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Journal
Vaccine, 33(26)

ISSN
0264-410X

Authors
Yoo, Byung-Kwang
Hasebe, Takuya
Szilagyi, Peter G

Publication Date
2015-06-01

DOI
10.1016/j.vaccine.2015.03.054

Peer reviewed

HHS Public Access

Author manuscript

Vaccine. Author manuscript; available in PMC 2016 June 12.

Published in final edited form as:

Vaccine. 2015 June 12; 33(26): 2997–3002. doi:10.1016/j.vaccine.2015.03.054.

Decomposing Racial/Ethnic Disparities in Influenza Vaccination among the Elderly

Byung-Kwang Yoo, MD, PhD[a], **Takuya Hasebe, PhD**[a], and **Peter G. Szilagyi, MD, MPH**[b]

Byung-Kwang Yoo: byoo@ucdavis.edu; Takuya Hasebe: thasebe@ucdavis.edu; Peter G. Szilagyi: pszilagyi@mednet.ucla.edu

[a]Department of Public Health Sciences, University of California Davis School of Medicine, Davis, CA, USA One Shields Ave. Medical Sciences 1C, Davis, CA 95616, U.S.A

[b]Department of Pediatrics, University of California Los Angeles (UCLA), Los Angeles, U.S.A. 10833 LeConte Avenue, Los Angeles, CA, USA

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= 6,095/19.2million). 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<.001), 25.7 pp (W-SH disparity, p<.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

Contact information for the corresponding author at all stages of refereeing and publication, also post-publication: Byung-Kwang Yoo, M.D., M.S., Ph.D., University of California Davis, School of Medicine, Department of Public Health Sciences, One Shields Ave. Medical Sciences 1C, Davis, CA 95616, U.S.A., Phone: +1-530-752-6375, Fax: +1-530-752-3239, byoo@ucdavis.edu, 2nd yoobk3@gmail.com.

Conflict of interest:

None of the authors have any possible conflict of interest to disclose.

Statement of Authors' Contributions

B.K. Yoo conceived and supervised the study and led the writing.

T. Hasebe assisted with the conceptualization of the study and the writing, and completed the empirical analyses.

P. Szilagyi assisted with the conceptualization of the study and the writing.

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.

Keywords

influenza vaccination; racial/ethnic disparities; elderly population; non-linear Oaxaca-Blinder decomposition method

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 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.

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.

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.

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, un-weighted/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.

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<.001) and 25.7 pp (W-SH, p<.001). Because of a statistically insignificant W-EH disparity (0.6 pp; p>.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 ($p<.02$). 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 ($p<.01$).

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<.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<.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/ethnical 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%.

Table 3's middle panel also indicates that the observable characteristics had a similar attribution to both W-AA and W-SH disparities, in terms of "share," in explaining disparities due to the difference-in-characteristics. For example, higher income had the largest "share" (about 21–23%) in exacerbating disparities, followed by supplemental private insurance (about 15%), high school graduation (around 7–8%) and having a regular physician (approximately 4–7%).

Table 3's bottom panel reports the detailed decomposition of the disparity contributed by the differences in the estimated coefficient (i.e., odds ratios (OR)) on each covariate in the logistic regression models summarized in Table 2. For instance, the estimated coefficient of having a "regular physician" was greater among White (OR=2.77 in Table 2), in terms of increasing the likelihood of the vaccine receipt, compared to that among AA (OR=1.33), which led to an increase of the W-AA disparity by 6.6 pp (i.e., the largest "share" of 47.09%, except the constant term). The "share" of the constant term indicates that out of the unadjusted total W-AA disparity in vaccination (14.1 pp), 48.22% (=6.8 pp/14.1 pp) was still unexplained by observable characteristics included in the regression model.

Table 3's bottom panel shows that the covariates (in the logistic regression models in Table 2) had different attributions to the W-SH disparity, compared to those to the W-AA disparity, concerning share in explaining disparities due to the difference-in-coefficients (odds ratio), i.e., coefficient effects. For instance, the attribution of "the coefficient effect of having a regular physician" had the largest share (47.09%) in exacerbating the W-AA disparity and the fourth largest share (4.37%) in exacerbating the W-SH disparity. On the other hand, the attribution of residential regions had the largest share (42.68%) in worsening the W-SH disparity and a very small share (0.76%) in "reducing" (not worsening) the W-AA disparity among coefficient effects.

