The Labor Market Consequences of Race Differences in Health

JOHN BOUND, TIMOTHY WAIDMANN,
MICHAEL SCHOENBAUM,
and JEFFREY B. BINGENHEIMER

University of Michigan, Urban Institute, and RAND

DIFFERENCES IN HEALTH STATUS ACROSS DIFFERENT race and ethnic groups in the United States, particularly between black and white Americans, have been the subject of considerable medical and social science research. For instance, numerous studies using a variety of health measures have shown the health of black men and women to be worse than that of whites (e.g., Manton, Patrick, and Johnson 1987). The health disadvantage of Native Americans, relative to that of whites, has also been documented extensively. Patterns for other major ethnic groups (e.g., Hispanics and Asians) have been somewhat more variable, depending on the measure, the age of the study sample, and other factors such as place of birth and acculturation (Hayward and Heron 1999; Shalala et al. 1999).

Systematic health disparities are likely to have profound—and self-reinforcing—consequences for the relative well-being of different population groups. In this article, we focus on one dimension of such consequences: the association between race differences in health status and race differences in labor market outcomes. In particular, the same groups for which health disparities relative to that of whites are consistently large also have significantly lower rates of employment, earnings, and individual and household income than whites do. It seems likely that these patterns are related. That is, poor health reduces individuals' ability to work as well as the productivity of those who do work. In addition,

The Milbank Quarterly, Vol. 81, No. 3, 2003
© 2003 Milbank Memorial Fund. Published by Blackwell Publishing,
350 Main Street, Malden, MA 02148, USA, and PO Box 1354,
9600 Garsington Road, Oxford OX4 2DQ, UK.

poor health increases individuals' demand for medical care but decreases the probability that they have access to private health insurance (particularly since private insurance is most affordable when offered as an employer-sponsored benefit). At the same time, social policies such as the progressive income tax structure, income transfer programs, and public health insurance are intended to offset some of these forces.

In earlier work, we documented the extent to which the poor health of blacks, relative to that of whites, can account for the generally lower employment rates of blacks nearing retirement age (Bound, Schoenbaum, and Waidmann 1995, 1996). For this article, we extended those analyses to other outcomes associated with labor market behavior, including earnings, household income, and participation in public income transfer programs; a broader age range; and additional race and ethnicity groups. Using white Americans as the reference case, we limited our analysis to the two racial/ethnic groups—blacks and Native Americans—whose health is systematically worse than whites' health. We then documented the distribution of labor-related outcomes for these two groups. Finally, we examined the extent to which differences in health status across the groups could account for outcome differences across those groups.

Data and Measures

We sought microdata that contained information about the respondents' demographic and health status, as well as their labor force behavior and labor-related outcomes such as earnings and income. Given our focus on race/ethnicity disparities, we needed data with sufficiently large samples to stratify our analyses by race and ethnicity. Given the strong age gradients on health, we also needed to be able to stratify them by age. In our view, the only data source meeting all these criteria was the U.S. Census. The data in our current study thus come from the 5 percent public use microdata sample (PUMS) of the 1990 U.S. Census, a nationally representative sample of the U.S. population. The PUMS is drawn from the random subset of U.S. Census respondents who completed the "long form" census questionnaire in 1990.

The PUMS contains data on the key domains of interest here, including the respondents' health and labor force status and individual and household income from various sources. However, as we discuss in detail later, the available measures for some domains, particularly health, are

fairly limited. In addition, the PUMS lacks certain kinds of information, such as data on health insurance coverage, which would have benefited this analysis.

Other data sources have much more detailed information about health, health insurance, and medical expenditures. For example, the National Health Interview Surveys (NHIS), the Medical Expenditure Panel Survey (MEPS), its predecessor the National Medical Expenditure Survey (NMES), and the Health and Retirement Study (HRS) all contain detailed measures of health status, and employment and income data, as well as oversamples of racial and ethnic minorities. Although the HRS's age range is too narrow for the present study, we did conduct extensive analyses using data from the MEPS. At best, however, the much smaller MEPS sample permitted analyses only of whites and blacks, and it did not support stratification by age. The findings for the broad age group analyzed in the MEPS were broadly consistent with those presented here, but their precision was substantially lower.

Labor-Related Outcomes

Because no single definitive outcome captures all the possible labor market effects of health disparities, we examined a range of related outcomes.

Employment. We calculated the effect of health disparities on the proportion of each population that is employed. For the purposes of our analyses, we defined employment as the performance of any sort of work in the week before April 1, 1990, the index date of the census questionnaire. This definition includes self-employed persons and members of the armed forces on active duty.

Average Weekly Earnings. The respondents reported both their earnings for 1989 and the number of weeks worked during 1989, and we restricted our analyses of weekly earnings to those respondents who had positive earnings in 1989. We calculated their annual earnings as the sum of income from wages, salary, commissions, tips and bonuses, and self-employment income from farm and nonfarm businesses, and then divided this by the number of weeks worked. For those persons employed by others, we added to their earnings the taxes that employers pay into the Social Security system (OASDI and Medicare), calculated using the applicable formulas for 1989 earnings (SSA 2000). We viewed this as deferred compensation. For similar reasons, we would have liked to assess total compensation, including the employer's cost of worker's

compensation and unemployment insurance, and health insurance and retirement benefits; however, data on these elements of compensation are not available in the census, and imputation based on industry and occupation of employment would have been unreliable. Tabulations using the Health and Retirement Survey (Barsky et al. 2002b) and the MEPS, which do contain such information, suggest that ignoring these forms of compensation would lead us to underestimate the effect of health on labor market outcomes by a small amount.

Participation in Public Transfer Programs. The respondents reported the amount of income they received in 1989 from Railroad Retirement or from Social Security, and we examined whether they received any such income. Since we were focusing primarily on people under age 65 in this analysis, most Social Security participation would be through Social Security Disability Insurance. In parallel analyses, we examined whether the respondents received any income in 1989 from public assistance, including Aid to Families with Dependent Children, Supplemental Security Income, and other public welfare sources. The results were qualitatively similar and are reported in an appendix to the working paper version of this article (<http://www.psc.isr.umich.edu/pubs/papers/rr03-535.pdf>).

Household Income. We calculated the respondents' total household income as the sum of the household's earned income and retirement benefits in 1989, excluding asset income (i.e., interest, royalties, rental income, and income from estates or trusts), plus income from Social Security and public assistance. We summed income across members of the same dwelling unit who were related by blood, adoption, marriage, foster care, or other family association.

We then subtracted income, property, and Social Security taxes. To calculate the household's tax burden, we used the data on all persons in the household to create tax-related variables (e.g., state, filing status, number of dependents, and age exemptions) as well as nonasset income disaggregated by category (i.e., own wage; spouse's wage if married filing jointly; farm and business income, alimony, and other cash income; pension and IRA distributions; gross Social Security income; nontaxable transfer income; and unemployment compensation) as inputs to TAXSIM. TAXSIM, a microsimulation model supported by the National Bureau of Economic Research, uses these data to calculate federal and state taxes for each filing unit. We assumed that couples who were married with spouses present filed jointly. Children and stepchildren of the

householder aged 18 and under and living in the household were considered dependents of the householder. Individuals over 19 and subfamilies in the household were considered separate tax-filing units.

