Population Estimation Error and Its Impact on 1991–1999 Cancer Rates*

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The error of closure in the 2000 census, or the difference between estimated and enumerated populations, poses special problems for public agencies that rely on census data. Nationally and at the state level, populations were only slightly underestimated, but underestimations were high in rapidly growing counties in the South and intermontaine West, as well as in New York City. Race-specific estimates proved far less reliable, with severe overestimates and underestimates of all racial groups in various counties nationwide. We offer explanations for the estimation error and discuss its impact on cancer rates and trends and its implications for cancer surveillance research. **Key Words: population estimates, error of closure, 2000 census, cancer rates.**

Introduction

The year 2000 census population counts differed substantially from published estimates in many age and race groups and geographic locations. These differences have important implications for a range of published government statistics that were based on these estimates. National, state, and county mortality rates, disease rates, injury rates, and crime rates for the years 1991 through 1999 will have to be revised on the basis of information from the new census. Since population estimates become less accurate the further they are removed from a census year, the greatest revisions will be to the 1999 rates and the least revisions will be to the 1991 rates.

The Atlanta metropolitan region was among the first places where the implications of this problem were noted. In the late 1990s, numerous health indicators suggested unusually poor health among blacks and unusual differences in disease rates between blacks and whites, prompting Georgia to initiate a major research program in response (*Cancer Letter* 2002; Wahlberg 2002). But the population of blacks proved to have been underestimated by approximately 18 percent and the population of whites overestimated by about 10 percent, meaning that Atlanta's health was never very different than that of the nation as a whole. While revised population estimates often serve to dampen or even nullify unusual trends, there are occasional instances where such trends can actually be magnified. The widespread decline in crime rates in American cities during the 1990s (Ouimet 2002), for example, turns out to have been somewhat understated, since total populations were generally underestimated. The population of New York City, to cite an extreme example, was underestimated by 539,000 people, or nearly 7 percent.

The difference between the projected populations for a census year and the actual enumeration for that year is known as the "error of closure." In this article we examine the geographic expression of the year 2000 errors of closure for the total population and for specific age and race groups. We offer hypotheses as to what might account for these errors and discuss the substantive impact that they have on cancer rates and, by extension, many other official

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government statistics. We use cancer rates published by the National Cancer Institute's Surveillance, Epidemiology, and End Results (SEER) program. The SEER program consists of a representative sample of high-quality state and county-based cancer registries that are the basis for calculating national cancer incidence rates (Hankey, Ries, and Edwards 1999). In addition, the SEER program publishes cancer mortality rates for the entire nation, based on death certificate information compiled by the National Center for Health Statistics. Metropolitan Atlanta, which we use as a recurring example, is included in the SEER program. In order to understand how errors as large as those in Atlanta and elsewhere arose, it is useful to begin with an examination of how the Census Bureau actually produces its estimates.

The Census Population Estimation Process

Population estimates by age, sex, and race are published by the Census Bureau on an annual basis for all U.S. counties. Estimates for prior years back to the most recent decennial census are also updated annually. In this article, we make use of the year 2000 estimates and accompanying revised estimates for 1991–1999. These estimates were not publicly released by the Census Bureau, but are quite similar to the publicly available 1999 estimate series (U.S. Census Bureau 2000). Estimates are produced by what is known as the Administrative Records Method (Word 1992; Batutis 1995; Judson, Popoff, and Batutis 2001; U.S. Census Bureau 2001). In this method, components of change in the population (births, deaths, internal migration, and immigration) are considered separately, with different administrative records used to measure each. The basic equation is:

$$\begin{aligned}&\text{Current year population}\\&\quad = \text{Previous year population}\\&\qquad + \text{births deaths} + \text{net domestic migration}\\&\qquad + \text{net immigration}\end{aligned}$$

Births and deaths are tabulated from birth certificates and death certificates. Net domestic migration is calculated by using federal tax returns for persons under sixty-five and Medicare records for persons over sixty-five. Two consecutive years of records are matched by social security number, and changes in county of residence are noted and used to compute a net migration rate. For tax returns, the match is based exclusively on the social security number of the primary filer. The data used to estimate net immigration are provided by the Immigration and Naturalization Service and include separate tabulations of legal immigrants, emigrants, refugees, and estimates of undocumented immigrants. Separate administrative records are used to tally the populations living in group quarters, comprising military personnel, college students, and prisoners.

Age, sex, and race-specific estimates are handled somewhat differently. Since federal tax returns do not contain this information, the net domestic migration component is calculated by using a 20 percent sample of the Social Security Administration Application File matched to tax returns. Since the level of geography of this file is the state, age, sex, and race estimates are only produced at the state level. To generate county-level estimates, a technique known as iterative proportional fitting or "raking" is used. Raking is a technique for filling in the cells of a table when the marginals of the table are known (Deming and Stephan 1940; Fagan and Greenberg 1985; Wong 1992).