Discussion

This decomposition analysis found that only about 45% of both W-AA and W-SH disparities in influenza vaccination among the elderly could be reduced by equalizing commonly observable characteristics among racial/ethnic groups. The present study's detailed OB method provides unique contributions to the literature by quantifying the extent to which specific advances in clinical care or policy could reduce disparities in influenza vaccination rates. For instance, strategies that might (a) equalize the proportion of patients who have a regular physician (e.g., by increasing the number of primary care physicians and the reimbursement for these physicians) or (b) equalize the proportion with private supplemental insurance (e.g., using public subsidies to purchase private supplemental insurance), could potentially reduce W-AA disparities by 2.8 pp or 19.79% (=(0.6+2.2) pp/14.1 pp). Also, the W-AA disparity could be further reduced by (c) increasing Medicaid enrollment among the AA group (e.g., expanding Medicaid eligibility), and (d) increasing Medicare HMO enrollment among the AA group to increase the influenza vaccination rates among enrollees. These policy implications are equally applicable for the W-SH disparities.

Out of these policy implications, Medicaid eligibility expansion and public subsidies for purchasing private supplemental insurance may reduce racial/ethnic disparities in incomes levels, a proxy for the financial barrier in healthcare access, which had a larger "share" (22%–24%) in our decomposition analysis. Additionally, increased proportion of patients with a regular physician would increase a chance for a patient to obtain knowledge about the importance of influenza vaccination from a physician. Consequent, this may mitigate the racial/ethnic disparities in education, a proxy for knowledge about healthcare in general, which also had a large "share" (7%–8%) in our decomposition analysis. Thus our novel model provides a "ceiling effect" to estimate the degree to which specific interventions might reduce disparities. Such policy implications with specific quantified goals are not provided by conventional simple regression analyses.

In terms of share in explaining disparities due to the difference-in-characteristics, the observable characteristics had a similar attribution to both W-AA and W-SH disparities. Conversely, regarding share in explaining disparities due to the difference-in-coefficients (odds ratio), the observable characteristics had variable attributions to W-AA and W-SH disparities. The attribution of a regular physician had the largest share (47%) in exacerbating the W-AA disparity and the fourth largest share (4.37%) in exacerbating W-SH disparity. These results are due to the smaller positive association between having a regular physician and vaccination among minorities, compared to that among Whites. Further studies are needed to assess why having a regular physician appears to have a greater effect for Whites than minorities with respect to influenza vaccinations.

Although not reported earlier, we chose the set of income categories in our final logit models in Table 2 against an alternative set of income categories (with different cut-off levels of $10,000 and $50,000) because of the following two reasons. First, the alternative set of income categories weakened the statistical significance level of the estimated coefficients for these income categories. Second, we selected the presented set of income categories based on the measures of goodness-of-fit for logit models, including Akaike Information Criterion and Bayesian Information Criterion.

The major limitation is that the findings are dependent on the comprehensiveness of covariates. Fortunately, this dataset contains large numbers of predisposing, enabling, and need-related, factors. Nevertheless, a large attribution of the constant (48% in share for W-AA and 79% for W-SH disparities) indicates the need for additional characteristics to be included in future studies. Examples might include more detailed information about healthcare providers, Medicaid programs, vaccine supply and household members [6, 22–24], which were not available in this dataset. Another minor limitation is collinearity among private insurance and income variables, which are likely to capture similar financial barriers. Because the correlation rates among these variables ranged from (−)0.39 (between the private insurance and a lower income category) to 0.48 (between the private insurance and a higher income category), the collinearity issue does not seem serious in terms of increasing standard errors for the estimated ORs.

In sum, our estimates based on the OB method are useful by quantifying the feasible goals of reducing disparities in influenza vaccination based on the currently available information and by highlighting the need to identify additional modifiable factors leading to disparities in influenza vaccinations.

