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Summarizing Social Disparities in Health

YUKIKO ASADA, YOKO YOSHIDA, and ALYCE M. WHIPP

Dalhousie University

Context: Reporting on health disparities is fundamental for meeting the goal of reducing health disparities. One often overlooked challenge is determining the best way to report those disparities associated with multiple attributes such as income, education, sex, and race/ethnicity. This article proposes an analytical approach to summarizing social disparities in health, and we demonstrate its empirical application by comparing the degrees and patterns of health disparities in all fifty states and the District of Columbia (DC).

Methods: We used the 2009 American Community Survey, and our measure of health was functional limitation. For each state and DC, we calculated the overall disparity and attribute-specific disparities for income, education, sex, and race/ethnicity in functional limitation. Along with the state rankings of these health disparities, we developed health disparity profiles according to the attribute making the largest contribution to overall disparity in each state.

Findings: Our results show a general lack of consistency in the rankings of overall and attribute-specific disparities in functional limitation across the states. Wyoming has the smallest overall disparity and West Virginia the largest. In each of the four attribute-specific health disparity rankings, however, most of the best- and worst-performing states in regard to overall health disparity are not consistently good or bad. Our analysis suggests the following three disparity profiles across states: (1) the largest contribution from race/ethnicity (thirty-four states), (2) roughly equal contributions of race/ethnicity and socioeconomic factor(s) (ten states), and (3) the largest contribution from socioeconomic factor(s) (seven states).

Conclusions: Our proposed approach offers policy-relevant health disparity information in a comparable and interpretable manner, and currently

Address correspondence to: Yukiko Asada, Department of Community Health and Epidemiology, Dalhousie University, 5790 University Avenue, Halifax, Nova Scotia, B3H 1V7, Canada (email: yukiko.asada@dal.ca).

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publicly available data support its application. We hope this approach will spark discussion regarding how best to systematically track health disparities across communities or within a community over time in relation to the health disparity goal of *Healthy People 2020*.

Keywords: health status disparities, methods, socioeconomic factors.

As it did in *Healthy People 2000* and *Healthy People 2010*, disparity once again plays a prominent role in the recently released *Healthy People 2020* (U.S. Department of Health and Human Services 1990, 2000, 2010), a decennial national road map for health in the United States. One of the road map's four overarching goals is to "achieve health equity, eliminate disparities, and improve the health of all groups." *Healthy People 2020* regards health disparity as an ethical concept of unfair health differences associated with certain characteristics or attributes (U.S. Department of Health and Human Services 2008, 2010).

Reporting the progress (or lack of progress) on eliminating health disparities and comparing them across communities and over time is fundamental for this renewed call to succeed (Truman et al. 2011). Among the various challenges of reporting on health disparity, one that is often overlooked is how best to report health disparities associated with multiple attributes. In *Healthy People 2020*, the key attributes of health disparities are race/ethnicity, gender, sexual identity and orientation, disability status or special health care needs, and geography (U.S. Department of Health and Human Services 2010). While recognizing the multidimensionality of health disparity is important, measuring all aspects of health disparity, even when all the relevant data are available, is a formidable task for researchers, policymakers, and community partners. This is the focus of this article, and we propose a new approach that measures health disparities associated with multiple attributes at the same time and summarizes them as the overall health disparity in the population.

Researchers and policymakers most commonly measure health disparities in a bivariate (Wolfson and Rowe 2001) or pair-wise (Truman et al. 2011) fashion, as a joint distribution of health and another attribute such as income, sex, or race/ethnicity. The degree of health disparity across groups within the chosen attribute (e.g., low-, middle-, and high-income groups) can be quantified by an index. An index can be simple (e.g., a range measure) or complex (e.g., the Concentration index) (Harper and Lynch 2005). A more sophisticated approach uses individual-level data rather than aggregate-level data to examine the level of health and the level of the attribute (e.g., income) of each individual rather than the average level of health of each group. Regardless of the unit of analysis (group or individual) or the disparity index used, the bivariate approach always measures health disparity in relation to one other attribute. The previous literature on this subject used this approach extensively (e.g., Cameron et al. 2009; Frohlich, Ross, and Richmond 2006; Harper et al. 2007; James et al. 2007; Mackenbach et al. 2003; Mustard and Etches 2003), and it has also influenced policymaking. For example, responding to the second goal of *Healthy People 2010*, "to eliminate health disparities among segments of the population, including differences that occur by gender, race or ethnicity, education or income, disability, geographic location, or sexual orientation" (U.S. Department of Health and Human Services 2000), analysts measured health disparities in a bivariate fashion (Hines et al. 2011). Measuring and reporting health disparities for *Healthy People 2020*, therefore, would most likely use a bivariate approach.

While the bivariate measurement approach has created a wealth of information useful for many purposes and contexts, this vast array of information obscures the overall picture of health disparities. Suppose that state A has large health disparity due to race/ethnicity but small disparities associated with sex, income, and education and that state B has modest health disparities due to each of these attributes. Given the different degrees of health disparities associated with various attributes from state to state, it is difficult to determine which state has the largest health disparities. Such a determination presumes a systematic mechanism to compare multiple bivariate health disparity relationships (e.g., health/race/ethnicity, health/sex, health/income, and health/education) across states, which is an ambitious task given the current state of the literature. Easily accessible information about the overall picture of health disparities could enhance policymaking, particularly if this information included a set of relevant bivariate disparities, since policy often develops around target groups.

To our knowledge, the only attempt to summarize multiple bivariate health disparities is the measure developed for the *Health of Wisconsin*

Report Card 2007 (Booske et al. 2007, 2010). After measuring the health disparities associated with different attributes (gender, education, rurality, and race/ethnicity) in a bivariate fashion, the Wisconsin researchers calculated the Index of Disparity, a modified version of the coefficient of variation developed by Pearcy and Keppel for *Healthy People 2010* (Pearcy and Keppel 2002; U.S. Department of Health and Human Services 2000), using all fourteen groups (two gender, three education, four rurality, and five race/ethnicity groups).

Although the information about the overall picture of health disparities in the population offered by this measure shows significant progress, this measure needs improvement regarding the following two properties. First, this measure is insensitive to the group's population size, as it treats all groups as having equal importance. Second, it uses the healthiest group as the reference group, regardless of attributes, and compares its health with the average health of the other groups (e.g., as the reference, the highest-income group's health is compared with the health of the low-education group, that of women, and that of rural residents). Measuring overall health disparity in this way does not readily offer between-group disparities specific to attributes (e.g., health disparities across education groups).

We expanded the Wisconsin researchers' approach by proposing a new analytic approach to summarizing social disparities in health. Our approach derives from the bivariate health disparity measure developed by Gastwirth (Gastwirth 2007), which has a number of attractive policy-relevant features, including intuitive between-group comparisons within each attribute (e.g., income groups) and the minimum (i.e., group rather than individual level) data requirement. While maintaining these features, we extended the Gastwirth index, originally developed to measure health disparity associated with a single attribute, to a summary measure of health disparities, which simultaneously accounts for multiple attributes. Our approach, an extended Gastwirth index, improves these two properties of the Wisconsin measure by incorporating sensitivity to the group size and preserving bivariate health disparity information. As an empirical demonstration, we applied our approach to the 2009 American Community Survey (U.S. Census Bureau n.d.a) and ranked overall health disparity as well as health disparities by income, education, sex, and race/ethnicity across all fifty states plus the District of Columbia (Washington, DC).

Methods

An Analytic Approach to Summarizing Social Disparities in Health

We start by measuring the *attribute-specific between-group health disparity* (attribute-specific disparity), by using the index proposed by Gastwirth (Gastwirth 2007), which employs the concept of the area under or between curves. Suppose that we are interested in the health disparity associated with education measured in three groups: no high school degree, high school degree or equivalent, and beyond high school degree. We can use any measure of health as long as it is expressed in a fraction. As in our actual analysis, we use as an example here the fraction of persons free from functional limitation in each group. To calculate the Gastwirth index, we order the three education groups, from the sickest to the healthiest. The width represents the group's population share, and the height represents the group's health. Figure 1 illustrates this ordering procedure using an example of Wyoming (which, in our analysis, has the smallest overall disparity) in the 2009 American Community Survey (U.S. Census Bureau n.d.a). The population share and the fraction of persons free from functional limitation of the three education groups, from low to high, are (0.085, 0.703), (0.308, 0.821), and (0.607, 0.871), respectively. The health of the healthiest education group (beyond high school degree)—87.1 percent of persons free of functional limitation—is set as the reference, against which we compare the other two groups' health. The shaded area in figure 1, the shortfalls of functional limitation for the lower two education groups multiplied by the population share of these groups, represents education-specific disparity in functional limitation. The value for this area is 0.030 (=[0.871 − 0.703] × 0.085 + [0.871–0.821] × 0.308), which can be interpreted as follows: in order to eliminate education-specific disparity, an additional 3.0 percent of the people in Wyoming must become free of functional limitation, and these people must come from the two lower-education groups. Attribute-specific disparity values are between zero and one ($0 \leq$ and <1). Zero means that all groups have the same health; thus, there is no disparity. A value close to one suggests a greater gap between groups; hence, there is a greater disparity between groups.

