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Estimating Racial Disparities in Economic Outcomes: An Application to Employer-sponsored Retiree Health Insurance and Access to Care

Helen Levy

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Helen Levy
University of Michigan

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Michigan Retirement and Disability Research Center, University of Michigan, P.O. Box 1248. Ann Arbor, MI 48104, mrdrc.isr.umich.edu, (734) 615-0422

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Estimating Racial Disparities in Economic Outcomes: An Application to Employer-Sponsored Retiree Health Insurance and Access to Care

Abstract

This paper reviews different approaches to estimating differences in economic outcomes across groups defined by race, with a focus on whether and how covariates such as education are incorporated in these analyses. My review focuses on the economics literature, but also draws lessons from research on health disparities. Using data from the Current Population Survey and the National Health Interview Survey, I present two examples of estimating Black-white differences in retiree health insurance and cost-related problems with access to medical care. The examples illustrate the importance of estimating Black-white gaps separately for men and for women, whether or not controls for education and other characteristics are included in the model.

Citation

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1. Introduction

What characteristics should researchers control for when estimating disparities in economic outcomes across racial groups? Many factors that can be thought of as "explaining" such disparities — for example, differences in educational attainment in an analysis of racial disparities in earnings — may themselves be due in part to systemic racism. Including such characteristics in a regression may therefore understate the impact of race. The literature offers empirical researchers very little practical guidance on how to address this problem (Schwabish and Kijakazi 2021).

In this paper, I review different methods for estimating racial differences in economic outcomes, with a focus on whether and how covariates such as education are incorporated in these analyses. I mainly review the literature in economics, which means that some key studies in the literature are about differences in hourly wages; but the methods are applicable to other economic outcomes, such as employment, labor force participation, nonwage elements of compensation such as health insurance, elements of deferred compensation such as pensions — really, any outcome for which one might want to analyze differences across groups. These groups need not be defined by race; my review includes some studies focusing primarily on male-female differences since the methodological question is similar whether the groups are defined by race, gender, or some other characteristic. I also selectively discuss work in health services research that estimates racial differences and disparities in health-related outcomes.

As examples, I present two empirical applications estimating Black-white gaps in economic outcomes for older Americans: employer-sponsored retiree health insurance and cost-related barriers to getting medical care. In both cases, I demonstrate the role played by other covariates — gender, marital status, education, and age — in "explaining" differences across groups defined by race. I conclude with a discussion of some practical implications for empirical researchers, while noting that many important issues remain unresolved.

2. Background

The idea that statistically controlling for differences across individuals might explain away some of what should in fact remain unexplained is present in the earliest papers on this topic. Versions of this question appear in the seminal work of Blinder (1973) and Oaxaca (1973), who independently developed the standard statistical decomposition used to analyze such differentials. Blinder (1973) analyzed both Black-white and male-female wage differentials, while Oaxaca (1973) analyzed male-female wage differentials. From Oaxaca (1973, pp. 698-699):

> *One difficulty with the present formulation of the wage equation is that it controls for what many would consider to be major sources of discrimination. By controlling for broadly defined occupation, we eliminate some of the effects of occupational barriers as sources of discrimination. As a result, we are likely to underestimate the effects of discrimination.*

Oaxaca's solution to this problem was to estimate models with and without controls for occupation, industry, and class of worker. The models without these controls, which Oaxaca referred to as the "personal characteristics wage regressions," included covariates measuring labor market experience, education, health, part-time status, migration, marital status, urbanicity, and (in some models) the presence of children.

Blinder (1973, p. 441) framed the problem somewhat differently:

> *In the intuitive model I have in mind, each individual is presented with endowments of human and non-human capitals and at some point in his life-cycle, jointly decides how far he wishes to pursue his formal education and to what occupational strata he aspires. Thus [education] and [occupation], the two chief determinants of the wage rate, are endogenous and simultaneously determined.*

Blinder's solution was to use family background variables to address this endogeneity. Again, from Blinder (1973, p. 440):

> *… the Michigan [Panel Study of Income Dynamics] data provide a rich set of variables pertaining to the individual's family background. These enable us to estimate a meaningful reduced-form equation which explains the wage rate only on the basis of characteristics which are truly exogenous to the individual (such as his father's education).*

In addition to father's education, Blinder's list of exogenous variables included (among others) age, region, and parents' income. The inclusion of parents' income and father's education in this list may strike the modern reader as odd, since it is inconceivable that parents' income and father's education would not have been affected by race and racism. Indeed, the 1967 data used by Blinder (1973) might have included some workers whose parents were born as enslaved persons. The choice of these variables arose in part due to how Blinder framed the problem. He was interested in separating discrimination from other factors, conditional on "the circumstances of [the worker's] birth" (p. 442) — implicitly starting the clock on racism at that point and ignoring what came before. This is consistent with the cultural and legal framework at the time, which focused on understanding whether employers were engaging in active discrimination based on race when faced with otherwise equally qualified applicants. At the same time, it is clear that framing the problem in this way precludes any role for the long-lasting impacts of centuries of systemic racism in the United States and is therefore unsatisfactory if the goal is to understand the full impact of race on labor market outcomes.

Subsequent studies have addressed this problem in different ways, but there is no consensus in the literature about the preferred approach for estimating racial disparities in wages or earnings. Reviews by Cain (1986) and Altonji and Blank (1999) provide overviews of the literature through the late 1990s. Some significant papers in this area include Smith and Welch (1989), Donohue and Heckman (1991), Bound and Freeman (1992), Neal and Johnson (1996), Heckman et al. (2000), and more recently, Bayer and Charles (2018). Neal and Johnson (1996) is particularly relevant for this review because it explicitly addresses the question of how factors included in wage regressions, such as post-secondary education, “could themselves be affected by market discrimination,” thereby potentially underestimating racial differences that may be due to discrimination. Neal and Johnson argue that differences in skill, which they measure using Armed Forces Qualification Test (AFQT) scores, help explain Black-white differences in wages, while acknowledging that the acquisition of skill (as reflected in AFQT score) is not an innate characteristic, as some have argued, but rather varies predictably with parental resources.

While this is all very interesting, it leaves empirical researchers without practical guidance about a number of simple questions: Should my regressions control for education? What about occupation? Should I describe what I am measuring as a difference or as a disparity? Some guidance on this last question may come from a different field, health policy, where a number of entities have offered slightly different definitions of these concepts. Hebert et al. (2008) provide an excellent discussion of the definitions of disparity offered by the federal Agency for Healthcare Research and Quality (AHRQ), the Institute of Medicine (IOM), and the World Health Organization (WHO). In a nutshell: AHRQ, which releases an annual National Healthcare Disparities Report, defines disparities as significant differences across groups that are larger than 10%.[1] The WHO definition quoted by Hebert et al. (2008) is “differences in health which are not only unnecessary and avoidable but, in addition, are considered unfair and unjust.”