Demographic Characteristics

We assigned each individual to one race/ethnicity category according to the responses to the census's racial identity and Hispanic ethnicity questions. We used non-Hispanic whites ("whites") as the reference group for our analyses. Of the race/ethnicity groups we could examine in the PUMS, only two had systematically worse health than whites, and we limited our analyses to these groups: non-Hispanic blacks ("blacks") and Native Americans and Alaska Natives ("Native Americans"). In this analysis, "Native Americans" include all those responding "Indian (Amer.)," "Eskimo," or "Aleut" to the race question, regardless of their response to the question about Hispanic origin (see Harris 1994 and Snipp 1989 for a discussion about identifying the Native American population using census data). One alternative data source we investigated (NMES) contains a special supplementary sample of Native Americans obtained by oversampling persons living on or near reservations. Nationwide, however, only about half those persons who identify themselves as Native American live in such areas (Snipp 1989). We also examined the health status of Asians and several different Hispanic groups, including residents of Puerto Rico, people of Puerto Rican descent in the United States, and Mexican Americans. These groups showed no consistent health disadvantage relative to that of whites, particularly after accounting for levels of educational attainment, and were thus excluded from this analysis.

Given the strong age gradients in health status and in the relationship between health and labor market outcomes, we stratified the respondents into age categories for all analyses (except as noted). Within age categories, we accounted for age using single-year dummy variables.

Except as noted, we accounted for education in our simulation models because of the strong relationship between education and health for all race/ethnicity groups and because of the substantial differences in the distribution of educational attainment across race/ethnicity groups. We measured education using five mutually exclusive dummy variables, indicating completion of the eighth grade or less, completion of some high school, high school graduation, completion of some college, and college graduation. For some analyses, we stratified respondents by education,

grouping together the first two categories (“high school dropouts”), the next two categories (“high school graduates”), and the last category (“college graduates”).

For analyses of household income, all analyses account for marital status, defined by a single variable indicating whether the individual was married and living with his or her spouse as of April 1, 1990. We noted that for models of household income, the demographic (and health) characteristics used for standardization were measured only for the individual; for example, the analyses do not explicitly account for race differences in the joint distribution of health among couples.

Health Status

The census uses only four health measures, each regarding physical disability: (1) whether the person has a physical, mental, or other health condition that has lasted for six or more months and that limits the kind or amount of work the person can do at a job; (2) whether such a condition prevents the person from working at a job; (3) whether such a condition makes it difficult for the person to go outside the home; and (4) whether such a condition makes it difficult for the person to take care of his or her own personal needs. The census’s questions regarding work, mobility, and personal care limitations represent three distinct questions. As a result, any pattern of responses to these questions is possible. In practice, those respondents who report mobility or personal care limitations usually also report limitations on the amount or kind of work they can do.

Unless otherwise noted, we accounted for three out of four of these measures in our analyses, excluding the indicator of whether the respondent was *unable* to work, out of concern that this measure might be particularly endogenous to labor force outcomes (Waidmann, Bound, and Schoenbaum 1995). In practice, however, simulations that controlled for all four of the census’s health measures yielded substantively similar results.

We recognize legitimate concerns about the validity of the census’s disability items, which are based on a mail-back questionnaire rather than an interview; are sometimes filled out by proxy respondents; and contain only general questions about functional limitation, which have been shown not to correspond precisely to more specific and detailed measures such as Activities of Daily Living (ADLs) or Instrumental Activities of

Daily Living (IADLs) assessed in other surveys (Andresen et al. 2000). To date, however, little empirical attention has been paid to the validity of the census's disability items.

One key question for this analysis was whether the differences across the populations in the responses to the census's questions accurately reflected the differences across these populations in regard to the age-specific functional capacities of the populations. The available evidence suggests that this may be the case. For instance, the patterns of functional limitations by age and race in our census sample were consistent with the evidence regarding disparities from other sources (e.g., Geronimus et al. 2001; Hayward and Heron 1999), thus lending "face validity" to the data. In addition, where they could be made, comparisons between census and National Health Interview Survey (NHIS) data showed similar patterns (e.g., Geronimus et al. 2001; Waidmann, Bound, and Schoenbaum 1995); the same was true for comparisons between the census and the National Long Term Care Survey (e.g., Crimmins, Saito, and Reynolds 1997; Waidmann, Bound, and Schoenbaum 1995). Census-type health questions have been shown to be correlated with clinical measures of morbidity across racial and ethnic groups (McGee et al. 1999). Finally, despite a slightly higher rate of nonresponses to one or more of the census's disability items by blacks (10%) than by whites (7%), our results were insensitive to whether we included or omitted respondents with imputed health measures.

A second key issue was whether the association between the census's disability measures and labor market outcomes accurately reflected the association between "true" health and labor market outcomes. Global self-reported measures of health, although subjective, are closely correlated with clinical measures of morbidity and predictive of subsequent death, health care utilization, and labor market behavior (Ferraro 1980; Idler and Benyamini 1997; LaRue et al. 1979; Maddox and Douglas 1973; Manning, Newhouse, and Ware 1982; Mossey and Shapiro 1982; Nagi 1969). Moreover, this appears to be true across racial and ethnic groups (McGee et al. 1999). Our results, reported later, mirror these findings, in that we observed a very strong association between the census's functional limitation measure and labor market outcomes, both overall and for different race/ethnicity groups.

Even if the census's health measures are reliable indicators of actual health, however, this does *not* necessarily mean that using such measures as proxies for health when examining racial differences in labor

market outcomes will yield valid results. At issue is whether the census's measures are systematically biased. There are a number of reasons to be suspicious of using the kind of survey measures available on the census for studying labor market outcomes (Anderson and Burkhauser 1984, 1985; Bound 1991; Parsons 1982; Waidmann, Bound, and Schoenbaum 1995). For instance, the respondents are being asked for subjective judgments, and there is no reason to expect that these judgments will be entirely comparable. Second, the responses may not be independent of the labor market outcomes of interest. Third, since health may represent one of the few "legitimate" reasons for a working aged man to be out of work, men out of the labor force may cite health limitations to rationalize their behavior. Each of these problems leads to a different kind of bias. The lack of comparability across individuals represents a measurement error that is likely to lead us to underestimate the impact of health on labor market outcomes, whereas the endogeneity of self-reported health is likely to lead us to exaggerate its impact. Biases in our estimation of health's impact on outcomes also induce biases on coefficients of any variables correlated with health.

In previous work, we took advantage of more detailed information on health status available in other datasets (e.g., the Health and Retirement Survey) to address the potential biases that may affect estimates using the kinds of measures available in the census (Bound 1991; Bound, Schoenbaum, and Waidmann 1996; Bound et al. 1998). Overall, this work suggests that findings regarding the effects of health on labor force outcomes have been consistent across different datasets, health measures, and estimation methods. Indeed, the results from this previous work suggest that the "naive" use of census-type health measures (or self-rated general health) tends to *understate* the effects of health on labor market outcomes.