After separately calculating attribute-specific disparity for each attribute, we compute the overall health disparity, by extending the

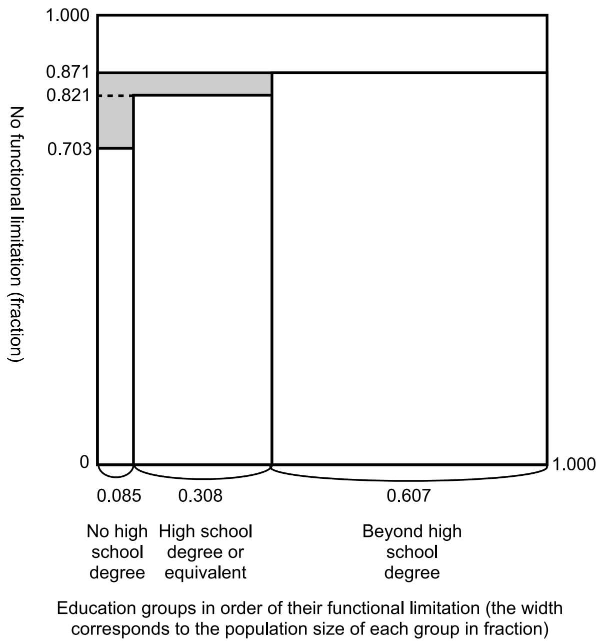

FIGURE 1. An example of the calculation of education-specific disparity in functional limitation using the Gastwirth index.

Notes: 1. All numbers are from Wyoming. All numbers are weighted, and functional limitation is age standardized using the U.S. 2000 standard population.
2. "No functional limitation" is defined as not having a limitation in any of the following six areas: hearing, vision, cognition, ambulation, self-care, and independent living.
3. To calculate the Gastwirth index, we ordered the three education groups from the sickest to the healthiest. The width represents the group's population share, and the height represents the group's health. The health of the healthiest education group (beyond high school degree) was set as the reference, against which we compared the other two groups' health.
4. The shaded area represents education-specific disparity in functional limitation. The value for this area is 0.030 ($=[0.871 - 0.703] \times 0.085 + [0.871 - 0.821] \times 0.308$), which can be interpreted as follows: in order to eliminate education-specific disparity, 3.0% more people in Wyoming must become free of functional limitation, and these people must come from the two lower-education groups.
5. Attribute-specific disparity values are between zero and one ($0\leq$ and <1). Zero means that all groups have the same health and thus no disparity. A greater value toward one suggests a greater gap between groups and hence a greater disparity between groups.
Source: U.S. Census Bureau n.d.a.

Gastwirth index. We define overall disparity as an average attribute-specific disparity in the population:

$$\text{Overall disparity} = \frac{\text{Sum of all attribute-specific disparities}}{\text{Number of attributes}} \quad (1)$$

In Wyoming, for example, attribute-specific disparity is 0.034 for income, 0.030 for education, 0.004 for sex, and 0.007 for race/ethnicity. Overall disparity in Wyoming is thus 0.018 (= [0.034 + 0.030+0.004 + 0.007] / 4). This value suggests that in order to eliminate disparity in functional limitation in Wyoming on average across the four attributes considered, an additional 1.8 percent of the population from the less healthy (and often disadvantaged) groups must become free from functional limitation. Similar to the attribute-specific disparity, overall disparity takes values between zero and one ($0\leq$ and <1). Zero indicates no disparity between any attribute-specific groups, while a value close to one suggests greater disparity between groups on average across attributes. Note that *Healthy People 2010* uses a "summary index" that summarizes between-group disparities (e.g., between high-education and low-education groups, and between high-education and middle-education groups) specific to one attribute (e.g., education) (Hines et al. 2011). This is different from our approach, which summarizes multiple attribute-specific disparities.

The same degree of overall disparity can come from different combinations of attribute-specific disparities. For this reason, we compute the contribution of each attribute-specific disparity to the overall disparity in the population as follows:

$$\text{Attribute contribution (\%)} = \frac{\text{Attribute-specific disparity related to one attribute}}{\text{Sum of all attribute-specific disparities}} \times 100 \tag{2}$$

For example, the contribution of education-specific disparity to overall disparity in Wyoming is 40 percent (=0.030 / [0.034 + 0.030 + 0.004 + 0.007] × 100). For comparison, we calculate the Wisconsin measure (Booske et al. 2007, 2010), the only other approach to summarizing social disparities in health of which we are aware. First we identify the healthiest group, regardless of its attributes. Next we calculate the sum of the differences in health between the healthiest and each of all the other groups and divide this sum by the total number of groups minus one.

Data

We use the 2009 American Community Survey (ACS) 1-year Public Use Microdata Sample (PUMS) file (publicly available from the U.S. Census Bureau's web page) (U.S. Census Bureau n.d.a). The ACS is a nationally representative population survey conducted by the U.S. Census Bureau, replacing the decennial census long-form questionnaire. The ACS's target population is people living in both households and institutional quarters, such as college and university dormitories and hospital and prison wards. Using a sequential mixed-mode strategy for sampling, the ACS has a very high response rate of 98.0 percent. The participants are first contacted via mail with the questionnaire, and those who do not respond are then contacted via telephone to complete the survey. A subsample of the remaining nonrespondents is contacted again in person. One household respondent provides the information for all the members of that household. The ACS questionnaire asks about demographics, economic, social, and financial characteristics, as well as disability status and health insurance.

The 2009 ACS 1-year PUMS file is a 1 percent sample of the 2009 ACS, containing more than 3 million records from households and group quarters (U.S. Census Bureau 2009b). For our analysis, we exclude records containing no person information (i.e., no person resides in the dwelling) (n = 107,716) and persons under age twenty-five to measure education of the respondents reliably (n = 949,834). After these exclusions, the sample size for our analysis is 2,080,894.

Measures

Health. The measure of health in our analysis is functional limitation. The respondents' functional limitation is derived from self-reported assessments of serious difficulty in four basic areas of functioning (hearing, vision, cognition, and ambulation) as well as self-reported assessments of difficulty in self-care (dressing or bathing, a component of the Activities of Daily Living [ADL]) and difficulty in independent living ("doing errands alone, such as visiting a doctor's office or shopping," a component of the Instrumental Activities of Daily Living [IADL]) (U.S. Census Bureau 2009a). The respondent has functional limitation if he or she has difficulty in any one of these six aspects and no functional limitation if he or she has difficulty in none of these six aspects. This variable has no missing values.

Attributes. We use income, education, sex, and race/ethnicity to measure disparities in functional limitation. Sex is binary. Race/ethnicity has five groups (Hispanic, non-Hispanic white, non-Hispanic black, non-Hispanic Asian/Hawaiian/Pacific Islander, or non-Hispanic other). Education has three groups (no high school degree, high school degree or equivalent, or beyond high school degree). Income groups are based on the poverty threshold, taking family size into account (below poverty threshold, 100 percent to 199 percent above poverty threshold, or 200 percent and above poverty threshold) following the U.S. Census Bureau's poverty threshold table for 2009 (U.S. Census Bureau n.d.b). Among all the attribute variables used in this study, only income has missing values (about 3%), even after the imputation conducted by the U.S. Census Bureau. Individuals without income information tend to report greater functional limitation than do individuals in other income groups. We keep these individuals in our analysis by assigning them to the lowest-income group, that is, below poverty threshold, as our sensitivity analysis suggests the minimum influence of the treatment of these missing values on the calculation of disparities.

