5–10,096
	CT	1331	4571.80	2080.00	15–15,411
	ZC	424	12,719.70	12,244.10	14–65,001
RI	BG	897	1,137.70	670.80	7–5,652
	CT	235	4,325.30	1,810.90	26–9,822
	ZC	70	14,335.20	13,234.80	63–53,763

MA, Massachusetts; RI, Rhode Island; BG, block group; CT, census tract; ZC, ZIP code. See refs. 19–23.

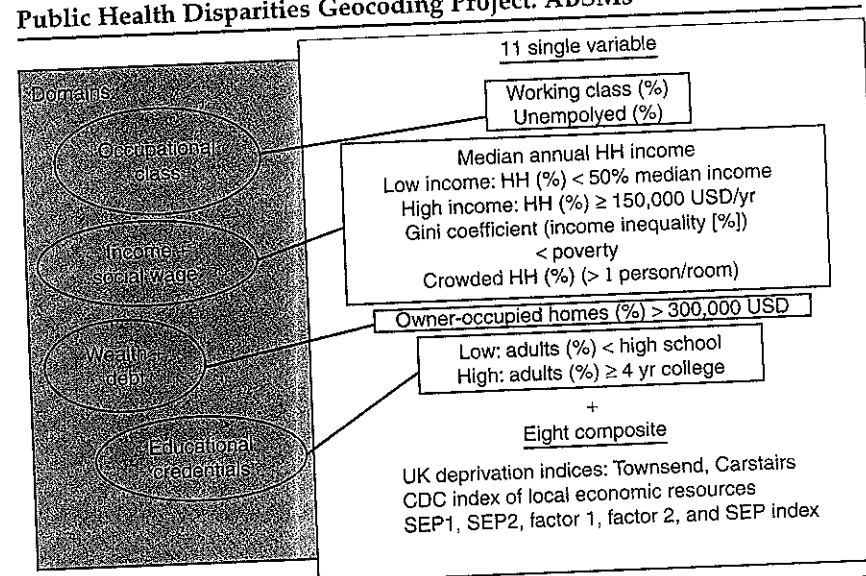
From this vantage, we generated 19 census-derived ABSMs, 11 single variable and eight composite, intended to capture diverse domains of socioeconomic position relevant to health (18–23,26). Listed in Table 4, these included: occupational class, income and income inequality, poverty, wealth, education, crowding, and combinations of these variables, including pre-established indices, such as the Townsend deprivation index, widely used in the United Kingdom, and also the Centers for Disease Control and Prevention index of local economic resources.

Last, regarding geocoding, overall we were able to geocode 92% of the nearly 1 million records to the BG level, 98% to the CT level, and 98.2% to the ZC level. Importantly, we found little difference in the percent geocoded by outcome, age, gender, or race/ethnicity, or for the birth and death records, by educational level. However, nearly 6% of the records with ZC could not be linked to 1990 census, either because they were for nonresidential sites or else were in ZCs created or changed after the 1990 census. This ZC discrepancy resulted in analyses by ZCs introducing a selection bias for some outcomes sufficiently severe to reverse, and the direction of the socioeconomic gradient wrongly detected with the CT and census BG measure—with the latter importantly in the same direction as reported in the literature when using individual-level measures of socioeconomic position (24).

Key Methodological Results, Caveats, and Recommendations: for Routine Monitoring, Use the CT Poverty Measure

As discussed in the *Project's* publications (18–29), our key findings (Fig. 4), based on analyses for each outcome by each state for the overall population and by racial/ethnic-gender group, were that:

Table 4
Public Health Disparities Geocoding Project: ABSMs



HH, household; CDC, socioeconomic position. See refs. 18–23, 26.

1. Measures of economic deprivation were most sensitive to expected socioeconomic gradients in health.
2. CT level analyses yielded the most consistent results with maximal geocoding (compared with the BG and ZC data).
3. These findings held for separate analyses conducted for white, black, and Hispanic women and men, and also for those outcomes that could be meaningfully analyzed among the smaller Asian and Pacific Islander and American Indian populations.
4. The single-variable measure “percent of persons below poverty” performed as well as more complex, composite measures of economic deprivation, such as the Townsend index.

Based on these results, we propose that US socioeconomic inequalities in health can be monitored with the common metric of the CT poverty measure. We further note that one advantage of this approach is that, unlike individual-level education and occupation, this measure can be applied to all persons, regardless of age and gender, whether in or out of school, and in or out of the paid labor force (19,55–59). Additionally, CT data can provide important information on social context that may affect population health (19,47–49,55–59), even as we recognize that this etiological hypothesis can only be tested in data sets that contain both individual- and area-level socioeconomic data.

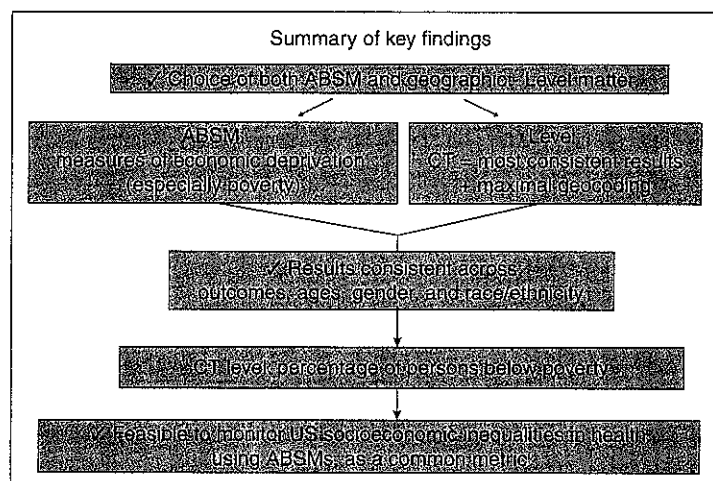


Fig. 4. Public Health Disparities Geocoding Project: summary of key findings (19–29).

Despite these appealing features, four caveats pertain to use of CT data for monitoring socioeconomic health inequities. The first concerns “ecological fallacy,” which occurs when both the dependent and independent variables are group-level data and confounding is introduced through the grouping process (19–23,48–50,60). The second is the “modifiable areal unit problem,” (60,61) in this case referring to whether CTs are meaningful entities relevant to shaping population health or can provide relevant data on socioeconomic heterogeneity within neighborhoods (19,56,62,63). The third pertains to etiological period, because without the study the CT data were measured only at the time of the decennial census and in a time period corresponding to that of the health outcomes of interest (19–23). The fourth concerns omitted variables and selection bias, whereby both can yield biased estimates of exposure-outcome associations and jeopardize valid causal inference (60,64–67).

First, regarding “ecological fallacy,” although this theoretically may be a problem, empirically research from the *Public Health Disparities Geocoding Project* suggests this potential fallacy is unlikely to introduce serious bias (19–23,28,29). Thus, for analyses for the two outcomes for which we had individual as well as CT socioeconomic data, i.e., birth and death records, the findings unambiguously demonstrated that the direction of the socioeconomic gradient was the same, and also was of similar magnitude, for both the individual-level and CT socioeconomic measures (28,29). The only exception occurred for mortality rates for deaths above age 65, whereby using the CT socioeconomic measures we found a linear association (more economic

deprivation associated with higher mortality) but using the individual-level education data, we found evidence of a nonlinear association, with rates highest among persons reported to have at least a high school diploma but less than 4 yr of college (29). This discrepancy was likely due to selective misclassification of the individual-level educational data (29), an inference supported by other mortality studies that have compared results based on verified educational data vs educational data from the death certificate (68,69). These earlier studies found the same “J-shaped” curve for mortality rates by educational level among older populations, which occurred because of the tendency of decedents with less than a high school education to be reported as having had at least a high school education (68,69).

Second, regarding the CT as an appropriate geographic unit, as noted previously, CT boundaries are drawn to be socially meaningful and to delimit administrative areas that are relevant to resource allocation (19,51,p. A-5). Thus, in addition to the various federal programs that use CT data to target resources for medical care, housing, and employment (52,53), cities use CT boundaries to define neighborhoods for public health department programs, school districts, and other municipal programs (19,50).

Third, for the purposes of monitoring, a measurement of socioeconomic position at the time the health outcome is diagnosed or reported is appropriate, insofar as the aim is to determine the population distribution of the burden of disease or death at the time that it occurs (19). While etiological research on the causal links between socioeconomic position and risk of poor health may want to use socioeconomic data from earlier time periods, at the individual as well as contextual level (6,55–59), along with data on other relevant covariates, such analyses address issues quite distinct from those of routine monitoring of socioeconomic inequities in health. Additionally, concerns about being restricted to solely decennial census data will soon no longer be warranted, given the anticipated availability of yearly CT data (based on 5-yr rolling averages) from the American Community Survey, starting in 2010 (70).

The fourth and final set of caveats, regarding the separate problems of omitted variables and selection bias (60,64–67), again pertain more to etiological investigations than monitoring health inequities. In the case of omitted variables, the concern is that an unmeasured common cause of risk of living in a certain type of CT and of having a certain health outcome could produce biased estimates of the associations between CT characteristics and the health outcome, and hence the observed socioeconomic gradient. However, the same concern would hold for any socioeconomic measure, including at the individual level. Moreover, from a monitoring perspective, the observed social distribution of health is the empirical entity at

issue—and which constitutes precisely the sort of needed spark for causal investigation of why the observed social patterning of morbidity and mortality exists. Health selection, in turn, could induce associations if poor health during childhood led to: (1) a reduced earning potential, hence increased risk of living in an economically disadvantaged CT (or, if data were available at other levels, having a low individual or family income) and (2) the specified health outcome (55,58,59,71). The growing body of lifecourse research nevertheless indicates that cumulative disadvantage, not just early life or adult conditions, is a powerful determinant of many health outcomes (2–6,72–74). Thus, to the extent current CT characteristics can be viewed as a summary of the economic trajectories leading to its population composition, this lessens, but again does not absolve, health selection as being a previous common cause leading to an association between CT characteristics and risk of a given health outcome. In summary, although it is essential to be aware of the limitations for causal inference for analyses that use geocoding and ABSMs or other types of socioeconomic measures, these limitations in no way undercut the utility of the methodology that has been described for the routine monitoring of socioeconomic inequalities in population health. Estimating the magnitude of the problem is a necessary first step, a prelude to analyzing cause and generating remedies—and we emphasize that only routine monitoring can show whether the absolute rates of disease and health inequities are getting better or worse over time.

Key Substantive Results: Socioeconomic Inequalities in Health, Overall and by Race/Ethnicity and Gender

Figure 5 accordingly illustrates what US public health data could look like, from birth to death, using our approach, using one common metric for socioeconomic position: the CT poverty level (19–23). For each outcome, we show the socioeconomic gradient for the total population and also by racial/ethnic-gender group. The point is not that the socioeconomic gradients depicted are novel, *per se*, but rather that the method presented newly allows these health inequities to be routinely documented and monitored, using existing public health surveillance systems, to guide efforts to address socioeconomic inequalities in health, at the national, state, or local level. Outcomes presented are as follows:

1. *Childhood*: low birthweight and blood lead levels.
2. *Sexually transmitted infections*: gonorrhea, chlamydia, and syphilis.
3. *Other infectious disease*: tuberculosis.
4. *Weapons-related injury*: gunshot wounds.
5. *Cancer incidence*: lung cancer, colon cancer, breast cancer, cervical cancer, and prostate cancer.

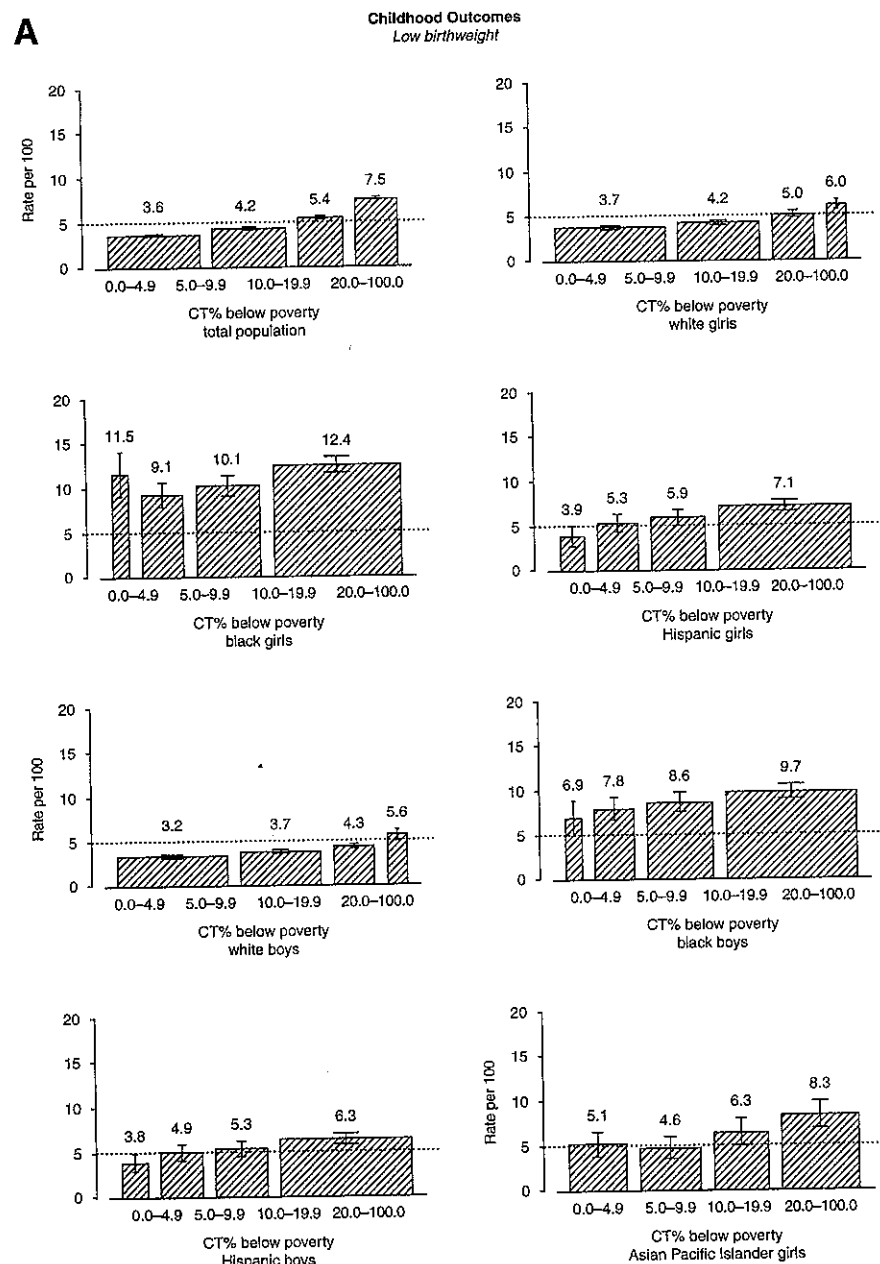


Fig. 5. (Continued)