The Institute of Medicine offered a definition of these terms in a 2003 report (Nelson 2002) that was motivated by persistent racial differences in access to medical care and the quality of care received. They proposed a relatively straightforward framework for thinking about racial differences and disparities in these outcomes, in which differences across minority and nonminority groups are posited to arise from three sets of factors: (1) clinical appropriateness and need, and patient preferences; (2) the operation of health care systems and the legal and regulatory climate; and (3) discrimination, biases, stereotyping, and uncertainty. In the IOM framework, a *disparity* is the portion of the difference that can be attributed to the latter two sets of factors (see Figure S-1 on p. 4 in Nelson 2002). This framework gave rise in practical terms to guidance for how to estimate disparities (McGuire et al. 2006; Cook et al. 2012); this guidance suggests controlling only for clinical appropriateness, need, and patient

[1] Recent versions of the annual AHRQ National Healthcare Disparities Report do not define what is meant by “disparities.” The 2006 version of this report cited by Hebert et al. (2008) as offering the definition given here is no longer available online.

preferences in order to isolate disparities across groups in a multivariate framework. Of course, the question of which variables reflect clinical appropriateness, need, and patient preferences remains subjective. Hebert et al. (2008) demonstrate the narrowing and, ultimately, reversal of an initially substantial Black-white disparity in neonatal mortality among very low birthweight infants with the successive inclusion of additional explanatory variables.

3. Empirical examples

I present empirical examples of estimating Black-white gaps for two different outcomes: employer-sponsored retiree health insurance coverage and cost-related difficulty accessing care. Most Medicare beneficiaries have some form of insurance coverage that supplements their Part A and B benefits; this coverage may come from Medicaid, Medicare Advantage, Medigap, or private coverage provided by a former employer. Private employer-sponsored retiree coverage is my first empirical example. Such coverage may come from one's own former employer or from a spouse's current or former employer. I analyze both own-employer retiree coverage (coverage from one's own former employer) and dependent retiree coverage (coverage from a spouse's current or former employer), as well as whether or not individuals have any employer-sponsored retiree coverage: that is, either own-employer or dependent retiree coverage. The other outcome I analyze as an empirical example is cost-related difficulty accessing medical care, which reflects reports of delayed and/or foregone medical care due to cost.

3.1 Empirical approach

For both sets of outcomes, I begin by documenting simple trends over time for groups of retirees defined by race (Black or white) and gender (male or female). I present trends in employer-sponsored retiree health insurance for the period 1995 through 2017; for access to care, available data cover the period 2010 through 2018. Next, for each set of outcomes, I estimate two different versions of the Blackwhite gap using pooled data over time: a simple mean difference across groups defined by race and a regression-adjusted gap that adjusts for age, education, and marital status in a simple linear probability model with the following specification:

$$\Pr(Y) = \beta_0 + \beta_1 \cdot (BLACK) + \beta_2 \cdot (X) + YEAR + \varepsilon \quad (1)$$

The vector *X* represents the controls for individual's age, education, and marital status. Education is included as a categorical variable (less than high school [omitted], high school graduate, some college, college degree or more); age in years is included as a linear variable; and marital status is an indicator for married or not. *YEAR* is a vector of year dummies. Each pair of estimates — the simple Black-white gap and the covariate-adjusted Black-white gap — is estimated first for the full sample pooling women and men and then separately for women and men.

3.2: Data

Data on employer-sponsored retiree health insurance

Data for my analysis of employer-sponsored retiree health insurance coverage come from the Current Population Survey (CPS) Annual Social and Economic Supplement (ASEC), which is conducted every year in March. The CPS-ASEC has been an official source of statistics on health insurance coverage since 1987.[2] The original ASEC health insurance questions recorded health insurance coverage of all family members during the calendar year prior to the survey: Did the individual have any coverage at all during the year and if so, what type(s)? Private insurance is coded as being in the respondent's own name (that is, the respondent is the policyholder rather than a dependent on the policy) or not, and whether the coverage was provided by an employer or a union. Thus, it is possible to identify retirees who have employer-sponsored coverage in their own name and those who are covered as a dependent on a spouse's policy. I use data from the 1996 through 2018 ASEC, corresponding to health insurance coverage held by respondents during calendar years 1995 through 2017.[3] There are two significant changes to the ASEC that affect the continuity of its health insurance data during this period. First, in survey year 2000 (affecting data for the 1999 reference period), the question sequence was changed to more thoroughly capture different sources of health insurance; this appears to have resulted in an increase in the number of people counted as having health insurance (Davern et al. 2003). Second, in survey year 2014, the health insurance questions were modified to capture information

[2] Questions about health insurance were included in the CPS-ASEC starting in 1980, but the Census Bureau did not start publishing official estimates using these data until 1987. More detail about the CPS health insurance questions is available at https://www.census.gov/programs-surveys/cps/technical-documentation/user-notes/health-insurance-user-notes/health-ins-cov-meas-asec-acs.html.

[3] The fact that the CPS-ASEC reference period is the prior calendar year can create confusion about which year is which. In this paper, I consistently describe results with the year of the survey reference period, rather than the year in which the survey was conducted. So, for example, when I refer to results "from 1995," these rely on data from the March 1996 CPS-ASEC, which asked questions about health insurance coverage held during 1995.

on coverage at the time of the survey in addition to during the prior calendar year, in addition to other modifications to the question sequence, which again increased the number of people counted as having coverage (Pascale 2016).[4] Thus, breaks in the data may occur in 1999 and 2013. While my analysis does not rely on the continuity of trends in the CPS-ASEC health insurance estimates, it is worth keeping in mind that some year-to-year changes may reflect measurement changes.

The full CPS-ASEC sample during this period includes between 130,000 and 217,000 respondents in each year. Individuals 65 and older make up 11% of this total; 70% of these older adults report that they did not work in the previous calendar year and the reason they give for not working is that they are retired. Keeping only retirees ages 65 or older in each year thus yields a sample of about 11,000 to 17,000 respondents in each year. Next, I drop the 14% of respondents who report a race other than Black or white; and an additional 2% \ who report that they do not have Medicare coverage. This yields an analytic sample of approximately 12,000 observations per year for studying outcomes related to retiree health insurance. Table A1 reports the size of my analytic sample of NHIS data by year, gender, and race.