Sources of Error in Administrative Records

All large population databases are imperfect and incomplete and contain the potential for systematic error. Judson, Popoff, and Batutis (2001) considered each of the administrative records used by the Census Bureau and theorized what kinds of errors were likely to occur. They then developed a regression model to predict whether a given county could be expected to be overestimated or underestimated, depending on its characteristics (see Lunn et al. 1998 for analogous work in Britain). Overall, the domestic migration rate in the country is underestimated, since not all moves are captured. This accounts for the tendency for growing areas to be underestimated (since some in-migrants are missed) and shrinking areas to be overestimated (since some out-migrants are missed).

Moves that are likely not to be captured include those by people below the income level required to file a tax return and moves accompanying a change in filing status, such as in the case of marriage or divorce. Another source of error results from people who move at the age of sixty-five, when the administrative records used to measure migration change from tax-return based to Medicare based. While many people retire and choose to move at this age, these moves will not be captured if they entail spanning two sets of administrative records. As a result, counties that serve as popular retirement destinations might be expected to be somewhat underestimated.

Even birth records are imperfect. There is a tendency for vital registrars to record the county of the hospital on a birth certificate, rather than the county of the mother's residence. Consequently, rural counties without a hospital tend to be underestimated. Other systematic problems generate biases in group quarters and immigration estimates. A summary of the most important variables identified by Judson, Popoff, and Batutis (2001) is given in Table 1.

Still another source of estimation error lies not with the estimation process, but with an inaccurate base year count. The undercount, or the net fraction of the population not enumerated in the decennial census, has shown a general decrease over time as a consequence of better databases (including geographic information systems) and improved enumeration techniques (Choldin 1994; Robinson, West, and Adlakha 2002). In fact, the Census Bureau has now estimated that the 2000 census most likely contained a slight net overcount, with undercounting confined to Hispanics, non-Hispanic blacks, Hawaiians or Pacific Islanders, and American Indians living off reservations (U.S. Census Bureau 2003). As all population estimates published by the Census Bureau are tied to actual decennial counts, not to undercount-adjusted populations, we would expect populations to be underestimated in proportion to the rate of change in the undercount. This rate of change, of course, varies geographically.

For example, in preparation for the 2000 census, New York City officials, believing their 1990 undercount to have been unusually severe, supplied more than 370,000 addresses that were either added during the 1990s or missed in previous censuses (Sachs 2001). They attribute some of the underestimate of 539,000 people to the simple fact that census forms were mailed to, and returned from, many addresses for the very first time. At the other extreme, overcounting was a problem in many rural areas where residences had more than one valid address, such as a rural route and a house number. In general, the amount of effort placed by a municipality on developing and maintaining accurate address databases should vary directly with its error of closure.

Problems with Race and Age-Specific Data

For race and age-specific data, the potential for error is much greater. Since the county-level race estimates are raked from state-level estimates, major problems arise when the race or age composition within a county changes.[1] Figure 1 shows counties in Georgia in which the black share of the population changed

Table 1 *Important Potential Sources of Bias in Administrative Records Used for Estimating Populations (after Judson, Popoff, and Batutis 2001, except for *)*

County Characteristic	Direction of Bias	Reason for Bias
High growth rate	Underestimate	Some in-migrants are not captured by tax return matching process.
Negative growth rate	Overestimate	Some out-migrants are not captured by tax return matching process.
Lack of hospital in county	Underestimate	Births may be misassigned to the county in which the hospital is located.
High % living on military bases & in college dorms	Underestimate	Lag in reporting of new quarters (but if quarters are being eliminated, then bias is opposite).
High % prisoners	Overestimate	Prisons have tendency to overreport.
High % over age 65 not enrolled in Medicare	Underestimate	These people are not captured in the Medicare database.
High % foreign born	Underestimate	Immigrants are less likely to be captured in administrative records.
High % poverty	Overestimate	Such counties tend to generate out-migrants less likely to have filed tax returns.
High % Native American	Underestimate	Native Americans are less likely to be captured in administrative records.
Retirement destination*	Underestimate	Some 65 year old in-migrants are not captured.

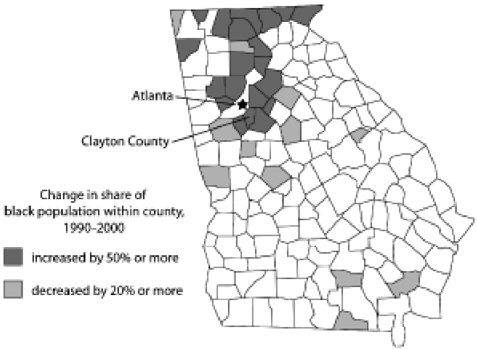

Figure 1 *Georgia counties with substantial changes in the black share of population between 1990 and 2000. Source: U.S. Bureau of the Census 1991, National Center for Health Statistics 2003.*

substantially between 1990 and 2000. Areas where the share increased had severely underestimated black populations, while areas where the share decreased had severely overestimated black populations. The Atlanta metropolitan region was particularly affected, with the most extreme estimation errors found in Clayton County, which grew from 24 percent black in 1990 to 53 percent black in 2000. Using the raking methodology, only 28 percent of the population of Clayton County was expected to be black, with the small increase governed by the relative increase in the share of black population in Georgia as a whole. As a consequence, the black population of Clayton County was underestimated by 51 percent and the white population was overestimated by 48 percent, even though its total population was underestimated by only 7 percent.

