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Original Research

Application of the nonlinear Blinder-Oaxaca decomposition to study racial/ethnic disparities in antiobesity medication use in the United States

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Abstract

Background: The nonlinear Blinder-Oaxaca (BO) decomposition method is gaining popularity in health services research because of its ability to explain disparity issues. The present study demonstrates the use of this method for categorical variables by addressing antiobesity medication use disparity.

Objective: To examine racial/ethnic disparity in antiobesity medication use and to quantify the observed factor contribution behind the disparity using the nonlinear BO decomposition.

Methods: Medical Expenditure Panel Survey data, 2002-2007, were used in this retrospective cross-sectional study. Adults with body mass index (BMI) >30, or BMI ≥ 27 and comorbidities such as hypertension, cardiovascular diseases, diabetes, or hyperlipidemia were included in the cohort ($N = 65{,}886{,}625$). Multivariable logistic regression was performed to examine racial/ethnic disparity in antiobesity medication use controlling for predisposing, enabling, and need factors. The nonlinear BO decomposition was used to identify the contribution of each predisposing, enabling, and need factors in explaining the racial/ethnic disparity and to estimate the residual unexplained disparity.

Results: Non-Hispanic Blacks were 46% (odds ratio [OR]: 0.54; 95% confidence interval [CI]: 0.35-0.83) less likely to use antiobesity drugs compared with non-Hispanic Whites, whereas no difference was observed between Hispanics and non-Hispanic Whites. A 0.22 percentage point of disparity existed between non-Hispanic Whites and Blacks. The nonlinear BO decomposition estimated a decomposition coefficient of -0.0013 indicating that the observed disparity would have been 58% higher ($-0.0013/0.0022$) if non-Hispanic Blacks had similar observed characteristics as non-Hispanic Whites. Age, gender, marital status, region, and BMI were significant factors in the decomposition model; only marital status explained the racial/ethnic disparity among all observed characteristics.

Conclusions: The study revealed that differences in the predisposing, enabling, and need characteristics (except marital status) did not successfully explain the racial/ethnic disparity in antiobesity medication use. Further studies examining racial/ethnic differences in individual beliefs, behavioral patterns, and provider prescription patterns are vital to understand these disparities.

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Introduction

The report published by Institute of Medicine, "Unequal Treatment: Confronting Racial and Ethnic Disparities in Health Care," documented substantial racial and ethnic disparities in health care use indicating that minorities receive lower quantity and quality of health care services compared with Whites.[1] In efforts to eliminate these disparities, the U.S. Department of Health and Human Services launched Healthy People 2010 (HP 2010).[2] Despite efforts by HP 2010, current evidence shows that the United States failed to achieve that goal and there has been no progression toward disparity elimination for more than half of the objectives.[3-5] Pharmaceutical services are an integral part of health care, and a recent review article demonstrated significant racial/ethnic disparities in the use of pharmaceutical services as well.[6]

Another important objective of HP 2010 was to reduce obesity prevalence from 23% in 1988-1994 to 15% in 2010. However, current obesity prevalence among U.S. adults is 33.8% (95% confidence interval [CI]: 31.6-36.0%), making the United States number 1 among all developed countries for obesity prevalence.[7,8] It is projected that by 2025-2030, almost 50% of adults in the United States will be obese.[9] In addition to the increasing obesity burden, significant racial/ethnic disparities exist in obesity prevalence. The U.S. Centers for Disease Control and Prevention reported that in 2006-2008, non-Hispanic Blacks (35.7%) had 51% higher obesity prevalence, and Hispanics (28.7%) had 21% higher obesity prevalence compared with non-Hispanic Whites (23.7%).[10] Because of the racial/ethnic disparities in obesity prevalence and in overall prescription medication use, disparities could exist in antiobesity medication use. Current literature provides equivocal evidence regarding racial/ethnic disparities in antiobesity medication use.[11,12] It is also reported that minority groups tend to use unproven methods of weight loss and are less likely to use evidence-based treatments.[13] Because of high prevalence of obesity in non-Hispanic Blacks and Hispanics, it is a matter of concern if disparities exist in the use of antiobesity medications. Identification of racial/ethnic disparities in antiobesity medication use, and examination of factors responsible for these disparities can assist in developing behavioral and/or policy interventions to overcome these disparities.