These issues are discussed more formally and at greater length in Bound (1991) and Bound, Schoenbaum, and Waidmann (1996) and in an appendix to the working paper version of this article (<http://www.psc.isr.umich.edu/pubs/papers/r03-535.pdf>).

Methods

We excluded those respondents with missing or imputed data on age, gender, race/ethnicity, education, health status, and the respective

labor-related outcomes examined here. All our analyses were conducted using the person-level weights developed to make the PUMS nationally representative. Our analysis sample included 5,487,713 white, 554,471 black, and 51,058 Native American respondents aged 25 and older. Because of possible age gradients in the relationships examined here, we stratified respondents into ten-year age groups. All analyses were conducted within these age strata.

We began by calculating descriptive statistics on the levels of poor health, educational attainment, and income for different race/ethnicity groups, by age and gender. We then used simple multivariate regressions to estimate the association between poor health and labor force outcomes and income, for different race/ethnicity groups. Finally, we used data on whites, blacks, and Native Americans to simulate what the distribution of outcomes would be among blacks and Native Americans if their health status were to rise to the levels actually observed among whites.

To implement these simulations, we reweighted the data on blacks and Native Americans so that the distribution of health characteristics in the reweighted sample matched the empirically observed distribution of health characteristics among whites with the same age and gender. We illustrate this procedure using a somewhat stylized example. Of the 45-to-54-year-old men in the 1990 Census, approximately 88 percent of whites and 75 percent of blacks were employed, and approximately 10 percent of whites and 17 percent of blacks identified themselves as having a health problem that limits the kind or amount of work they could do. The employment rates for both whites and blacks were much higher for men who did not have a health limitation than for men who did have one (figure 1). The overall rate for whites represents the weighted average of the rates for the two white populations:

$$(1) \quad E_W = E_{WU} S_{WU} + E_{WL} S_{WL}$$

where E_W represents the overall nonemployment rate for whites; E_{WU} and E_{WL} represent the employment rates for the unlimited and limited populations, respectively; and S_{WU} and S_{WL} represent the share of the white population without and with limitations. The overall employment rate for blacks, E_B , can be expressed in analogous fashion:

$$(2) \quad E_B = E_{BU} S_{BU} + E_{BL} S_{BL}$$

FIG. 1. Proportion employed, by limitation status (men aged 45 to 54).

FIG. 2. Standardized proportion employed (men aged 45 to 54).

Here, reweighting the black data means reweighting the black health-specific employment rates (E_{BU} and E_{BL}) using the white population shares (S_{WU} and S_{WL}):

$$(3) \quad \hat{E}_B = E_{BU} S_{WU} + E_{BL} S_{WL}$$

In our example, when blacks were reweighted using the white prevalence of health limitations, their employment rate rose from approximately 75 percent to 81 percent (figure 2). This method of “direct standardization” is a basic tool used by demographers (Kitagawa 1964).

Researchers typically interpret equation (3) in terms of a counterfactual, that is, what would happen to black employment rates if the

distribution of health among blacks improved to match that of whites. However, this interpretation supposes that when the health status of blacks improves, employment rates conditional on health status would remain the same. This is unlikely to happen, though, since policy interventions that improve the health of blacks are likely to affect the employment rates among blacks both with and without health limitations. Alternatively, one can interpret equation (3) as a descriptive statement. Subtracting (3) from (1) yields

$$(4) \quad E_W - \hat{E}_B = [E_{WU} - E_{BU}]S_{WU} + [E_{WL} - E_{BL}]S_{WL}$$

The interpretation of (4) is easiest when the racial employment differentials are similar for those that are and are not limited (i.e., $[E_{WU} - E_{BU}] \approx [E_{WL} - E_{BL}]$). In this case, the gap in employment between whites and reweighted blacks is just the employment gap conditional on limitation status. More generally, the employment gap can be interpreted as the weighted average of disability-specific gaps in employment, where the weights (S) are based on the white health distribution. If reweighting makes little difference and the expression in equation (4) remains very close to the raw difference in employment rates, this suggests that health disparities do not make an important contribution to the racial gap in employment rates. But if we find that reweighting does make a significant difference, as we do for some age groups, this suggests that health disparities do contribute to the gap in employment rates. Thus, while reweighted employment rates (as in {3}) may not be an accurate estimate of the counterfactual, comparisons between actual and reweighted employment rates do give us a sense of the relative importance of health disparities in explaining employment rate disparities.

In this example, we standardized blacks to have the health characteristics of whites, an approach that is conceptually consistent with the societal goal of improving outcomes among disadvantaged groups. But it also is possible to standardize whites to the black distribution of health. In the example at hand, these alternative simulations produce substantively similar results because the effect of health limitations on employment is similar for blacks and whites. In general, however, the two alternative simulations need not account for similar fractions of the overall black/white gap in the outcome of interest (cf. Barsky et al. 2002a).

An important issue guided our empirical analyses. Our focus was on the association between health status and labor-related outcomes. However, blacks and Native Americans also are disadvantaged relative to whites with respect to other characteristics, particularly educational attainment, that are themselves associated with both health status and labor-related outcomes. Standardizing the health characteristics of blacks to white levels also, implicitly, raises educational attainment in the standardized population. Since the probability of employment increases sharply with education, our simple example confounds the labor force effects of black/white disparities in health with the effects of such disparities in education. Standardizing on educational attainment alone would raise analogous issues.

In general, there is no way to identify the separate effects of health disparities and education disparities on labor-related outcomes using our simulation methods. We therefore conducted multiple simulations controlling for age, age and health, age and education, and age, education, and health. Comparing simulations that standardize on age alone with ones that standardize on age and health tends to overestimate the effect of health per se on employment differentials, since the effects of "health" include the effects of the part of education that is correlated with health. But comparing simulations that standardize on age and education with ones that standardize on age, education, and health tends to underestimate the impact of health disparities, since it ignores the impact of health disparities that are correlated with educational disparities. Thus the true effect of disparities in health per se is likely to lie somewhere between these bounds. For our example (figure 2), black/white disparities in health thus account for somewhere between 21 and 39 percent of the black/white gap in employment.¹

The method just described is appropriate for standardizing on a limited number of categorical variables (e.g., age, or the dichotomous measure of health limitation used in figures 1 and 2). But we are interested in more complex reweighting. We therefore used multivariate standardization techniques that are conceptually analogous to direct standardization but can incorporate many, and continuous, stratifying variables (Barsky et al. 2002a; DiNardo, Fortin, and Lemieux 1996; Heckman, Ichimura, and Todd 1998).

To illustrate, we extend our simple example to a case in which we want to simulate the effect on employment of reweighting blacks to reflect the distribution of health and other characteristics observed among whites. To do this, we first restrict the sample to black and white respondents.

We then estimate a logistic regression in which the dependent variable is one if the respondent is black, and zero otherwise. Explanatory variables include health and other characteristics, such as age and education, depending on the simulation of interest. Also included are interactions between health and education. The parameter estimates can be used to calculate the predicted probability that a person with a particular set of explanatory variables will be observed in the black sample.