Changing self-identification of race is also an important source of estimation error. The number of people identifying themselves as American Indians/Alaska Natives, in particular, grew substantially in the 1990s. Reasons for this change include increased pride of heritage, more liberal standards for tribal inclusion, and the booming popularity of genealogical research (Morello 2001; Snell 2001). No element of the Administrative Records Method is able to identify or measure this kind of cultural shift, and American Indians/Alaska Natives ended up being underestimated by about 18 percent nationwide.

The race issue is further complicated by changes in the official federal definition of race that went into effect in 1997 (Office of Management and Budget 1997, 2000; Robbin 2000). With this redefinition, the Asian/Pacific Islander race group was subdivided into separate Asian and Native Hawaiian/Other Pacific Islander race groups for the purpose of tabulations. Also, for the first time, people were allowed to identify themselves as being from any combination of race groups. Any comparison of race between 1990 and 2000 is thus problematic, since peoples' self-identification, as well as the official government classification, was not stable. Difficulties in racial classification are not limited to these issues; they extend to ambiguous classifications of certain ethnic groups, inconsistent race assignment rules across government agencies, and deeper epistemological questions (Bhopal and Donaldson 1998; Hahn 1999; Robbin 1999; Schein 2002). All of these problems have led to sincere calls for the abolition of racial classification altogether (Fullilove 1998; Oppenheimer 2001). But race, despite all its baggage, still emerges as an important distinguishing variable in a great number of epidemiologic and other social studies. Given that these data will continue to be used widely, it is important to have the best possible understanding of their uses and limitations (Kaufman 1999; Kaufman and Cooper 2001).

In this article, we attempt to minimize the problem of changing race definitions by making use of the results of a bridging algorithm developed by the National Center for Health Statistics (2003). This algorithm allocates people from the current thirty-one race combinations back to the four pre-1997 categories by using results from the National Health Interview Survey (Benson and Marano 1998; Parker and Makuc 2002; Parker et al. 2002). Participants in this survey who indicated membership in multiple race groups were subsequently asked which they considered to be their primary race. The results were tallied by age, sex, Hispanic ethnicity, and geographic location and proportionally applied to all of the multiple-race respondents in the 2000 census. The advantage of this bridging algorithm over others (Allen and Turner 2001; Grieco 2002) is that it attempts to model how people would have filled out their census form had the race question remained unchanged from 1990. As it happens, the populations of whites, blacks, and Asians/Pacific Islanders (except in the state of Hawaii) are fairly insensitive to the choice of bridging method, since the number of multiple-race persons is a small fraction of the single-race populations of these groups. This is not true of American Indians/Alaska Natives, where the "white and American Indian/Alaska Native" combination is nearly as prevalent as American Indian/Alaska Native alone. Other bridging methods would therefore potentially yield underestimates for American Indians/Alaska Natives that are quite different than the 18 percent figure we report.

Mapping the Error of Closure

Figures 2 and 3 show year 2000 population estimation accuracy, by county, for the total U.S. population and selected age and race groups. Maps of estimation error are problematic because they may be biased toward emphasizing certain parts of the country (Gelman and Price 1999). Absolute errors tend to be greatest in large urban counties. Los Angeles County, for example, was underestimated by 86,000 people, the tenth largest error in the country and an amount larger than the entire population of about 80 percent of U.S. counties. But this was actually a very accurate estimate, off by only 0.9 percent. In contrast, percent errors tend to be greatest in sparsely populated rural counties. The fifty counties with the highest percent error have a median population size of about 8,000, versus 25,000 for all counties. The fact that high percent errors tend to be found in rural counties also masks the fact that rural counties were estimated more accurately, if less precisely (Table 2).

It is reasonable that the determination of whether a county was overestimated or underestimated should take into account the population size of the county. Accordingly, the maps shown in Figures 2 and 3 make use of a flexible definition of an "accurate" estimate, whereby the absolute percent estimation error in each county was compared with the standard deviation of the percent estimation error in the one hundred most similarly sized counties. An estimate that fell within one such moving standard deviation was considered accurate. For the total population of the U.S., a large county such as Philadelphia needed to be estimated to within about 3 percent to qualify as accurate, while a county in rural west Texas only needed to be within about 12 percent. For age and race-specific populations, variance in the estimates was higher, and so looser standards of accuracy applied. For blacks in a county such as Philadelphia, for example, an estimate within 11 percent was considered accurate, while in a small rural county an estimate within 48 percent qualified as accurate. The maps are useful at showing spatial patterns in the estimates but are not useful in evaluating the intrinsic quality of the estimates, since about two-thirds of the counties on each map (i.e., those within one standard deviation) were considered accurate.

