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Decomposing racial/ethnic disparities in influenza vaccination among the elderly

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ABSTRACT

While persistent racial/ethnic disparities in influenza vaccination have been reported among the elderly, characteristics contributing to disparities are poorly understood. This study aimed to assess characteristics associated with racial/ethnic disparities in influenza vaccination using a nonlinear Oaxaca–Blinder decomposition method. We performed cross-sectional multivariable logistic regression analyses for which the dependent variable was self-reported receipt of influenza vaccine during the 2010–2011 season among community dwelling non-Hispanic African–American (AA), non-Hispanic White (W), English-speaking Hispanic (EH) and Spanish-speaking Hispanic (SH) elderly, enrolled in the 2011 Medicare Current Beneficiary Survey (MCBS) (un-weighted/weighted $N = 6{,}095/19.2$million). Using the nonlinear Oaxaca–Blinder decomposition method, we assessed the relative contribution of seventeen covariates – including socio-demographic characteristics, health status, insurance, access, preference regarding healthcare, and geographic regions – to disparities in influenza vaccination. Unadjusted racial/ethnic disparities in influenza vaccination were 14.1 percentage points (pp) (W–AA disparity, $p < 0.001$), 25.7 pp (W–SH disparity, $p < 0.001$) and 0.6 pp (W–EH disparity, $p > .8$). The Oaxaca–Blinder decomposition method estimated that the unadjusted W–AA and W–SH disparities in vaccination could be reduced by only 45% even if AA and SH groups become equivalent to Whites in all covariates in multivariable regression models. The remaining 55% of disparities were attributed to (a) racial/ethnic differences in the estimated coefficients (e.g., odds ratios) in the regression models and (b) characteristics not included in the regression models. Our analysis found that only about 45% of racial/ethnic disparities in influenza vaccination among the elderly could be reduced by equalizing recognized characteristics among racial/ethnic groups. Future studies are needed to identify additional modifiable characteristics causing disparities in influenza vaccination.

1. Introduction

Racial/ethnic disparities in influenza vaccination among US elderly remain [1] despite the fact that Medicare coverage has eliminated out-of-pocket expenditures for influenza vaccination since 1993 [2]. The "unadjusted" influenza vaccination rate during the 2012–2013 was 67.9% among non-Hispanic white Medicare elderly (aged 65 or older), which was 13.4 and 2.1 percentage points (pp) higher than non-Hispanic African–American and Hispanic elderly, respectively [3].

Past studies have revealed racial/ethnic disparities in influenza vaccination, after adjusting for various observable characteristics in multiple regression models, such as socioeconomic status and health status [4–9]. However, these empirical studies have not measured the degree to which these known covariates contribute to disparities.

A statistical technique – the Oaxaca–Blinder decomposition (OB) method [10–12] – enables us to decompose the influenza vaccination disparities into (a) the disparity that stems from differences in observable characteristics (e.g., income or health insurance) across racial/ethnical groups, and (b) the disparity due to the different effects of these characteristics across racial/ethnic groups, which are represented by the differences in the regression coefficients. Equalizing the observable characteristics can eliminate the former disparity but not the latter. This latter disparity may be partly due to different effects of these characteristics across

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racial/ethnic groups – e.g., the different effects of income on vaccination across racial/ethnic groups. There has been limited use of the OB method, particularly the non-linear BO method, in health care fields [13–15]. To the best of our knowledge, our study is the first to apply the Oaxaca–Blinder decomposition method for quantifying sources of disparities in any type of vaccination. We hypothesized that even if known covariates were equalized across racial/ethnical groups, disparities in influenza vaccination would remain, suggesting that other unmeasured factors (perhaps related to health system factors) might play a role.

2. Methods

Since the Oaxaca–Blinder (OB) decomposition method has not been widely used in health services research, this section explains the general concept of the OB decomposition, followed by the empirical analytical methods used to address the present study's specific research question.

2.1. Oaxaca–Blinder decomposition (OB) method

One major distinction between a simple regression model and an OB method is that the former simple model is applied among a population including both W and AA groups, when examining a potential disparity in a dependent variable between these two groups. The simple regression model concludes the presence of a racial disparity when the coefficient of a race variable is estimated to be statistically different from zero, after controlling for other covariates in the same regression model. This simple regression model usually does not include an interaction term between a race variable and each covariate, but rather implicitly assumes that the effect of each covariate (e.g., insurance) is the same between the two groups (e.g., White and African American elderly). On the other hand, an OB method runs two regression models for each of the W and AA groups. Conceptually, these regressions are equivalent to the simple regression model with additional interaction terms between a race variable and each covariate. The differences in the coefficients partly explain the disparity of the dependent variable. The OB method is further explained in the Appendix with mathematical equations.