Based on these predicted probabilities, or propensities, blacks who have characteristics that are more typical of whites are weighted *up*, and those whose characteristics are more representative of the overall black sample are weighted *down*. The reweighted (or counterfactual) distribution from group *a* can then be used to calculate any characteristic of the counterfactual outcome distribution (mean, median, percentiles) or to depict the entire distribution of outcomes (kernel density estimation). Simulation methods are described in further detail by Barsky and colleagues (2002a) and in an appendix to the working paper version of this article (<http://www.psc.isr.umich.edu/pubs/papers/rr03-535.pdf>).

The results of these standardizations identify the extent to which those differences in health observed between blacks and whites can account for differences between these groups in labor-related outcomes. We emphasize that we do not necessarily interpret this accounting as causal, in the sense that ameliorating the health differences would necessarily yield proportional reductions in the black/white disparities in labor-related outcomes. Furthermore, to the extent that observed health differences do not fully account for such disparities, we do not interpret the residual differences in outcomes as being causally related to being black in any meaningful way. At best, the remaining difference may be interpreted as an estimate of the importance of factors other than health that affect race differences in earnings. At minimum, it is a measure of the average gap in each outcome between blacks and whites, conditional on health.

Findings

Because of space limitations, we present the results for only two age groups: 25 to 34 and 55 to 64. Except as noted, the patterns vary monotonically with age. Details of the other age groups are provided in an appendix to the working paper version of this article (<http://www.psc.isr.umich.edu/pubs/papers/rr03-535.pdf>).

Descriptive Statistics

Figures 3 (for men) and 4 (for women) plot the prevalence of various types of health limitation by age and race/ethnicity. For each of the four measures, prevalence rates are low for men and women in

FIG. 3a. Proportion with work limitation, male.

FIG. 3b. Proportion unable to work, male.

FIG. 3c. Proportion with mobility limit, male.

Figures plotted are 5-year moving averages of weighted single-year prevalence estimates.

FIG. 3d. Proportion with personal care limit, male.

their twenties and thirties but begin to rise after that. For each measure, the prevalence is higher for blacks and Native Americans than for whites, and it rises with age more steeply for them than it does for whites. As a result, prevalence rates tend to diverge with age, so that

the absolute difference between whites and blacks/Native Americans increases.

Table 1 gives the prevalence of poor health by race/ethnicity, overall and by level of educational attainment. The results show that the prevalence of each indicator of poor health is higher for blacks and Native

FIG. 4a. Proportion with work limitation, female.

FIG. 4b. Proportion unable to work, female.

FIG. 4c. Proportion with mobility limit, female.

Figures plotted are 5-year moving averages of weighted single-year prevalence estimates.

FIG. 4d. Proportion with personal care limit, female.

Americans than for whites, overall and within each education category. The rates for blacks and Native Americans are more similar, with prevalence being higher for blacks in some cells and for Native Americans in others. The overall prevalence of poor health rises with age. In general,

TABLE 1
Proportion of People with Health Conditions That Limit Work, Mobility,
or Personal Care

Age	Education Group ^a	Male			Female		
		White	Black	Native American	White	Black	Native American
25–34		Health Limits Kind or Amount of Work					
	Whole sample	0.054	0.080	0.095	0.043	0.057	0.081
	<i>Ed standardized to whites</i>	—	0.062	0.063	—	0.047	0.055
	HS dropouts	0.136	0.151	0.140	0.113	0.109	0.117
	HS grads	0.054	0.066	0.083	0.042	0.049	0.073
55–64	Coll grads	0.016	0.020	0.038	0.018	0.022	0.042
	Whole sample	0.200	0.285	0.350	0.165	0.295	0.317
	<i>Ed standardized to whites</i>	—	0.240	0.321	—	0.254	0.288
	HS dropouts	0.318	0.347	0.414	0.275	0.376	0.384
	HS grads	0.184	0.225	0.305	0.134	0.225	0.255
25–34	Coll grads	0.095	0.133	0.210	0.085	0.116	0.206
		Health Prevents Work					
	Whole sample	0.018	0.043	0.037	0.017	0.031	0.040
	<i>Ed standardized to whites</i>	—	0.029	0.020	—	0.023	0.022
	HS dropouts	0.072	0.102	0.069	0.069	0.077	0.070
55–64	HS grads	0.015	0.029	0.027	0.015	0.023	0.033
	Coll grads	0.002	0.004	0.009	0.003	0.006	0.004
	Whole sample	0.130	0.224	0.269	0.125	0.248	0.260
	<i>Ed standardized to whites</i>	—	0.175	0.225	—	0.205	0.222
	HS dropouts	0.246	0.291	0.355	0.236	0.332	0.343
25–34	HS grads	0.108	0.155	0.204	0.093	0.173	0.181
	Coll grads	0.038	0.069	0.083	0.047	0.068	0.116
		Health Limits Mobility					
	Whole sample	0.012	0.025	0.021	0.011	0.019	0.023
	<i>Ed standardized to whites</i>	—	0.017	0.008	—	0.014	0.010
55–64	HS dropouts	0.047	0.061	0.039	0.045	0.047	0.035
	HS grads	0.009	0.016	0.015	0.009	0.014	0.021
	Coll grads	0.002	0.005	0.011	0.003	0.004	0.005
	Whole sample	0.044	0.090	0.099	0.054	0.115	0.116
	<i>Ed standardized to whites</i>	—	0.071	0.086	—	0.098	0.100
55–64	HS dropouts	0.085	0.118	0.129	0.101	0.149	0.151
	HS grads	0.035	0.060	0.075	0.040	0.085	0.079
	Coll grads	0.016	0.030	0.044	0.023	0.040	0.076

(continued)

TABLE 1—*Continued*

		Male			Female		
				Native			Native
Age	Education Group ^a	White	Black	American	White	Black	American
Health Limits Personal Care							
25–34	Whole sample	0.019	0.067	0.050	0.016	0.066	0.048
	<i>Ed standardized to whites</i>	—	0.055	0.026	—	0.057	0.035
	HS dropouts	0.053	0.108	0.086	0.050	0.111	0.072
	HS grads	0.017	0.058	0.036	0.015	0.060	0.043
	Coll grads	0.007	0.031	0.038	0.007	0.030	0.017
55–64	Whole sample	0.048	0.123	0.106	0.049	0.127	0.100
	<i>Ed standardized to whites</i>	—	0.103	0.091	—	0.112	0.090
	HS dropouts	0.083	0.150	0.138	0.087	0.157	0.124
	HS grads	0.041	0.096	0.078	0.038	0.101	0.072
	Coll grads	0.019	0.057	0.053	0.021	0.062	0.087

Note: ^a “Ed standardized” includes whole sample, with distribution of education standardized to white levels.

Source: Authors’ calculations using 1990 U.S. Census.

the size of the absolute disparity between whites and the other two groups rises somewhat with age, but the percentage of disparity does not vary consistently by age.