Acknowledgments

We thank Tomoko Sasaki, PhD, for her literature search and editing.

Financial disclosure:

Supported by National Institutes of Health (NIH)/National Institute on Aging (NIA) Grant #: R03AG042646.

Appendix

The detailed explanation of

Although we performed the newly developed extension of "nonlinear" OB method, we start with describing the "linear" OB method in the context of the White (W)-African American (AA) disparity in order to explain the essence of the OB method.

The linear Oaxaca-Blinder decomposition can be written as

$$\bar{y}^{W}-\bar{y}^{AA}=\sum_{k=1}^{K}(\overline{X}_{k}^{W}-\overline{X}_{k}^{AA})\widehat{\beta}_{k}^{AA}+\sum_{k=1}^{K}\overline{X}_{k}^{W}(\widehat{\beta}_{k}^{W}-\widehat{\beta}_{k}^{AA})$$

where the superscripts W and AA stand for the race groups, $\bar{y}$ is the outcome of interest averaged over each group, and $\bar{X}_k$ is the k-th covariate averaged over each group. The coefficients $\hat{\beta}$ are estimated by the ordinary least squares (OLS) regressions from each group. The left-hand side of the equation is the observed disparity in the vaccination rates between White and African American groups. The first summation on the right side of the equation measures (a) the disparity due to the differences in characteristics ("characteristic effect"). The second summation measures (b) the disparity due to the different effects of the observed characteristics ("coefficient effect"). Furthermore, the detailed decomposition subdivides these effects into the contributions of each covariate. Namely, $(\overline{X}_{k}^{W}-\overline{X}_{k}^{AA})\widehat{\beta}_{k}^{AA}$ and $\overline{X}_{k}^{W}(\widehat{\beta}_{k}^{W}-\widehat{\beta}_{k}^{AA})$ measure the contribution of the k-th covariate into the "characteristic effect" and "coefficient effect," respectively, e.g., the W-AA difference in the insurance coverage level and the differential effects of insurance coverage between these two race groups.

The dependent variable in the present study is influenza vaccine receipt. Since this variable is binary, it is more appropriate to use a logistic model than an OLS model to obtain coefficients. Therefore, the decomposition analysis needs to be nonlinear. The "nonlinear" OB decomposition can be written as

$$\bar{y}^{W}-\bar{y}^{AA}=\left[\overline{F(X^{W}\widehat{\beta}^{W})}-\overline{F(X^{AA}\widehat{\beta}^{W})}\right]+\left[\overline{F(X^{AA}\widehat{\beta}^{W})}-\overline{F(X^{AA}\widehat{\beta}^{AA})}\right]$$

where $\hat{\beta}$ are estimated by logit model, and $F()$ is the cumulative distribution function of the logistic distribution. Note that X and β in this expression are in a vector form. As above, the first square parenthesis measures the "characteristic effect" and the second parenthesis measures the “coefficient effect.” Due to the nonlinearity of the factors, the detailed decomposition is not as straightforward as the “linear” decomposition. The literature has developed different approaches [19, 20]. Some prior studies [13–15] used a non-linear decomposition developed by Fairlie [25]. This approach replaces each covariate of one group with that of the other group to quantify the contribution of each covariate. However, the problem with this approach is that the result changes with the order of the replacement. Our study takes a different approach that linearizes the characteristic and coefficient effects by a first-order Taylor expansion [12].

The detailed decomposition with dummy (categorical) variables entails an identification problem. Specifically, the choice of reference category affects the decomposition. To address this issue, we followed the solution proposed by Yun [19]. To conduct the detailed nonlinear decomposition, we used the user-written Stata’s command “mvcdcmp” [20]. For the statistical inference, we conducted a bootstrap resampling method. Each resampling takes the stratification of the survey into account and iterated 500 times.