Data on cost-related problems with access to medical care

Data for my analysis of health care access problems come from the annual National Health Interview Survey for 2010 through 2018. These surveys included two

[4] A third change, the introduction of a new data processing system in 2019, affected CPS-ASEC health insurance estimates but falls outside the period I analyze. More information on the recent changes to the health insurance questions is available at https://www.census.gov/newsroom/blogs/research-matters/2019/09/cps-asec.html. This page includes a very helpful figure (Figure 5) showing the breaks in trend in the fraction of the population that is uninsured associated with the changes described here.

questions measuring problems with access: Family-level respondents are asked on behalf of themselves and their family members, “During the past twelve months, have you delayed seeking medical care/has medical care been delayed for anyone in the family] because of worry about the cost” and “During the past twelve months, was there any time when [you/someone in the family] needed medical care, but did not get it because [you/the family] couldn't afford it?” Follow-up questions identify which family member experienced the problem. Thus, for each member of the family, I have measures of whether care has been delayed or foregone because of cost. I combine these into a single measure, coding anyone with either delayed or foregone care as having a cost-related access problem.

The full NHIS sample during this period includes between 70,000 to 112,000 respondents of all ages in each year. Individuals 65 and older make up 14% of this total; 83% of these older adults report that they are not working at the time of the survey. I consider these individuals (over 65 and not working) to be retirees. (This is, necessarily, a more expansive definition of who is a retiree than the one I used in the CPS data, where I also required that they report that their reason for not working is that they are retired. NHIS does not have comparable data on the reason a respondent is not working.) Keeping only retirees ages 65 and older in each year yields a sample of about 8,000 to 13,000 respondents in each year. Next, I drop the 16% of respondents who report a race other than Black or white. This yields a sample of approximately 10,000 observations per year for studying problems with access to care. Table A2 reports the size of my analytic sample of NHIS data by year, gender, and race.

4. Results

4.1 Descriptive statistics, pooling data across years

Table 1 presents descriptive statistics for the sample of retirees 65 and older in the CPS (Panel A) and NHIS (Panel B). Average age is around 75 (slightly younger for Black men, slightly older for white women). There are striking differences in the probability of marriage in both data sources. In the CPS, white men are the most likely to be married (73%), followed by Black men (57%), white women (45%) and Black women (26%). The patterns are very similar in the NHIS although the estimates are slightly different (a few percentage points). Educational attainment also varies by race and gender, with Black men having the least education; 42% of Black men in the CPS sample did not graduate from high school. Comparable figures for other groups in the CPS are 37% for Black women, 20% for white men, and 19% for white women. It is impossible to ignore the fact that these patterns are likely the result of systemic racism and discrimination. The youngest individuals in my analytic sample are those who turned 65 in 2018 and the oldest are those who are 85 or older as of 1995, so birth years range from before 1910 to 1953. Therefore, the entire sample was born before the U.S. Supreme Court struck down the practice of school segregation based on race in *Brown v. Board of Education* in 1954, and the oldest members of the group were already well into adulthood when this happened. The median retiree in my sample was born in 1932 (CPS) or 1940 (NHIS).

In terms of insurance outcomes in the CPS, on average, 23% of retirees 65 and older have their own employer-sponsored coverage, and another 7% have such coverage as a dependent, so that in all nearly a third have private employer-sponsored health insurance in addition to Medicare. White men are most likely to have such coverage, either in their own name or overall, and Black women are the least likely to have it. Interestingly, white women are far more likely than other subgroups defined by race and gender to have dependent coverage, offsetting their lower rates of own-employer retiree coverage so that their overall rate of employer retiree coverage is nearly identical to that of Black men (28%). In the NHIS, access problems are relatively uncommon in this age group thanks to Medicare, but are nonetheless much more common for Black women (8.3%) and Black men (6.0%) than white women (4.5%) or white men (3.6%).

4.2 Trends in outcomes

Figure 1 shows trends in own-employer health insurance for white and Black retirees 65 and older from 1988 through 2017. This figure pools data for men and women. Until 2007, white retirees were significantly more likely than Black retirees to have such coverage. The two series converged around 2007, driven largely by an increase in coverage among Black retirees. Five years later, both white and Black retirees experienced sharp declines in own-employer coverage. Thus, the pooled (male and female together) data suggest the closing of a significant Black-white gap over time.

Figure 2, which shows these trends separately for male and female retirees, tells a somewhat different story. While the overall story is the same for men and women — convergence in rates of own-employer coverage for Black and white retirees, followed by declines for both groups — the convergence happened a full decade earlier for women than men: 1999 versus 2009. The subsequent decline in coverage is, in absolute terms, smaller for women (whose rates of coverage start out at a lower level) than for men.

Adding retiree coverage held as a dependent adds further complexity to the story. Rates of dependent coverage (Figure 3) are similarly low for both Black and white male retirees throughout the period 1988 through 2017; for female retirees, white women are consistently about twice as likely as their Black counterparts to have such coverage. This is driven in part by higher rates of marriage among white female retirees than among Black female retirees. Then again, white *male* retirees also have higher rates of marriage than their Black counterparts, so it’s not just that white women are more likely than Black women to be married; it must also be the case that the men to whom they are married are more likely to have employer-sponsored insurance that can cover a retired spouse.

Interestingly, this complexity is largely masked when looking at whether retirees have employer health insurance from either source (that is, as a policyholder or as a dependent) in Figure 4: For both men and women, there is a significant Black-white gap in such coverage until about 2010, when the gap disappears and coverage declines for everyone.

The story for trends in delayed or foregone medical care due to cost is simpler. There is a persistent Black-white gap over time in access to medical care (Figure 5), and the gap is fairly similar for men and women (though somewhat noisier for men), as shown in Figure 6.

4.3 Controlling for covariates

The discussion has already touched on the role of marriage in explaining health insurance coverage; what about other covariates? As described above, to simplify this stage of the analysis and focus on the role of the covariates, I estimate regressions using the specification in Equation (1) above with data for all years during the period 1995 through 2017. I estimate three sets of regressions: men and women together, women only, and men only. Each set contains two models, one with and one without covariates, so there are six results for each outcome. The models with controls include as covariates education (less than high school graduate [omitted], high school graduate, some college, college or more), age, and marital status, in addition to the Black indicator variable that is in all the models.

Table 2's Panel A presents results for the health insurance outcomes from the CPS. In the analysis that includes both male and female retirees, there are significant Black-white gaps in all outcomes — own-employer coverage, dependent coverage, and coverage from either source ranging from 3 to 6 percentage points in the models without controls. Adding controls substantially reduces these gaps, to 1 or 2 percentage points, although these smaller gaps remain statistically significant. These results are not particularly surprising. The results estimated separately for women and men are more interesting. In particular, the Black-white gap in the probability of having one's own employer health insurance is small and insignificant (0.2 to 0.3 of a percentage point) for women with or without controls, while it is significant and substantial for men regardless of the inclusions of controls (2.5 to 5.8 percentage points). Thus, an immediate lesson is that estimating "the" Black-white gap for both men and women at the same time may not yield an accurate picture of differences by race. For other outcomes in Panel A of Table 2 — dependent coverage, any coverage — the differences by gender, including both the main effect and the change in the coefficient when controls are included in the model, are less striking. Adding covariates reduces the magnitude of the Black-white gap in these outcomes for both men and women but the gap remains significant, except in the case of dependent coverage for men.