Figure 2 depicts year 2000 population estimation accuracy for the total population of the U.S. and for the population above age sixty-five (for clarity, some of the independent cities of Virginia, which are politically equivalent to counties, were merged with their surrounding county). While there is much variation, the patterns are not random. Underestimation of the total population is most pronounced in the Southeast, the intermontaine West, central California, and urban mid-Atlantic counties. These generally correlate with dynamic, growing areas of the country. Among the areas where the total population was overestimated, southern Texas and the Ohio Valley are disproportionately represented. These are areas that correlate with high poverty rates and, in some cases, shrinking populations.

Nationally, the underestimate for the sixty-five and over group (0.6 percent) is smaller than for the population as a whole (0.9 percent), suggesting that Medicare records are better than administrative records on the whole at measuring population. The map patterns are similar to those for the total population, but some important differences exist. In a number of urban areas where the overall population was underestimated or correctly estimated, including New York, Miami, San Francisco, Los Angeles, and Minneapolis, the sixty-five-and-over population was overestimated. This is in part a consequence of the raking methodology. Rather than remaining constant over the decade, the share of the senior population living in many large urban centers has declined. In New York State, 8.1 percent of the state's seniors were projected as living in Manhattan, but the 2000 census showed that only 7.6 percent of the seniors were there; consequently, Manhattan's senior population was overestimated by about 8 percent. Overall, the

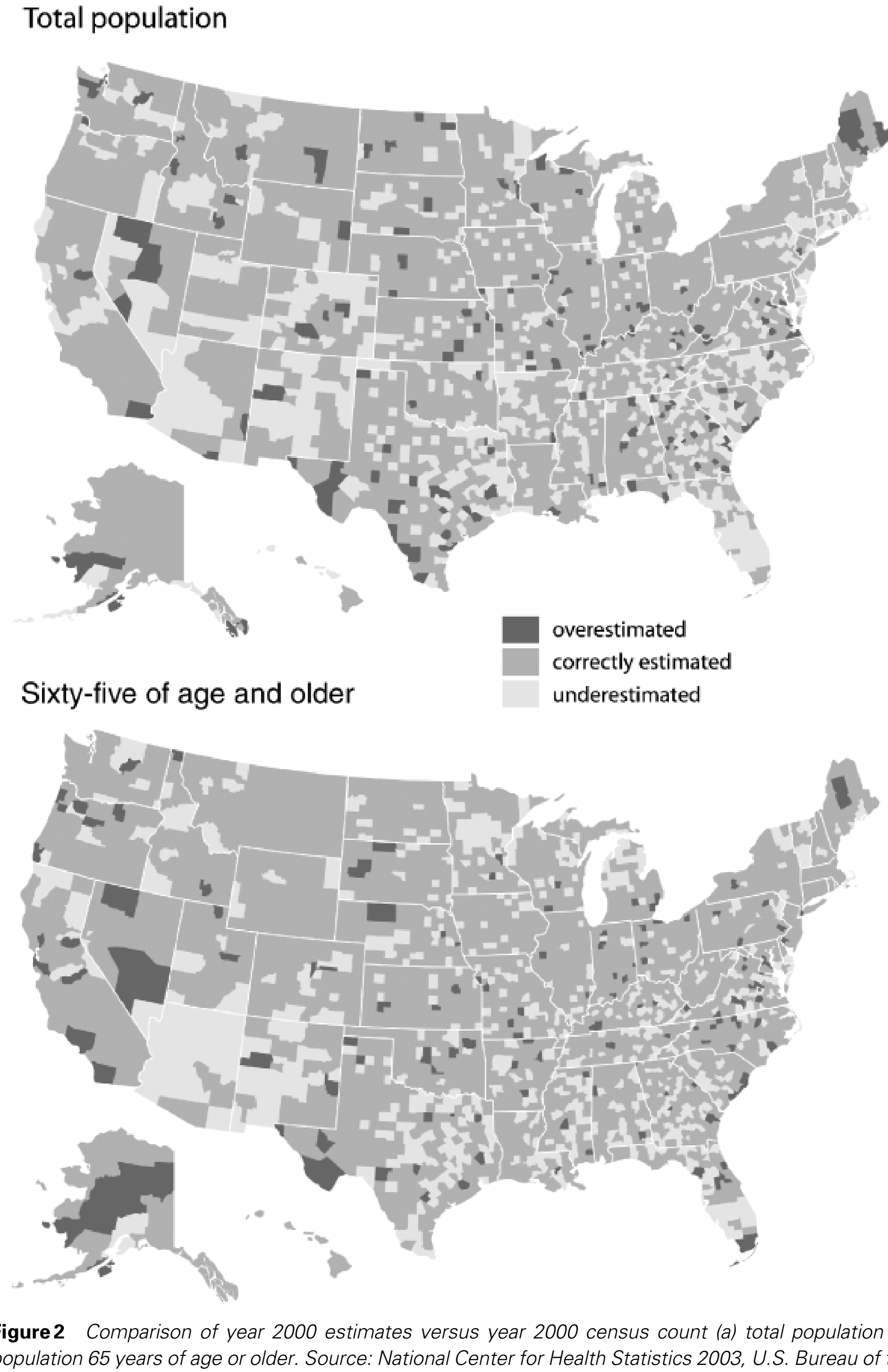

Figure 2 *Comparison of year 2000 estimates versus year 2000 census count (a) total population (b) population 65 years of age or older. Source: National Center for Health Statistics 2003, U.S. Bureau of the Census unpublished 2000 estimate series.*