Analysis

For each of the fifty states plus Washington, DC, we calculate attribute-specific disparities for income, education, sex, and race/ethnicity, overall disparity, attribute contributions, and the Wisconsin measure, as explained earlier. Although the ACS contains individual-level data, our analysis requires only aggregate-level estimates of the population size and the fraction of persons free from functional limitation in each of the thirteen groups (three groups for income, three for education, two for sex, and five for race/ethnicity) in each state. All estimates are weighted using the person weights provided by the 2009 1-year ACS PUMS file. The fraction of functional limitation in each group is age standardized using the 2000 U.S. standard population (Klein and Schoenborn 2001; National Cancer Institute n.d.). To avoid unreliable estimates, when the sample size of the reference group is less than fifty and the 95 percent confidence intervals for the fraction of persons free from functional limitation in the reference (healthiest) group and the second healthiest group overlap, we combine the groups. Accordingly, to calculate race/ethnicity–specific disparity, six states (Maine, Montana, North Dakota, South Dakota, Vermont, and Wyoming) have combined groups as the reference group.

Based on these calculations, we rank and map all the states according to overall disparity. In addition, we examine whether any patterns exist between overall and attribute-specific disparities across states. To do so, we estimate Spearman's rank correlation coefficients between rankings based on overall and attribute-specific disparities. Furthermore, we draw up profiles of disparities across the states according to the attribute that makes the largest contribution to overall disparity in each state. We follow an ad hoc rule to consider attribute contributions within ±5 percent as the same. In Wyoming, for example, the attribute contribution for income, education, sex, and race/ethnicity is, respectively, 45.77 percent, 40.26 percent, 4.76 percent, and 9.21 percent. We thus consider that income makes the largest contribution and that sex makes the smallest contribution. We use Stata 11 (StataCorp 2009) and Microsoft Excel 2011 for our analyses.

Results

Generally, our results show a lack of consistency in the rankings of overall and attribute-specific disparities in age-adjusted rates of functional limitation across states. None of the best-performing states in overall disparity, as reported in table 1, fare consistently well in all of the four attribute-specific disparity rankings. The strength of correlations between rankings by attribute-specific disparities is generally weak to modest. For example, across all states Spearman's correlation coefficient for the rankings by sex- and race/ethnicity–specific disparities is 0.11, and that by income- and race/ethnicity–specific disparities is 0.48 (appendix 1), with two exceptions. First, rankings by income- and education-specific disparities tend to be similar (Spearman's correlation coefficient of 0.83). Second, the worst-performing states, as reported in table 1, have similar rankings across overall and income-, education-, and race/ethnicity–specific disparities.

The states thus appear to have different profiles of attribute-specific health disparities, and three profiles emerge from our examination of attribute contribution to overall disparity (figure 2). In a large

TABLE 1
States with the Smallest and Largest Disparities in Functional Limitation, 2009

Six States with the Smallest Overall Disparity			*Five States with the Largest Overall Disparity*		
	Disparity	Contribution (%)		Disparity	Contribution (%)
Wyoming			Mississippi		
Overall (1, 8)	0.018		Overall (47, 41)	0.061	
Income (12)	0.034	45.77	Income (49)	0.069	28.37
Education (14)	0.030	40.26	Education (47)	0.060	24.54
Sex (27)	0.004	4.76	Sex (20)	0.003	1.16
Race/Ethnicity* (4)	0.007	9.21	Race/Ethnicity (43)	0.112	45.93
Hawaii			Alabama		
Overall (2, 1)	0.021		Overall (48, 45)	0.062	
Income (2)	0.024	28.20	Income (47)	0.062	25.01
Education (5)	0.025	29.30	Education (49)	0.064	25.95
Sex (41)	0.008	9.28	Sex (10)	0.002	0.77
Race/Ethnicity (6)	0.028	33.21	Race/Ethnicity (46)	0.119	48.26
Minnesota			Arkansas		
Overall (2, 21)	0.021		Overall (49, 48)	0.063	
Income (16)	0.036	44.30	Income (46)	0.061	24.20
Education (11)	0.029	34.97	Education (46)	0.059	23.73
Sex (41)	0.008	9.55	Sex (27)	0.004	1.72
Race/Ethnicity (5)	0.009	11.18	Race/Ethnicity (49)	0.126	50.35
Nevada			Kentucky		
Overall (4, 5)	0.022		Overall (50, 50)	0.078	
Income (1)	0.022	24.92	Income (50)	0.070	22.63
Education (1)	0.017	19.08	Education (51)	0.073	23.41
Sex (1)	0.000	0.00	Sex (20)	0.003	1.08
Race/Ethnicity (21)	0.050	55.99	Race/Ethnicity (50)	0.165	52.89

Continued

TABLE 1—*Continued*

Six States with the Smallest Overall Disparity			*Five States with the Largest Overall Disparity*		
	Disparity	Contribution (%)		Disparity	Contribution (%)
Montana			West Virginia		
Overall (5, 3)	0.023		Overall (51, 51)	0.083	
Income (18)	0.037	39.99	Income (51)	0.077	23.21
Education (18)	0.032	33.88	Education (50)	0.072	21.66
Sex (50)	0.020	21.54	Sex (45)	0.012	3.77
Race/Ethnicity* (3)	0.004	4.59	Race/Ethnicity (51)	0.170	51.37
New Jersey					
Overall (5, 4)	0.023				
Income (4)	0.027	29.36			
Education (16)	0.031	34.20			
Sex (20)	0.003	3.41			
Race/Ethnicity (8)	0.030	33.03			

Notes: 1. States are listed according to the degree of overall disparity, from the smallest to the largest.
2. Numbers in parentheses for overall disparity are the ranking by our proposed approach and the ranking by the Wisconsin measure, respectively, from the smallest to the largest.
3. The number in parentheses for each of the attribute-specific disparities is the ranking by our proposed approach, from the smallest to the largest.
4. "No functional limitation" is defined as not having a limitation in any of the following six areas: hearing, vision, cognition, ambulation, self-care, and independent living.
5. Overall disparity is an average of the income-, education-, sex-, and race/ethnicity–specific disparities in each state.
6. For example, the overall disparity of 0.018 in Wyoming suggests that in order to eliminate disparity in functional limitation in Wyoming on average across the four attributes considered, an additional 1.8% of the population from the less healthy (and often disadvantaged) groups must become free from functional limitation.
7. For example, the income-specific disparity of 0.034 in Wyoming suggests that in order to eliminate education-specific disparity, 3.4% more people in Wyoming must become free of functional limitation, and they must come from lower-income groups.
8. Due to the small numbers (cell counts less than 50), combined groups, rather than a single group, are used as the reference in the calculation of race/ethnicity–specific disparity in Wyoming and Montana (marked with an asterisk).
9. All analyses are weighted, and functional limitation is age standardized using the U.S. 2000 standard population.

Source: U.S. Census Bureau n.d.a.

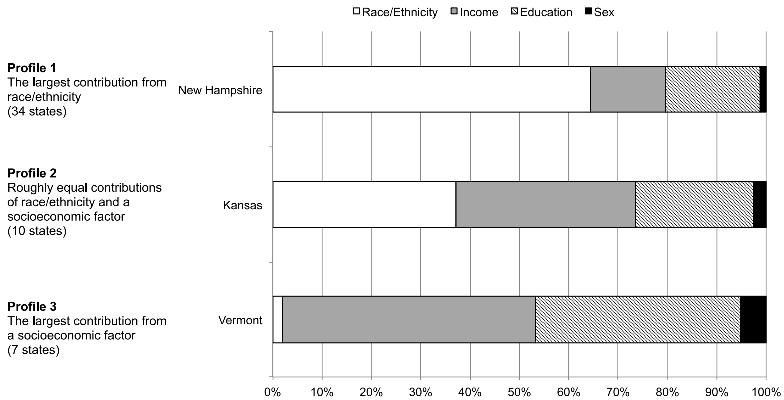

FIGURE 2. Three profiles of attribute-specific disparities in functional limitation across the United States, 2009.