While the overall prevalence of poor health is inversely related to educational attainment, there do not appear to be consistent gradients in health disparities across education categories. Table 1 also includes a row in each panel showing the prevalence of each health measure, accounting for race/ethnicity disparities in the distribution of education. Across all ages, differences in education account for between 52 and 84 percent of the race/ethnicity disparities in the census’s health measures. This finding is consistent with earlier research (e.g., Schoenbaum and Waidmann 1997).

Poor Health- and Labor-Related Outcomes

Tables 2 and 3 present the effects of multivariate regression analyses that examine the association between health status and employment, earnings, and participation in public assistance programs and Social Security.

TABLE 2
Parameter Estimate for the Effect of Health Limitation on Labor Market Outcomes

Age	Education Group ^c	Employed ^a				Log Weekly Earnings ^b			
		Men		Women		Men		Women	
		White	Black	Native American	White	Black	Native American	White	Black
25-34	Pooled sample	-2.32	-2.36	-1.54	-1.32	-1.95	-1.33	-0.33	-0.25
	HS dropouts	-2.38	-2.42	-1.54	-1.53	-2.05	-1.19	-0.37	-0.36
	HS grads	-2.33	-2.34	-1.54	-1.33	-1.92	-1.41	-0.31	-0.20
	Coll grads	-1.98	-2.08	-1.98	-0.96	-1.97	-0.75	-0.32	-0.22
55-64	Pooled sample	-2.23	-2.84	-2.49	-1.82	-2.59	-2.06	-0.25	-0.24
	HS dropouts	-2.68	-3.13	-2.82	-2.17	-2.72	-2.10	-0.22	-0.26
	HS grads	-2.09	-2.53	-2.43	-1.70	-2.48	-2.17	-0.22	-0.20
	Coll grads	-1.74	-2.20	-1.30	-1.51	-2.29	-1.99	-0.36	-0.30
Maximum Standard Error ^d		0.05	0.18	0.58	0.04	0.14	0.50	0.02	0.07
								0.03	0.07
									0.26

Notes: "Poor health" is represented as a dummy variable that is 1 if respondent's health limits or prevents work; other explanatory variables are age and educational attainment (within education category, as appropriate). Models are stratified by race/ethnicity and gender.

^a Logistic regression, with dependent variable that is 1 if respondent was working for pay on April 1, 1990.

^b Linear regression, with dependent variable being the natural log of average weekly earnings among those with nonzero earnings in 1989, weighted by the number of weeks worked.

^c Pooled sample includes all levels of education; other rows are restricted to respondents in respective categories of educational attainment.

^d Represents largest standard error estimate for any cell within the column.

Source: Authors' calculations using 1990 U.S. Census.

Poor health is captured by a dummy variable indicating whether the respondents' health limits the amount or type of work they can perform. These models also include age and education as explanatory variables. Models are stratified by race/ethnicity, age, and gender. The first row reports the result of models for the overall sample in each race/ethnicity-, age-, and gender-specific cell, while the remainder report the results for models that are stratified for educational category. Cell values represent the parameter estimate for poor health from the respective regressions. All regressions control for age and education.

The first panel of table 2 shows the association between poor health and employment status. We used logistic regression to model this outcome, so the cell entries contain logit parameters. These can be interpreted as the difference between people with and without health limitations in the log odds of employment. Alternatively, the coefficients can be exponentiated to give the odds of employment for people with health limitations relative to people without health limitations.

The parameter estimates are negative and very large in every gender, age, education, and race/ethnicity cell, confirming that the association between self-reported work limitations and employment is very strong across all these population groups. Thus, for instance, the coefficient of -2.32 for 25-to-34-year-old black men implies that, controlling for age and education, the log odds for this group of being employed is 2.32 lower for those reporting a limitation than for those not reporting a limitation; that is, the odds of being employed for those reporting a limitation is roughly one-tenth the odds of being employed for someone not reporting a limitation ($e^{-2.32} \approx 1/10$).

Parameter estimates are generally similar for younger white and black men, although the effect of work limitations on employment is somewhat stronger for black men at older working ages. This pattern is consistent with expectations, since limitations among black men are likely to be more severe than those among whites and since black men tend to have more physically demanding jobs. For Native American men, the effect of work limitations on employment is generally weaker than for whites. The parameter estimates for white and Native American women are generally similar, and those for black women are consistently larger (in absolute value).

The second panel of table 2 shows the association between poor health and the natural log of weekly earnings for respondents who reported positive earnings in 1989. Regressions are weighted by the number of

weeks worked, so that people working more weeks receive more weight and the samples should be representative of the working population in a typical week. The cell entries contain parameter estimates for the effect of work limitations from linear regression models; these coefficients can be interpreted loosely as the percent reduction in weekly earnings associated with a work limitation. With one exception, the effect of poor health was negative and large—reducing earnings by 20 to 40 percent—in every gender, age, education, and race/ethnicity cell. The sizes of the effects were generally similar across ethnicity groups, and there were no apparent patterns in the differences that do exist.

Table 3 presents logit parameter estimates for the effect of work limitations on participation in public assistance and Social Security. With the exception of the top age category in the table, individuals in this age

TABLE 3
Parameter Estimate for the Effect of Health Limitation on Receipt of Income from Public Transfer Programs

Age	Education Group ^b	Any Income from Social Security ^a					
		Men			Women		
		White	Black	Native American	White	Black	Native American
25–34	Pooled sample	3.12	3.19	3.26	2.51	1.99	1.70
	HS dropouts	3.22	2.99	3.37	2.23	1.67	1.59
	HS grads	3.13	3.32	3.34	2.60	2.20	1.76
	Coll grads	2.81	3.13	2.39	2.75	2.46	—
55–64	Pooled sample	2.05	1.63	1.56	1.31	1.08	1.41
	HS dropouts	2.01	1.56	1.28	1.08	0.93	1.03
	HS grads	2.10	1.76	2.06	1.45	1.35	1.92
	Coll grads	1.85	1.83	1.62	1.37	1.29	5.30
Maximum Standard Error ^c		0.09	0.38	0.38	1.55	0.09	0.29

Notes: “Poor health” is represented as a dummy variable that is 1 if respondent’s health limits or prevents work; other explanatory variables are age and education (within education category, as appropriate). Blank cells are due to low participation rates plus limited sample size.

^a Logistic regression, with dependent variable that is 1 if respondent received any income from Social Security (SSDI or ESRD) in 1989.

^b Pooled sample includes all levels of education; other rows are restricted to respondents in respective categories of educational attainment.

^c Represents largest standard error estimate for any cell within the column.

Source: Authors’ calculations using 1990 U.S. Census.

range participated in Social Security through the Disability Insurance Program or if they had end-stage renal disease. For both outcomes, the parameter estimates were positive and very large for every population group listed. In most age, gender, and ethnicity categories, the parameter estimates were somewhat to substantially higher for college graduates than for those with less education. With a few exceptions, the effect of poor health on participation in public assistance was larger for whites than for blacks, and for blacks than for Native Americans. Most of the exceptions were among college graduates, perhaps because the overall prevalence of public assistance was lowest for this group. In general, the same ethnicity gradients held for women with respect to the receipt of Social Security, and there were no consistent ethnicity patterns for men.