2.2. Specific analytical method

We conducted a cross-sectional analysis in 2014, using 2011 Medicare Current Beneficiary Surveys (MCBS) [16]. The study population included community dwelling non-Hispanic African–American (AA), non-Hispanic white (White/W), and Hispanic Medicare beneficiaries (aged 65 or older, unweighted/weighted $N = 6{,}095/19.2$ million). Since past studies indicated that White–Hispanic disparities are largely explained by language differences among the elderly and middle-aged populations [5,6,17], we also distinguished English-speaking Hispanic (EH) and Spanish-speaking Hispanic (SH) beneficiaries based on whether Spanish was used in a MCBS interview.

Following the OB method [10,11], we first ran the multivariable logistic model where the dependent variable was self-reported receipt of influenza vaccine during the 2010–2011 season, for each of four racial/ethnic groups. The included covariates were classified into (a) predisposing characteristics (e.g., demographics), (b) enabling characteristics (e.g., Medicare Health Maintenance Organization (HMO)) and (c) need-related characteristics (e.g., health status), listed in Table 1, following the Andersen's behavioral model [18] previously applied to influenza vaccination [5,17]. Using the regression results, we then computed the contribution to disparities from each covariate [12,19,20]. All analyses used STATA [21].

This study's protocol was approved by the IRB at University of California, Davis.

3. Results

Table 1 summarizes observed characteristics across racial/ethnic groups in this study. The influenza vaccination rate among White enrollees was 75.7%. Unadjusted racial/ethnic disparities in influenza vaccination were 14.1 pp (W–AA disparity, $p < 0.001$) and 25.7 pp (W–SH, $p < 0.001$). Because of a statistically insignificant W–EH disparity (0.6 pp; $p > 0.8$), we do not present its decomposition analysis results in Tables 2 and 3 (results are available upon request).

Table 1 also shows that there was no statically significant difference in all of the need-related characteristics, i.e., health conditions, across the four racial/ethnic groups. On the other hand, these racial/ethnic groups significantly differed regarding most of the predisposing characteristics and all of the enabling characteristics. As an example, the proportion having private supplemental insurance and a regular physician was highest among the W group, followed by the EH group, the AA group and the SH group ($p < 0.02$). Conversely, the proportion of enrollment in Medicare HMO and Medicaid was highest among the SH group, followed by the EH group or the AA group ($p < 0.01$).

Table 2 presents coefficient (odds ratio) estimates across racial/ethnic groups in multivariable logistic regression models. This table indicates that the association between a certain covariate and the dependent variable could vary substantially across racial/ethnic groups. For instance, age, private supplemental insurance and highest income category (≥$40,000) are estimated to have a statistically positive association ($p < 0.01$) only among the White group. On the other hand, "avoiding medical care when sick" has a comparable association in terms of its sign, statistical significance ($p < 0.01$) and magnitude across the three groups included in Table 2.

Table 3 indicates the results of the decomposition analysis for each of the three pairs of racial/ethnic disparities in influenza vaccination. This table's top panel (three rows) shows the aggregated decomposition results, e.g., the W–AA disparity (14.1 pp) was decomposed to difference-in-characteristics-attributable disparity (6.0 pp) and difference in-coefficients-attributable disparity (8.1 pp). These two components account for 42.39% (=6.0 pp/14.1 pp) and 57.61% (=8.1 pp/14.1 pp) of the disparity, respectively, as shown in the column "Share." These results imply that the W–AA disparity in vaccination could be reduced by only 42.39% even if the AA group becomes equivalent to Whites in all the covariates in the regression models. Likewise, the W–SH disparity could be reduced by, at most, 47.74% even if the SH group becomes equivalent to Whites in all the covariates.

Table 3's middle panel (Due to difference-in-characteristics) reports the detailed decomposition contributed by the racial/ethnic differences in each covariate. For instance, the W–AA difference in mean proportion of high school graduation (W = 83.3% and AA = 53.4% in Table 1) was attributed to 1.2 pp among the 14.1 pp total W–AA disparity in vaccination, i.e., its "share" is 8.54% (=1.2 pp/14.1 pp). On the other hand, the W–AA difference in the mean proportion of "Medicare HMO" (W = 27.3% and AA = 39.0% in Table 1) was attributed to the *reduction* in the W–AA vaccination disparity with a "share" of 3.44%. Among all the characteristics in Table 3, annual income categories had the largest magnitude of contributions due to "difference-in-characteristics." Aggregating three income categories (including the reference income group), the differences in the income levels account for 3.3 pp out of 14.1pp (the share of 23.58%). Second to the income categories, having supplemental private insurance has a magnitude of 2.2 pp with a "share" of 15.60%.