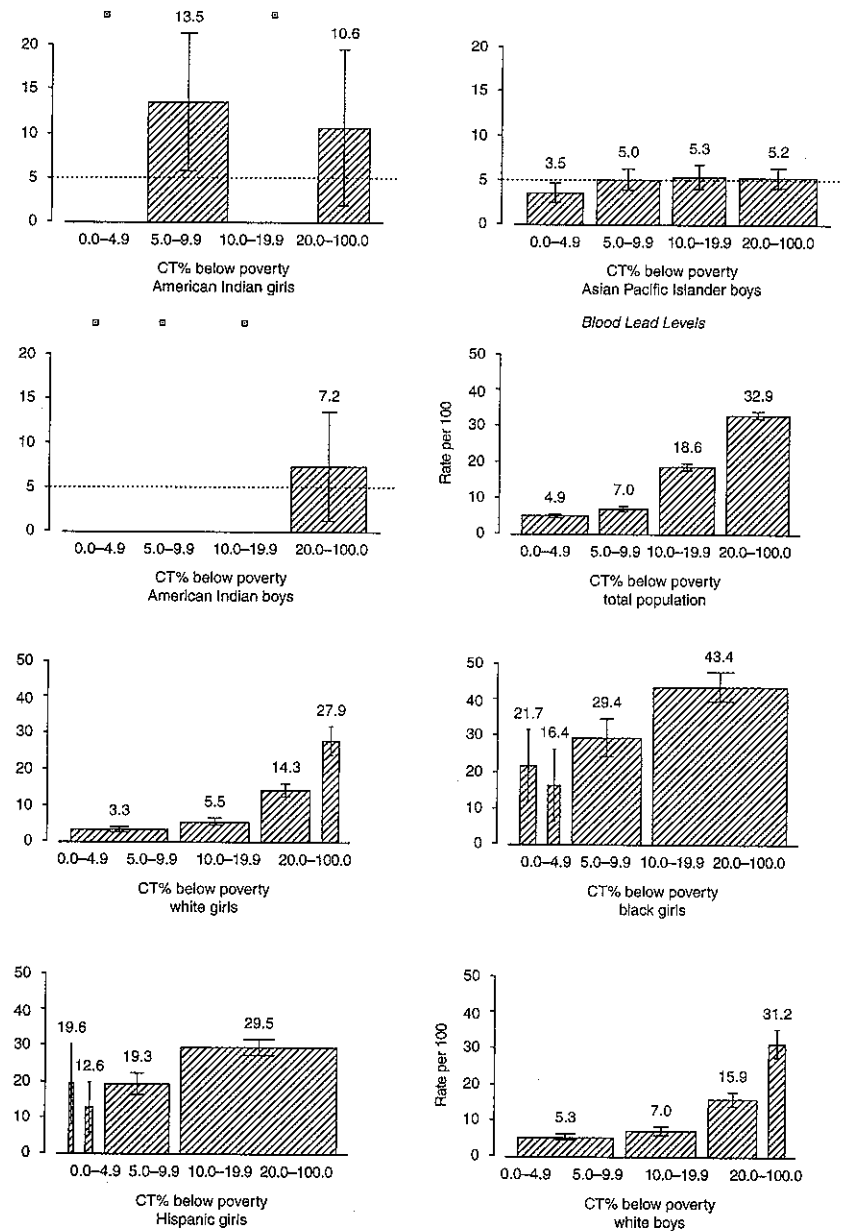


Fig. 5. (Continued)

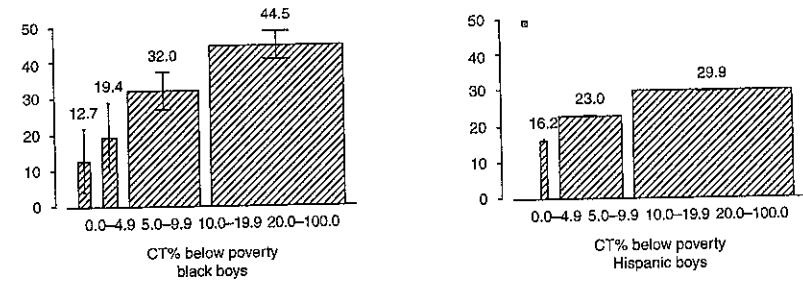


Fig. 5. (Continued)

6. *Mortality*: premature mortality (death before age 65), heart disease mortality, cancer mortality, diabetes mortality, HIV mortality, and homicide.

In all cases, except for the childhood outcomes, rates are age-standardized to the 2000 US standard million (75).

The format of each figure provides information on the rate of the health outcome by each of the four designated socioeconomic strata, ranging from CTs with less than 5% of the population below the poverty level to CTs where 20% or more of the population lives below poverty (the federal definition of a "poverty area" [76]). The height of each bar indicates the age-standardized rate (or, in the case of low birthweight and childhood lead poisoning, the proportion); the actual numerical value of rate is provided at the top of the bar, along with a vertical line displaying the rate's 95% confidence interval (CI). The width of each bar in turn is proportional to the size of the population living in each of the four socioeconomic stratum (<5, 5-9.9, 10-19.9, and ≥20%, respectively, of the population below poverty). Consequently, for those populations living chiefly in the least poor CTs, for example, white non-Hispanics, the width of the bars is greatest for the least poor socioeconomic stratum and thinnest for the high poverty tracts. By contrast, among populations at high risk of living in a poverty area CT, for example, the black and Hispanic populations, the width of the bar is much greater for the high-compared with low poverty socioeconomic stratum. The graphic approach to displaying the data in Fig. 5 accordingly enables simultaneous presentation of information on the absolute rates, whereas visually facilitating comprehension of the relative and absolute difference across socioeconomic strata and also the population burden, in terms of which socioeconomic stratum has the worst rates and also generates the most cases (because a wide bar with a low rate may yield more cases, in absolute terms, than a thin bar with high rates) (19-23,77). Finally, wherever applicable, a dashed line has been included to show the *Healthy People 2000* objective for those outcomes for which such an objective was specified (78).

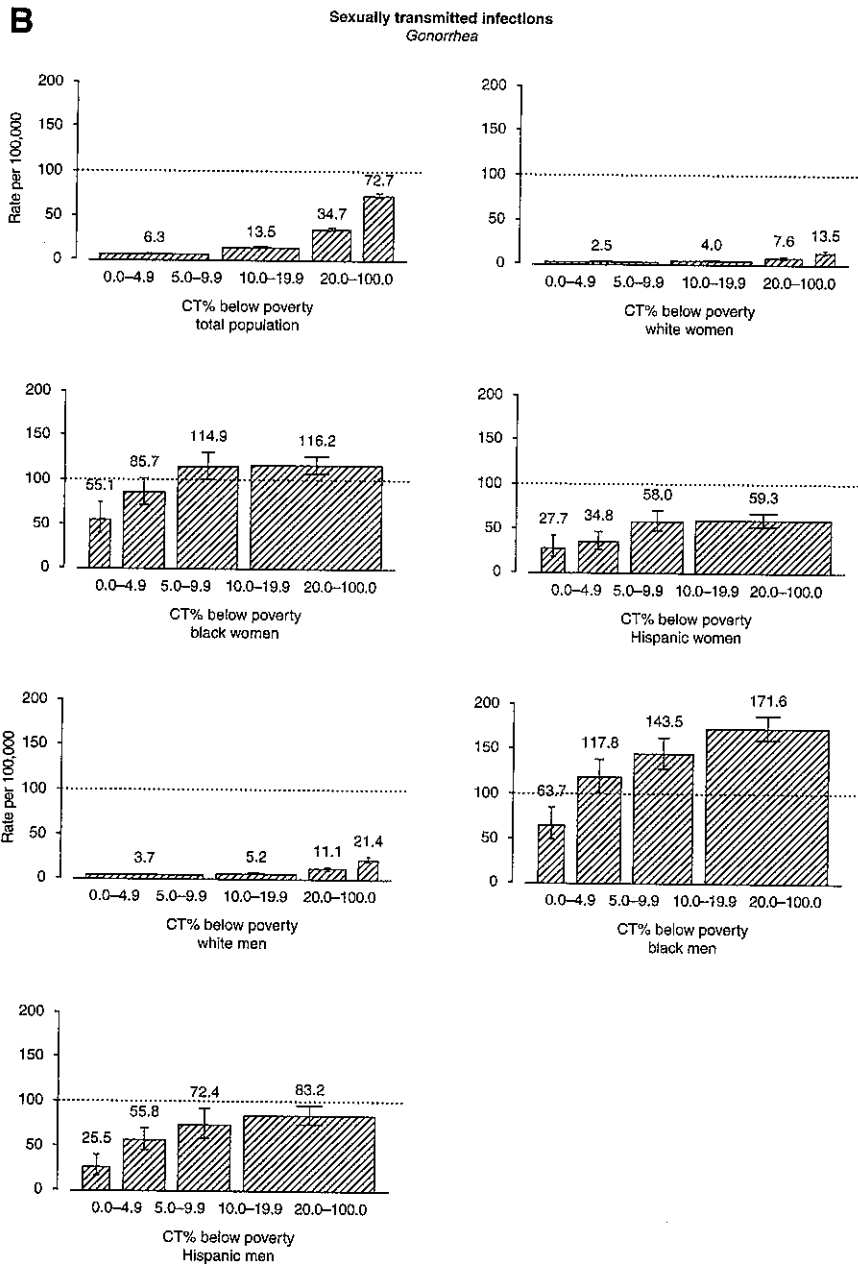


Fig. 5. (Continued)

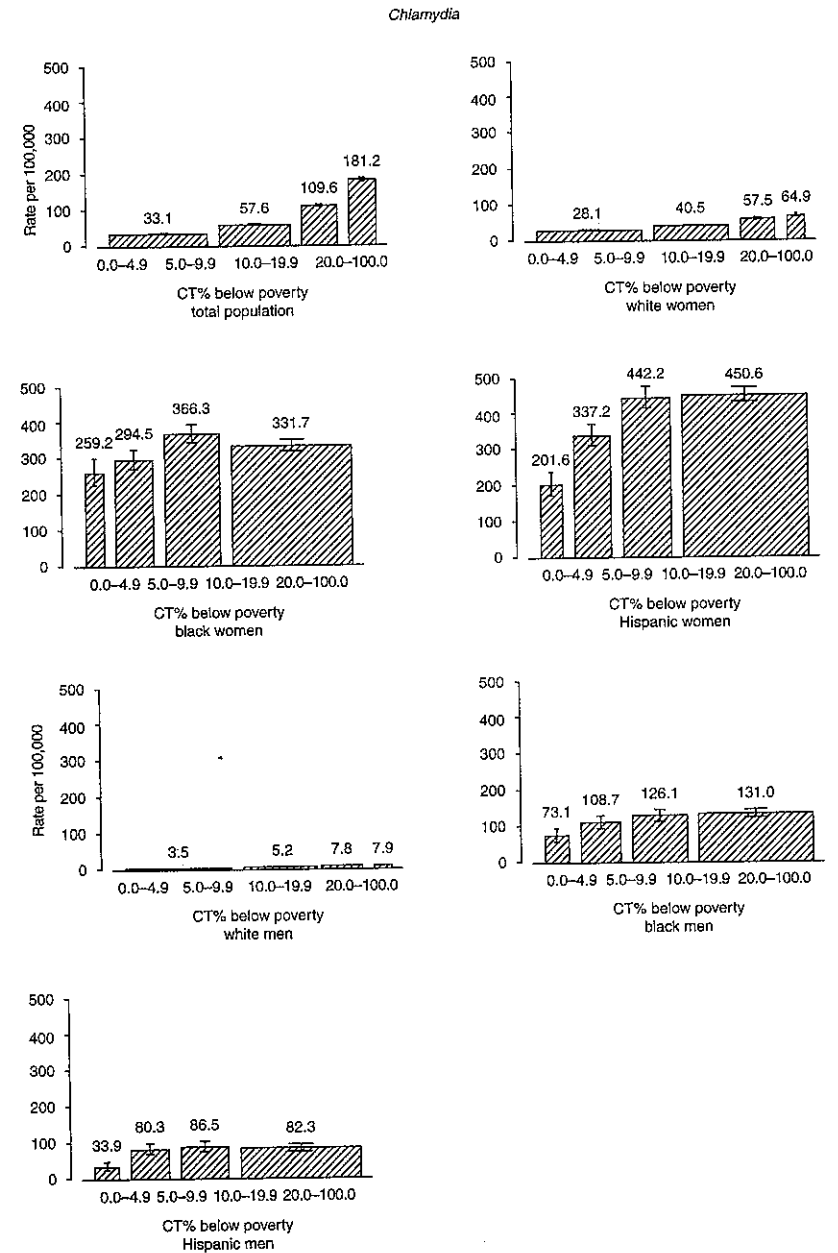


Fig. 5. (Continued)