Simulations

In the remainder of this section, we report the results of simulations in which we reweighted the black and Native American samples to reflect the distribution of age, education, and health status observed among whites in our census sample. Tables 4 through 6 show the simulation results, stratified by gender and age. In each table, the first row for each age category lists the actual level of the outcome of interest among whites. The remaining rows give the simulated level of the outcome for blacks and Native Americans after accounting for race/ethnicity differences in age, age and education, age and health, and age, education, and health. Empirically, race/ethnicity differences in age alone accounted for little to none of the disparity in any outcome. As a result, the level in the "age" row was very close to the actual (unadjusted) level observed among blacks and Native Americans.

The first panel of table 4 gives the simulations for employment. Comparing the first two rows in each age category shows that employment rates were substantially lower for black and Native American men and women than for whites (except for black women aged 55 to 64). Comparing the third and fourth rows with the first indicates that education and health disparities could account for a substantial fraction, but not all, of the race/ethnicity disparities in employment (except for black women). For example, 90 percent of white men aged 25 to 34 were employed, compared with an (age-adjusted) rate of 73 percent of black men in that age group. If blacks in this group had the same distribution of education and health as whites, we estimate that their employment rate would

TABLE 4
Simulated Labor Force Outcomes for Blacks and Native Americans

Age	Reweighted by	Proportion Employed ^a				Mean Weekly Earnings ^b			
		Men		Women		Men		Women	
		Black	Native American	Black	Native American	Black	Native American	Black	Native American
25-34	White (actual)	0.900	0.900	0.719	0.719	\$595	\$595	\$408	\$408
	Age	0.729	0.703	0.655	0.567	\$464	\$488	\$386	\$320
	Age, education	0.778	0.758	0.709	0.646	\$498	\$551	\$408	\$356
	Age, health	0.744	0.717	0.664	0.580	\$463	\$488	\$386	\$319
55-64	Age, education, health	0.783	0.765	0.712	0.653	\$497	\$554	\$408	\$356
	White (actual)	0.654	0.654	0.440	0.440	\$835	\$835	\$397	\$397
	Age	0.545	0.486	0.441	0.342	\$612	\$670	\$430	\$388
	Age, education	0.597	0.554	0.491	0.407	\$693	\$745	\$462	\$438
Maximum Standard Error ^c	Age, health	0.590	0.558	0.499	0.396	\$614	\$683	\$435	\$379
	Age, education, health	0.615	0.604	0.527	0.450	\$694	\$759	\$464	\$429
		1.6E-05	1.8E-04	1.2E-05	1.5E-04	\$0.07	\$0.83	\$0.05	\$0.70

Notes: Table shows outcomes for blacks and Native Americans, standardizing for race/ethnicity differences in various characteristics.

“White” row represents actual level of each outcome observed among whites in the age category.

“Age” indicates that distribution of age among blacks and Native Americans is standardized to the white distribution.

“Education” indicates that distribution of education among blacks and Native Americans is standardized to the white distribution.

“Health” indicates that distribution of work limitation among blacks and Native Americans is standardized to the white distribution.

a Outcome is 1 if the respondent was working for pay on April 1, 1990, and 0 otherwise.

b Outcome is mean and median weekly earnings, among those with nonzero earnings in 1989, weighted by number of weeks worked.

c Represents largest standard error estimate for any cell within the column.

Source: Authors’ calculations using 1990 U.S. Census.

increase to 78 percent, thus narrowing the original differential by nearly one-third.

The fraction of race/ethnicity differences in employment that are accounted for by health disparities increases substantially with age. For instance, following the logic described in the Methods section, health disparities account for at least 3 percent (lower bound, comparing the age row with the age and health row) and at most 9 percent (upper bound, comparing the age and education row with the age, education, and health row) of the employment gap between black and white men aged 25 to 34—but between 17 and 41 percent of the gap between black and white men aged 55 to 64. This pattern is similar for Native American men and for black and Native American women. Interestingly, health disparities account for a larger fraction of the race/ethnicity gap in employment for women than they do for men. Older black women's employment rates were essentially equivalent to those for white women. When accounting for health disparities, the employment rates of black women were substantially higher than that of their white counterparts.

The second panel of table 4 presents the simulations for the weekly earnings of those with positive earnings in 1989. The mean earnings for black and Native American men and women in each age group were substantially lower than for whites. As in the first panel, adjusting for race/ethnicity differences in education accounted for a substantial fraction of these disparities. For instance, for men, education differences accounted for between one-third and one-half the earnings gap between employed black and Native American men and whites. We estimated that if employed black women in most age categories had the educational distribution of whites, they would have higher mean earnings.

Notably, although health *per se* is strongly associated with earnings (cf. table 2), race/ethnicity disparities in health account for little to none of the disparities in earnings, for any of the age, gender, and race/ethnicity categories. The large effect of health on employment effectively eliminated any measured health differences among the employed. Our findings regarding median earnings were substantively similar, and the results are in an appendix to the working paper version of this article (<http://www.psc.isr.umich.edu/pubs/papers/rr03-535.pdf>).

Table 5 shows the results for participation in Social Security. Participation was somewhat lower among whites than among blacks or Native Americans, for each age and gender group. However, these differences nearly disappeared in the older age category in the table. For

TABLE 5
Simulated Participation in Social Security by Blacks and Native Americans

Age	Reweighted by ^a	Men		Women	
		Black	Native American	Black	Native American
25–34	<i>White (actual)</i>	0.012	0.012	0.011	0.011
	Age	0.015	0.015	0.018	0.020
	Age, education	0.012	0.012	0.015	0.016
	Age, health	0.012	0.011	0.017	0.018
	Age, education, health	0.011	0.011	0.015	0.015
55–64	<i>White (actual)</i>	0.189	0.189	0.210	0.210
	Age	0.193	0.215	0.210	0.218
	Age, education	0.166	0.194	0.194	0.211
	Age, health	0.173	0.182	0.189	0.186
	Age, education, health	0.158	0.166	0.180	0.182
Maximum Standard Error ^b		1.3E-05	1.5E-04	1.0E-05	1.3E-04

Notes: ^a Simulations are analogous to those in table 4. Outcome is 1 if the respondent received any income from Social Security in 1989 and 0 otherwise.

^b Represents largest standard error estimate for any cell within the column.

Source: Authors' calculations using 1990 U.S. Census.

all age groups, health differences accounted for a very large fraction of race/ethnicity disparities in Social Security participation, and often more than the fraction accounted for by education disparities. The reason is presumably the structural relationship between poor health and eligibility for Social Security Disability Insurance. For men, health and education differences accounted for all, or nearly all, the race/ethnicity differences in Social Security participation (although the base rates were relatively low).