Blinder and Oaxaca developed regression-based decomposition methods, referred to as Blinder-Oaxaca (BO) decomposition, to explain wage inequalities between blacks and whites or between men and women.[14,15] The BO method decomposes the difference in an outcome variable between 2 groups into 2 components: explained component and unexplained component. The original BO decomposition method was developed for continuously distributed dependent variables such as wage; hence, it has limited applicability in health services research. A recently introduced nonlinear BO decomposition method is an extension of the linear method and is gaining popularity in health services research because of its applicability to categorical variables.[16-25] The nonlinear BO decomposition helps estimate the percentage contribution of individual observed characteristics to overall differences between 2 groups (explained component). It also helps quantify the unexplained component because of unobserved heterogeneity.[16,26] The present study uses the nonlinear BO method to estimate the explained and unexplained components of a dichotomous antiobesity medication use variable. The study aims to identify observed factors such as insurance coverage, education, source of care, and baseline health status, which might contribute to racial/ethnic disparity. Identification of observed factors that significantly contribute to racial/ethnic disparity in antiobesity medication use can help develop appropriate policies and interventions targeting these factors.

The objectives of this study were as follow: (1) to examine racial/ethnic disparities in antiobesity medication use among non-Hispanic Blacks versus non-Hispanic Whites, and Hispanics versus non-Hispanic Whites, and (2) contingent upon results of the first objective, to identify and quantify observed factor contribution behind racial/ethnic disparity in antiobesity medication use using the nonlinear BO decomposition.

Methods

Data and study design

This retrospective cross-sectional study used data from the Medical Expenditure Panel Survey (MEPS), 2002-2007. The MEPS, conducted by Agency for Health Research and Quality, is

a national survey data with stratified multistage probability design representing noninstitutionalized U.S. population. The household component of MEPS collects information on demographic characteristics, health condition, health status, use of medical services, charges and source of payments, access and satisfaction with care, health insurance coverage, income, and employment. Oversampling of minority racial/ethnic groups, accuracy in capturing prescription drug use and generalizability at national level makes MEPS an ideal database to study racial/ethnic disparities in prescription drug use.[27]

The study used 3 public use files: (1) full year consolidated file, (2) medical conditions file, and (3) prescribed medicines file. All 3 files were merged together at person level for each year separately and merged files were then pooled together from 2002 to 2007. All adults ($\geq$20 years of age) who met the medical criteria to use antiobesity drugs were included in the study; pregnant women were excluded because body mass index (BMI) classification is not applicable to them. Medical criteria to use antiobesity drugs for adults were defined as BMI $>$30 (clinically obese) or BMI $\geq$27 with at least 1 comorbid condition, such as hypertension, cardiovascular diseases, diabetes, or hyperlipidemia.[28,29] Presence of sleep apnea as a comorbidity also justifies the use of antiobesity medications, but it was not possible to identify this condition from MEPS, as sleep apnea is coded within organic sleep disorders.

Conceptual framework and variables

Andersen's health service utilization model was used to develop the statistical equation under study. This model classifies determinants of an individual's health service utilization into predisposing, enabling, and need characteristics.[30] Predisposing characteristics determine the baseline propensity of an individual to use health services. Enabling characteristics refer to community and personal resources an individual has to use services. Need characteristics refer to perceived and actual need of an individual, which drives the use of health services.

Dependent variable

The dependent variable was a dichotomous variable indicating the use of antiobesity medications. Antiobesity medications were identified from the prescribed medicines file. They included all anorexiant drugs and orlistat, a lipase inhibitor.

Independent variables

- Predisposing characteristics included race/ethnicity, age, gender, marital status, and education. Race/ethnicity was classified into 4 mutually exhaustive categories: non-Hispanic Whites, non-Hispanic Blacks, Hispanic, and others (American Indian/Alaska Native, Asians, and Native Hawaiian/Pacific Islander). Age was measured as a continuous variable. Education was divided into 3 categories: $<$12 years of education, 12-15 years of education, and $>$15 years of education. Marital status was measured as a dichotomous variable, that is, married or unmarried.
- Enabling characteristics included income, health insurance coverage, prescription insurance coverage, usual source of health care, urban residence, and region. Income was divided into 3 categories based on % of federal poverty limits (FPLs). Individuals were categorized as poor ($<$100% FPL), low income (100-200% FPL), middle income to high income ($>$200% FPL). All individuals were categorized as insured or uninsured for health and prescription insurance coverage. Usual source of health care was measured as a dichotomous variable indicating whether or not a person had a specific doctor's office, clinic, or health center they usually visit. Metropolitan statistical area (MSA) was dichotomized as urban versus rural. U.S. census regions were categorized as Northeast, Midwest, South. and West.
- Need characteristics included BMI, comorbidity, activities of daily living (ADLs), instrumental activities of daily living (IADLs), and general health status. BMI was measured as a continuous variable. According to the National Heart Lung and Blood Institute (NHLBI) guideline, presence of comorbidities such as coronary heart disease, hypertension, type II diabetes, and hyperlipidemia puts an obese individual at a very high risk for mortality. A dichotomous variable for comorbidity was created to capture presence of any of the above comorbidities. ADLs/IADLs were measured as dichotomous variables based on whether or not the patients needed help to perform any ADL/IADL. Self-perceived general health status was classified into 2 categories: fair/poor and excellent/very good/good health status.