Syphilis

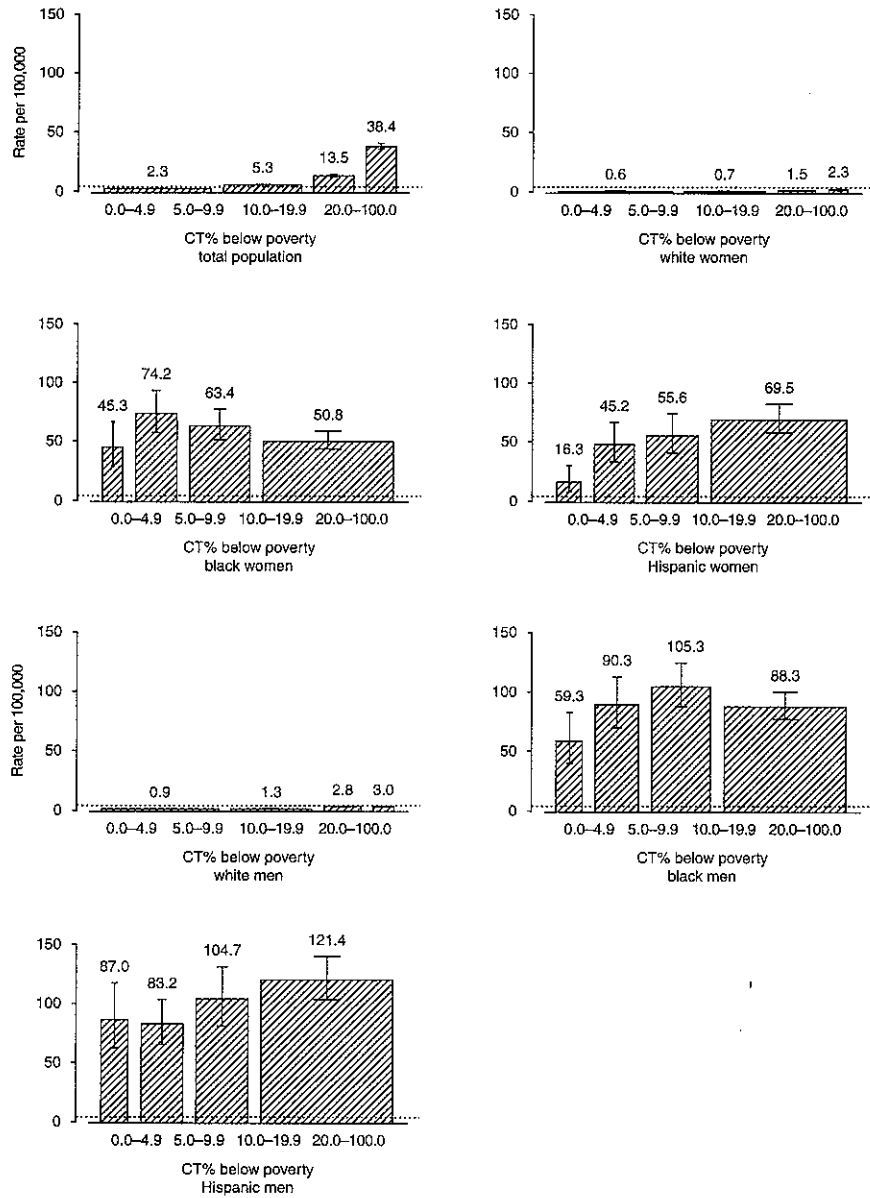


Fig. 5. (Continued)

Tuberculosis

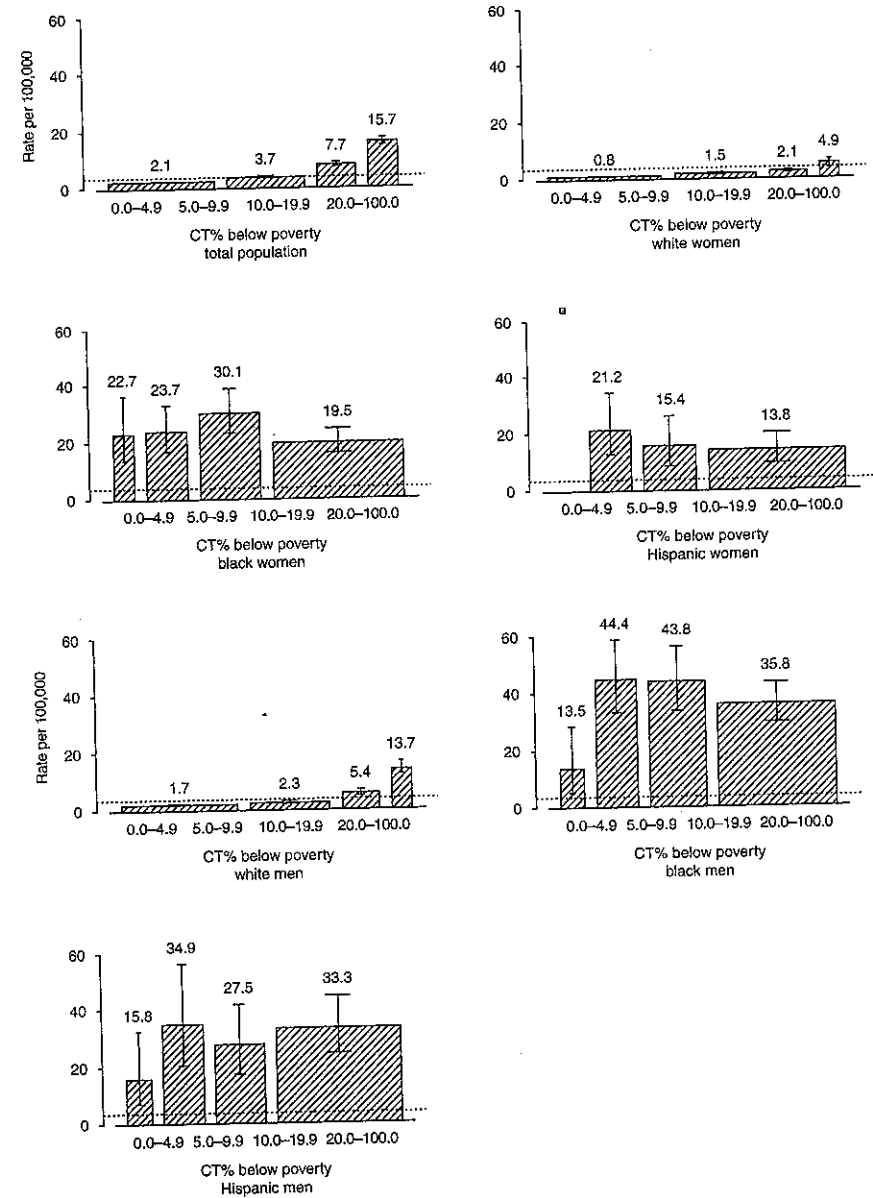


Fig. 5. (Continued)

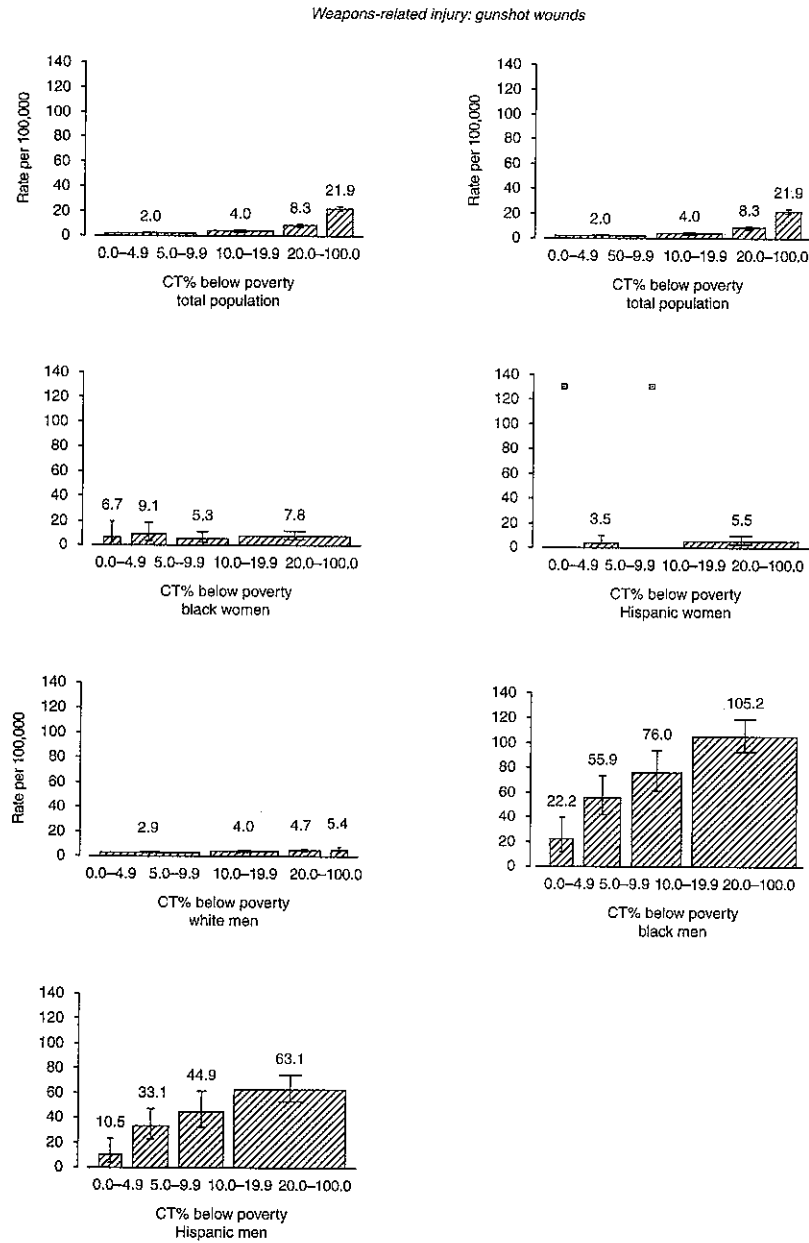


Fig. 5. (Continued)

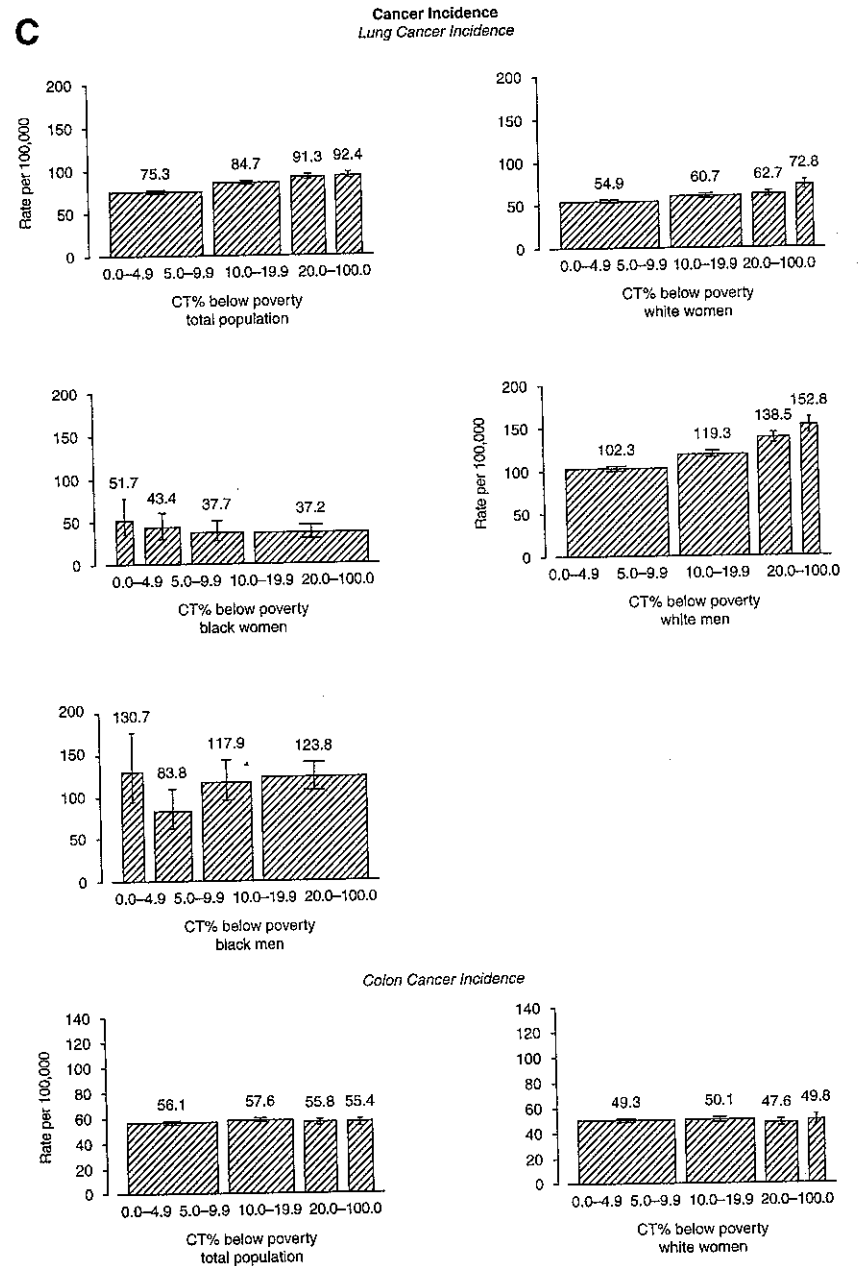


Fig. 5. (Continued)