Finally, table 6 presents the simulation results for mean household income (net of taxes and public transfers). Not surprisingly, mean household income is substantially higher for whites than for blacks and Native Americans. The results suggest that health disparities accounted for relatively little of the substantial race/ethnicity gap in household income, for men or women. However, through age 65 the explanatory power of health disparities increased consistently with age, presumably reflecting the age gradient in the relationship between health disparities and employment observed in table 4 (the explanatory power of health disparities declined slightly with age after age

TABLE 6
Simulated Mean Household Income after Taxes and Transfers

Age	Reweighted by ^a	Men		Women	
		Black	Native American	Black	Native American
25–34	<i>White (actual)</i>	\$27,122	\$27,122	\$28,583	\$28,583
	Age	\$18,369	\$16,862	\$17,117	\$17,863
	Age, education	\$20,723	\$19,530	\$19,195	\$20,329
	Age, health	\$18,714	\$17,212	\$17,381	\$18,242
	Age, education, health	\$20,844	\$19,660	\$19,304	\$20,581
55–64	<i>White (actual)</i>	\$31,607	\$31,607	\$25,221	\$25,221
	Age	\$22,024	\$20,193	\$15,438	\$15,392
	Age, education	\$26,839	\$24,110	\$17,816	\$17,980
	Age, health	\$23,110	\$21,911	\$16,634	\$16,750
	Age, education, health	\$27,345	\$25,257	\$18,486	\$19,165
Maximum Standard Error ^b		\$0.93	\$17.21	\$0.36	\$5.55

Notes: ^a Simulations are analogous to those in table 4. Outcome is net household income in 1989 from nonasset sources, subtracting income, property, and FICA and Social Security taxes, and adding transfers from Social Security and public assistance.

^b Represents largest standard error estimate for any cell within the column.

Source: Authors' calculations using 1990 U.S. Census.

65; detailed results are included in an appendix to the working paper version of this article (<http://www.psc.isr.umich.edu/pubs/papers/rr03-535.pdf>). Health disparities accounted for a maximum of 15 percent of the race/ethnicity gap in mean income (for Native American versus white men aged 55 to 64).

In contrast, disparities in education accounted for a much larger fraction of the race/ethnicity gap in mean household income. Our findings regarding median income were substantively similar (these are available by request). There are a number of reasons for this result. First, education disparities were strongly associated with disparities in earnings among the employed, in addition to being associated with disparities in employment. In contrast, health disparities were associated only with the latter. In addition, household earnings included the spouse's earnings (among married couples), which helped reduce the economic effects of one partner's poor health. In contrast, given the very strong patterns of assortative mating, the education of spouses was strongly correlated, reinforcing

the association between respondents' own education and household income.

Discussion

Using microdata from the 1990 Census, we documented strong associations between the health and labor market outcomes for blacks, Native Americans, and whites. For each of these groups, those people who reported having a health problem that limited their work were dramatically less likely to be working than were similarly educated individuals without such limitations. In addition, among those who were working, people with health limitations typically earned between 20 and 40 percent less than did people without such limitations.

Overall, we found that blacks and Native Americans had worse labor market outcomes, worse health, and lower educational attainment than did their white counterparts. Race/ethnicity disparities in health could account for a significant part of the differences in employment rates between blacks and Native Americans, on the one hand, and whites, on the other, particularly among men and women 45 to 64 years old. In contrast, the observed race/ethnicity disparities in health among *employed* people were relatively small, leading to our finding that health disparities appeared to contribute very little to disparities in weekly earnings among race/ethnicity groups. To examine whether this finding was an artifact of using the census's health measures, we conducted analogous simulations using the Health and Retirement Survey and the more detailed health measures available there, and the results were substantively similar.

We also found that health disparities could account for a significant part of the higher participation rates among blacks and Native Americans in public assistance programs and especially Social Security, relative to whites' rates. These results combined with those for employment to produce some association between race/ethnicity disparities in health and disparities in household income, particularly among people aged 45 to 64. Both this age gradient and that for employment suggest that health differences—possibly due to the accumulated economic disadvantage over the lifetime—reinforce the economic disadvantage of blacks and Native Americans relative to whites that is evident at all ages. Overall, however, health disparities accounted for relatively little of the

race/ethnicity gaps in income, which appeared to be associated much more strongly with disparities in education (this was true despite the strong association between health and earnings).

One could think of our analyses as addressing the following counterfactual: Suppose the health disparities between blacks and Native Americans, on the one hand, and whites, on the other, were eliminated. What effect would this have on the employment and earnings of blacks and Native Americans? The reciprocal relationship between health status and economic status, however, calls into some question the meaningfulness of the counterfactual that motivates our analysis. For instance, to the extent to which health disparities are a consequence of race/ethnicity differences in access to health care, it is possible to imagine eliminating such disparities without first eliminating economic disparities among the races. Alternatively, to the extent that health disparities are initially due to economic disparities, it is impossible to imagine eliminating health disparities without first eliminating economic disparities directly. It is for this reason that we have described our work as primarily an accounting exercise.

As we stated, the health measures available in the 1990 Census are limited in a number of ways, which could lead us to over- or underestimate the effect of health on labor market outcomes (Bound 1991). They also could induce a bias on estimates of the impact of race/ethnicity on outcomes, regardless of whether we correctly measured the impact of health itself. But earlier research suggests that the various potential sources of bias apparently balance out one another (Bound 1991; Bound, Schoenbaum, and Waidmann 1996; Bound et al. 1998).

Our indicators of the labor market "costs" of health disparities also are limited. For instance, omitting such factors as health insurance and private pensions is likely to lead us to understate race/ethnicity disparities in labor-related outcomes. With the caveat that health care use is endogenous with respect to health insurance coverage and economic status, we also would have liked to account for out-of-pocket spending on medical care, since one reason that poor health reduces economic well-being is because sick people buy medical care.

Finally, the health disparities between blacks and Native Americans and whites are likely to have substantial impacts on well-being not captured in this analysis. The measures of economic disparity examined here do not incorporate the costs of premature mortality, but it is clear that any comprehensive conceptualization of economic disadvantage could,

and should, account for this (Murphy and Topel 2001). Nor do they capture the value of health for time not spent on market work (Hirth et al. 2000) or the impact of anticipated poor health or mortality on human capital investments (Geronimus 1987; Geronimus, Bound, and Waidmann 1999; Meltzer 2001). As these papers make clear, such costs are likely to be substantial.

ENDNOTE

1. Specifically, we calculated the upper bound by comparing the actual gap between whites and blacks ($0.885 - 0.753 = 0.132$) with the gap between whites and blacks with health standardized to white levels ($0.885 - 0.805 = 0.080$). Using this approach, the difference in employment rates attributable to health differences is 0.052 ($0.132 - 0.080$), or 39% of the actual gap. We calculated the lower bound of 21% by comparing the gap between whites and blacks with education standardized to white levels ($0.885 - 0.795 = 0.090$) with the gap between whites and blacks with education and health standardized to white levels ($0.885 - 0.823 = 0.062$). Here the difference in employment rates attributable to health is 0.028 ($0.090 - 0.062$), 21% of the actual gap.