For access to care (Panel B of Table 2), the Black-white gap in access to care is larger for women than for men (3.9% versus 2.4%). Both gaps are small but statistically significant, and for both men and women, as in the pooled sample, the effect of adding covariates is to reduce the magnitude of the coefficient although the coefficient itself remains statistically significant.

5. Discussion

Returning to the question posed at the outset of this paper, what characteristics should researchers control for when estimating disparities in economic outcomes across racial groups? One clear lesson from the decades of studies that have grappled with this question, either directly or by revealed preference, in their choice of what models to run, is that there is no simple answer to this question.

Nonetheless, I draw two lessons from all of this. The first is that attempting to analyze Black-white gaps using a pooled sample that includes both men and women potentially obscures important differences by gender. As evidenced by the example of employer-sponsored retiree health insurance, Black-white gaps can be quite different for men and women. Many significant papers in the historical literature on Black-white wage gaps indirectly address this problem by analyzing data only on men. Indeed, this practice persists today.[5] Both then and now, the exclusion of data on women from these studies is often not evident from their titles; the lightly fictionalized title of a recent paper that used data only on men is “Changes in Returns to Schooling over Time.” This is an unfortunate omission, given the relative lack of research focusing on the economic outcomes of women, including but not limited to racial disparities in those outcomes. Public and private entities that support research on economic outcomes may want to consider whether policies on the inclusion of women and minorities in economic research, modeled on the policy of the National Institutes of Health,[6] would help ensure that the results of funded research are generalizable to the entire population. Journals may want to require studies that do not use data on women to include the phrase “among men” (or something similar) in their titles to indicate that the analysis represents less than half of the U.S. population.

The second lesson is that what covariates to include is inextricably linked with what question the model is intended to address. The IOM framework discussed above (Nelson 2002) is a useful starting point: Is the goal to estimate a difference, or a disparity (using these terms as they are defined by IOM)? Understanding the goal will help inform the choice of covariates. For example, thinking of the historical context of

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[5] Consider the following footnote, taken from a 2021 paper about wages in a top field journal in economics: “We focus on men for two main reasons: (i) including women during early adulthood would require us to model their fertility decisions, which is outside the scope of the present analysis, and (ii) much of the literature that has studied human capital formation to which our analysis is comparable has focused on men.” In other words, “we study men because we have always studied men.” Note, also, the assumption implicit in their first assertion that men’s fertility need not be modeled; this may be true, but this reflects societal inequities that in turn shape labor market inequities.

[6] https://grants.nih.gov/policy/inclusion/women-and-minorities.htm

early work on wage differentials, including the work of Blinder (1973) and Oaxaca (1973), the goal as understood at the time may have been to see whether workers who were identical except for race were earning different amounts, as evidence of possible discrimination by current employers. Thus, the inclusion of many covariates made sense. This is a fundamentally different undertaking from an analysis such as Bayer and Charles (2018), who are interested in tracking *overall* economic progress of Black men over time without first subtracting, in effect, changes “explained” by lower rates of education.

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Tables and figures

Table 1: Characteristics of Black and white Retirees 65 and older, by race and gender

Panel A: CPS Annual Social and Economic Supplement, 1995 through 2017 (pooled)

	White men	Black men	White women	Black women
Employer-sponsored retiree health insurance:				
…from one's own employer	0.299	0.241	0.185	0.182
…as a dependent	0.048	0.040	0.091	0.038
…either own or dependent coverage	0.347	0.281	0.276	0.220
Age	74.8	73.9	75.6	74.7
Education < high school graduate	0.198	0.415	0.190	0.373
Education = high school graduate	0.333	0.301	0.425	0.327
Education = some college	0.207	0.164	0.219	0.172
Education ≥ college	0.262	0.120	0.166	0.127
Married	0.727	0.571	0.448	0.264
Sample n (unweighted)	101,734	12,605	142,566	20,065

Panel B: National Health Interview Survey, 2010 through 2018 (pooled)

	White men	Black men	White women	Black women
Access problem due to cost of care	0.036	0.060	0.045	0.083
Age	74.5	73.3	75.2	74.4
Education < high school graduate	0.145	0.326	0.152	0.313
Education = high school graduate	0.285	0.297	0.361	0.307
Education = some college	0.252	0.225	0.272	0.229
Education ≥ college	0.317	0.153	0.216	0.152
Married	0.711	0.551	0.478	0.264
Sample n (unweighted)	33,082	4,410	42,794	6,949

Table 2: Black-white gaps in economic outcomes for retirees 65 and older,

effect of adding controls and estimating separate models for men & women

	(1) Women & Men No controls	(2) Women & Men Includes controls	(3) Women No controls	(4) Women Includes controls	(5) Men No controls	(6) Men Includes controls
Panel A: CPS Annual Social and Economic Supplement, 1995 through 2017 (pooled) Outcomes = Employer-sponsored health insurance (EHI), by source of coverage						
Dependent EHI	-0.036***	-0.007***	-0.056***	-0.012***	-0.008**	0.004
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Any EHI	-0.061***	-0.020***	-0.056***	-0.018***	-0.066***	-0.025***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)
Sample n	260,214	260,214	152,810	152,810	107,404	107,404
Panel B: National Health Interview Survey, 2010 through 2018 (pooled) Outcome = Health care delayed or foregone due to cost						
Access problem	0.033***	0.018***	0.039***	0.022***	0.024***	0.009**
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Sample n	87,235	85,882	49,743	48,936	37,492	36,946

Notes: 1. Standard errors in parentheses; 2. * p<0.05; ** p<0.01; *** p<0.001; 3. The entry in each cell is the coefficient on the “Black” indicator variable from a linear regression. Each row has a different outcome variable and each column represents a different model, where differences across models are defined by whether the sample includes only women, only men, or both; and whether the model includes only the Black indicator variable (columns 1, 3, 5) or also includes controls for education (less than high school graduate [omitted], high school graduate, some college, college or more), age, and marital status. See Equation (1) in the paper.