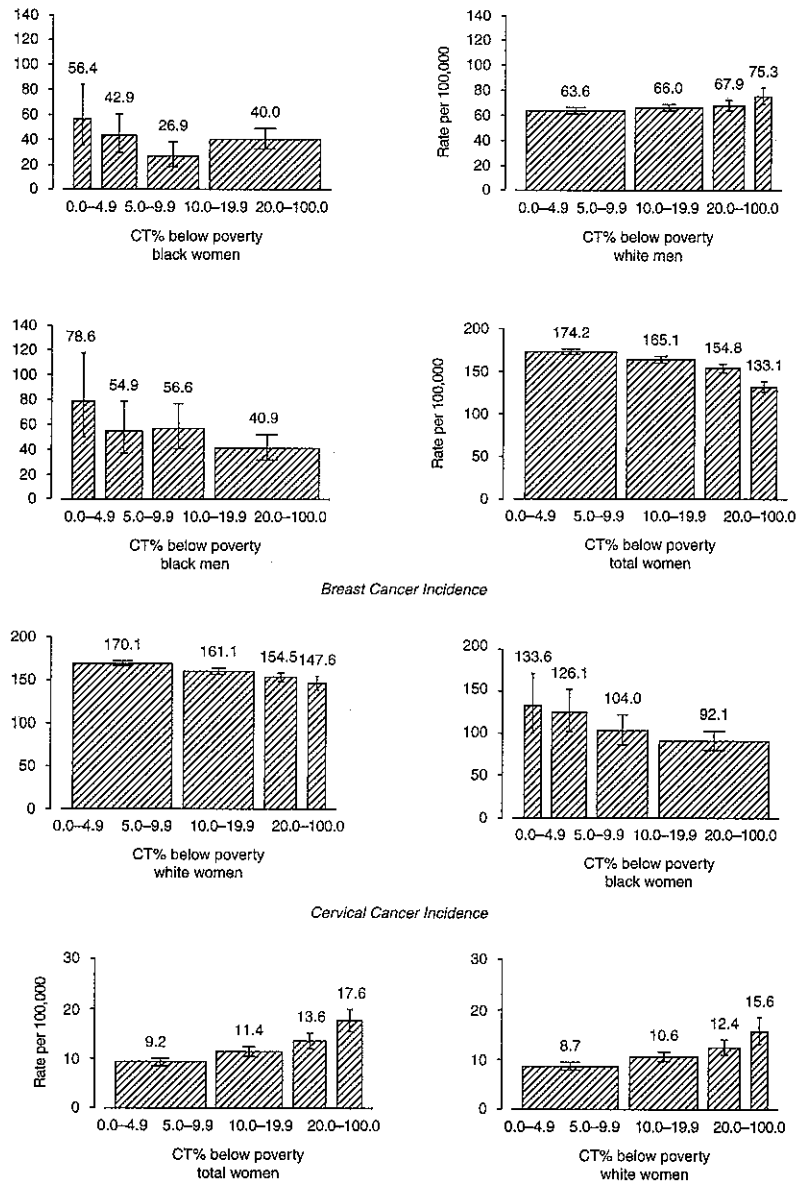


Fig. 5. (Continued)

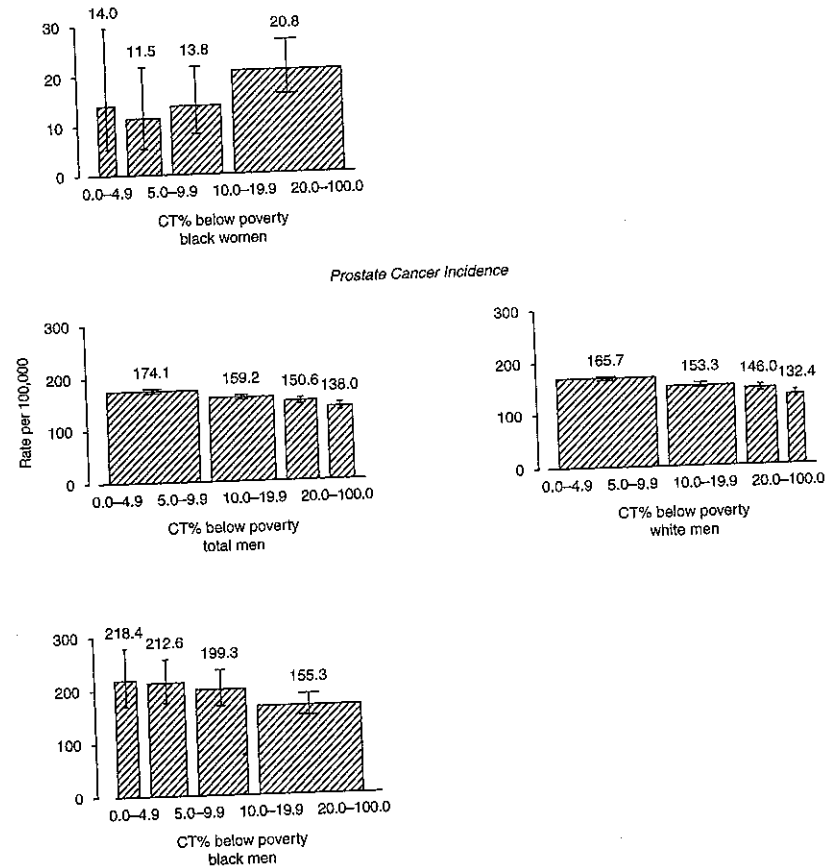


Fig. 5. (Continued)

In the case of low birthweight, what stands out first, is that, among the total population there is a clear poverty gradient, with risk of low birthweight two times higher among births occurring in the most vs least impoverished tracts (i.e., 7.5 vs 3.6%). Second, the *Healthy People 2000* goal for low birthweight births was met a decade ahead of schedule in all but the most impoverished areas, which lagged far behind. Third, the racial/ethnic-gender analyses further showed that whereas this pattern held for the white non-Hispanic population, among the black population, an early attainment of the *Healthy People 2000* low birthweight objective was not met within any of the socioeconomic strata.

Results are similar for childhood lead poisoning. Within the total population, there was a sevenfold excess among those living in the most vs least

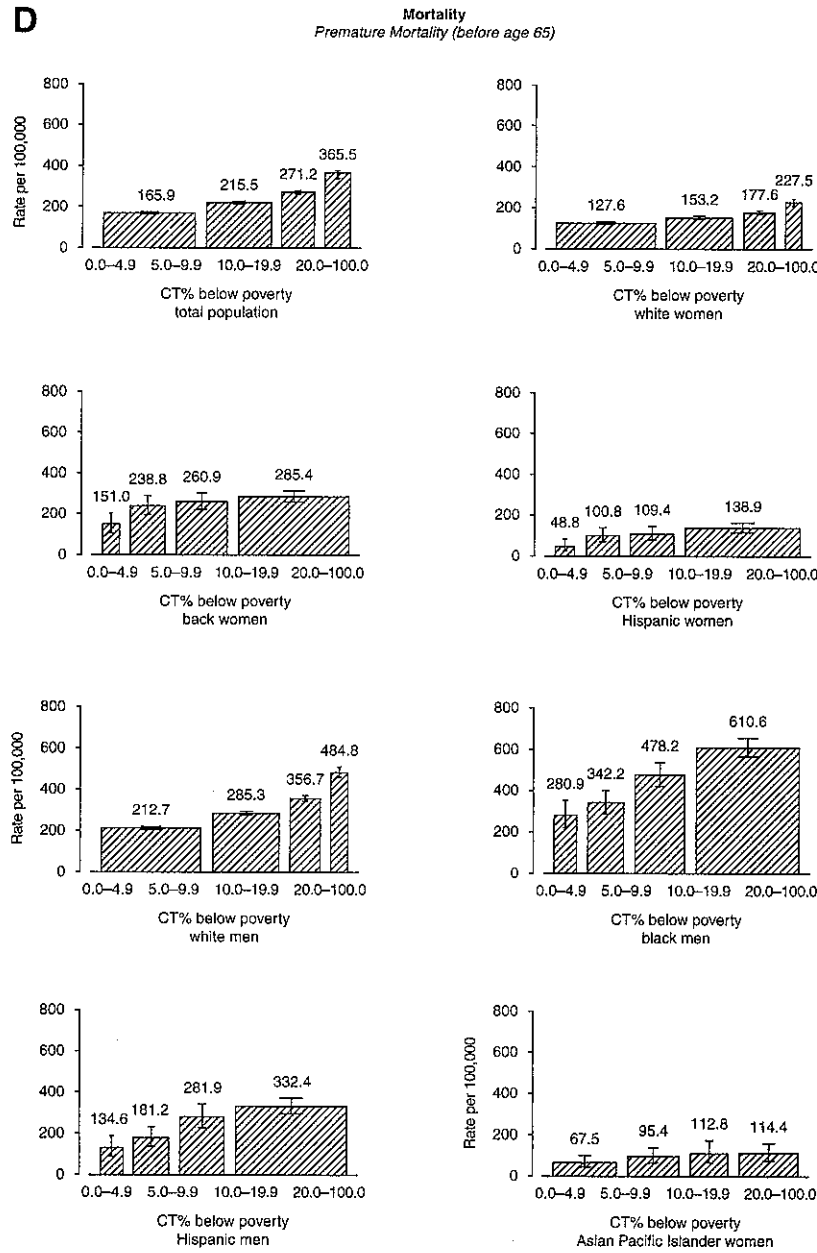


Fig. 5. (Continued)

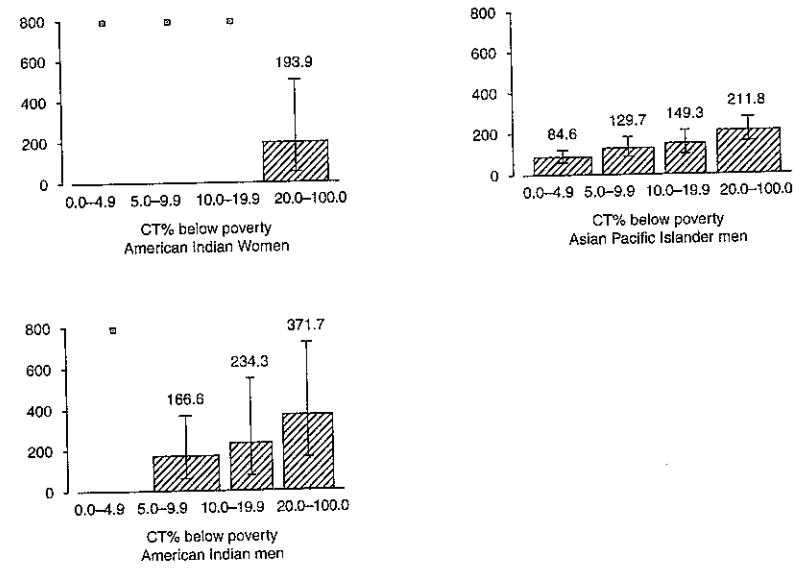


Fig. 5. (Continued)

impoverished CTs, i.e., 33 vs 5%; no *Healthy People 2000* objective is shown because none was set. Additionally, the highest proportions of children with lead poisoning were observed among the black girls and boys living in the poorest CTs. Moreover, in every socioeconomic stratum, a higher proportion of black and Hispanic children compared with white children had lead poisoning (except among Hispanics in the poorest CTs, whose rates were similar to those of non-Hispanic whites in the poorest CTs).

Socioeconomic gradients were likewise evident for each of the sexually transmitted infections and also tuberculosis, with persons living in the least poor CTs the most likely, overall and in each racial/ethnic group, to have the lowest rate of registered cases of the disease, whereas persons in the poorer tracts had higher rates. For example, in the case of syphilis among the total population, the relative risk, comparing persons living the poorest compared with least poor CTs was 17-fold (38.4 vs 2.3 per 100,000). Within the total population, moreover, only rates in the least impoverished tracts met the *Healthy People 2000* objectives a decade in advance. This latter finding again chiefly reflected the low rates among the white population, because among both the black and Hispanic populations, rates in none of the socioeconomic strata dipped below the *Healthy People 2000* objective.

Regarding nonfatal gun shot injury, within the total population, the relative risk, comparing persons in the most to least poor CTs was 11-fold, or about

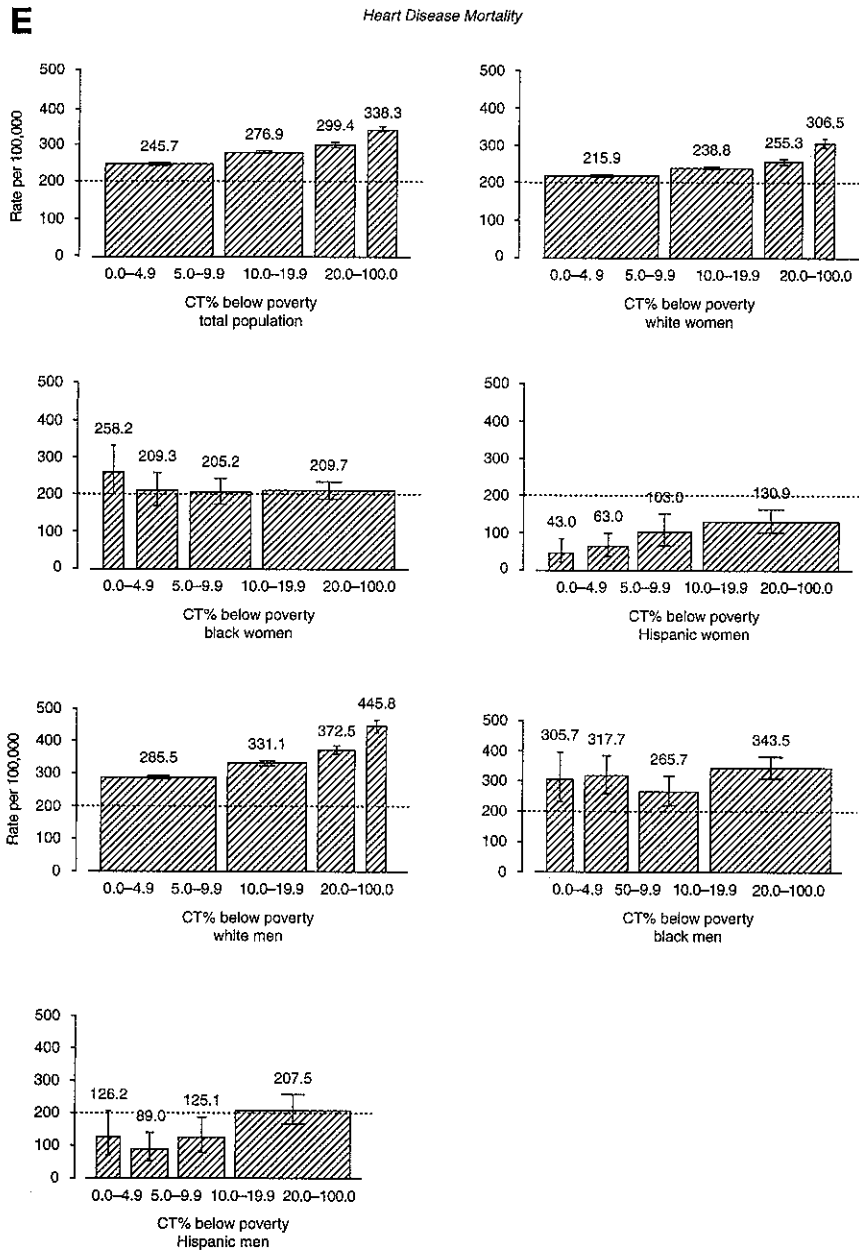


Fig. 5. (Continued)