Statistical analysis

All statistical analyses were adjusted for MEPS complex survey design to generalize results at

a national level. As the study used data from 2002 to 2007, all results were presented as a weighted average, calculated as total number of observations in 6 years divided by 6. Chi-square and *t* tests were performed to test for differences among different racial/ethnic groups for categorical and continuous variables, respectively.

Bivariate logistic regression models were used to estimate the unadjusted association of each independent variable with antiobesity medication use. Multivariable logistic regression models were used to identify antiobesity medication use disparity between non-Hispanic Whites, non-Hispanic Blacks, and Hispanics. Predisposing, enabling, and need characteristic variables were added sequentially in logistic regression models to assess the differential impact of each characteristic on race/ethnicity for antiobesity medication use. Dummy variables for year were also included in the final model.

Blinder-Oaxaca decomposition

The BO decomposition method decomposes differences in a dependent variable between 2 groups into 2 components:

1. The "explained" component that captures differences in observed or measurable characteristics.
2. The "unexplained" component that cannot be explained by the observed factors in the data.

Linear BO decomposition method

The linear BO decomposition method was originally developed by Blinder and Oaxaca to explain wage difference between whites and blacks and between men and women.[14,15] The original decomposition method used continuous dependent variables such as wage, payment, and expenditure. Since its development, this method has been widely used in the field of labor economics.

For example, to decompose disparities of prescription medication expenditure between whites and blacks, an ordinary least square regression for each group (whites and blacks) is estimated as follows:

$$\overline{Y}_w = \hat{\beta}_{w0} + \sum_{j=1}^{N} \overline{X'}_{wj}\,\hat{\beta}_{wj} \tag{1}$$

$$\overline{Y}_b = \hat{\beta}_{b0} + \sum_{j=1}^{N} \overline{X'}_{bj}\,\hat{\beta}_{bj} \tag{2}$$

where, subscript b = blacks and w = whites,

$\overline{Y}$ = mean of prescription drug expenditure,

$\hat{\beta}_0$ = estimated intercept,

$\hat{\beta}_j$ = column vector of estimated slope coefficient for set of j regressors, $\overline{X}'_j$.

The difference in the above 2 estimated equations decomposes disparity in prescription drug expenditure between blacks and whites into 2 components:

Component–I is because of the difference in mean of observed variables (explained component), and component–II is because of the difference in intercepts and coefficients from Equations 1 and 2 (unexplained component).

$$\bar{Y}_w - \bar{Y}_b = \underbrace{\sum_{j=1}^{N} \left(\overline{X}'_{wj} - \overline{X}'_{bj}\right)\hat{\beta}_{wj}}_{\text{(component - I)}} + \underbrace{\left(\hat{\beta}_{w0} - \hat{\beta}_{b0}\right) + \left(\hat{\beta}_{w0} - \hat{\beta}_{b0}\right) + \sum_{j=1}^{N} \overline{X}'_{bj}\left(\hat{\beta}_{wj} - \hat{\beta}_{bj}\right)}_{\text{(component - II)}}$$

Nonlinear BO decomposition method

As linear decomposition method dealt only with continuous variables, it had limited application in health services research. In the last decade, Fairlie[16] extended the original linear decomposition method to nonlinear models such as logit and probit models, thereby extending its applicability to categorical variables. The present study's dependent variable was a dichotomous antiobesity medication use variable. Hence, nonlinear BO decomposition technique was used to decompose racial/ethnic disparity in antiobesity medication use.