Notes: 1. "No functional limitation" is defined as not having a limitation in any of the following six areas: hearing, vision, cognition, ambulation, self-care, and independent living.
2. The profiles of disparities are based on the attribute(s) that makes the largest contribution to overall disparity in each state. We consider attribute contributions within ±5% as the same.
3. Due to the small numbers (cell counts less than 50), combined groups, rather than a single group, are used as the reference in the calculation of race/ethnicity–specific disparity in the six states (Maine, Montana, North Dakota, South Dakota, Vermont, and Wyoming).
4. New Hampshire has the largest contribution from race/ethnicity (64%) among all the states, followed by 19% from education and 15% from income.
5. Kansas has the largest roughly equal contributions from race/ethnicity and a socioeconomic factor across all the states. The contribution of race/ethnicity is 37%; that of income is 36%; and that of education is 24%.
6. Vermont has the largest contribution from a socioeconomic factor among all the states: income and education have a contribution of 51% and 42%, respectively, while race/ethnicity has a 2% contribution.
7. Regardless of the profile of health disparities, in all states, except Montana, sex-specific health disparity is the smallest of the four attribute-specific disparities.
8. All analyses are weighted, and functional limitation is age standardized using the U.S. 2000 standard population.
Source: U.S. Census Bureau n.d.a.

majority of the states (thirty-four), race/ethnicity–specific disparity has the biggest contribution to overall disparity (profile 1). An example of a state in profile 1 is New Hampshire, in which race/ethnicity has a 64 percent contribution to overall disparity—the largest contribution from race/ethnicity among all states—followed by 19 percent from education and 15 percent from income. In ten states, race/ethnicity and socioeconomic factor(s) (income and/or education) have roughly equal contributions to overall disparity (profile 2). For example, Kansas, which of all the states has the largest (roughly equal) contributions from race/ethnicity and a socioeconomic factor, the contribution of race/ethnicity is 37 percent, that of income is 36 percent, and that of education is 24 percent.

Finally, seven states have the largest contribution from socioeconomic factor(s) (income and/or education) (profile 3). In Vermont, which of all the states has the largest contribution from a socioeconomic factor, income and education contribute 51 percent and 42 percent, respectively, while race/ethnicity contributes 2 percent. Regardless of the profile of health disparities, in all states except Montana, sex-specific health disparity is the smallest of the four attribute-specific disparities. In four states (California, Nevada, New York, and Pennsylvania) we observed no sex-specific disparity. The largest degree of sex-specific disparity is 0.020 in Montana and North Dakota, suggesting that an additional 2 percent of men must become free of functional limitation in order to eliminate sex-specific disparity in these states (see appendix 2 for each state's attribute-specific disparities and their contributions to overall disparity).

The measure of overall disparity gives a summary view of attribute-specific disparities in each state (table 1 and appendixes 2 and 3). Wyoming exhibits the smallest overall disparity, in which in order to eliminate disparities in functional limitation on average across the four attributes examined, an additional 1.8 percent of the population from the less healthy (and often disadvantaged) groups must become free of functional limitation. West Virginia, in contrast, shows the largest overall disparity, in which an improvement similar to that in Wyoming must be made by an additional 8.3 percent of the population. The map of the overall disparity ranking (figure 3) does not show a clear geographic pattern, although it does indicate a divide between north (small) and south (large). The ranking of overall disparity is most closely correlated with that of race/ethnicity–specific disparity, with Spearman's correlation coefficient of 0.91. Most of the rankings of overall disparity according to our proposed measure and the Wisconsin measure are similar (table 1 and appendixes 1, 3, and 4), with Spearman's correlation coefficient of 0.91, although in five states (Georgia, Louisiana, Maine, Minnesota, and Vermont), the rankings differ by more than ten placements.

Discussion

In this article we proposed an analytic approach to summarizing social disparities in health and demonstrated its application using the 2009 ACS. Our approach expands the effort to integrate information

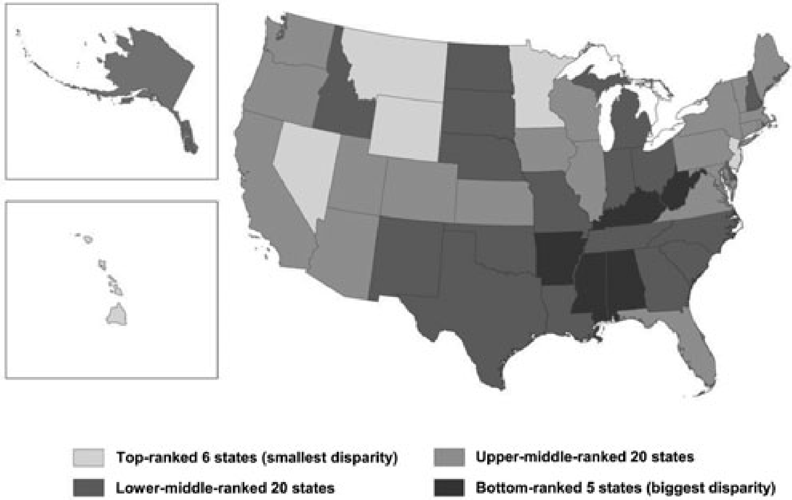

FIGURE 3. State ranking of overall disparity in functional limitation, 2009.

Notes: 1. "No functional limitation" is defined as not having a limitation in any of the following six areas: hearing, vision, cognition, ambulation, self-care, and independent living.
2. Overall disparity is an average of the income-, education-, sex-, and race/ethnicity–specific disparities in each state.
3. Rankings are based on the degree of overall health disparity, from the smallest to the largest.
4. All analyses are weighted, and functional limitation is age standardized using the U.S. 2000 standard population.
Source: U.S. Census Bureau n.d.a.

about multiple bivariate health disparities for policy relevance. One attractive feature of our proposed approach is its ability to measure and compare multiple bivariate health disparities. Our approach reveals that states generally did not perform consistently better or worse across all the income-, education-, sex-, and race/ethnicity–specific disparities that we examined. This result indicates that examining only one attribute-specific health disparity provides partial information about health disparities in the population and underscores the importance of a systematic examination of multiple health disparities in the population health assessment. Despite the historical emphasis on race/ethnicity-specific health disparity in the United States, we have shown that it is unlikely that it tells the whole story of health disparities.

A comparative assessment of multiple attribute-specific disparities also allows us to identify patterns of disparities common across the states. Our analysis shows that of the four attributes we examined, sex-specific disparity was the smallest in all but one state. Moreover, three typical profiles of disparities emerge across the states, with the most prevalent profile, observed in two-thirds of all states, having the largest contribution from race/ethnicity–specific disparity among the four attributes. Whether our observation of the general patterns of disparities indicates the seriousness of (or lack thereof) sex- and race/ethnicity–specific health disparities, however, requires careful interpretation. The consistently small sex-specific disparity probably was due to our choice of the particular measurement of health, functional limitation. If we were to use other measures of health, such as life expectancy, we might not observe such a small disparity. A large race/ethnicity–specific disparity probably can be traced to the non-Hispanic Asian/Pacific Islander group that we used in our analysis as the reference in most states. That is, this group sets a high reference level (the fraction of persons free from functional limitation ranges from 0.870 to 0.985) but has a small population size relative to that of other racial/ethnic groups (the population share ranges from 0.5% to 8%). The high reference level set by a small group creates a large shortfall shared by the majority of the population. For example, in West Virginia, which had the largest race/ethnicity–specific disparity in our calculation, the fraction of persons free from functional limitation and the population share of each racial/ethnic group are, respectively, 0.939 and 0.5 percent for non-Hispanic Asian/Pacific Islanders, 0.777 and 0.8 percent for Hispanics, 0.771 and 94.5 percent for non-Hispanic whites, 0.753 and 2.9 percent for non-Hispanic blacks, and 0.586 and 1.3 percent for non-Hispanic others. With the reference set by the non-Hispanic Asian/Pacific Islander group, the disparity is calculated as 0.170, but if the reference is set by the non-Hispanic white group, the disparity is 0.003.

As we did, previous population health reports have also tried examining multiple attribute-specific health disparities. *Healthy People 2010 Final Review* is one of the most recent, and notable, examples (Hines et al. 2011). One of our main contributions is to expand this effort by providing a measure of overall health disparity. The use of the interpretable 0–1 index makes it easier to compare across states and across time if desired. For example, we showed that to eliminate state-level disparities in functional limitation on average across the four attributes considered, an additional 2 to 8 percent of the population from the less healthy (and often disadvantaged) groups must become free from functional limitation. Easily comparable and interpretable information about overall health disparity in turn facilitates a dialogue about policy. Monitoring health disparities is the fundamental exercise that supports the health disparity goals of *Healthy People 2020*, for example, and our approach offers ready answers to questions such as where we are (as this study shows), how far we have come (by applying our approach to historical data), and what a challenging, yet feasible, future goal should be.