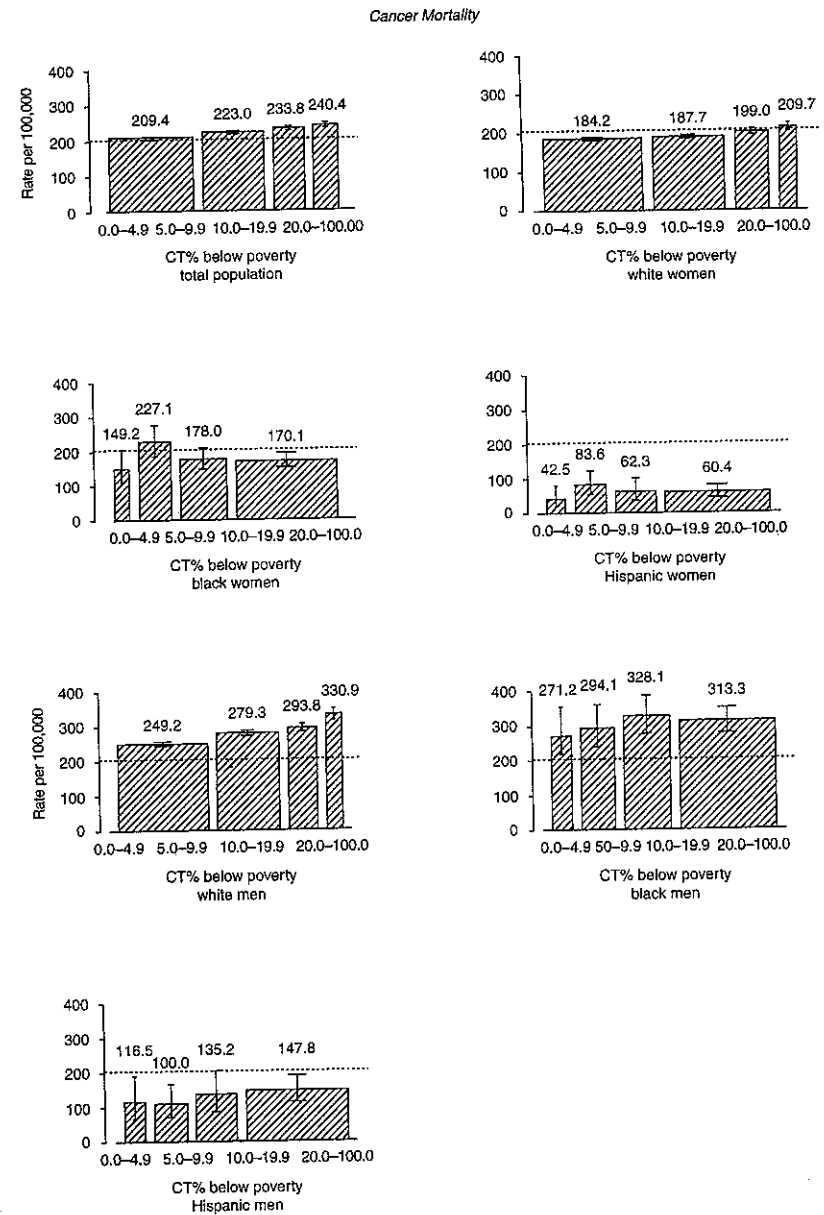


Fig. 5. (Continued)

Diabetes Mortality

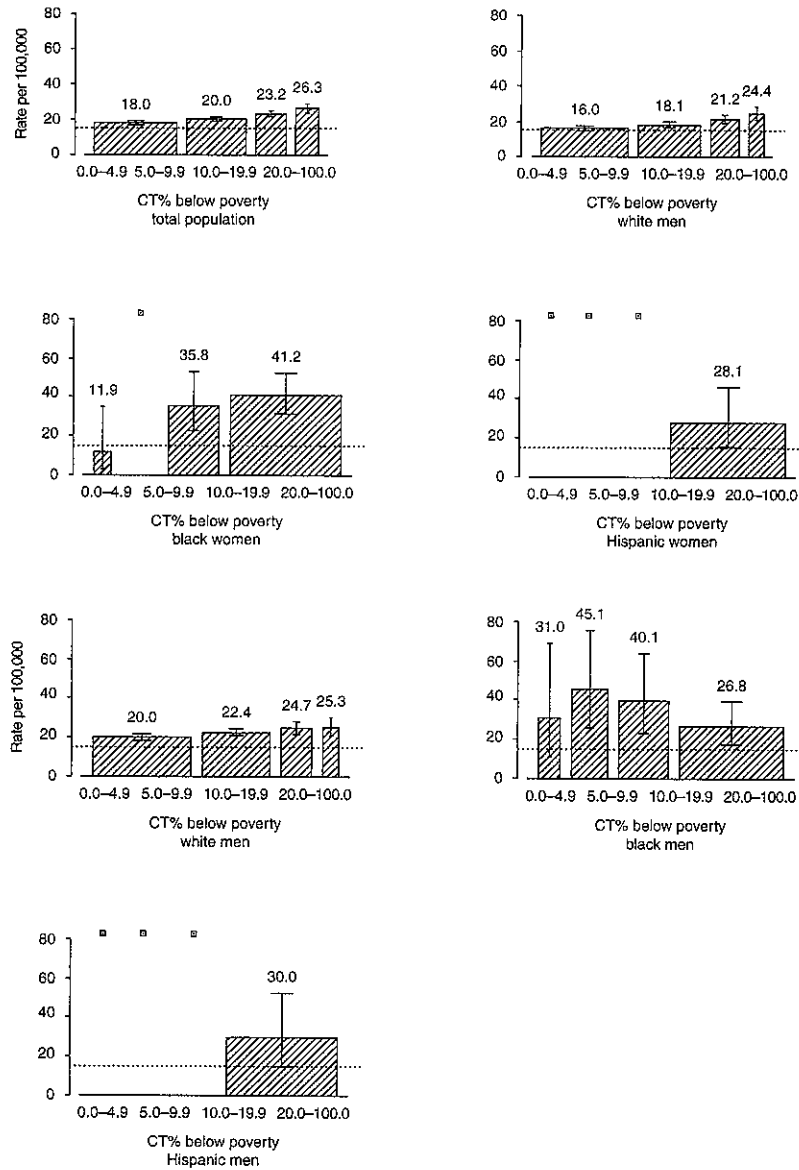


Fig. 5. (Continued)

HIV Mortality

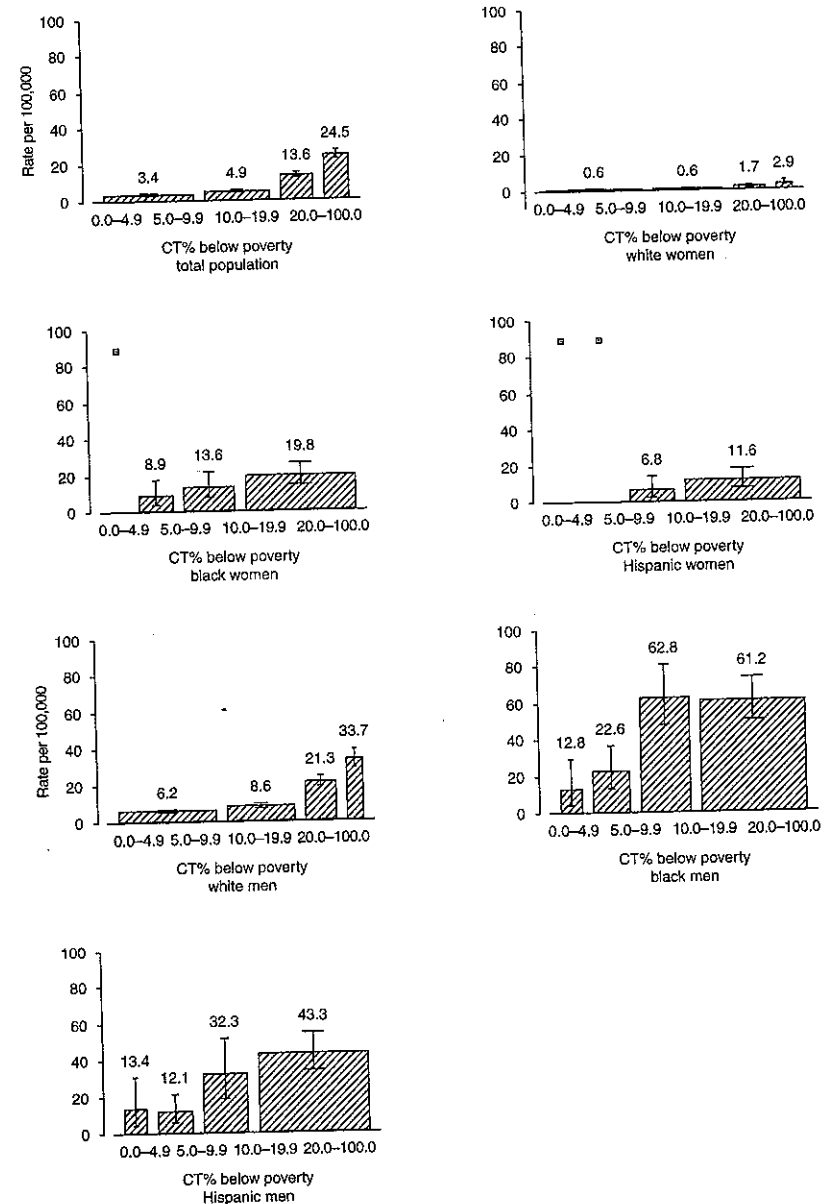


Fig. 5. (Continued)

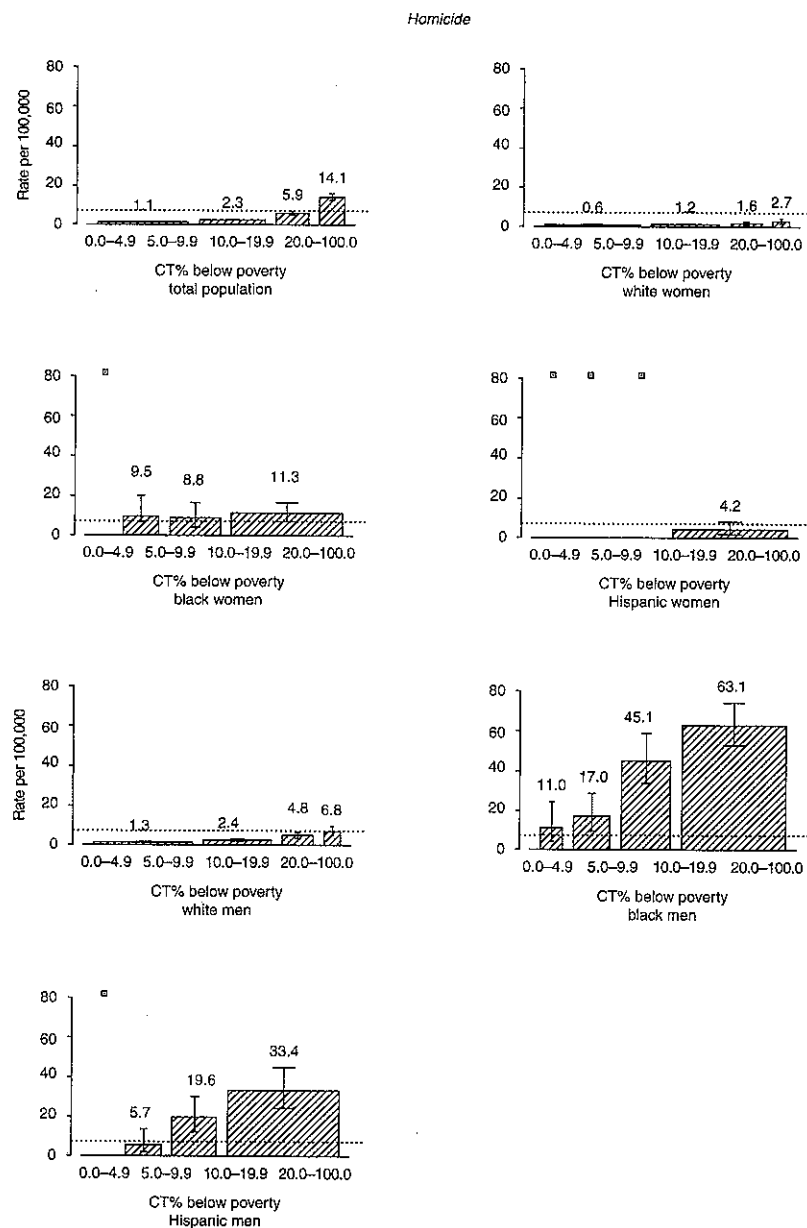


Fig. 5. (Continued) Public Health Disparities Geocoding Project: socioeconomic inequalities in health, from birth until death, for total population and by race/ethnicity and gender, Massachusetts and Rhode Island, ca. the 1990 US census (19).

22 vs 2 per 100,000. Of note, this pattern was chiefly driven by the pronounced socioeconomic gradient among the black and Hispanic men, whereby rates were, respectively, 22 and 10.5 per 100,000 among those in the least poor CTs, but 105 and 63 among those in the poorest CTs.