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Table 1

Observed Characteristics Across Racial/Ethnic Groups (Mean)[a]

	W[b]	AA[c]	SH[d]	EH[e]	Difference from White (W)					
					AA	P>|z|	SH	P>|z|	EH	P>|z|
Influenza vaccine receipt	0.757	0.616	0.499	0.750	−−0.141	1.9E-09	−0.257	<1.0E-09	−0.006	8.2E-01
(a) Predisposing characteristics										
Female	0.550	0.591	0.563	0.539	0.041	6.4E-02	0.012	7.0E-01	−0.011	7.2E-01
Age (>74)	0.443	0.405	0.439	0.384	−0.037	9.8E-02	−0.004	8.9E-01	−0.058	5.1E-02
High school[f]	0.833	0.534	0.383	0.581	−0.299	<1.0E-09	−0.450	<1.0E-09	−0.252	1.5E-08
Avoid med care[g]	0.254	0.267	0.342	0.286	0.013	5.7E-01	0.088	3.9E-03	0.031	3.8E-01
Household size[h]	1.867	2.066	2.452	2.471	0.199	3.4E-04	0.584	1.7E-09	0.603	8.6E-08
Metropolitan[i]	0.743	0.822	0.975	0.888	0.078	1.1E-01	0.232	<1.0E-09	0.145	1.8E-04
Region: Midwest	0.252	0.152	0.020	0.107	−0.101	7.5E-04	−0.232	<1.0E-09	−0.146	2.8E-06
Region: South	0.351	0.595	0.663	0.289	0.244	7.0E-09	0.312	7.8E-15	−0.062	2.8E-01
Region: West	0.202	0.077	0.211	0.494	−0.125	3.2E-09	0.009	8.1E-01	0.292	1.7E-04
(b) Enabling characteristics										
Medicare HMO[j]	0.273	0.390	0.579	0.438	0.117	8.7E-07	0.306	<1.0E-09	0.165	2.6E-07
Medicaid	0.066	0.273	0.328	0.228	0.207	4.4E-16	0.262	4.5E-13	0.162	2.6E-07
Private insurance	0.606	0.326	0.121	0.381	−0.281	<1.0E-09	−0.485	<1.0E-09	−0.226	2.1E-14
Income (<$15,000)	0.204	0.509	0.726	0.346	0.305	<1.0E-09	0.522	<1.0E-09	0.142	3.1E-05
Income (≥$40,000)	0.390	0.155	0.058	0.247	−0.234	<1.0E-09	−0.331	<1.0E-09	−0.143	1.4E-05
Regular physician	0.950	0.919	0.860	0.919	−0.031	1.7E-02	−0.090	5.2E-06	−0.031	1.2E-01
(c) Need-related characteristics										
ADL limitation[k]	0.255	0.286	0.302	0.293	0.031	1.0E-01	0.047	2.7E-01	0.038	2.5E-01
IADL limitation[l]	0.247	0.273	0.289	0.290	0.026	3.0E-01	0.042	2.1E-01	0.043	1.9E-01
Chronic disease	0.627	0.666	0.657	0.663	0.039	9.2E-02	0.030	2.8E-01	0.036	2.4E-01

[a] Sample size for each racial ethnic group (un-weighted/weighted N): W (4999/15.98 million), AA (538/1.55 million), SH (286/0.79 million), and EH (272/0.92 million).

[b] W = non-Hispanic White

[c] AA = non-Hispanic African American

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[d] SH = Spanish-speaking Hispanic

[e] EH = English-speaking Hispanic

[f] High School = 1 if having a high school diploma; = 0 otherwise

[g] Avoid med care = 1 if avoiding medical care when sick; = 0 otherwise

[h] Household size = continuous variable (≥1)

[i] Metropolitan = 1 if residing in a metropolitan area; = 0 otherwise

[j] Medicare HMO = 1 if enrolled in Medicare Health Maintenance Organization (HMO); = 0 otherwise

[k] ADL limitation = 1 if a subject has at least one limitation in Activities of Daily Living (ADL); = 0 otherwise

[l] IADL limitation = 1 if a subject has at least one limitation in Instrumental Activities of Daily Living (IADL); = 0 otherwise

Table 2

Coefficient (Odds Ratio (OR)) Estimates Across Racial/Ethnic Groups in Multivariable Logistic Regression Models (Dependent variable = self-reported influenza vaccine receipt during the 2010–2011 season)[a,b]