The policy applicability of our approach crucially depends on data availability. Our approach requires only aggregate-level data, a measure of health by group defined by the attributes that analysts wish to use. Such data are often publicly available for states or large counties. Although in our empirical demonstration we used individual-level data to obtain the group-level estimates, it is possible to apply our approach using only aggregate-level information, such as that from CDC Wonder (Centers for Disease Control and Prevention n.d.). In addition, our approach can be used with different measures of health and for county-level analysis, for example, by using the Selected Metropolitan/Micropolitan Area Risk Trends (SMART) Behavioral Risk Factor Surveillance System (BRFSS) (Office of Surveillance, Epidemiology, and Laboratory Services n.d.). Certain data constraints still apply though. Even in our state-level analysis, our racial/ethnic groups are not as refined as the seven racial/ethnic groups recommended by *Healthy People 2010* (Hines et al. 2011; U.S. Department of Health and Human Services 2000), owing to our desire for reliability. Nonetheless, the proposed approach is practical within the current data infrastructure in the United States. Future application of the proposed approach, especially to small areas, such as counties, will benefit from variance estimation or uncertainty bounds to ensure the data's reliability. This is not a pressing issue for this study, however, as it uses the ACS, with more than 2 million observations for the state-level analysis with relatively large group categories. Different methods of variance estimation depend on the particular data used in the analysis, but given the complex sampling methods used in most population-based data, the appropriate variance estimation methods likely involve replication methods (Rust and Rao 1996).

The high correlation between rankings of overall disparities based on the Wisconsin measure and our approach gives face validity to our approach. Discrepancies, however, do exist and are large for some states (appendix 4). They likely come from differences in two measurement properties and, fundamentally, relate to value questions of what we wish to measure as health disparities. The first difference is sensitivity to the group's population size. The Wisconsin measure is insensitive, meaning that it treats all groups as having the same population size, whereas our approach is sensitive, reflecting the population size of each group in the measurement. Thus, when the population sizes of less healthy groups are proportionally larger, all else being equal, our approach gives a worse ranking than the Wisconsin measure does. The choice of the two measures is value laden: whether we should consider the same health gap as worse if it is experienced by a proportionally greater number of people (Asada 2007; Temkin 1993). According to the current literature on the measurement of health disparities, the answer is yes (Harper and Lynch 2005; Wagstaff, Paci, and van Doorslaer 1991), which corresponds to our proposed approach.

Another difference between the Wisconsin measure and our approach is the selection of the reference group. According to the Wisconsin measure, the reference group is the healthiest group in the population, while in our approach the reference group is set separately for each attribute. Accordingly, when the healthiest group in the population is much healthier than the healthiest groups among other attributes, all else being equal, the Wisconsin measure gives a worse ranking than our approach does. The literature currently does not agree on the reference group (Asada 2007; Harper and Lynch 2005). We argue, however, that a common understanding of health disparities relates to attribute-specific between-group health disparities and that it is intuitive to set the reference separately for each attribute. Whether or not it sets the reference for each attribute, a summary measure is most informative when it preserves information regarding attribute-specific between-group health disparities, as our approach does.

Our proposed approach thus has a number of attractive features: a uniform assessment of multiple attribute-specific disparities, interpretable and comparable information on the overall picture of disparities in the population, a minimum data requirement, and sensitivity to the group's population size. As does any measure of disparity, however, our approach has important constraints that analysts should recognize, namely, nonmutual exclusivity and a crude assessment of fairness. First, our proposed approach (and the Wisconsin measure) is a composite measure of health disparities associated with mutually nonexclusive attributes. This means that each attribute-specific health disparity is likely confounded by other attribute-specific health disparities. This is clearly the case in our analysis for income and education, as is evident from the high correlation between rankings of these attribute-specific disparities. When attributes are correlated in a predictable direction (e.g., the poor tend to be uneducated), all else being equal, the overall disparity calculated by our approach is larger than it would be if there were no such correlation.

While we believe this property is compatible with a commonly shared sense of when health disparity is worse, some analysts may wish to assess the health disparities associated with mutually exclusive attributes. For example, in a recent article, Williams and his colleagues argue for the importance of an "intersectional perspective" that integrates multiple social statuses simultaneously (Williams et al. 2012). This can be accomplished by refining groups. In our data, the thirteen groups from four attributes can be segmented mutually exclusively into ninety groups. Our sensitivity analysis suggests that mutually exclusive overall disparity is much larger than nonmutually exclusive overall disparity (e.g., respectively, 0.158 and 0.018 for Wyoming, 0.122 and 0.021 for Hawaii, 0.127 and 0.021 for Minnesota, 0.224 and 0.063 for Arkansas, 0.222 and 0.078 for Kentucky, and 0.232 and 0.083 for West Virginia). This is not because of the increased number of groups but because of the increased gap between the healthiest group and the least healthy group, with the former having a greater impact than the latter, given its role as the reference against which all other groups are compared.

The choice between mutually exclusive and nonexclusive measures depends on the purpose of the measurement. Nonmutually exclusive measures appear to capture basic ethical and policy concerns. It is unlikely that we would, for example, discredit the importance of sex-specific health disparity if it were mainly explained by the generally lower education and income levels of women than men. Because the value we attach to the attribute sex is socially meaningful, the information about sex-specific health disparity would still be important even if the causal mechanisms were compounded with other attributes. In contrast, a mutually exclusive measure can help us understand health disparities well by identifying the specific attributes of the healthiest and least healthy persons. Notice that at the end of the refinement of mutually exclusive groups, we measure health disparity across individuals. As we increase the number of mutually exclusive groups, each group becomes smaller, and at the end, there is one person in each mutually exclusive group, which is measuring health disparity across individuals. Thus, if the purpose of the measurement is to understand health disparities well, our approach with refined mutually exclusive groups is cumbersome. Individual-level analysis would be better suited for this purpose.

The second constraint in our approach is the crude assessment of fairness. Our proposed approach builds on the common practice of measuring health disparity in association with an attribute, one attribute at a time. Any measurement of health disparities involves ethical judgment (Asada 2007; Harper et al. 2010), which is implicit in both this common bivariate measurement approach and our proposed approach. Our analysis reflects, for example, the following ethical judgments. By identifying attributes to examine, we implicitly make an ethical judgment that the health disparities associated with these attributes are unfair. By using an age-standardized measure of health, we are implicitly declaring that health disparities due to age are not of ethical concern; while by not using a sex-standardized measure of health, we are implicitly suggesting that health disparities due to sex are unfair. By treating each attribute-specific health disparity equally, we are implicitly judging that all attribute-specific health disparities are equally important.

There is a growing literature that opposes such implicit and crude assessments of fairness and calls for more sophisticated and explicit approaches (Fleurbaey and Schokkaert 2009, 2011). This critique is largely aimed at the wide use of the Concentration index. Using the Concentration index, analysts start by measuring the health disparity associated with one particular attribute and, using its decomposition, explain what factors might cause that attribute-specific health disparity (O'Donnell, van Doorslaer, and Lindelow 2007). Fleurbaey and Schokkaert argue that rather than starting by focusing on one particular attribute, analysts should examine as many attributes as possible, classify them into groups—such as biologically determined health endowments, individual preferences, available information, social background, and health care supply—and make an explicit judgment as to which of these are "legitimate" (i.e., pose no ethical concern) and "illegitimate" (i.e., lead to unfairness) causes of health inequality (Fleurbaey and Schokkaert 2009, 2011).

Though attractive, the feasibility of empirical application and the policy usefulness of this alternative sophisticated approach await future assessment. Few data sets offer information about determinants of health to the extent of allowing refined ethical judgments, as Fleurbaey and Schokkaert suggest. Such rich, individual-level data are hard to find for small jurisdictions, in which the health of a population is increasingly reported (County Health Rankings and Roadmaps n.d.; United Health Foundation n.d.). Moreover, despite the intensive research and policy efforts over the past decades, there has been no agreed-on, precise definition of health disparity or inequity (Norheim and Asada 2009). Given this, parallel to the effort to encourage explicit, sophisticated assessments of fairness, we believe there is room for the development of a simple approach that builds on the common practice with incremental improvements, as we have proposed.