In the case of cancer incidence, we observed the expected socioeconomic gradients. Thus, incidence rates increased with poverty level of the CT for lung cancer and cervical cancer, decreased with decreased poverty level for breast cancer, and did not display a clearcut socioeconomic gradient for colon cancer. For example, for cervical cancer, within the total population, women living in the poorest CTs were at twofold the risk compared with women in the least poor CTs, i.e., rates of 18 vs 9 per 100,000, and this pattern held for both the white and black women (the only groups large enough for meaningful analyses of cervical cancer incidence rates).

Finally, for mortality, clear socioeconomic gradients within the total population, with risk highest for persons in the poorest CTs, were evident for all of the outcomes, especially premature mortality, heart disease, diabetes, HIV/AIDS, and homicide, and to a lesser extent, cancer mortality (reflecting in part the different directions of the socioeconomic gradient for such disease as lung cancer vs breast cancer). For the leading cause of death, heart disease mortality, the excess risk, comparing persons in the most to least poor CTs, was 1.4-fold, resulting in an absolute excess of nearly 100 deaths per 100,000; persons in the least poor CTs were also the furthest along in meeting the *Healthy People 2000* objective. Moreover, the socioeconomic patterning of mortality was consistent across all racial/ethnic-gender groups, with the exception of heart disease mortality among black women (for whom there was no clear socioeconomic gradient).

In other words, for none of these outcomes are there trivial socioeconomic gradients. Yet, in current US public health reports, these gradients are routinely ignored and unreported.

Further underscoring the magnitude of these disparities, Fig. 6 shows the population attributable fraction (PAF) in relation to CT poverty. The key message is that for half of the outcomes, over half of all cases would have been prevented if the age-specific rates among persons living in the most impoverished CTs were the same as those of persons living in the least impoverished CTs (19). To our knowledge, our *Project's* analyses are the first to calculate state-level PAFs in relation to poverty.

Tables 5 and 6 in turn hint at what these types of analyses could reveal about socioeconomic gradients within racial/ethnic gender groups and the contribution of socioeconomic inequality to racial/ethnic health disparities. Using the example of premature mortality, an important indicator of social disparities in both health status and access to health services, Table 5 shows

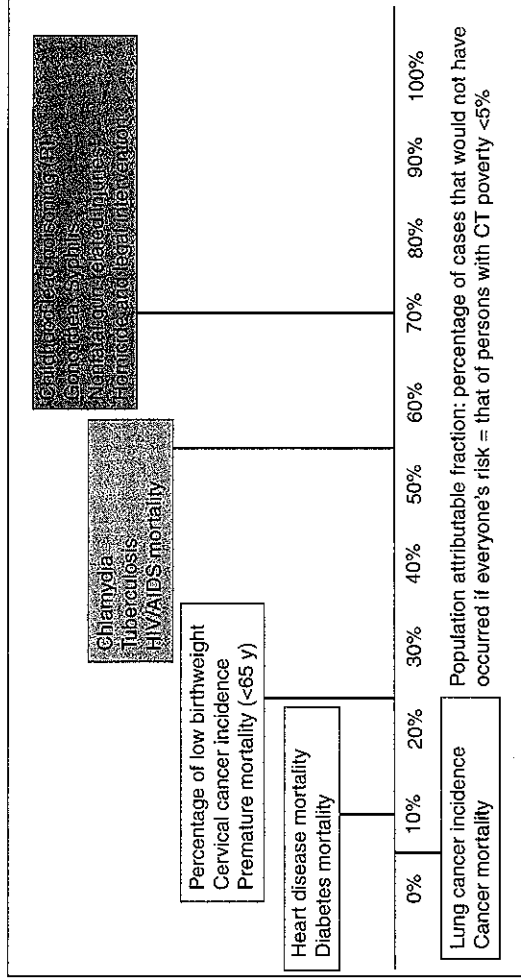


Fig. 6. Public Health Disparities Geocoding Project: PAF in relation to CT poverty, Massachusetts and Rhode Island, ca. the 1990 US census (19).

Table 5
Public Health Disparities Geocoding Project: Premature Mortality Rates (death before 65 yr of age), by Race/Ethnicity, Gender, and CT Poverty Level, Massachusetts, 1989-1991 (19)

Persons below poverty (CT [%])	White men			Black men			White women			Black women			Hispanic women		
	N	Percentage	Rate ^a	IRR (95% CI)	RII (95% CI)	N	Percentage	Rate ^a	IRR (95% CI)	RII (95% CI)	N	Percentage	Rate ^a	IRR (95% CI)	RII (95% CI)
<5	3,203,500	47	212.7	(1)	2.6	3,234,468	46	127.6	(1)	1.9	8	151	48.8	(1)	2.4
5-9.9	2,145,999	31	285.3	1.3 (1.2, 1.4)	(2.5, 2.8)	2,205,174	32	153.2	1.2 (1.1, 1.3)	(1.7, 2.0)	16	238.8	1.6 (0.8, 3.2)	(1.3, 2.0)	
10-19.9	983,442	14	356.7	1.7 (1.5, 1.8)		1,012,152	14	177.6	1.4 (1.2, 1.6)		24	260.9	1.7 (0.9, 3.3)		
≥20	537,120	8	484.8	2.3 (2.0, 2.5)		535,689	8	227.5	1.8 (1.5, 2.1)		52	285.4	1.9 (1.0, 3.5)		
<5	42,777	11	280.9	(1)	2.7	34,530	8	151	(1)	1.6	8	151	48.8	(1)	2.4
5-9.9	69,978	17	342.2	1.2 (0.7, 2.1)	(2.2, 3.2)	696,663	16	238.8	1.6 (0.8, 3.2)	(1.3, 2.0)	16	238.8	1.6 (0.8, 3.2)	(1.3, 2.0)	
10-19.9	96,048	24	478.2	1.7 (1.0, 2.8)		101,934	24	260.9	1.7 (0.9, 3.3)		24	260.9	1.7 (0.9, 3.3)		
≥20	197,895	49	610.6	2.2 (1.4, 3.4)		220,539	52	285.4	1.9 (1.0, 3.5)		52	285.4	1.9 (1.0, 3.5)		
<5	41,931	11	134.6	(1)	2.8	37,938	9	48.8	(1)	2.4	9	48.8	1.6 (0.6, 7.2)	(1.7, 3.4)	
5-9.9	64,854	16	181.2	1.4 (0.6, 3.0)	(2.2, 3.6)	64,392	16	100.8	2.1 (0.6, 7.2)	(1.7, 3.4)	16	100.8	2.1 (0.6, 7.2)	(1.7, 3.4)	
10-19.9	81,999	21	281.9	2.1 (1.0, 4.4)		84,606	21	109.4	2.2 (0.7, 7.6)		21	109.4	2.2 (0.7, 7.6)		
≥20	205,635	52	332.4	2.5 (1.2, 4.9)		221,898	54	138.9	2.8 (0.9, 8.0)		54	138.9	2.8 (0.9, 8.0)		

Table 6
Public Health Disparities Geocoding Project: Black/White Disparities in Premature Mortality IRRs for Death Before 65 yr of Age, by CT Poverty Level, Massachusetts, 1989–1991

Persons below poverty (CT [%])	Black/white IRR ^a (95% CI)	
	Men	Women
<5	1.4 (1.3, 1.5)	1.4 (1.2, 1.5)
5–9.9	1.5 (1.4, 1.7)	1.6 (1.4, 1.8)
10–19.9	1.3 (1.1, 1.5)	1.7 (1.4, 2.0)
≥20	1.3 (1.1, 1.6)	1.2 (1, 1.6)
Overall	2.0 (1.9, 2.1)	1.9 (1.8, 2.0)
Adjusted for percentage below poverty (CT)	1.4 (1.4, 1.5)	1.5 (1.4, 1.6)

IRR, incidence rate ratios; CT, census tract; CI, confidence interval.

^aAll models adjusted for age, using Poisson regression models.

See ref. 19.

two key findings. First, whereas almost half the white women and men lived in CTs with less than 5% of persons below poverty, half of the black and Hispanic population lived in CTs with 20% or more below poverty. Second, within each racial/ethnic gender group, there were marked socioeconomic disparities in premature mortality, with relative risks ranging from 1.6–2.8.

Additionally, as shown in Table 6, within each economic stratum, a black excess for premature mortality remained apparent. Even so, adjusting solely for the single relatively crude measure of CT poverty reduced the overall age-adjusted twofold black excess risk of premature mortality down to “only” a 40–50% excess. Whereas from an etiological perspective, it would be critical to use more detailed measures of lifetime socioeconomic position to quantify its contribution to observed racial/ethnic disparities in health (55,58–59), from the standpoint of monitoring, use of appropriate ABSMs can do much to reveal both socioeconomic gradients in health status within diverse racial/ethnic groups, as well as clarify that racial/ethnic inequalities in socioeconomic position continue to play an important role in generating racial/ethnic health disparities. For this reason, the approach utilized in our *Project* has been used to frame data analysis and interpretation of both national and state publications on socioeconomic inequalities in health (79–80).

IMPLICATIONS OF THE PROJECT FOR MONITORING AND ANALYZED HEALTHCARE DISPARITIES

Turning finally to healthcare disparities, we note that the methods of the *Public Health Disparities Geocoding Project* can be used with any health

database, and not just with public health surveillance records. Indeed, within the health services literature, diverse examples can be found whereby investigators have linked medical record or hospital discharge data to a variety of ABSMs, at diverse geographic levels, to examine healthcare disparities (81,82). Types of questions typically asked have included:

1. Who is at greatest risk of having inadequate access to needed healthcare, including screening, preventive care, and treatment? (82–88).
2. What is the magnitude of socioeconomic disparities in health status, health behaviors, and treatment outcomes among patients enrolled in a particular health plan? (89–93).
3. Should data on the socioeconomic composition of health plan members be included as an adjustment factor for comparing health system performance? (94).
4. Are there socioeconomic inequities in performance of procedures, referrals, and other outcomes indicative of healthcare system performance (independent of patient health status)? (83,92,95).

Literature on these topics nevertheless remains scant, with ABSMs only just starting to be used by health service researchers to address the lack of socioeconomic data in most medical records (81). The net implication is that there is ample opportunity for more healthcare systems, researchers, and advocates to use tools like those provided by the *Public Health Disparities Geocoding Project* to document, investigate, and address healthcare disparities.

For this approach to be best used in healthcare disparities research, however, it will be important to address an important problem: apparently, the most commonly used area-based socioeconomic data for documenting healthcare disparities are ZC-level socioeconomic data (81,88,91,94,95). In part, this practice appears to have arisen because the ZC is the only address or geographic information provided in hospital discharge records or readily obtainable from health records without the added step and expense of geocoding the address data (12). Yet, as noted above, use of ZC data should be discouraged on multiple grounds, including the large size and economic heterogeneity of their population and also because of the possibility of introducing serious bias owing to spatiotemporal mismatches between census and ZC data (to the point of reversing the direction of the actual socioeconomic gradient [24]). Compounding these problems, starting with the 2000 decennial census, ZC data are no longer available as a geographic unit for which US census socioeconomic data are available (24,54). The US census made the decision to no longer provide these data because, in their words, “carrier routes for one ZC may intertwine with those of one or more ZCs” such that “this area is more conceptual than geographic” (96, p. 22). To “overcome the difficulties in precisely defining the land area covered by each ZC” (54), starting with the 2000 Census, the US Census Bureau accordingly created a new statistical

Table 7
Technical Definitions of and Distinctions Between ZCs and ZCTAs.

Definition of ZCTA	Distinction between ZCTA and ZC
<p>"ZCTAs are a new statistical entity developed by the US Census Bureau for tabulating summary statistics from Census 2000. This new entity was developed to overcome the difficulties in precisely defining the land area covered by each ZC. Defining the extent of an area is necessary in order to accurately tabulate census data for that area. ZCTAs are generalized area representations of US postal service (USPS) ZC service areas. Simply put, each one is built by aggregating the Census 2000 blocks, whose addresses use a given ZC, into a ZCTA which gets that ZC assigned as its ZCTA code. They represent the majority USPS five-digit ZC found in a given area. For those areas where it is difficult to determine the prevailing five-digit ZC, the higher-level three-digit ZC is used for the ZCTA code. As the ZC used by the majority of addresses in an area for the ZCTA code is taken, some addresses will end up with a ZCTA code different from their ZCs. Also, some ZCs represent very few addresses (sometimes only one) and therefore will not appear in the ZCTA universe"</p>	<p>"Even though the codes may appear the same, the addresses and areas covered by these areas may not be the same. Data users who wish to compare 1990 and 2000 data are strongly advised to determine and evaluate any coverage differences that exist before making any comparisons. There are several reasons for this caution: The USPS has extensively modified ZCs over the last 10 yr. Even though a 1990 ZC matches a Census 2000 ZCTA code, there is no guarantee that these cover the same geographic area. Also, some ZCs in the 1990 data products were discontinued by the USPS, and new ZCs were created; ZCTAs and the 1990 census ZC areas were delineated using different methodologies and therefore may not have comparable coverage area or size; and The Census 2000 ZCTAs will include some dedicated PO box ZCs. All dedicated PO box ZCs were excluded as ZC areas in 1990. The resulting 1990 areas include data for both PO box ZCs and the ZCs that provides street or rural route delivery to the surrounding area"</p>

PO, post office; USPS, US postal service; ZC, ZIP code; ZCTA, ZIP code tabulation areas. See refs. 54 and 97.

entity built from census blocks: the five-digit ZIP code tabulation areaTM (ZCTA) (97). Of note, ZCTAs and ZCs sharing the same five-digit code may not necessarily cover the same area (see Table 7) (98), such that ZCs obtained by self-report or from addresses in medical records cannot be assumed to correspond to census-defined ZCTAs.

New interest in improving hospital records, to improve understanding of healthcare disparities (1,12,99), however, could readily lead to improved geocoding of medical records. For example, in the city of Boston, The Mayor's Task Force on Health Disparities, in conjunction with the Boston Public Health Commission, in 2005, launched an initiative to improve and standardize collection of racial/ethnic and socioeconomic data in medical records, which has secured the participation of all of the largest Boston hospitals (99). In addition to specifying that educational level should be routinely collected, the Boston Public Health Commission recognizes the utility of having address information routinely geocoded to the CT level. Of note, the US Census Bureau now provides a free online tool to identify any address geocodes, including those for its CT, one single address at a time (100). Use of this tool could readily be coupled with the input of patients' addresses at time of enrollment in a health plan or when billing occurs.