To obtain the nonlinear BO decomposition, first, separate logistic regression models for non-Hispanic Whites and non-Hispanic Blacks were estimated as follows:

$$Y_w = F\left(X_w \widehat{\beta}_w\right) \quad (3)$$

$$Y_b = F\left(X_b \widehat{\beta}_b\right) \quad (4)$$

where, subscript b = Blacks and w = Whites.

Difference in Equations 3 and 4 will decompose the disparity in antiobesity medication use into 2 components:

$$\bar{Y}_w - \bar{Y}_b = \underbrace{\left[\sum_{i=1}^{N^w} \frac{F\left(X_i^w \hat{\beta}^w\right)}{N^w} - \sum_{i=1}^{N^b} \frac{F\left(X_i^b \hat{\beta}^w\right)}{N^b}\right]}_{\text{(component - I)}} + \underbrace{\left[\sum_{i=1}^{N^b} \frac{F\left(X_i^b \hat{\beta}^w\right)}{N^b} - \sum_{i=1}^{N^b} \frac{F\left(X_i^b \hat{\beta}^b\right)}{N^b}\right]}_{\text{(component - II)}}$$

Where, component–I is because of the difference in mean of observed variables (explained component) and component–II is because of the difference in coefficients (unexplained component). In Fairlie's nonlinear BO method, a 1-to-1 matching of observations between Blacks and Whites is required to identify the contribution of individual factors/characteristics. As the number of observations among Blacks and Whites were not equal, a random subsample of observations were selected from the majority group (Whites) and matched with the minority group (Blacks) based on the ranking of predicted probability of the dependent variable. The matched sample was then used to calculate the contribution of each factor in explaining disparity. In the present study, 1000 random subsamples of Whites were used to eliminate biased estimations because of subsampling. The final decomposition estimate was an average of these 1000 samples.

Two statistical softwares, SAS 9.2 (SAS Institute, Cary, NC) and STATA 11 (StataCorp, College Station, TX) were used to perform statistical analyses. This study was approved by the University of Houston Committees for the Protection of Human Subjects.

Results

The final cohort consisted of 43,470 adults who met the medical criteria (weighted sample size = 395,319,750). All results were presented as weighted average (395,319,750/6 = 65,886,625).

Table 1 provides descriptive statistics for the analytical cohort (weighted sample size = 65,886,625) by race/ethnicity. Most of the people in the cohort were non-Hispanic White (68.39%), followed by non-Hispanic Black (14.97%), Hispanics (12.73%), and others (3.91%). Mean age of the cohort was 50.38 ± 0.17 with 51% men. Almost 41% of people were married and more than 80% people had education above 12 years. One out of 10 individuals had income <100% FPL and more than 8 out of 10 individuals had a usual source of health care. More than 87% of people had health insurance and 65% were insured for prescription medication coverage. The mean BMI was 33.66 ± 0.05, and 58% had at least 1 comorbid condition. Eight out of 10 patients reported good, very good, or excellent health status and, 4% and 8% people needed assistance in performing ADLs and IADLs, respectively.

Bivariate regression results

Table 2 shows results for bivariate regression analysis. Among people who met the medical criteria only 0.61% of individuals used the drugs. Results indicated that non-Hispanic Blacks (0.44% users) were significantly less likely to take antiobesity drugs than non-Hispanic Whites (0.66% users) (odds ratio [OR]: 0.67; 95% CI: 0.46-0.97), whereas no difference was found between Hispanics (0.45% users) and others (1.00% users) when compared with non-Hispanic Whites.

Several characteristics were significant predictors of antiobesity medication use in a bivariate regression. Higher age (OR: 0.98; 95% CI: 0.97-0.99) was associated with lower medication use. Females (OR: 2.14; 95% CI: 1.55-2.94) and individuals with intermediate education of 12-15 years (OR: 1.91; 95% CI: 1.27-2.87) were more likely to use medication. Having a usual source of health care (OR: 2.15; 95% CI: 1.25-3.73) was associated with higher antiobesity medication use. Higher BMI (OR: 1.025; 95% CI: 1.02-1.03) was a significant predictor of antiobesity

Table 1
Descriptive statistics of analytic cohort by race/ethnicity[a]