In summary, the analytic approach we propose in this article offers policy-relevant health disparity information, both summary information about the health disparities observed in the population and information about attribute-specific health disparities, in a comparable and interpretable manner. Its measurement properties capture commonly held conceptions of health disparities, and currently publicly available data support its application. With these strengths, it is our hope that this approach will spark a discussion regarding how best to systematically track health disparities across communities or within a community over time in relation to the health disparity goal of *Healthy People 2020*.

References

Asada, Y. 2007. *Health Inequality: Morality and Measurement*. Toronto: University of Toronto Press.

Booske, B.C., A.M. Kemph, J.K. Athens, D.A. Kindig, and P.L. Remington. 2007. Health of Wisconsin Report Card. Madison: University of Wisconsin Population Health Institute. Available at http://uwphi.pophealth.wisc.edu/programs/match/healthiest-state/report-card/2007/reportCard.pdf/ (accessed November 16, 2012).

Booske, B.C., A.M.K. Rohan, D.A. Kindig, and P.L. Remington. 2010. Grading and Reporting Health and Health Disparities. *Preventing Chronic Disease* 7(1):A16. Available at http://www.ncbi.nlm.nih.gov/pmc/articles/PMC2811511/?tool=pubmed (accessed December 6, 2011).

Cameron, M.N., P. Fines, R. Wilkins, and M.C. Wolfson. 2009. Income Disparities in Health-Adjusted Life Expectancy for Canadian Adults, 1991 to 2001. *Health Reports* 20(4):1–10.

Centers for Disease Control and Prevention. n.d. CDC Wonder. Available at http://wonder.cdc.gov (accessed August 7, 2012).

County Health Rankings and Roadmaps. n.d. Available at http://www.countyhealthrankings.org (accessed August 7, 2012).

Fleurbaey, M., and E. Schokkaert. 2009. Unfair Inequalities in Health and Health Care. *Journal of Health Economics* 28(1):73–90.

Fleurbaey, M., and E. Schokkaert. 2011. Equity in Health and Health Care. In *Handbook of Health Economics*, Vol. 2, ed. M.V. Pauly, T.G. McGuire, and P.P. Barros, 1003–92. Waltham, MA: North Holland.

Frohlich, K.L., N. Ross, and C. Richmond. 2006. Health Disparities in Canada Today: Some Evidence and a Theoretical Framework. *Health Policy* 79(2/3):132–43.

Gastwirth, J.L. 2007. A Graphical Summary of Disparities in Health Care and Related Summary Measures. *Journal of Statistical Planning and Inference* 137(3):1059–65.

Harper, S., N.B. King, S.C. Meersman, M.E. Reichman, N. Breen, and J. Lynch. 2010. Implicit Value Judgments in the Measurement of Health Inequalities. *The Milbank Quarterly* 88(1):4–29. Available at http://www.milbank.org/publications/the-milbank-quarterly/featured-articles/article/3474/implicit-value-judgments-in-the-measurement-of-health-inequalities (accessed November 8, 2012).

Harper, S., and J. Lynch. 2005. *Methods for Measuring Cancer Disparities: Using Data Relevant to Healthy People 2010 Cancer-Related Objectives*. NCI Cancer Surveillance Monograph Series 6, NIH Publication No.: 05-5777. Bethesda, MD: National Cancer Institute. Available at http://seer.cancer.gov/publications/disparities/measuring_disparities.pdf (accessed December 6, 2011).

Harper, S., J. Lynch, S. Burris, and G.D. Smith. 2007. Trends in the Black-White Life Expectancy Gap in the United States, 1983–2003. *JAMA* 297(11):1224–32.

Hines, R., D. Lesley, D. Huang, J. Pearcy, C. Rose, K. Rosendorf, and M. Talih. 2011. *Healthy People 2010* Final Review. Washington, DC: National Center for Health Statistics, Centers for Disease Control and Prevention. Available at http://www.cdc.gov/nchs/healthy_people/hp2010/hp2010_final_review.htm (accessed March 2, 2012).

James, P.D., R. Wilkins, A.S. Detsky, P. Tugwell, and D.G. Manuel. 2007. Avoidable Mortality by Neighbourhood Income in Canada: 25 Years after the Establishment of Universal Health Insurance. *Journal of Epidemiology & Community Health* 61(4):287–96.

Klein, R.J., and C.A. Schoenborn. 2001. Age Adjustment Using the 2000 Projected U.S. Population. *Healthy People 2010 Statistical Notes* 20:1–9. Available at http://www.cdc.gov/nchs/data/statnt/statnt20.pdf (accessed August 7, 2012).

Mackenbach, J.P., V. Bos, O. Andersen, M. Cardano, G. Costa, S. Harding, A. Reid, Ö. Hemström, T. Valkonen, and A.E. Kunst. 2003. Widening Socioeconomic Inequalities in Mortality in Six Western European Countries. *International Journal of Epidemiology* 32(5):830–37.

Mustard, C.A., and J. Etches. 2003. Gender Differences in Socioeconomic Inequality in Mortality. *Journal of Epidemiology & Community Health* 57(12):974–80.

National Cancer Institute. n.d. Surveillance Epidemiology and End Results. Standard Populations (Millions) for Age-Adjustment. Available at http://seer.cancer.gov/stdpopulations/ (accessed November 14, 2012).

Norheim, O.F., and Y. Asada. 2009. The Ideal of Equal Health Revisited: Definitions and Measures of Inequity in Health Should Be Better Integrated with Theories of Distributive Justice. *International Journal for Equity in Health* 8(1):40. Available at http://www.equityhealthj.com/content/8/1/40/ (accessed August 7, 2012).

O'Donnell, O., E. van Doorslaer, and M. Lindelow. 2007. *Analyzing Health Equity Using Household Survey Data: A Guide to Techniques and Their Implementation*. Washington, DC: World Bank.

Office of Surveillance, Epidemiology, and Laboratory Services. n.d. *SMART: BRFSS City and County Data*. Available at http://www.cdc.gov/brfss/smart/technical_infodata.htm (accessed March 2, 2012).

Pearcy, J., and K. Keppel. 2002. A Summary Measure of Health Disparity. *Public Health Reports* 117(3):273–80.

Rust, K.F., and J.N. Rao. 1996. Variance Estimation for Complex Surveys Using Replication Techniques. *Statistical Methods in Medical Research* 5(3):283–310.

StataCorp. 2009. *Stata Statistical Software: Release 11*. College Station, TX.

Temkin, L.S. 1993. *Inequality*. Oxford: Oxford University Press.

Truman, B.I., C.K. Smith, K. Roy, Z. Chen, R. Moonesinghe, J. Zhu, C. Gorway Crawford, and S. Zaza. 2011. Rationale for Regular Reporting on Health Disparities and Inequalities—United States. *Morbidity and Mortality Weekly Report*, Supplement 60(01):3–10. Available at http://www.cdc.gov/mmwr/preview/mmwrhtml/su6001a2.htm?s_cid=su6001a2_w (accessed December 6, 2011).

United Health Foundation. n.d. America's Health Rankings. Available at http://www.americashealthrankings.org (accessed August 7, 2012).

U.S. Census Bureau. n.d.a. American Community Survey (ACS) Public Use Microdata Sample (PUMS) 2009 1-Year. Washington, DC: U.S. Government Printing Office. Available at http://factfinder2.

census.gov/faces/nav/jsf/pages/searchresults.xhtml?refresh=t (accessed November 12, 2012).

U.S. Census Bureau. n.d.b. Poverty Table: Poverty Thresholds for 2009 by Size of Family and Number of Related Children under 18 Years. Available at http://www.census.gov/hhes/www/poverty/data/threshld/thresh09.html (accessed November 14, 2012).

U.S. Census Bureau. 2009a. *American Community Survey: Puerto Rico Community Survey 2009 Subject Definitions*. Washington, DC: U.S. Government Printing Office. Available at http://www.census.gov/acs/www/Downloads/data_documentation/SubjectDefinitions/2009_ACSSubjectDefinitions.pdf (accessed November 14, 2012).

U.S. Census Bureau. 2009b. *Design and Methodology: American Community Survey*. Washington, DC: U.S. Government Printing Office. Available at http://www.census.gov/acs/www/Downloads/survey_methodology/acs_design_methodology.pdf (accessed November 14, 2012).

U.S. Department of Health and Human Services. 1990. *Healthy People 2000*. Washington, DC: U.S. Government Printing Office. Available at http://odphp.osophs.dhhs.gov/pubs/HP2000/ (accessed December 6, 2011).