CONCLUSION: DATA, POLITICS, AND HEALTH INEQUITIES

In conclusion, data on disparities in health status and healthcare are essential, both to understand the magnitude of the problems that are confronted and to increase accountability for—and hence the likelihood of—eliminating these preventable sources of suffering. The continued absence of socioeconomic data in US public health and medical records is a serious problem, one neither innocent nor inevitable. Fortunately, the tools provided by the *Public Health Disparities Geocoding Project* offer one potential solution to overcoming this obstacle. It is the responsibility, as public health and medical professionals, to end the pernicious cycle of "no data, no problem" (13,14). Using available methods and concept, we instead can bring to public attention the existence of socioeconomic disparities in health status and healthcare, within and across diverse racial/ethnic groups as well as show how they contribute to persistent and unacceptable racial/ethnic disparities in health, in conjunction with racial discrimination and other forms of social inequality manifested in each and every economic strata (4,101). The goal is to generate knowledge that, if put into action, can inform current efforts to promote social justice and equity in health status and healthcare.

ACKNOWLEDGMENTS

This work was funded by the National Institutes of Health (1 R01HD36865-01), through the National Institute of Child Health and Human Development and the Office of Behavioral and Social Science Research. Principal Investigator, Nancy Krieger.

REFERENCES

1. Smedley, B. D., Stith, A. Y., and Nelson, A. R. (eds.) (2003) *Unequal Treatment: Confronting Racial and Ethnic Disparities in Health Care*. Committee on Understanding and Eliminating Racial and Ethnic Disparities in Health Care, Board on Health Sciences Policy, Institute of Medicine, National Academy Press, Washington, DC.
2. Levy, B. S. and Sidel, V. W. (eds.) (2006) *Social Injustice and Public Health*. Oxford University Press, New York.
3. Navarro, V. and Muntaner, C. (eds.) (2004) *Political and Economic Determinants of Population Health and Well-Being: Controversies and Developments*. Baywood Pub. Co., Amityville, NY.
4. Krieger, N. (ed.) (2004) *Embodying Inequality: Epidemiologic Perspectives*. Baywood Publishing Co., Amityville, NY.
5. Krieger, N. (2005) Embodiment: a conceptual glossary for epidemiology. *J. Epidemiol. Community Health* **59**, 350–355.
6. Krieger, N. and Davey Smith, G. (2004) Bodies count & body counts: social epidemiology & embodying inequality. *Epidemiol. Rev.* **26**, 92–103.
7. Krieger, N., Chen, J. T., and Ebel, G. (1997) Can we monitor socioeconomic inequalities in health? A survey of US Health Departments' data collection and reporting practices. *Public Health Rep.* **112**, 481–491.
8. Friedman, D. J., Hunter, E. L., and Parrish, R. G. (2002) *Shaping a Vision of Health Statistics for the 21st Century*. Washington, DC: Department of Health and Human Services Data Council, Centers for Disease Control and Prevention, National Center for Health Statistics, and National Committee on Vital and Health Statistics. Available at: <http://www.ncvhs.hhs.gov/hsvision/>, accessed May 3, 2006.
9. *National Healthcare Disparities Report, 2005*. Agency for Healthcare Research and Quality, Rockville, MD. Available at: <http://www.ahrq.gov/qual/nhdr05/nhdr05.htm>, accessed May 3, 2006.
10. Ver Ploeg, M. and Perrin, E. (eds.) (2004) *Eliminating Health Disparities: Measurement and Data Needs. Panel on DHHS Collection of Race and Ethnicity Data*. National Academies Press, Washington, DC.
11. Desrosières, A. (1998) *The Politics of Large Numbers: A History of Statistical Reasoning*. Transl. Camille Naish. Harvard University Press, Cambridge, MA.
12. Friedman, D. J., Hunter, E. L., and Parrish, R. G., II. (eds.) (2005) *Health Statistics: Shaping Policy and Practice to Improve the Public's Health*. Oxford University Press, Oxford.
13. Krieger, N. (1992) The making of public health data: paradigms, politics, and policy. *J. Public Health Policy* **13**, 412–427.
14. Krieger, N. (2004) Data, "race," and politics: a commentary on the epidemiologic significance of California's Proposition 54. *J. Epidemiol. Community Health* **58**, 632–633.
15. Krieger, N., Rowley, D. L., Herman, A. A., Avery, B., and Phillips, M. T. (1993) Racism, sexism, and social class: implications for studies of health, disease, and well-being. *Am. J. Prev. Med.* **9**(Suppl), 82–122.
16. Krieger, N. and Fee, E. (1996) Measuring social inequalities in health in the United States: an historical review, 1900–1950. *Int. J. Health Serv.* **26**, 391–418.

17. Chase, A. (1977) *The Legacy of Malthus: The Social Costs of the New Scientific Racism*. Knopf, New York.
18. Krieger, N., Waterman, P. D., Chen, J. T., Rehkopf, D. H., and Subramanian, S. V. Geocoding and monitoring US socioeconomic inequalities in health: an introduction to using area-based socioeconomic measures—*The Public Health Disparities Geocoding Project* monograph. Harvard School of Public Health, Boston, MA. Available at: <http://www.hsph.harvard.edu/thegeocoding-project/>, accessed May 3, 2006.
19. Krieger, N., Chen, J. T., Waterman, P. D., Rehkopf, D. H., and Subramanian, S. V. (2005) Painting a truer picture of US socioeconomic and racial/ethnic health inequalities: the *Public Health Disparities Geocoding Project*. *Am. J. Public Health* **95**, 312–323.
20. Krieger, N., Chen, J. T., Waterman, P. D., Rehkopf, D. H., and Subramanian, S. V. (2003) Race/ethnicity, gender, and monitoring socioeconomic gradients in health: a comparison of area-based socioeconomic measures—*The Public Health Disparities Geocoding Project*. *Am. J. Public Health* **93**, 1655–1671.
21. Krieger, N., Waterman, P. D., Chen, J. T., Soobader, M. J., and Subramanian, S. (2003) Monitoring Socioeconomic Inequalities in Sexually Transmitted Infections, Tuberculosis, and Violence: Geocoding and Choice of Area-Based Socioeconomic Measures—*The Public Health Disparities Geocoding Project* (US). *Public Health Rep.* **118**, 240–260.
22. Krieger, N., Chen, J. T., Waterman, P. D., Soobader, M. J., Subramanian, S. V., and Carson, R. (2003) Choosing area based socioeconomic measures to monitor social inequalities in low birth weight and childhood lead poisoning: *The Public Health Disparities Geocoding Project* (US). *J. Epidemiol. Community Health* **57**, 186–199.
23. Krieger, N., Chen, J. T., Waterman, P. D., Soobader, M. J., Subramanian, S. V., and Carson, R. (2002) Geocoding and monitoring of US socioeconomic inequalities in mortality and cancer incidence: does the choice of area-based measure and geographic level matter? *The Public Health Disparities Geocoding Project*. *Am. J. Epidemiol.* **156**, 471–482.
24. Krieger, N., Waterman, P., Chen, J. T., Soobader, M. J., Subramanian, S. V., and Carson, R. (2002) Zip code caveat: bias due to spatiotemporal mismatches between zip codes and US census-defined geographic areas—*The Public Health Disparities Geocoding Project*. *Am. J. Public Health* **92**, 1100–1102.
25. Krieger, N., Waterman, P., Lemieux, K., Zierler, S., and Hogan, J. W. (2001) On the wrong side of the tracts? Evaluating the accuracy of geocoding in public health research. *Am. J. Public Health* **91**, 1114–1116.
26. Krieger, N., Zierler, S., Hogan, J. W., et al. (2003) Geocoding and measurement of neighborhood socioeconomic position, in *Neighborhoods and Health*, (Kawachi, I. and Berkman, L. F., eds.), Oxford University Press, New York, pp. 147–178.
27. Subramanian, S. V., Chen, J. T., Rehkopf, D. H., Waterman, P. D., and Krieger, N. (2005) Racial disparities in context: A multilevel analysis of neighborhood variations in poverty and excess mortality among black populations in Massachusetts. *Am. J. Public Health* **95**, 260–265.

28. Subramanian, S. V., Chen, J. T., Rehkopf, D. R., Waterman, P. D., and Krieger, N. (2006) Comparing individual and area-based socioeconomic measures for the surveillance of health disparities: a multilevel analysis of Massachusetts births, 1988–92. *Am. J. Epidemiol.* **164**, 823–834.
29. Rehkopf, D. H., Haughton, L., Chen, J. T., Waterman, P. D., Subramanian, S. V., and Krieger, N. (2006) Monitoring socioeconomic disparities in death: comparing individual-level education and area-based socioeconomic measures. *Am. J. Public Health* **96**, 2135–2138.
30. National Center for Health Statistics. *Health, United States, 2005*. Washington, DC. US Department of Health and Human Services, 2006. Available at: <http://www.cdc.gov/nchs/hus.htm>, accessed May 3, 2006.
31. US Department of Health and Human Services. *Healthy People 2010* (Conference edition, in two volumes). Washington, DC. US Govt Printing Office, 2000. Available at: <http://www.health.gov/healthypeople>, accessed May 3, 2006.
32. Krieger, N. (1992) Overcoming the absence of socioeconomic data in medical records: validation and application of a census-based methodology. *Am. J. Public Health* **82**, 703–710.
33. Krieger, N. (2006) A century of census tracts: health and the body politic (1906–2006). *J. Urban Health* **83**, 355–361.
34. Krieger, N. (1994) Epidemiology and the web of causation: has anyone seen the spider? *Soc. Sci. Med.* **39**, 887–903.
35. Krieger, N. (2001) Theories for social epidemiology in the 21st century: an ecosocial perspective. *Int. J. Epidemiol.* **30**, 668–677.
36. Krieger, N. (2004) Ecosocial theory, in *Encyclopedia of Health and Behavior*. (Anderson, N., ed.), Sage, Thousand Oaks, CA, 292–294.
37. Sigerist, H. E. (1951) *A History of Medicine. Vol. I: Primitive and Archaic Medicine*. Oxford University Press, (reissued: 1979), NY, pp. 259–260.
38. Sigerist, H. E. (1961) *A History of Medicine. Vol. II: Early Greek, Hindu, and Persian Medicine*. Oxford University Press, NY, (reissued: 1987), p. 240.
39. Rosen, G. (1993) *A History of Public Health*. (1958). Introduction by Elizabeth Fee; Bibliographical essay and new bibliography by Edward T. Morman. Expanded ed. Johns Hopkins University Press, Baltimore, MD.
40. Porter, D. (1999) *Health, Civilization and the State: A History of Public Health from Ancient to Modern Times*. Routledge, London.
41. Krieger, N. (2000) Epidemiology and social sciences: towards a critical re-engagement in the 21st century. *Epidemiol. Rev.* **11**, 155–163.
42. Krieger, N. (1987) Shades of difference: theoretical underpinnings of the medical controversy on black-white differences, 1830–1870. *Int. J. Health Serv.* **17**, 258–279.
43. Villermé, L. R. (1826) Rapport fait par M. Villermé, et lu à l'Académie royale de Médecine, au nom de la Commission de statistique, sur une série de tableaux relatifs au mouvement de la population dans les douze arrondissements municipaux de la ville de Paris, pendant les cinq années 1817, 1817, 1819, 1820 et 1821. *Arch. Gén. Méd.* **10**, 216–247.

44. Coleman, W. (1982) *Death is a Social Disease: Public Health and Political Economy in Early Industrial France*. University of Wisconsin Press, Madison, WI, pp. 149–163.
45. Engels, F. (1845). *The Condition of the Working Class in England*. (Translated by Henderson, W. O. and Chaloner, W. H. (1958)). Stanford University Press, Stanford, CA, pp. 120–121.
46. Stevenson, W. H. (ed.) (1989) *Blake, The Complete Poems, 2nd ed.*, Longman, London, 491–492.
47. Subramanian, S. V., Jones, K., and Duncan, C. (2003) Multilevel methods for public health research, in *Neighborhoods and Health*, (Kawachi, I. and Berkman, L., eds.), Oxford University Press, Oxford, pp. 65–111.
48. Diez-Roux, A. V. (2000) Multilevel analysis in public health research. *Annu. Rev. Public Health* **21**, 171–192.
49. Sampson, R. J. and Morenoff, J. D. (2002) Assessing neighborhood effects: social processes and new directions in research. *Annu. Rev. Sociol.* **28**, 443–478.
50. Cromley, E. K. and McLafferty, S. L. (2002) *GIS and Public Health*. Guilford Press, New York.
51. US Bureau of the Census. *Geographical Areas Reference Manual*. US Dept of Commerce, 1994, Washington, DC, pp. 9–12, A-5. Available at: <http://www.census.gov/geo/www/garm.html>, accessed May 3, 2006.
52. Department of Housing and Urban Development. Qualified Census Tracts and Difficult Development Areas. Available at: <http://www.huduser.org/datasets/qct/qct99home.html>, accessed May 3, 2006.
53. Health Resources and Services Administration. Health Professional Shortage Areas. Available at: <http://bhpr.hrsa.gov/shortage/>, accessed May 3, 2006.
54. US Bureau of Census. Census 2000 ZIP Code[®] Tabulation Areas (ZCTAs[™]). Available at: <http://www.census.gov/geo/ZCTA/zcta.html>, accessed May 3, 2006.
55. Krieger, N., Williams, D., and Moss, N. (1997) Measuring social class in US public health research: concepts, methodologies and guidelines. *Annu. Rev. Public Health* **18**, 341–378.
56. Carstairs, V. (2000) Socio-economic factors at areal level and their relationship with health, in *Spatial Epidemiology: Methods and Applications*, (Elliott, P., Wakefield, J., Best, N., and Briggs, D., eds.), Oxford University Press, Oxford, pp. 51–67.
57. Sorensen, A. (1994) Women, family, and class. *Annu. Rev. Sociol.* **20**, 27–47.
58. Lynch, J. and Kaplan, G. (2000) Socioeconomic position, in *Social Epidemiology*, (Berkman, L. and Kawachi, I., eds.), Oxford University Press, Oxford, pp. 13–35.
59. Galobardes, B., Shaw, M., Lawlor, D. A., Lynch, J. W., and Davey Smith, G. (2006) Indicators of socioeconomic position (part 2). *J. Epidemiol. Community Health.* **60**, 95–101.
60. Waller, L. A. and Gotway, C. A. (2004) *Applied Spatial Statistics for Public Health Data*. Wiley-Interscience, Hoboken, NJ.
61. Oppenshaw, S. and Taylor, P. J. (1981) The Modifiable Areal Unit Problem, in *Quantitative Geography*, (Wrigley, N. and Bennett, R. J., eds.), Routledge and Kegan Paul, London, pp. 60–69.