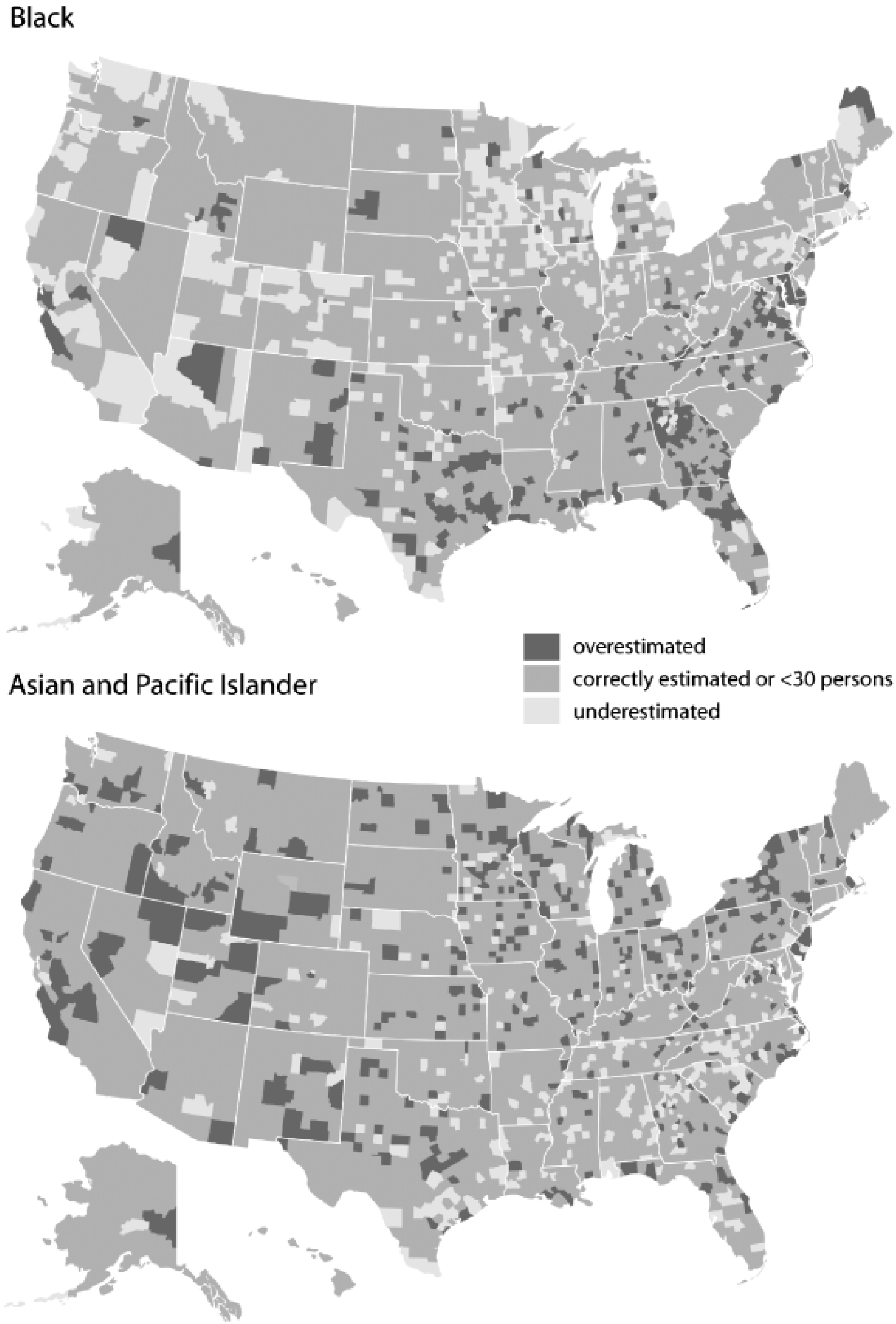

Figure 3 *Comparison of year 2000 estimates versus year 2000 census count: (a) blacks; (b) Asians and Pacific Islanders. Source: National Center for Health Statistics 2003, U.S. Bureau of the Census unpublished 2000 estimate series.*

Table 2 *Relationship of County Population Size to Accuracy and Precision of Population Estimates. Sources: National Center for Health Statistics 2003, U.S. Census Bureau Unpublished 2000 Estimate Series*

County Size	Population Range (Thousands)	Average Percent Error	Standard Deviation of Percent Error
100 largest	557–9,519	−3	3
100 median	24–26	−2	5
100 smallest	0.1–1.5	−1	12

impacts of changing age composition are much less dramatic than those seen with changing race composition.