U.S. Department of Health and Human Services. 2000. *Healthy People 2010*. Washington, DC: U.S. Government Printing Office. Available at http://www.healthypeople.gov/2010/ (accessed December 6, 2011).

U.S. Department of Health and Human Services. 2008. The Secretary's Advisory Committee on National Health Promotion and Disease Prevention Objectives for 2020. Phase I Report: Recommendations for the Framework and Format of *Healthy People 2020, Section IV: Advisory Committee Findings and Recommendations*. Washington, DC: U.S. Government Printing Office.

U.S. Department of Health and Human Services. 2010. *Healthy People 2020*. Washington, DC: U.S. Government Printing Office. Available at http://www.healthypeople.gov/2020/default.aspx (accessed December 6, 2011).

Wagstaff, A., P. Paci, and E. van Doorslaer. 1991. On the Measurement of Inequalities in Health. *Social Science & Medicine* 33(5):545–57.

Williams, D.R., E.Z. Kontos, K. Viswanath, J.S. Haas, C.S. Lathan, L.E. MacConaill, J. Chen, and J.Z. Ayanian. 2012. Integrating Multiple Social Statuses in Health Disparities Research: The Case of Lung Cancer. *Health Services Research* 49(3), part II:1255–77.

Wolfson, M., and G. Rowe. 2001. On Measuring Inequalities in Health. *Bulletin of the World Health Organization* 79(6):553–60.

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APPENDIX 1

Spearman Correlation Coefficients between Rankings of Overall Disparity and Attribute-Specific Disparities in Functional Limitation, 2009

		Attribute-Specific Disparity			
	Overall Disparity	Income	Education	Sex	Race/ Ethnicity
Overall Disparity	1.00				
Attribute-Specific Disparity					
Income	0.75	1.00			
Education	0.68	0.83	1.00		
Sex	0.10	0.01	−0.14	1.00	
Race/Ethnicity	0.91	0.48	0.39	0.11	1.00

Notes: 1. "No functional limitation" is defined as not having a limitation in any of the following six areas: hearing, vision, cognition, ambulation, self-care, and independent living.
2. Overall disparity is an average of income-, education-, sex-, and race/ethnicity–specific disparities in each state.
3. Rankings are based on the degree of disparity, from the smallest to the largest.
4. All analyses are weighted, and functional limitation is age standardized using the U.S. 2000 standard population.
Source: U.S. Census Bureau n.d.a.

APPENDIX 2
Attribute-Specific Disparities in Functional Limitation, 2009

State	Income		Education	
	Disparity	Contribution (%)	Disparity	Contribution (%)
Alabama	0.062	25.01	0.064	25.95
Alaska	0.024	16.78	0.027	19.20
Arizona	0.031	27.87	0.025	22.79
Arkansas	0.061	24.20	0.059	23.73
California	0.032	33.52	0.028	29.03
Colorado	0.029	25.63	0.023	20.35
Connecticut	0.031	27.75	0.035	31.24
DC	0.056	25.97	0.047	21.87
Delaware	0.037	21.84	0.036	21.30
Florida	0.035	26.41	0.033	24.93
Georgia	0.043	29.76	0.043	30.07
Hawaii	0.024	28.20	0.025	29.30
Idaho	0.041	19.93	0.026	12.86
Illinois	0.036	31.39	0.030	26.28
Indiana	0.047	28.89	0.041	25.01
Iowa	0.039	29.46	0.029	22.37
Kansas	0.049	36.43	0.032	23.93
Kentucky	0.070	22.63	0.073	23.41
Louisiana	0.051	30.67	0.052	31.16
Maine	0.059	44.65	0.058	43.80
Maryland	0.027	25.55	0.033	31.12
Massachusetts	0.039	32.12	0.041	33.67
Michigan	0.047	25.24	0.043	23.19
Minnesota	0.036	44.30	0.029	34.97
Mississippi	0.069	28.37	0.060	24.54
Missouri	0.055	24.74	0.048	21.69
Montana	0.037	39.99	0.032	33.88
Nebraska	0.041	26.45	0.025	16.38
Nevada	0.022	24.92	0.017	19.08
New Hampshire	0.029	15.21	0.037	19.15
New Jersey	0.027	29.36	0.031	34.20
New Mexico	0.043	21.25	0.041	20.23
New York	0.040	34.71	0.036	31.41
North Carolina	0.051	28.92	0.045	25.46
North Dakota	0.035	19.37	0.033	18.58
Ohio	0.053	28.20	0.049	26.07
Oklahoma	0.060	30.71	0.046	23.27
Oregon	0.038	28.74	0.029	21.76
Pennsylvania	0.049	35.77	0.047	34.80

Continued

APPENDIX 2—*Continued*

	Income		Education	
State	Disparity	Contribution (%)	Disparity	Contribution (%)
Rhode Island	0.049	38.61	0.048	38.41
South Carolina	0.052	23.06	0.051	22.82
South Dakota	0.042	25.23	0.022	13.15
Tennessee	0.063	28.29	0.060	26.86
Texas	0.042	28.44	0.037	24.93
Utah	0.029	30.07	0.023	23.61
Vermont	0.048	51.25	0.039	41.61
Virginia	0.039	31.04	0.043	34.78
Washington	0.035	31.85	0.031	28.71
West Virginia	0.077	23.21	0.072	21.66
Wisconsin	0.037	34.74	0.033	30.94
Wyoming	0.034	45.77	0.030	40.26

	Sex		Race/Ethnicity	
State	Disparity	Contribution (%)	Disparity	Contribution (%)
Alabama	0.002	0.77	0.119	48.26
Alaska	0.009	6.59	0.081	57.42
Arizona	0.002	1.78	0.053	47.57
Arkansas	0.004	1.72	0.126	50.35
California	0.000	0.00	0.036	37.46
Colorado	0.004	3.92	0.057	50.11
Connecticut	0.004	3.71	0.042	37.30
DC	0.012	5.49	0.100	46.67
Delaware	0.003	1.66	0.094	55.21
Florida	0.002	1.82	0.062	46.83
Georgia	0.002	1.45	0.056	38.72
Hawaii	0.008	9.28	0.028	33.21
Idaho	0.018	8.91	0.120	58.30
Illinois	0.004	3.58	0.045	38.75
Indiana	0.002	1.48	0.073	44.62
Iowa	0.006	4.79	0.057	43.37
Kansas	0.003	2.56	0.049	37.09
Kentucky	0.003	1.08	0.165	52.89
Louisiana	0.003	1.89	0.061	36.29
Maine*	0.012	8.94	0.003	2.60
Maryland	0.005	4.50	0.041	38.83
Massachusetts	0.002	1.95	0.039	32.27
Michigan	0.004	2.08	0.092	49.48
Minnesota	0.008	9.55	0.009	11.18

Continued

APPENDIX 2—*Continued*

	Sex		Race/Ethnicity	
State	Disparity	Contribution (%)	Disparity	Contribution (%)
Mississippi	0.003	1.16	0.112	45.93
Missouri	0.002	1.07	0.117	52.49
Montana*	0.020	21.54	0.004	4.59
Nebraska	0.007	4.44	0.081	52.73
Nevada	0.000	0.00	0.050	55.99
New Hampshire	0.002	1.27	0.123	64.37
New Jersey	0.003	3.41	0.030	33.03
New Mexico	0.013	6.43	0.106	52.09
New York	0.000	0.00	0.039	33.88
North Carolina	0.001	0.54	0.080	45.08
North Dakota*	0.020	11.13	0.092	50.92
Ohio	0.002	1.01	0.085	44.72
Oklahoma	0.006	3.18	0.084	42.84
Oregon	0.004	2.95	0.062	46.55
Pennsylvania	0.000	0.00	0.040	29.44
Rhode Island	0.001	0.84	0.028	22.15
South Carolina	0.006	2.53	0.115	51.58
South Dakota*	0.009	5.60	0.092	56.02
Tennessee	0.002	1.07	0.097	43.78
Texas	0.000	0.33	0.068	46.29
Utah	0.001	1.02	0.044	45.30
Vermont*	0.005	5.15	0.002	1.99
Virginia	0.001	1.15	0.041	33.04
Washington	0.005	4.98	0.037	34.46
West Virginia	0.012	3.77	0.170	51.37
Wisconsin	0.003	2.76	0.034	31.56
Wyoming*	0.004	4.76	0.007	9.21

Notes: 1. "No functional limitation" is defined as not having a limitation in any of the following six areas: hearing, vision, cognition, ambulation, self-care, and independent living.
2. For example, the income-specific disparity of 0.034 in Wyoming suggests that in order to eliminate education-specific disparity, 3.4% more people in Wyoming must become free of functional limitation, and they must come from lower-income groups.
3. For example, in Wyoming the attribute contribution of income, 45.77%, means that 45.77% of the overall disparity comes from income-specific disparity.
4. Due to the small numbers (cell counts less than 50), combined groups, rather than a single group, are used as the reference in the calculation of race/ethnicity–specific disparity in the six states marked with an asterisk.
5. All analyses are weighted, and functional limitation is age standardized using the U.S. 2000 standard population.
Source: U.S. Census Bureau n.d.a.