	White[c]			AA[d]			SH[e]		
	OR	95% C.I.	P>|z|	OR	95% C.I.	P>|z|	OR	95% C.I.	P>|z|
(a) Predisposing characteristics									
Female	1.14	(0.97, 1.34)	1.2E-01	1.04	(0.69, 1.59)	8.4E-01	0.75	(0.44, 1.27)	2.9E-01
Age (>74)	1.53	(1.35, 1.74)	<1.0E-09	1.23	(0.78, 1.93)	3.8E-01	1.48	(0.90, 2.44)	1.3E-01
High school[f]	1.24	(1.00, 1.54)	5.5E-02	1.14	(0.72, 1.80)	5.7E-01	1.39	(0.67, 2.87)	3.8E-01
Avoid med care[g]	0.61	(0.52, 0.73)	<1.0E-09	0.49	(0.29, 0.84)	1.0E-02	0.43	(0.26, 0.72)	2.0E-03
Household size[h]	0.97	(0.88, 1.06)	5.3E-01	1.00	(0.85, 1.18)	9.8E-01	1.09	(0.93, 1.28)	2.7E-01
Metropolitan[i]	1.03	(0.83, 1.28)	7.8E-01	1.02	(0.51, 2.02)	9.6E-01	1.61	(0.79, 3.25)	1.9E-01
Region: Midwest	1.00	(0.76, 1.33)	9.8E-01	0.98	(0.53, 1.83)	9.6E-01	0.31	(0.05, 2.10)	2.4E-01
Region: South	0.97	(0.72, 1.32)	8.6E-01	1.18	(0.68, 2.03)	5.6E-01	0.15	(0.04, 0.51)	4.0E-03
Region: West	0.78	(0.58, 1.05)	1.1E-01	1.19	(0.42, 3.39)	7.4E-01	0.27	(0.08, 0.94)	4.3E-02
(b) Enabling characteristics									
Medicare HMO[j]	1.25	(1.01, 1.54)	4.0E-02	1.64	(1.05, 2.55)	3.2E-02	1.10	(0.54, 2.25)	7.8E-01
Medicaid	1.10	(0.80, 1.52)	5.6E-01	0.89	(0.52, 1.54)	6.8E-01	1.90	(0.95, 3.82)	7.6E-02
Private insurance	1.52	(1.26, 1.84)	<1.0E-09	1.37	(0.81, 2.29)	2.4E-01	1.75	(0.90, 3.40)	1.1E-01
Income (<$15,000)	0.72	(0.58, 0.90)	5.0E-03	0.98	(0.61, 1.58)	9.4E-01	1.15	(0.57, 2.29)	7.0E-01
Income (≥$40,000)	1.40	(1.18, 1.66)	<1.0E-09	1.46	(0.74, 2.87)	2.7E-01	0.53	(0.15, 1.91)	3.3E-01
Regular physician	2.77	(2.05, 3.74)	<1.0E-09	1.33	(0.63, 2.78)	4.6E-01	2.42	(0.99, 5.89)	5.6E-02
(c) Need-related characteristics									
ADL limitation[k]	1.11	(0.91, 1.34)	3.1E-01	1.20	(0.73, 1.97)	4.7E-01	0.97	(0.48, 1.95)	9.4E-01
IADL limitation[l]	1.07	(0.87, 1.32)	5.3E-01	1.27	(0.77, 2.10)	3.6E-01	1.31	(0.73, 2.37)	3.7E-01
Chronic disease	1.57	(1.32, 1.85)	<1.0E-09	2.91	(1.88, 4.50)	<1.0E-09	1.85	(0.96, 3.57)	6.9E-02

[a]Decomposition analysis for W-EH (English-speaking Hispanic) was not presented due to no statistical difference in vaccination rate (p>0.8 in Table 1)

[b]Sample size for each racial ethnic group (un-weighted/weighted N): W (4999/15.98 million), AA (538/1.55 million), and SH (286/0.79 million).