Independent variables	Total, N = 65,886,625 (100%)	Non-Hispanic Whites, N = 45,060,397 (68.39%)	Non-Hispanic Blacks, N = 9,861,633 (14.97%)	Hispanics, N = 8,387,969 (12.73%)	Others, N = 2,576,624 (3.91%)
Predisposing characteristics					
Age					
Mean ± standard error (SE)	50.38 ± 0.17	52.29 ± 0.20	47.30 ± 0.32[b]	44.40 ± 0.28[c]	48.31 ± 0.54[d]
Gender					
Male	51.08	53.31	40.84[b]	51.73	49.25[d]
Female	48.92	46.69	59.16	48.27	50.65
Marital status[e]					
Married	40.76	63.71	39.45[b]	58.28[c]	59.58[d]
Unmarried	59.22	36.29	60.45	41.66	40.36
Education[e] (yr)					
<12	19.88	14.78	22.13[b]	44.82[c]	19.09[d]
12-15	59.29	61.69	61.33	45.37	54.71
>15	20.24	23.16	15.51	8.60	25.20
Enabling characteristics					
Income[e]					
<100% FPL	11.10	7.95	19.43[b]	17.55[c]	13.37[d]
100-200% FPL	18.18	15.30	22.87	27.57	19.96
>200% FPL	70.12	76.75	57.70	54.88	66.67
Health insurance coverage					
Insured	87.92	8.35	14.45[b]	29.34[c]	12.11[d]
Uninsured	12.08	91.65	85.55	70.66	87.89
Prescription insurance coverage					
Insured	65.22	70.05	58.35[b]	48.21[c]	62.39[d]
Uninsured	34.78	29.95	41.65	51.79	37.61
Usual source of health care[e]					
Yes	83.07	86.80	79.51[b]	67.06[c]	83.75[d]
No	16.36	12.76	19.38	32.31	15.79
Urban residence					
MSA	79.86	76.21	87.45[b]	91.15 [c]	77.95
Non-MSA	20.14	23.79	12.55	8.85	22.05
Region					
Northeast	17.94	19.35	16.14[b]	13.96[c]	13.19[d]
Midwest	23.05	27.32	18.74	7.27	16.33
South	39.13	35.74	56.89	39.03	30.72
West	19.88	17.60	8.22	39.74	39.77
Need characteristics					
BMI					
Mean ± SE	33.66 ± 0.05	33.42 ± 0.06	34.80 ± 0.13[b]	33.71 ± 0.09	33.29 ± 0.22
Comorbidity					
Yes	57.67	60.91	55.80[b]	41.66[c]	60.27
No	42.33	39.09	44.20	58.34	39.73
ADL[e]					
Yes	4.14	4.03	4.99[b]	3.54	4.81
No	95.84	95.96	95.01	96.42	95.19

(*Continued*)

Table 1 (*Continued*)

Independent variables	Total, N = 65,886,625 (100%)	Non-Hispanic Whites, N = 45,060,397 (68.39%)	Non-Hispanic Blacks, N = 9,861,633 (14.97%)	Hispanics, N = 8,387,969 (12.73%)	Others, N = 2,576,624 (3.91%)
IADL					
Yes	7.96	7.87	9.44[b]	5.79[c]	10.85[d]
No	92.04	92.13	90.56	94.21	89.15
General health status					
Fair/poor	21.23	19.73	24.84[b]	23.79[c]	25.19[d]
Excellent/very good/good	78.77	80.27	75.16	76.21	74.81
Survey year					
2002	14.95	15.14	15.41	13.93	13.16
2003	15.43	15.43	16.33	14.62	14.59
2004	16.56	16.60	16.63	15.75	18.17
2005	17.13	17.11	17.02	17.19	17.69
2006	17.51	17.35	16.87	19.00	18.03
2007	18.42	18.37	17.74	19.51	18.36

[a] Percentage are listed as column percentage among each characteristics.

[b] Comparison between Blacks and Whites, reference is White. Chi-square tests for categorical variables and *t* test for continuous variables significant at $P < .05$.

[c] Comparison between Hispanics and Whites, reference is White. Chi-square tests for categorical variables and *t* test for continuous variables significant at $P < .05$.

[d] Comparison between Others and Whites, reference is White. Chi-square tests for categorical variables and *t* test for continuous variables significant at $P < .05$.

[e] Numbers may not add up to 100% due to missing values.

medication use. Individuals who needed help with ADLs (OR: 2.18 95% CI: 1.29-3.66) or IADLs (OR: 1.73; 95% CI: 1.09-2.74) and had lower self-reported health (OR: 1.46; 95% CI: 1.04-2.05) were more likely to use antiobesity medications.