References

- Anderson, K.H., and R.V. Burkhauser. 1984. The Importance of the Measure of Health in Empirical Estimates of the Labor Supply of Older Men. *Economics Letters* 16:375–80.
- Anderson, K.H., and R.V. Burkhauser. 1985. The Retirement-Health Nexus: A New Measure of an Old Puzzle. *Journal of Human Resources* 20:315–30.
- Andresen, E.M., C.A. Fitch, P.M. McLendon, and A.R. Meyers. 2000. "Reliability and validity of disability questions for US Census 2000," *American Journal of Public Health*, 90:1297–9.
- Barsky, R., J. Bound, K.K. Charles, and J.P. Lupton. 2002a. Accounting for the Black-White Wealth Gap: A Nonparametric Approach. *Journal of American Statistical Association* 97:663–73.
- Barsky, R., J. Bound, K.K. Charles, and J.P. Lupton. 2002b. A Precise Characterization of the Black-White Wealth Gap. Unpublished manuscript, University of Michigan.
- Bound, J. 1991. Self-Reported vs. Objective Measures of Health in Retirement Models. *Journal of Human Resources* 26:106–38.
- Bound, J., M. Schoenbaum, and T. Waidmann. 1995. Race and Education Differences in Disability Status and Labor Force Attachment. *Journal of Human Resources* 30(suppl.):S227–67.

- Bound, J., M. Schoenbaum, and T. Waidmann. 1996. Race Differences in Labor Force Attachment and Disability Status. *The Gerontologist* 36:311–21.
- Bound, J., M. Schoenbaum, T. Stinebrickner, and T. Waidmann. 1998. Modeling the Effects of Health on Retirement Behavior. Paper presented to the National Bureau of Economic Research Summer Institute, Cambridge, MA, July.
- Crimmins, E., Y. Saito, and S.L. Reynolds. 1997. Further Evidence on Recent Trends in the Prevalence and Incidence of Disability among Older Americans from Two Sources: The LSOA and the NHIS. *Journals of Gerontology*, series B: *Psychological Sciences and Social Sciences* 52B:S5971.
- DiNardo, J., N.M. Fortin, and T. Lemieux. 1996. Labor Market Institutions and the Distribution of Wages, 1973–1992: A Semiparametric Approach. *Econometrica* 64(5):1001–44.
- Ferraro, K.F. 1980. Self-Ratings of Health among the Old and Old-Old. *Journal of Health and Social Behavior* 21:377–83.
- Geronimus, A.T. 1987. On Teenage Childbearing and Neonatal Mortality in the United States. *Population and Development Review* 13(2):245–79.
- Geronimus, A.T., J. Bound, and T.A. Waidmann. 1999. Health Inequality and Population Variation in Fertility-Timing. *Social Science and Medicine* 49(12):1623–36.
- Geronimus, A.T., J. Bound, T. Waidmann, C. Colen, and D. Steffick. 2001. Inequality in Life Expectancy, Functional Status, and Active Life across Selected Black and White Populations in the United States. *Demography* 38:227–51.
- Harris, D. 1994. The 1990 Census Count of American Indians. *Social Science Quarterly* 75(2):580–93.
- Hayward, M.D., and M. Heron. 1999. Racial Inequality in Active Life among Adult Americans. *Demography* 36(1):77–91.
- Heckman, J.J., H. Ichimura, and P.E. Todd. 1998. Matching as an Econometric Evaluation Estimator. *Review of Economic Studies* 65:261–94.
- Hirth, R.A., M.E. Chernew, E. Miller, A.M. Fendrick, and W.G. Weissert. 2000. Willingness to Pay for a Quality-Adjusted Life Year: In Search of a Standard. *Medical Decision Making* 20(3):332–42.
- Idler, E., and Y. Benyamini. 1997. Self-Rated Health and Mortality: A Review of Twenty-seven Community Studies. *Journal of Health and Social Behavior* 39:21–37.
- Kitagawa, E. 1964. Standardized Comparisons in Population Research. *Demography* 1:296–315.

- LaRue, A., L. Bank, L. Jarvic, and M. Hewtland. 1979. Health in Old Age: How Physicians' Rating and Self-Ratings Compare. *Journal of Gerontology* 34:687-91.
- Maddox, G., and E. Douglas. 1973. Self-Assessment of Health: A Longitudinal Study of Elderly Subjects. *Journal of Health and Social Behavior* 14:87-93.
- Manning, W.G., J.P. Newhouse, and J.E. Ware Jr. 1982. The Status of Health in Demand Estimation, or Beyond Excellent, Good, Fair and Poor. In *Economic Aspects of Health*, edited by V.R. Fuchs, 143-84. Chicago: University of Chicago Press.
- Manton, K., C. Patrick, and K. Johnson. 1987. Health Differentials between Blacks and Whites: Recent Trends in Morbidity and Mortality. *Milbank Quarterly* 65(suppl. 1):129-99.
- McGee, D.L., Y. Liao, G. Cao, and R.S. Cooper. 1999. Self-Reported Health Status and Mortality in a Multiethnic U.S. Cohort. *American Journal of Epidemiology* 149(1):41-6.
- Meltzer, D.O. 2001. Effects of Health Disparities on Educational Investments. Paper presented to the National Institute of Health Conference on Health Disparities, December, Washington, D.C.
- Mossey, J.M., and E. Shapiro. 1982. Self-Rated Health: A Predictor of Mortality among the Elderly. *American Journal of Public Health* 72:800-8.
- Murphy, K.M., and R.H. Topel. 2001. Black-White Differences in the Economic Value of Improving Health. Paper presented to the National Institute of Health Conference on Health Disparities, December, Washington, D.C.
- Nagi, S.Z. 1969. Congruency in Medical and Self-Assessment of Disability. *Industrial Medicine* 38:74-83.
- Parsons, D.O. 1982. The Male Labor Force Participation Decision: Health, Reported Health, and Economic Incentives. *Economica* 49:81-91.
- Schoenbaum, M., and T. Waidmann. 1997. Race, Socioeconomic Status and Health: Accounting for Race Differences in Health in the U.S. Elderly. *Journals of Gerontology* 52(special issue):61-73.
- Shalala, D.E., M.H. Trujillo, G.J. Hartz, and E.L. Paisano. 1999. *Trends in Indian Health*. <http://www.ihs.gov/PublicInfo/Publications/trends98/trends98.asp>. Washington, D.C.: U.S. Department of Health and Human Services.
- Snipp, C.M. 1989. *American Indians: The First of This Land*. New York: Russell Sage.
- Social Security Administration (SSA). 2000. *Social Security Bulletin: Annual Statistical Supplement, 2000*. Washington, D.C.: U.S. Government Printing Office.

Waidmann, T., J. Bound, and M. Schoenbaum. 1995. The Illusion of Failure: Trends in Self-Reported Health of the U.S. Elderly. *Milbank Quarterly* 73(2):253–87.

Acknowledgments: Financial support was provided through a contract from the National Institutes of Health and by the National Institute on Aging (R01 AG17579-01). We are grateful to Seema Thomas for her able research assistance and to Raynard Kington and Arline Geronimus, participants in the National Institutes of Health Conference on Health Disparities, Washington, D.C., 2001, and three anonymous reviewers for helpful comments on earlier drafts.

Address correspondence to: John Bound, Population Studies Center, University of Michigan, 426 Thompson Street, P.O. Box 1248, Ann Arbor, MI 48106-1248 (e-mail: jbound@umich.edu).