Figure 3 depicts estimation accuracy for the total population of blacks and Asians/Pacific Islanders. These maps follow the identical format as the previous figure except that estimates involving fewer than thirty people were disregarded.[2] Overall, blacks were underestimated to a much greater extent (3.5 percent) than the population as a whole, with striking county-level patterns. The serious estimation problems in Georgia are readily apparent, echoed by similar problems in Virginia and California. Meanwhile, states with more limited population dynamism, like South Carolina, had estimates that proved to be on target in nearly every county. In general, southern counties were more likely to be overestimated, while counties in the north tended to be underestimated, suggesting the existence of a northward migration trend that is being inadequately captured by administrative records. The number and location of underestimated counties in Pennsylvania, Indiana, and the upper Midwest further suggest that blacks are moving away from traditional urban centers, albeit in small numbers.

For Asians/Pacific Islanders, the nationwide underestimate was 4 percent. As with blacks, numerous within-state population shifts created problems with the county-level estimates. In California, the statewide estimate was nearly exact (overestimated by just 0.4 percent), but an Asian influx to Silicon Valley was missed, with Santa Clara County underestimated by 84,000 people (18 percent). In New York State, both an expansion and shifting of the Asian population was insufficiently anticipated: statewide, the estimate was short by 94,000 people (8 percent), but in Brooklyn and Queens, the combined underestimate was 128,000. Other areas with overestimates include much of the upper Midwest and mid-Atlantic, with underestimates more common in the South. These broad patterns are again suggestive of long-range migration trends that are not being adequately captured by administrative records.

While not included as a figure, the estimation pattern for American Indians/Alaska Natives deserves comment. Nearly all parts of the country were systematically underestimated, as might be expected given the national 18 percent underestimation for this race group. Notable exceptions are found in Alaska and Arizona, where estimates were much more nearly on target, and Nevada and Hawaii, which actually overestimated their American Indian populations. Generally speaking, estimates were more accurate in areas where American Indians/Alaska Natives comprise a significant portion of the population, but substantial underestimates in Oklahoma belie this relationship.

Impacts on Rates and Trends

Figure 4 displays the revisions to selected age-adjusted cancer rates resulting from revised population estimates for 1995–1999 for each of the eleven SEER registries and for the eleven registries combined.[3] While these examples constitute only a tiny sample of the gamut of revised cancer rates, we find them to be representative of the scope of changes seen. Each graph displays all invasive cancers with both sexes combined; higher variability would be found if sex-specific and cancer site-specific rates were graphed. Figure 4a shows the revised age-adjusted rates for all races combined, and the rate revisions are uniformly small and negligible for the SEER program as a whole. Figure 4b shows the same information, limiting the sample to children aged 0 to 19. Again the rate revisions are uniformly small, though all in the same direction, indicating that the population proved to be younger than had been estimated. Figures 4c and 4d depict race-specific age-adjusted rates for blacks and Asians/Pacific Islanders, respectively, revealing some dramatic revisions. At first glance, it might seem that much of this is due to small numbers and hence unstable rates: there are relatively few Asian/Pacific Islanders in New Mexico, for example. Each rate, however, is based on at least 140

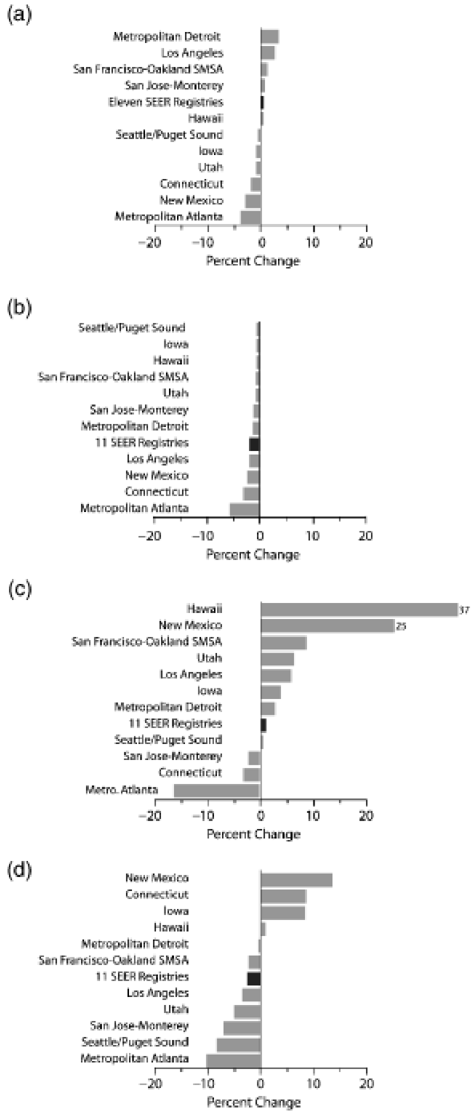

Figure 4 *Examples of revisions to cancer rates, 1995–1999, for areas included in the SEER program: (a) All cancer incidence, all races, both sexes; (b) All cancer incidence, all races, children aged 0 to 19, both sexes; (c) All cancer incidence, blacks, both sexes; (d) All cancer incidence, Asians and Pacific Islanders, both sexes. Rates are age-adjusted by five-year age groups to the year 2000 population standard. Source: National Cancer Institute 2002, 2003b.*

cases, so this is not an issue. In fact, many of the largest revisions involve large numbers of cases, including blacks in metropolitan Atlanta (1,263 cases), and Asians/Pacific Islanders in metropolitan Atlanta (948 cases), Seattle/Puget Sound (3,172 cases), and Connecticut (966 cases). This is consistent with race-specific rates being more influenced by unmodeled within-state mobility patterns than by random estimation error.