APPENDIX 3
Overall Disparity in Functional Limitation Calculated by the Proposed Approach and the Wisconsin Measure, 2009

	Overall Disparity	
State	Proposed Approach	Wisconsin Measure
Alabama	0.062	0.155
Alaska	0.035	0.113
Arizona	0.028	0.080
Arkansas	0.063	0.160
California	0.024	0.064
Colorado	0.029	0.092
Connecticut	0.028	0.085
DC	0.054	0.130
Delaware	0.043	0.132
Florida	0.033	0.089
Georgia	0.036	0.081
Hawaii	0.021	0.057
Idaho	0.051	0.156
Illinois	0.029	0.079
Indiana	0.041	0.116
Iowa	0.033	0.101
Kansas	0.033	0.098
Kentucky	0.078	0.199
Louisiana	0.042	0.087
Maine*	0.033	0.119
Maryland	0.026	0.072
Massachusetts	0.031	0.099
Michigan	0.046	0.133
Minnesota	0.021	0.094
Mississippi	0.061	0.135
Missouri	0.056	0.166
Montana*	0.023	0.068
Nebraska	0.038	0.121
Nevada	0.022	0.071
New Hampshire	0.048	0.155
New Jersey	0.023	0.069
New Mexico	0.051	0.123
New York	0.029	0.074
North Carolina	0.044	0.115
North Dakota*	0.045	0.135
Ohio	0.047	0.134
Oklahoma	0.049	0.117
Oregon	0.033	0.099
Pennsylvania	0.034	0.105

Continued

APPENDIX 3—*Continued*

State	Overall Disparity	
	Proposed Approach	Wisconsin Measure
Rhode Island	0.031	0.095
South Carolina	0.056	0.145
South Dakota*	0.041	0.112
Tennessee	0.056	0.139
Texas	0.037	0.094
Utah	0.024	0.077
Vermont*	0.024	0.093
Virginia	0.031	0.084
Washington	0.027	0.082
West Virginia	0.083	0.215
Wisconsin	0.027	0.082
Wyoming*	0.018	0.076

Notes: 1. "No functional limitation" is defined as not having a limitation in any of the following six areas: hearing, vision, cognition, ambulation, self-care, and independent living.
2. Overall disparity measured by the proposed approach is an average of income-, education-, sex-, and race/ethnicity–specific disparities in each state.
3. For example, the overall disparity of 0.018 in Wyoming measured by the proposed approach suggests that in order to eliminate disparity in functional limitation in Wyoming on average across the four attributes considered, an additional 1.8% of the population from the less healthy (and often disadvantaged) groups must become free from functional limitation.
4. Due to the small numbers (cell counts less than 50), combined groups, rather than a single group, are used as the reference in the calculation of race/ethnicity–specific disparity in the six states marked with an asterisk.
5. The Wisconsin measure is calculated by (1) identifying the healthiest group, regardless of its attributes; (2) calculating the sum of the differences in health between the healthiest and each of all the other groups; and (3) dividing this sum by the total number of groups minus one.
6. For example, the Wisconsin measure of 0.076 in Wyoming suggests that the average difference in the fraction of persons free from functional limitation between the healthiest group and that of all other groups is 7.6%.
7. All analyses are weighted, and the functional limitation is age standardized using the U.S. 2000 standard population.
Source: U.S. Census Bureau n.d.a.

APPENDIX 4
Rankings of Overall Disparity in Functional Limitation Measured by the Proposed Approach and the Wisconsin Measure, Attribute-Specific Disparities in Functional Limitation, and Disparity Profiles, 2009

	Overall		Attribute-Specific				
State	Wisconsin Measure	Proposed Measure	Income	Education	Sex	Race/ Ethnicity	Disparity Profile
Alabama	45	48	47	49	10	46	1
Alaska	30	27	2	9	43	32	1
Arizona	11	13	9	5	10	22	1
Arkansas	48	49	46	46	27	49	1
California	2	7	11	10	1	10	2
Colorado	19	15	6	3	27	24	1
Connecticut	16	13	9	24	27	17	1
DC	37	43	43	38	45	41	1
Delaware	38	34	18	25	20	39	1
Florida	18	21	13	20	10	27	1
Georgia	12	28	30	33	10	23	1
Hawaii	1	2	2	5	41	6	2
Idaho	47	41	26	8	49	47	1
Illinois	10	15	16	14	27	19	1
Indiana	32	31	32	30	10	30	1
Iowa	27	21	22	11	37	24	1
Kansas	24	21	35	18	20	20	2
Kentucky	50	50	50	51	20	50	1
Louisiana	17	33	38	44	20	26	2
Maine*	34	21	44	45	45	2	3
Maryland	6	10	4	20	34	15	1
Massachusetts	25	18	22	31	10	12	2
Michigan	39	37	32	33	27	36	1
Minnesota	21	2	16	11	41	5	3
Mississippi	41	47	49	47	20	43	1
Missouri	49	44	42	40	10	45	1
Montana*	3	5	18	18	50	3	3
Nebraska	35	30	26	5	40	32	1
Nevada	5	4	1	1	1	21	1
New Hampshire	45	39	6	27	10	48	1
New Jersey	4	5	4	16	20	8	2
New Mexico	36	41	30	31	48	42	1
New York	7	15	25	25	1	12	2
North Carolina	31	35	38	36	6	31	1
North Dakota*	41	36	13	20	50	36	1

Continued

APPENDIX 4—*Continued*

	Overall		Attribute-Specific				
State	Wisconsin Measure	Proposed Measure	Income	Education	Sex	Race/ Ethnicity	Disparity Profile
Ohio	40	38	41	42	10	35	1
Oklahoma	33	40	45	37	37	34	1
Oregon	25	21	21	11	27	27	1
Pennsylvania	28	26	35	38	1	14	3
Rhode Island	23	18	35	40	6	6	3
South Carolina	44	44	40	43	37	44	1
South Dakota*	29	31	28	2	43	36	1
Tennessee	43	44	48	47	10	40	1
Texas	21	29	28	27	1	29	1
Utah	9	7	6	3	6	18	1
Vermont*	20	7	34	29	34	1	3
Virginia	15	18	22	33	6	15	2
Washington	13	11	13	16	34	11	2
West Virginia	51	51	51	50	45	51	1
Wisconsin	13	11	18	20	20	9	2
Wyoming*	8	1	12	14	27	4	3

Notes: 1. “No functional limitation” is defined as not having a limitation in any of the following six areas: hearing, vision, cognition, ambulation, self-care, and independent living.
2. The rankings are based on the degree of disparity, from the smallest to the largest.
3. Overall disparity measured by the proposed approach is an average of income-, education-, sex-, and race/ethnicity–specific disparities in each state.
4. Overall disparity measured by the Wisconsin measure is calculated by (1) identifying the healthiest group, regardless of its attributes; (2) calculating the sum of the differences in health between the healthiest and each of all the other groups; and (3) dividing this sum by the total number of groups minus one.
5. Due to the small numbers (cell counts less than 50), combined groups, rather than a single group, are used as the reference in the calculation of race/ethnicity–specific disparity in the six states marked with an asterisk.
6. The disparity profile is based on attribute contributions to overall disparity measured by the proposed approach. In states with profile 1, race/ethnicity has the largest contribution. In states with profile 2, race/ethnicity and socioeconomic factor(s) (income and/or education) have roughly equal contributions. In states with profile 3, socioeconomic factor(s) (income and/or education) has the largest contribution.
7. All analyses are weighted, and functional limitation is age standardized using the U.S. 2000 standard population.
Source: U.S. Census Bureau n.d.a.