62. Macintyre, S., Ellaway, A., and Cummin, S. (2002) Place effects on health: how can we conceptualise, operationalise and measure them? *Soc. Sci. Med.* **55**, 125–139.
63. O'Campo, P. (2003) Invited commentary: advancing theory and methods for multilevel models of neighborhoods and health. *Am. J. Epidemiol.* **157**, 9–13.
64. Winship, C. and Morgan, S. L. (1999) The estimation of causal effects from observational data. *Annu. Rev. Sociol.* **25**, 659–706.
65. Angrist, J. D. and Krueger, A. (2001) Instrumental variables and the search for identification: from supply and demand to natural experiments. *J. Econ. Perspect.* **15**, 69–85.
66. Hernán, M. A., Hernández-Díaz, W., Werler, M. M., and Mitchell, A. A. (2002) Causal knowledge as a prerequisite for confounding evaluation: an application to birth defects epidemiology. *Am. J. Epidemiol.* **155**, 176–184.
67. Hernán, M. A., Hernández-Díaz, S., and Robins, J. M. (2004) A structural approach to selection bias. *Epidemiology* **15**, 615–625.
68. Sorlie, P. D. and Johnson, N. J. (1996) Validity of education information on the death certificate. *Epidemiology* **7**, 437–439.
69. Makuc, D. M., Feldman, J. J., and Mussolino, M. E. (1997) Validity of education and age as reported on death certificates. American Statistical Association: *1996 Proc. Soc. Sci. Stat. Section* 102–106.
70. US Census Bureau. American Community Survey. Data release dates. Available at: <http://www.census.gov/acs/www/SBasics/DataDiss/RelDates.htm>, accessed May 3, 2006.
71. Smith, J. P. (1999) Healthy bodies and thick wallets: the dual relation between health and economic status. *J. Econ. Perspect.* **13**, 145–166.
72. Ben-Shlomo, Y. and Kuh, D. (2002) A life course approach to chronic disease epidemiology: conceptual models, empirical challenges and interdisciplinary perspectives. *Int. J. Epidemiol.* **31**, 285–293.
73. Davey Smith, G. (ed.) (2003) *Health Inequalities: Lifecourse Approaches*. Policy Press, Bristol, UK.
74. Wilkinson, R. and Marmot, M. (eds.) (2005) *Social Determinants of Health: The Solid Facts, 2nd ed.*, World Health Organization, Geneva, Switzerland.
75. Anderson, R. N. and Rosenberg, H. M. (1998) Age standardization of death rates: implementation of the year 2000 standard; National Vital Statistics Reports: Vol 37, no. 3. National Center for Health Statistics, Hyattsville, MD.
76. US Bureau of the Census. Poverty areas. Available at: <http://www.census.gov/population/socdemo/statbriefs/povarea.html>, accessed May 3, 2006.
77. Wagstaff, A., Paci, P., and van Doorslaer, E. (1991) On the measurement of inequalities in health. *Soc. Sci. Med.* **33**, 545–557.
78. US Department of Health and Human Services. *Healthy People 2000: National Health Promotion and Disease Prevention Objectives*. Government Printing Office, 1991 (DHHS Pub. No. (PHS) 91-50213), Washington, DC.
79. Singh, G. K., Miller, B. A., Hankey, B. F., and Edwards, B. K. (2003) *Area Socioeconomic Variations in US Cancer Incidence, Mortality, Stage, Treatment, and Survival, 1975–1999*. NCI Cancer Surveillance Monograph Series, No. 4.: National Cancer Institute, NIH Pub. No. 03-5417, Bethesda, MD.

80. Washington State Department of Health. *The Health of Washington State 2004 supplement. A statewide assessment addressing health disparities by race, ethnicity, poverty and education*. Available at: <http://www.doh.wa.gov/HWS/HWS2004supp.htm>, accessed May 3, 2006.
81. Fremont, A. M., Bierman, A., Wickstrom, S. L., et al. (2005) Use of geocoding in managed care setting to identify quality disparities—How indirect measures of race/ethnicity and socioeconomic status can be used by the nation's health plans to demonstrate disparities. *Health Aff.* **24**, 516–526.
82. Fiscella, K. (2004) Socioeconomic status disparities in healthcare outcomes—selection bias or biased treatment? *Med. Care* **42**, 939–942.
83. Braveman, P. A., Egerter, S. A., Cubbin, C., and Marchi, K. S. (2004) An approach to studying social disparities in health and health care. *Am. J. Public Health* **94**, 2139–2148.
84. Glazier, R. H., Creatore, M. I., Gozdyra, P., et al. (2004) Geographic methods for understanding and responding to disparities in mammography use in Toronto, Canada. *J. Gen. Int. Med.* **19**, 952–961.
85. Phillips, R. L., Jr., Kinman, E. L., Schnitzer, P. G., Lindbloom, E. J., and Ewigman, B. (2000) Using geographic information systems to understand health care access. *Arch. Fam. Med.* **9**, 971–978.
86. Brooks-Gunn, J., McCormick, M. C., Klebanov, P. K., and McCarton, C. (1998) Health care use of 3-year-old low birth weight premature children: effects of family and neighborhood poverty. *J. Pediatr.* **132**, 971–975.
87. Siepmann, D. B., Mann, N. C., Hedges, J. R., and Daya, M. R. (2000) Association between prepayment systems and emergency medical service use among patients with acute chest discomfort syndrome. *Ann. Emerg. Med.* **35**, 573–578.
88. Gornick, M. E., Eggers, P. W., Reilly, T. W., et al. (1996) Effects of race and income on mortality and use of services among Medicare beneficiaries. *N. Engl. J. Med.* **335**, 791–799.
89. Press, R., Carrasquillo, O., Nickolas, T., Radhakrishnan, J., Shea, S., and Barr, R. G. (2005) Race/ethnicity, poverty status, and renal transplant outcomes. *Transplantation* **80**, 917–924.
90. Adams, A. S., Mah, C., Soumerai, S. B., Zhang, F., Barton, M. B., and Ross-Degnan, D. (2003) Barriers to self-monitoring of blood glucose among adults with diabetes in an HMO: a cross sectional study. *BMC Health Serv. Res.* **3**, 6. Available at: <http://www.biomedcentral.com/1472-6963/3/6>, accessed May 3, 2006.
91. Pappas, G., Hadden, W. C., Kozak, L. J., and Fisher, G. F. (1997) Potentially avoidable hospitalizations: inequalities in rates between US socioeconomic groups. *Am. J. Public Health* **87**, 811–816.
92. Shen, J. J., Wan, T. T. T., and Perlin, J. B. (2001) An exploration of the complex relationship of socioecologic factors in the treatment and outcome of acute myocardial infarction in disadvantaged populations. *Health Serv. Res.* **36**, 711–732.
93. Shishebor, M. H., Litaker, D., Pothier, C. E., and Lauer, M. (2006) Association of socioeconomic status with functional capacity, heart rate recovery, and all-cause mortality. *JAMA* **295**, 784–792.

94. Zaslavsky, A. M. and Epstein, A. M. (2005) How patients' sociodemographic characteristics affect comparisons of competing health plans in California on HEDIS® quality measures. *Int. J. Qual. Health Care* 17, 67–74.
95. Philbin, E. R., McCullough, P. A., DiSalvo, T. G., Dec, G. W., Jenkins, P. L., and Weaver, W. D. (2000) Socioeconomic status is an important determinant of the use of invasive procedures after acute myocardial infarction in New York State. *Circulation* 2000 Nov 7;102(suppl 3), III107–III115.
96. US Bureau of Census. Geographics changes for Census 2000 + glossary. Available at: <http://www.census.gov/geo/www/tiger/glossary.html>, accessed May 3, 2006.
97. US Bureau of Census. ZIP Code® Tabulation Area (ZCTA™) Frequently Asked Questions. Available at: <http://www.census.gov/geo/ZCTA/zctafaq.html>, accessed May 3, 2006.
98. US Bureau of Census. Census 2000 ZCTAs ZIP Code Tabulation Areas Technical Documentation. Available at: http://www.census.gov/geo/ZCTA/zcta_tech_doc.pdf, accessed May 3, 2006.
99. Boston Public Health Commission—Disparities Project. Mayor's Task Force Blueprint Report. Issued on: June 23, 2005. Available at: http://www.bphc.org/director/disp_blueprint.asp? accessed May 1, 2006.
100. US Census Bureau. American Fact Finder. Address Search. Available at: http://factfinder.census.gov/home/saff/main.html?_lang=en, accessed May 3, 2006.
101. Krieger, N. (1999) Embodying inequality: a review of concepts, measures, and methods for studying health consequences of discrimination. *Int. J. Health Serv.* 29, 295–352. Reprinted and updated as: Krieger, N. (2000) Discrimination and health, in *Social Epidemiology*, (Berkman, L. and Kawachi, I., eds.), Oxford University Press, Oxford, pp. 36–75.

By ten things is the world created,
By wisdom and by understanding,
And by reason and by strength,
By rebuke and by might,
By righteousness and by judgment,
By loving kindness and by compassion.

—Talmud Higaga 12A

Eliminating Healthcare Disparities in America

Beyond the IOM Report

Edited by

Richard Allen Williams, MD

*Clinical Professor of Medicine
The David Geffen School of Medicine at UCLA*

*President/CEO
The Minority Health Institute, Inc.
Los Angeles, California*

*Chairman of the Board,
Institute for the Advancement of Multicultural
and Minority Medicine
Washington, DC*

 **HUMANA PRESS**
TOTOWA, NEW JERSEY

2007

Contents

<i>About the Editor</i>	vii
<i>Foreword</i>	ix
<i>Preface</i>	xv
<i>Introduction</i>	xix
<i>Acknowledgments</i>	xxv
<i>Contributors</i>	xxvii

I. UNDERLYING CAUSES OF HEALTHCARE DISPARITIES

1. Historical Perspectives on Healthcare Disparities:

Is the Past Prologue?

Richard Allen Williams, M.D. 3

2. Epidemiology of Racial and Ethnic Disparities in Health and Healthcare

*George A. Mensah, M.D., FACP, FACC
and Maleeka J. Glover, ScD, M.P.H.* 21

3. Cultural Diversity in Medicine and in Healthcare Delivery

Richard Allen Williams, M.D. 41

II. CURRENT PROBLEMS

4. Healthcare and the Politics of Race

M. Gregg Bloche, M.D., J.D. 67

5. Barriers to Eliminating Disparities in Clinical Practice:

Lessons From the IOM Report "Unequal Treatment"

*Joseph R. Betancourt, M.D., M.P.H.
and Angela Maina, B.S.* 83

6.	Second-Class Medicine: Implications of Evidence-Based Medicine for Improving Minority Access to the Correct Pharmaceutical Therapy <i>Randall W. Maxey, M.D., Ph.D.</i> and <i>Richard Allen Williams, M.D.</i>	99
7.	The Diversity Benefit: How Does Diversity Among Health Professionals Address Public Needs? <i>Brian D. Smedley, Ph.D.</i>	121
III. APPROACHES TO CORRECTING THE PROBLEMS		
8.	Eliminating Disparities in Healthcare Through Quality Improvement <i>Kevin Fiscella, M.D., M.P.H.</i>	141
9.	Eliminating Racial Discrimination in Healthcare: A Call for State Healthcare Anti-Discrimination Law <i>Vernellia R. Randall, M.S.N., J.D.</i>	179
10.	Quality of Care and Health Disparities: The Evolving Role of Government <i>Garth N. Graham, M.D., M.P.H.</i>	197
11.	The Role of Communities in Eliminating Healthcare Disparities: Getting Down to the Grass Roots <i>JudyAnn Bigby, M.D.</i>	221
12.	The Potential Impact of Performance Incentive Programs on Racial Disparities in Healthcare <i>Alyna T. Chien, M.D., M.S.</i>	237
IV. EXAMPLES OF WHAT WORKS		
13.	Monitoring Socioeconomic Determinants for Healthcare Disparities: Tools From the Public Health Disparities Geocoding Project <i>Nancy Krieger, Ph.D., Pamela D. Waterman, M.P.H., Jarvis T. Chen, ScD, S.V. Subramanian, Ph.D., and David H. Rehkopf, ScD</i>	259

14.	The Association of Black Cardiologists: A Small-Group Success Story <i>Richard Allen Williams, M.D.</i>	307
15.	Breathe Easy In Seattle: Addressing Asthma Disparities Through Healthier Housing <i>James W. Krieger, M.D., M.P.H., Tim K. Takaro, M.D., M.P.H., M.S. and Janice C. Rabkin, M.P.H., Ph.D.</i>	313
16.	Access Health Solutions: A Minority Physician Network Model That Works <i>Kathy B. Jackson, Ph.D.</i>	341
17.	Carolinas Association for Community Health Equity-CACHE: A Community Coalition to Address Health Disparities in Racial and Ethnic Minorities in Mecklenburg County North Carolina <i>Yele Aluko, M.D.</i>	365
V. CONCLUDING RECOMMENDATIONS		
18.	Principles for Eliminating Racial and Ethnic Disparities in Healthcare <i>John Z. Ayanian, M.D., M.P.P.</i> and <i>Richard Allen Williams, M.D.</i>	377
	<i>Index</i>	391