When cancer trends are considered, the revised population estimates typically result in a change in the magnitude of the rate, but not the shape of the trend line. This is a consequence of the typical practice of applying the error of closure proportionally over time (University of Virginia 2002). Using this approach for the period 1991–1999, for example, 10 percent of the error of closure is applied to the 1991 estimate, 20 percent is applied to the 1992 estimate, and so on. (Since the estimates are based on a July 1 population and the decennial census counts are based on an April 1 population, the actual percentages are adjusted to reflect a three-month offset). This technique is probably the best alternative in the absence of any other information, but it does assume that estimation error across the decade increases smoothly and continuously. The reality may be far different, as events such as military base closures and prison construction can result in very rapid population change. Migration patterns are also discontinuous to the extent they are influenced by economic cycles. An area that had a sluggish economy in the early 1990s but a booming economy in the late 1990s would be expected to see its population growth concentrated in the late 1990s, making the estimates for the early part of the decade too high.

Figure 5 shows examples of how cancer rates changed as a result of intercensal estimates based on the year 2000 error of closure, with the dashed lines representing the rates as they existed prior to 2003 and the solid lines representing the revised rates (cancer data from National Cancer Institute 2002, National Cancer Institute 2003b). Again, these examples only constitute a small sample of the gamut of adjusted cancer rates, but we find them to be representative. Figure 5a depicts the age-adjusted mortality rate for all cancers for the entire United States (fifty states plus the District of Columbia). The modest downward trend of 0.6

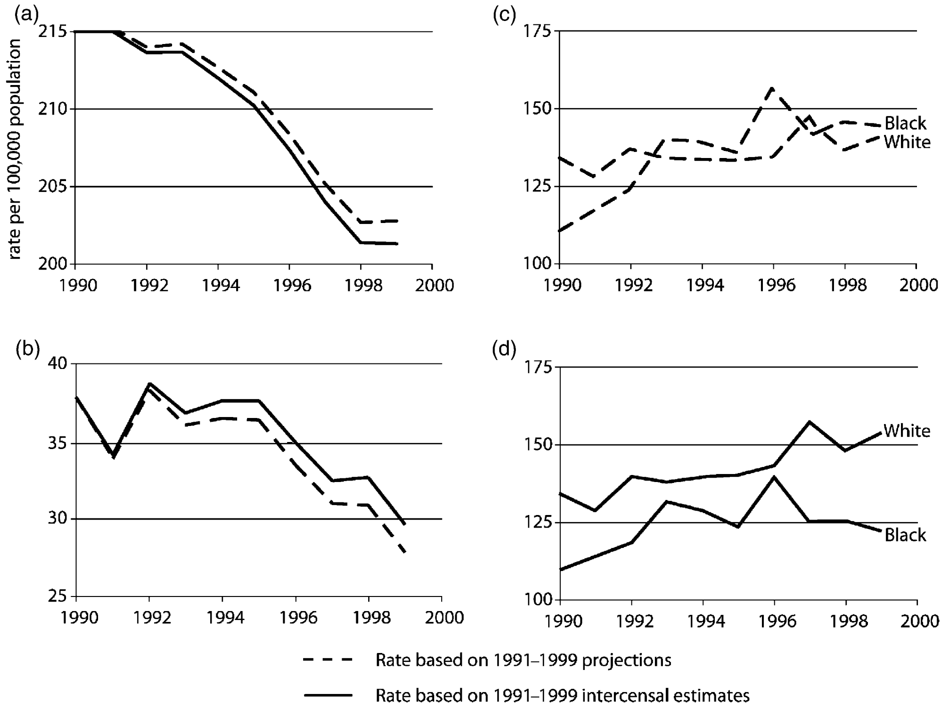

Figure 5 *Examples of revisions to cancer trends, 1991–1999, using information from 2000 census: (a) U.S., all cancer mortality, all races; (b) New York City, prostate cancer mortality, all races; (c and d) Atlanta metropolitan area, breast cancer incidence, blacks and whites. Note the different vertical scales used. Rates are age-adjusted by five-year age groups to the year 2000 population standard. Source: National Cancer Institute 2002, 2003b.*

percent per year was magnified by a tenth of a percent, which is consistent with the small underestimate of the national population and even smaller underestimate of the older age groups that heavily influence age-adjusted cancer rates. In Figure 5b, prostate cancer mortality rates in New York City are seen to have had an upward revision resulting from the overestimate of the elderly population in New York City, dampening the overall downward trend.