Figure 1: Own employer health insurance, Black versus white retirees ages 65+

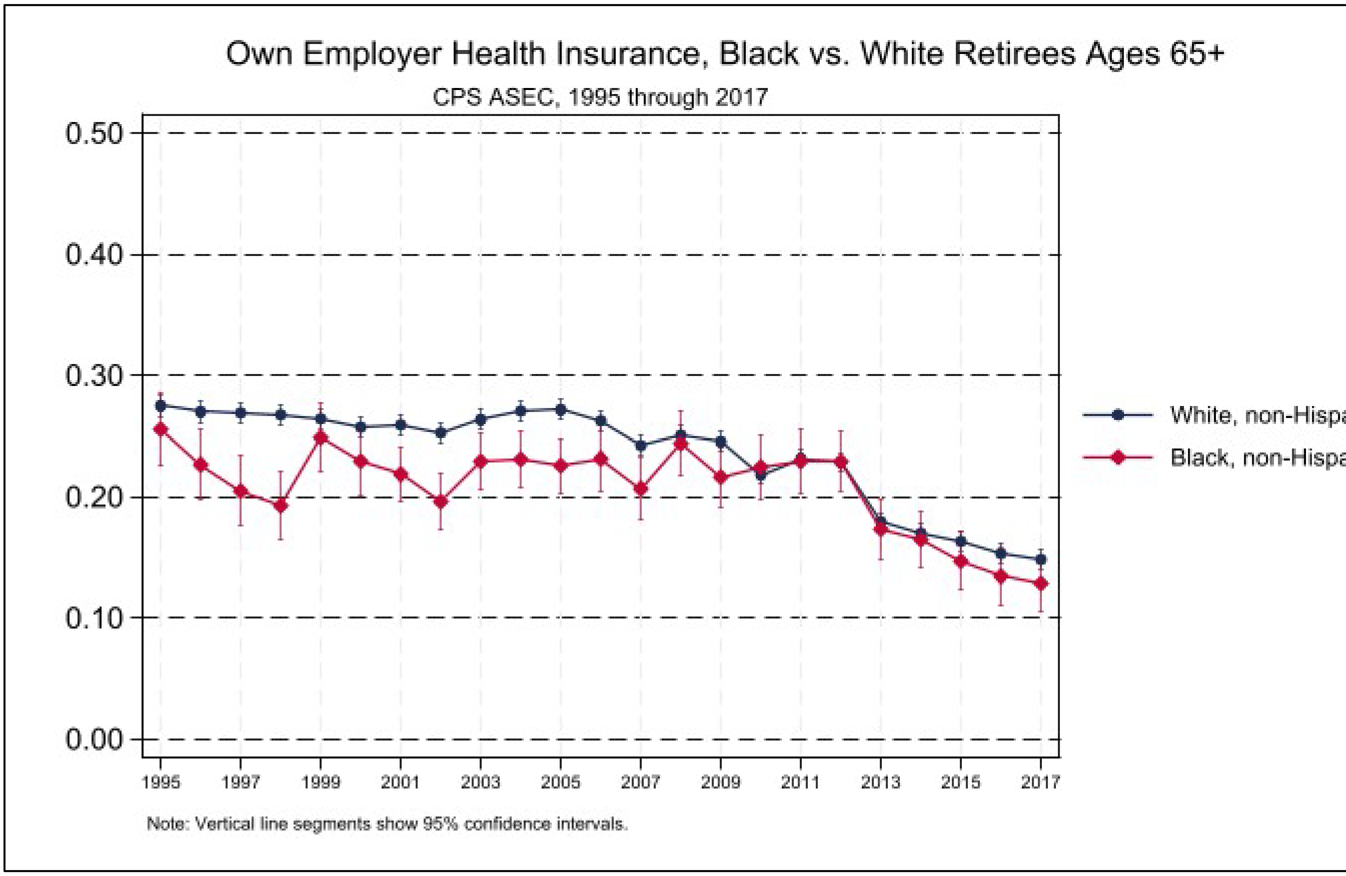


Figure 2: Own Employer health insurance, Black versus white retirees ages 65+

CPS ASEC, 1995 through 2017

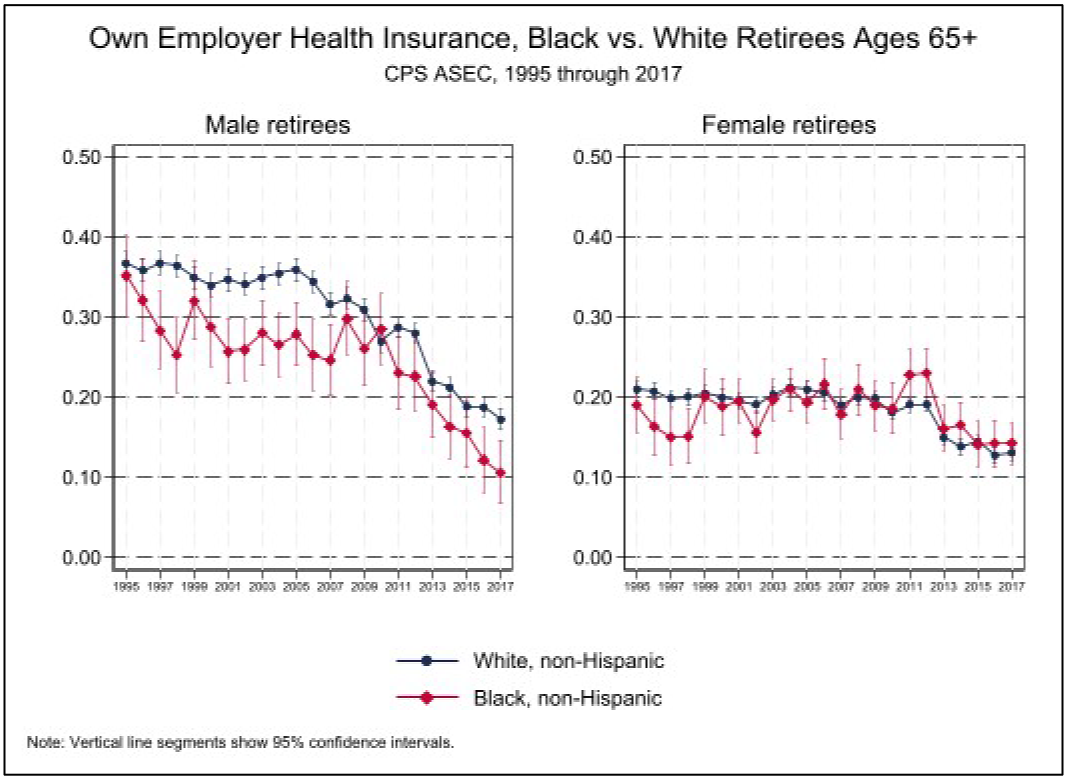


Figure 3: Dependent employer health insurance, Black versus white retirees ages 65+, CPS ASEC, 1995 through 2017