[c]W = non-Hispanic White

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[d] AA = non-Hispanic African American

[e] SH = Spanish-speaking Hispanic

[f] High School = 1 if having a high school diploma; = 0 otherwise

[g] Avoid med care = 1 if avoiding medical care when sick; = 0 otherwise

[h] Household size = continuous variable (≥1)

[i] Metropolitan = 1 if residing in a metropolitan area; = 0 otherwise

[j] Medicare HMO = 1 if enrolled in Medicare Health Maintenance Organization (HMO); = 0 otherwise

[k] ADL limitation = 1 if a subject has at least one limitation in Activities of Daily Living (ADL); = 0 otherwise

[l] IADL limitation = 1 if a subject has at least one limitation in Instrumental Activities of Daily Living (IADL); = 0 otherwise

Table 3

Decomposition Analysis for Racial/Ethnic Disparity in Influenza Vaccination Among Medicare Elderly Beneficiaries (2010–2011 season)[a]

	W[b] - AA[c]				W[b] - SH[d]			
	Est.	95% C.I.	P>|z|[e]	Share (%)	Est.	95% C.I.	P>|z|[e]	Share (%)
Total difference	0.141	(0.095, 0.187)	2.7E-09	100.00	0.257	(0.197, 0.318)	<1.0E-09	100.00
Difference-in-characteristics	0.060	(0.037, 0.082)	1.6E-07	42.39	0.123	(0.085, 0.161)	1.9E-10	47.74
Difference-in-coefficients	0.081	(0.032, 0.131)	1.3E-03	57.61	0.134	(0.068, 0.201)	8.2E-05	52.26
Due to difference-in-characteristics[f]								
(a) Predisposing characteristics								
Female	−0.001	(−0.003, 0.001)	2.9E-01	−0.70	<0.001	(−0.002, 0.002)	7.5E-01	−0.12
Age (>74)	0.003	(−0.001, 0.007)	1.1E-01	2.11	<0.001	(−0.005, 0.005)	8.9E-01	0.13
High school[g]	0.012	(0.001, 0.023)	2.6E-02	8.54	0.019	(0.002, 0.036)	2.7E-02	7.42
Avoid med care[h]	0.001	(−0.003, 0.005)	5.6E-01	0.81	0.008	(0.002, 0.015)	1.1E-02	3.29
Household size[i]	0.001	(−0.003, 0.005)	5.4E-01	0.79	0.003	(−0.007, 0.014)	5.1E-01	1.34
Metropolitan[j]	<0.001	(−0.003, 0.002)	7.2E-01	−0.32	−0.001	(−0.009, 0.006)	7.2E-01	−0.54
Region[k]	−0.004	(−0.012, 0.004)	2.8E-01	−3.09	0.002	(−0.008, 0.013)	6.7E-01	0.90
(b) Enabling characteristics								
Medicare HMO[l]	−0.005	(−0.010, 0.000)	5.1E-02	−3.44	−0.013	(−0.026, -0.001)	3.1E-02	−5.20
Medicaid	−0.004	(−0.015, 0.007)	4.9E-01	−2.68	−0.005	(−0.020, 0.010)	5.1E-01	−1.95
Private insurance	0.022	(0.011, 0.033)	5.9E-05	15.60	0.040	(0.023, 0.058)	7.2E-06	15.56
Income[k]	0.033	(0.020, 0.046)	5.1E-07	23.58	0.055	(0.032, 0.078)	2.1E-06	21.49
Regular physician	0.006	(0.000, 0.011)	3.6E-02	4.19	0.018	(0.007, 0.029)	1.3E-03	7.05
(c) Need-related characteristics								
ADL limitation[m]	−0.001	(−0.002, 0.001)	4.2E-01	−0.42	−0.001	(−0.003, 0.001)	4.1E-01	−0.37
IADL limitation[n]	<0.001	(−0.002, 0.001)	6.2E-01	−0.23	−0.001	(−0.003, 0.002)	6.2E-01	−0.22
Chronic disease	−0.003	(−0.007, 0.001)	9.9E-02	−2.35	−0.003	(−0.008, 0.003)	3.6E-01	−1.04
Due to difference-in-coefficients (odds ratios)[o]								