Figures 5c and 5d show age-adjusted breast cancer incidence rates for white and black women in metropolitan Atlanta based on the initial post-1990 census population estimates (5c) and on the revised intercensal estimates (5d). The pattern in Figure 5c was of particular concern to cancer surveillance researchers in Atlanta because it indicated that overall breast cancer incidence rates for black women in the mid-to-late 1990s had surpassed those for whites for the first time, a finding not seen elsewhere in the country (Georgia Center for Cancer Statistics 2002). After corrections to the population denominators were implemented, however, the breast cancer incidence rates for black women were reduced to levels below those for whites, as expected (5d).

Discussion

Population-based cancer surveillance data is widely recognized as an essential component in identifying and prioritizing populations for prevention initiatives, screening programs, and etiologic research (Howe et al. 2001; Lee 2001). To this end, significant improvements have been made in the breadth and depth of available data in recent years (Wingo et al. 2003). Some of these data have been made accessible through sophisticated Web-based data analysis and visualization tools (National Cancer Institute 2003a). How the data and the visualization tools are used to inform programs, policy, and research priorities is, at best, an inexact science. There are many stakeholders and many ways to summarize the data, and interpretations often differ. Sudden, sharp, dramatic trends and patterns tend to attract attention, even though such results often stem from the population estimation issues described in this article, changes in coding definitions and categories, changes in reporting practices, or random variability. Even when a trend is unmistakable, such as the poorer cancer survival exhibited by underserved populations, there is a tendency to choose dramatic illustrative examples. For example, the Intercultural Cancer Council chose to highlight the 33 percent elevation in cancer mortality among white males in Wirt County, West Virginia (Leffall 2001), although the poverty rate there is close to the state average and surrounding counties have similar SES characteristics and lower mortality.

Still, there is no question that higher-quality and higher-quantity data lend themselves to a more informed disease control and public health planning process. Sharp, sudden changes in trends or patterns, such as those described here, can diminish confidence in the utility of a surveillance system, particularly when not all stakeholders can appreciate the difficulties and complexities of data analysis. When data shortcomings are known, it makes sense to incorporate this knowledge. For example, the SEER program has developed a method to adjust rates, based on the expected number of delayed case reports (Clegg et al. 2002).

These results have implications for researchers focusing on small geographic areas. Recent years have witnessed an increasing demand by funding agencies, legislators, advocacy groups, and members of the public for analyses on areas smaller than individual counties in an effort to obtain etiologic clues (Kirby 1996; Wakefield and Elliot 1999; Taylor 2001; Krieger 2002). Geographers have made particular contributions in this topic area (Gatrell and Löytönen 1998). The fact that age and race-specific county population estimates are not especially reliable necessarily hinders such efforts. While our examples were confined to states and metropolitan areas, more severe rate adjustments would be seen if individual counties or portions of counties were considered.

Additionally, countless published research studies that made use of 1990s population estimates are potentially affected by the revised population estimates, particularly those that involved comparisons between race groups or geographic areas. To cite one of many possible examples, the finding by Holman et al. (2001) that American Indians/Alaska Natives in 1994 had an age-adjusted infectious disease hospitalization rate that was 21 percent higher than the U.S. population as a whole may be largely attributable to population estimation error. While small confidence limits were placed on the respective rates being compared (7 percent for the American Indians/Alaska Natives rate and 2 percent for the U.S. rate), these confidence limits only reflect error in the number of hospitalizations. Indeed, it is standard practice to regard only the numerator as a source of error when calculating disease rates (Estève, Benhamou, and Raymond 1994). As a consequence, confidence intervals for reported rates are always too narrow. A possible exception could be argued for the decennial census years, but even these population counts have potential error in the form of undercount or overcount. Building on the work of Swanson, Kintner, and McGehee (1995), we intend to develop a technique for confidence interval estimation that incorporates both numerator and denominator error.

Conclusions

The accuracy of population counts is often taken for granted by geographic researchers. We have demonstrated how this oversight can result in the computation of misleading rates and trends that are at risk of being translated into misguided policies. It is our hope that this article represents a step toward minimizing this problem in the future, particularly as the use of population-based surveillance data continues to broaden. To this end, we encourage the development and use of estimates that are able to incorporate known population dynamism that cannot be captured by administrative records. Finally, and most strongly, we urge that unusual trends occurring late in a decade be interpreted with extreme caution. ■

Notes

[1] The same technically holds true for data by sex, but sex ratios within and between counties in a state over a decade are quite stable.

[2] Aside from estimates of such small populations being of dubious value, below about thirty persons, the flexible definition of "accurate" encountered limitations, as the distribution of estimates became skewed, with overestimates being more likely than underestimates. Below about fifteen persons, the moving standard deviation typically exceeded the estimate, making it impossible for a county to be underestimated. This was resulting in spurious patterns of overestimation in places like the Dakotas.

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