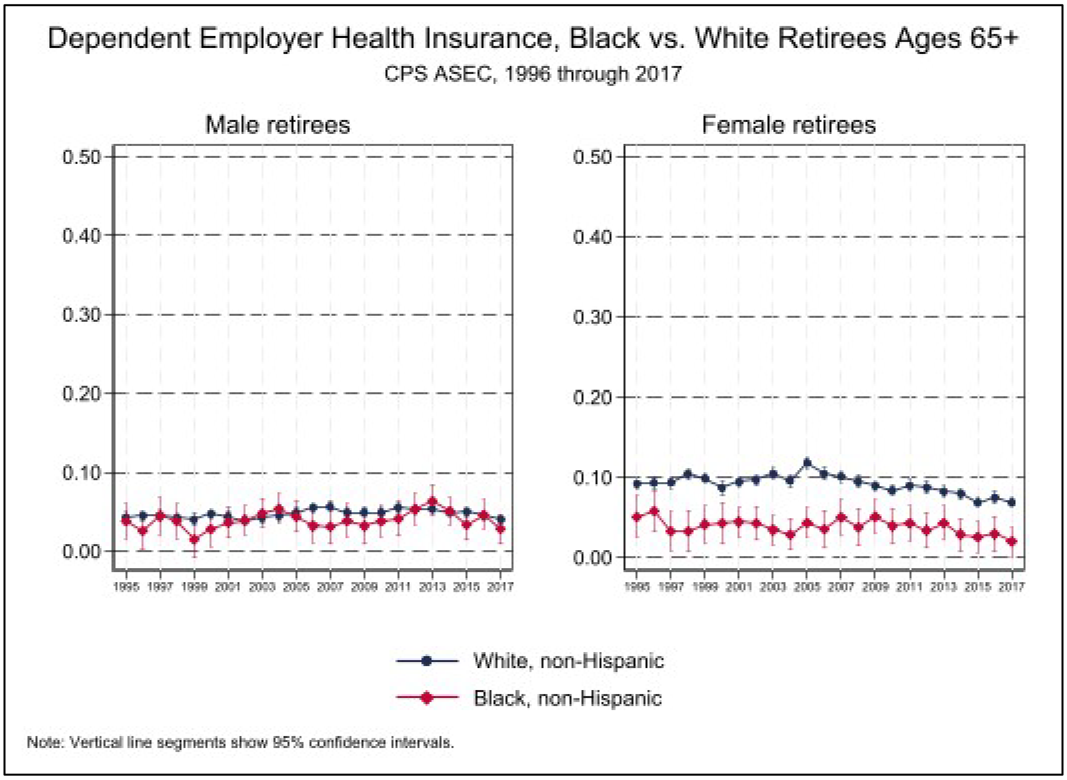


Figure 4: Any employer health insurance, Black versus white retirees ages 65+

CPS ASEC, 1995 through 2017

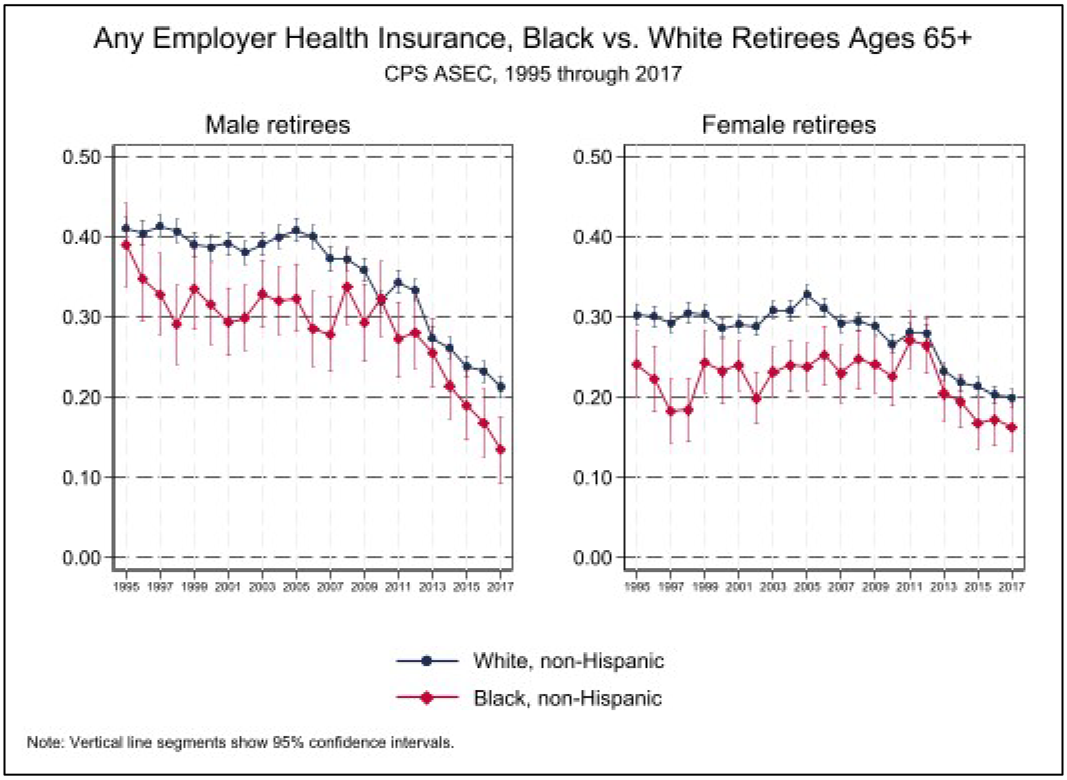


Figure 5: Foregone/delayed medical care, Black versus white retirees ages 65+

NHIS, 2010 through 2018

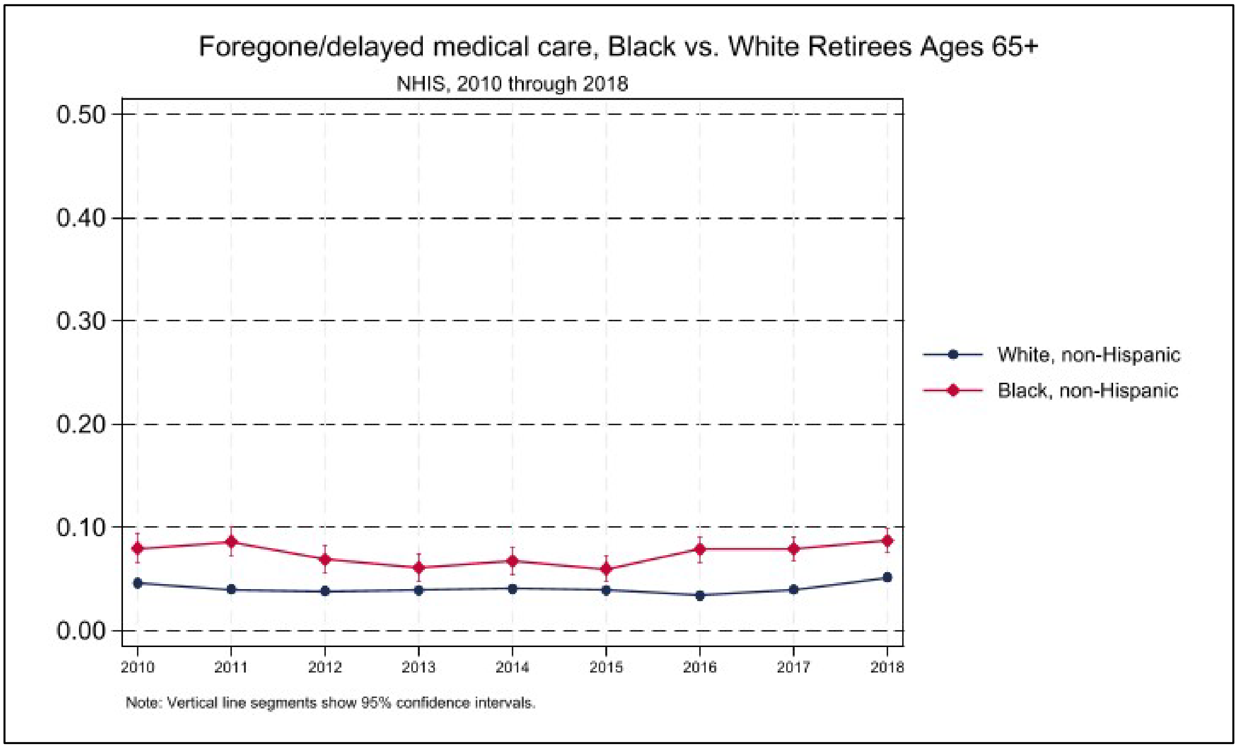
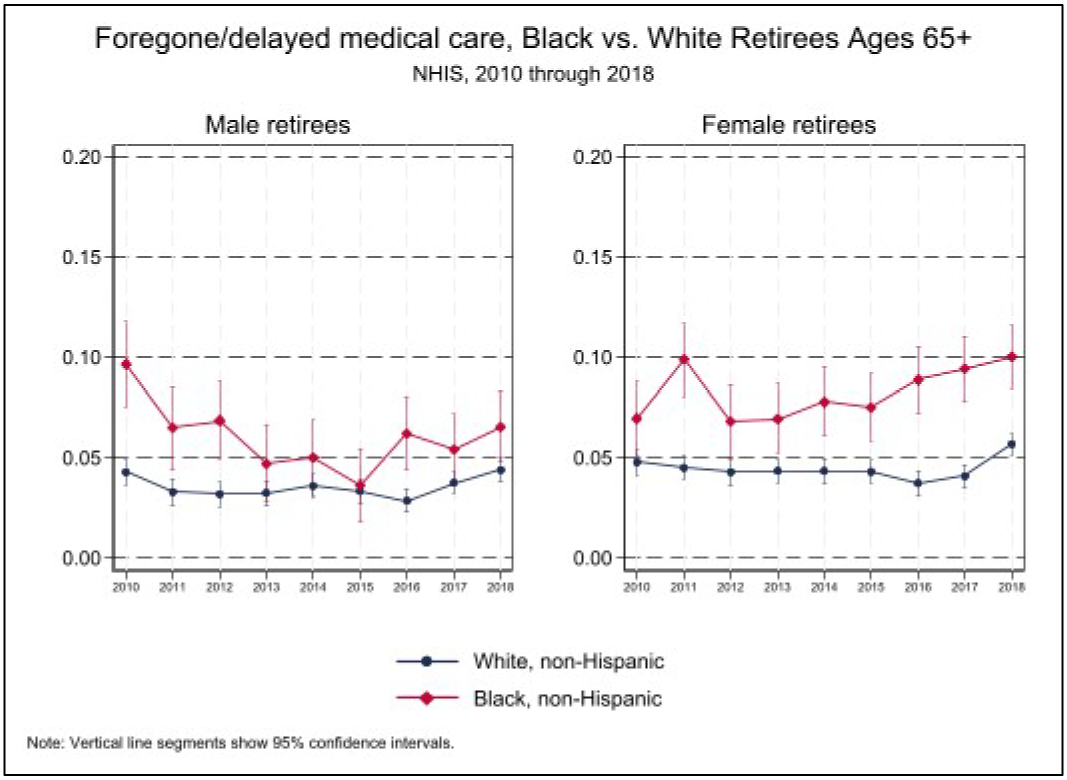


Figure: Foregone/delayed medical care by gender, Black versus white retirees ages 65+, NHIS, 2010 through 2018



Appendix

Table A1: Current Population Survey Annual Social and Economic Supplement, 1988 through 2017, sample size and unweighted distribution by race and gender, retirees ages 65+

	N	White men	Black men	White women	Black women
1995	10,119	0.378	0.024	0.554	0.043
1996	10,332	0.374	0.027	0.554	0.045
1997	10,251	0.384	0.030	0.543	0.044
1998	10,284	0.375	0.030	0.545	0.049
1999	10,107	0.373	0.031	0.543	0.053
2000	9,989	0.374	0.034	0.540	0.052
2001	12,965	0.357	0.048	0.518	0.077
2002	12,681	0.356	0.051	0.514	0.079
2003	12,462	0.365	0.047	0.510	0.079
2004	12,416	0.369	0.046	0.508	0.077
2005	12,102	0.366	0.044	0.515	0.075
2006	12,071	0.359	0.051	0.515	0.076
2007	12,120	0.356	0.050	0.518	0.077
2008	12,233	0.364	0.045	0.516	0.075
2009	12,670	0.372	0.047	0.503	0.078
2010	12,393	0.361	0.050	0.508	0.080
2011	12,566	0.371	0.047	0.509	0.073
2012	12,886	0.368	0.051	0.500	0.081
2013	13,174	0.369	0.050	0.503	0.078
2014	13,457	0.368	0.053	0.495	0.084
2015	12,745	0.368	0.054	0.492	0.086
2016	13,235	0.370	0.055	0.491	0.083
2017	13,712	0.361	0.060	0.488	0.091

Table A2: Sample size and unweighted distribution by race and gender, National Health Interview Survey, 2010 through 2018, retirees ages 65+