	W[b] - AA[c]				W[b] - SH[d]			
	Est.	95% C.I.	P>|z|[e]	Share (%)	Est.	95% C.I.	P>|z|[e]	Share (%)
(a) Predisposing characteristics								
Female	0.002	(−0.009, 0.012)	7.5E-01	1.20	0.006	(−0.007, 0.019)	3.6E-01	2.36
Age (>74)	−0.005	(−0.016, 0.007)	4.3E-01	−3.23	−0.001	(−0.011, 0.010)	9.2E-01	−0.21
High school[g]	0.001	(−0.006, 0.007)	8.5E-01	0.43	0.003	(−0.019, 0.025)	7.8E-01	1.20
Avoid med care[h]	−0.011	(−0.059, 0.037)	6.5E-01	−7.78	−0.013	(−0.041, 0.015)	3.6E-01	−5.00
Household size[i]	−0.014	(−0.139, 0.110)	8.2E-01	−10.04	−0.067	(−0.215, 0.081)	3.8E-01	−26.02
Metropolitan[j]	0.001	(−0.054, 0.056)	9.8E-01	0.62	−0.049	(−0.243, 0.145)	6.2E-01	−18.89
Region[k]	0.001	(−0.054, 0.056)	9.7E-01	0.76	0.110	(−0.036, 0.256)	1.4E-01	42.68
(b) Enabling characteristics								
Medicare HMO[l]	0.006	(−0.008, 0.021)	3.9E-01	4.57	0.002	(−0.012, 0.017)	7.6E-01	0.87
Medicaid	−0.010	(−0.049, 0.028)	6.0E-01	−7.30	0.022	(−0.019, 0.063)	3.0E-01	8.43
Private insurance	−0.004	(−0.030, 0.022)	7.6E-01	−2.86	0.012	(−0.094, 0.118)	8.2E-01	4.69
Income[k]	−0.010	(−0.063, 0.043)	7.1E-01	−6.99	−0.104	(−0.224, 0.016)	9.0E-02	−40.35
Regular physician	0.066	(−0.037, 0.170)	2.1E-01	47.09	0.011	(−0.082, 0.105)	8.1E-01	4.37
(c) Need-related characteristics								
ADL limitation[m]	0.004	(−0.031, 0.038)	8.3E-01	2.75	−0.006	(−0.044, 0.032)	7.6E-01	−2.31
IADL limitation[n]	0.008	(−0.029, 0.046)	6.6E-01	5.88	0.010	(−0.033, 0.053)	6.5E-01	3.86
Chronic disease	−0.022	(−0.071, 0.027)	3.7E-01	−15.71	−0.006	(−0.034, 0.022)	6.7E-01	−2.39
Constant[p]	0.068	(−0.130, 0.266)	5.0E-01	48.22	0.203	(−0.114, 0.521)	2.1E-01	78.97

[a] Decomposition analysis for W-EH (English-speaking Hispanic) disparity was not presented due to no statistical difference in vaccination rate (p>0.8 in Table 1)

[b] W = non-Hispanic White

[c] AA = non-Hispanic African American

[d] SH = Spanish-speaking Hispanic

[e] p-value is based on bootstrap, replicated 500 times.

[f] Differences-in-covariates (mean) are summarized in Table 1.

[g] High School = 1 if having a high school diploma; = 0 otherwise

[h] Avoid med care = 1 if avoiding medical care when sick; = 0 otherwise

[i] Household size = continuous variable (≥1)

[j] Metropolitan = 1 if residing in a metropolitan area; = 0 otherwise

[k] aggregating all category variables

[l] Medicare HMO = 1 if enrolled in Medicare Health Maintenance Organization (HMO); = 0 otherwise

[m] ADL limitation = 1 if a subject has at least one limitation in Activities of Daily Living (ADL); = 0 otherwise

[n] IADL limitation = 1 if a subject has at least one limitation in Instrumental Activities of Daily Living (IADL); = 0 otherwise

[o] Differences-in-coefficients (odds ratios), estimated by a multivariable regression model, are summarized in Table 2.

[p] Constant term contains contributions of unobservable factors (residual in a regression model).