	N	White men	Black men	White women	Black women
2010	7,213	0.347	0.066	0.483	0.105
2011	8,760	0.371	0.057	0.484	0.088
2012	9,464	0.374	0.055	0.483	0.088
2013	9,736	0.370	0.059	0.481	0.091
2014	10,968	0.377	0.050	0.493	0.080
2015	10,637	0.379	0.051	0.485	0.084
2016	11,729	0.399	0.038	0.503	0.061
2017	9,575	0.393	0.042	0.502	0.064
2018	9,153	0.391	0.044	0.498	0.067

Table A3: Coefficients on covariates, Black-white gaps in economic outcomes for retirees 65 and older, outcome = own employer-sponsored retiree health insurance

	(1) Women & Men No controls	(2) Women & Men Includes controls	(3) Women No controls	(4) Women Includes controls	(5) Men No controls	(6) Men Includes controls
Black	-0.027***	-0.009***	-0.003	-0.002	-0.058***	-0.025***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)
Female		-0.112***				
		(0.002)				
Married		-0.037***		-0.083***		0.032***
		(0.002)		(0.002)		(0.003)
HS		0.071***		0.064***		0.084***
		(0.002)		(0.003)		(0.004)
Some coll.		0.101***		0.093***		0.114***
		(0.003)		(0.003)		(0.004)
College+		0.171***		0.176***		0.166***
		(0.003)		(0.003)		(0.004)
Age		-0.002		-0.005		0.001
		(0.003)		(0.004)		(0.005)
Age^2		-0.000		0.000		-0.000
		(0.000)		(0.000)		(0.000)
Observations	260,214	260,214	152,810	152,810	107,404	107,404

Notes: Standard errors in parentheses; * p<0.05, ** p<0.01, *** p<0.001. Survey year dummies not reported. See also notes for Table 2

Table A3: Coefficients on covariates, Black-white gaps in economic outcomes for retirees 65 and older, outcome = own employer-sponsored retiree health insurance

	(1) Women & Men No controls	(2) Women & Men Includes controls	(3) Women No controls	(4) Women Includes controls	(5) Men No controls	(6) Men Includes controls
Black	-0.027***	-0.009***	-0.003	-0.002	-0.058***	-0.025***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)
Female		-0.112***				
		(0.002)				
Married		-0.037***		-0.083***		0.032***
		(0.002)		(0.002)		(0.003)
HS		0.071***		0.064***		0.084***
		(0.002)		(0.003)		(0.004)
Some coll.		0.101***		0.093***		0.114***
		(0.003)		(0.003)		(0.004)
College+		0.171***		0.176***		0.166***
		(0.003)		(0.003)		(0.004)
Age		-0.002		-0.005		0.001
		(0.003)		(0.004)		(0.005)
Age^2		-0.000		0.000		-0.000
		(0.000)		(0.000)		(0.000)
Observations	260,214	260,214	152,810	152,810	107,404	107,404

Notes: Standard errors in parentheses; * p<0.05, ** p<0.01, *** p<0.001. Survey year dummies not reported. See also notes for Table 2.

Table A4: Coefficients on covariates, Black-white gaps in economic outcomes for retirees 65 and older, outcome = employer-sponsored retiree health insurance as a dependent

	(1)	(2)	(3)	(4)	(5)	(6)
	Women & Men	**Women & Men**	Women	Women	Men	Men
	No **controls**	**Includes controls**	No **controls**	**Includes controls**	No **controls**	**Includes controls**
Black	-0.036***	-0.007***	-0.056***	-0.012***	-0.008**	0.004
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Female		0.086***				
		(0.001)				
Married		0.169***		0.224***		0.085***
		(0.001)		(0.002)		(0.002)
HS		0.014***		0.019***		0.003
		(0.001)		(0.002)		(0.002)
Some coll.		0.011***		0.018***		0.003
		(0.002)		(0.002)		(0.002)
College+		0.015***		0.024***		0.007**
		(0.002)		(0.002)		(0.002)
Age		-0.026***		-0.017***		-0.034***
		(0.002)		(0.003)		(0.003)
Age^2		0.000***		0.000***		0.000***
		(0.000)		(0.000)		(0.000)
Observations	260,214	260,214	152,810	152,810	107,404	107,404

Notes: Standard errors in parentheses; * p<0.05, ** p<0.01, *** p<0.001. Survey year dummies not reported. See also notes for Table 2

Table A5: Coefficients on covariates, Black-white gaps in economic outcomes for retirees 65 and older, outcome = any employer-sponsored retiree health insurance

	(1) Women & Men No controls	(2) Women & Men Includes controls	(3) Women No controls	(4) Women Includes controls	(5) Men No controls	(6) Men Includes controls
Black	-0.061***	-0.020***	-0.056***	-0.018***	-0.066***	-0.025***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)
Female		-0.031***				
		(0.002)				
Married		0.105***		0.112***		0.095***
		(0.002)		(0.002)		(0.003)
HS		0.081***		0.080***		0.084***
		(0.002)		(0.003)		(0.004)
Some coll.		0.112***		0.110***		0.116***
		(0.003)		(0.003)		(0.004)
College+		0.179***		0.193***		0.167***
		(0.003)		(0.004)		(0.004)
Age		-0.027***		-0.020***		-0.033***
		(0.003)		(0.004)		(0.006)
Age^2		0.000***		0.000***		0.000***
		(0.000)		(0.000)		(0.000)
Observations	260,214	260,214	152,810	152,810	107,404	107,404

Notes: Standard errors in parentheses; * p<0.05, ** p<0.01, *** p<0.001. Survey year dummies not reported. See also notes for Table 2

Table A6: Coefficients on covariates, Black-white gaps in economic outcomes for retirees 65 and older, outcome = delayed/foregone health care due to cost

	(1) Includes Women & Men No controls	(2) Includes Women & Men Includes controls	(3) Women No controls	(4) Women Includes controls	(5) Men No controls	(6) Men Includes controls
Black	0.033***	0.018***	0.039***	0.022***	0.024***	0.009**
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Female		0.002				
		(0.001)				
Married		-0.040***		-0.046***		-0.034***
		(0.001)		(0.002)		(0.002)
HS		-0.024***		-0.019***		-0.030***
		(0.002)		(0.003)		(0.003)
Some coll.		-0.015***		-0.007*		-0.027***
		(0.002)		(0.003)		(0.003)
College+		-0.036***		-0.036***		-0.039***
		(0.002)		(0.003)		(0.003)
Age		-0.019***		-0.017***		-0.022***
		(0.003)		(0.004)		(0.004)
Age^2		0.000***		0.000***		0.000***
		(0.000)		(0.000)		(0.000)
Observations	87,235	85,882	49,743	48,936	37,492	36,946

Notes: Standard errors in parentheses; * p<0.05, ** p<0.01, *** p<0.001. Survey year dummies not reported. See also notes for Table 2.