Multivariable regression results

Table 3 shows results for multivariable logistic regression where predisposing characteristics were added first, and enabling and need characteristics were added subsequently. As a group, all 3 characteristics were statistically significant (predisposing, $P < .001$; enabling, $P < .001$; need, $P < .001$). In model I, with only predisposing variables, non-Hispanic Blacks were 43% less likely to use antiobesity drugs (OR: 0.57; 95% CI: 0.40-0.87). Inclusion of enabling and need characteristics in the multivariable model had a very small effect on the ORs associated with non-Hispanic Blacks. After the addition of enabling and need characteristics, the odds of antiobesity medication use by non-Hispanic Blacks was 45% (OR: 0.55, 95% CI: 0.36-0.85) and 46% (OR: 0.54; 95% CI: 0.35-0.83) lower, respectively. The remaining 2 racial/ethnic groups, that is, Hispanics and others did not have not statistically significantly difference in medication use compared with non-Hispanic Whites.

Among predisposing characteristics, increase in age was associated with less likelihood of medication use (OR: 0.971; 95% CI: 0.959-0.982) and females were more than 2 times likely to use antiobesity medications (OR: 2.12; 95% CI: 1.53-2.99). Individuals with 12-15 years of education were 75% more likely to receive medication (OR: 1.75; 95% CI: 1.08-2.83) compared with individuals with less than high school education; however, there was no difference among individuals with higher education (>15 years) compared with less than high school education. Among enabling characteristics, persons having usual source of health care were more than 2 times likely to use antiobesity drugs (OR: 2.13; 95% CI: 1.17-3.88). People with higher BMI were more likely to use antiobesity medications (OR: 1.02; 95% CI: 1.01-1.03). ADLs, IADLs, and general health status were no longer significant in the final model after predisposing, enabling, and need characteristics were included.

Table 2
Antiobesity medication use rate and bivariate logistic regression model results for antiobesity medication use

Independent variables	Total number of patients who meet medical criteria to use antiobesity drugs, N = 65,886,625 (100%)	Patients who are taking antiobesity medications, N = 40,190,841 (0.61%)	Bivariate OR (95% CI)	*P* value
Predisposing characteristics				
Race/ethnicity				
Whites	45,060,398	0.66	Reference	
Blacks	9,861,634	0.44	0.67 (0.46-0.97)	.033
Hispanics	8,387,969	0.45	0.68 (0.40-1.18)	.177
Others	2,576,624	1.00	1.54 (0.90-2.63)	.119
Age[a]				
Mean ± standard error (SE)	50.38 ± 0.17	45.88 ± 1.02	0.98 (0.97-0.99)	<.001
Gender				
Male	33,658,064	0.39	Reference	
Female	32,228,562	0.84	2.14 (1.55-2.94)	<.001
Marital status				
Unmarried	26,857,930	0.53	Reference	
Married	39,021,260	0.67	1.27 (0.93-1.71)	.130
Education (yr)				
<12	13,094,982	0.37	Reference	
12-15	39,061,428	0.71	1.91 (1.27-2.87)	.001
>15	13,335,135	0.56	1.50 (0.86-2.59)	.149
Enabling characteristics				
Income				
<100% FPL	7,313,825	0.55	Reference	
100-200% FPL	11,976,582	0.51	0.93 (0.55-1.55)	.768
>200% FPL	49,596,218	0.64	1.18 (0.78-1.80)	.430
Health insurance coverage				
Uninsured	7,961,764	0.36	Reference	
Insured	57,924,862	0.65	1.80 (1.00-3.25)	.051
Prescription insurance coverage				
Uninsured	22,914,159	0.53	Reference	
Insured	42,972,466	0.65	1.22 (0.89-1.68)	.222
Usual source of health care				
No	10,777,763	0.31	Reference	
Yes	54,733,894	0.67	2.15 (1.25-3.73)	.006
Urban residence				
Non-MSA	13,268,581	0.75	Reference	
MSA	52,618,044	0.58	0.77 (0.55-1.08)	.123
Region				
Northeast	11,821,482	0.54	Reference	
Midwest	15,187,302	0.51	0.96 (0.58-1.59)	.862
South	25,779,104	0.75	1.39 (0.91-2.13)	.125
West	13,098,738	0.52	0.97 (0.56-1.66)	.902
Need characteristics				
BMI[b]				
Mean ± SE	33.66 ± 0.05	36.08 ± 0.45	1.025 (1.02-1.03)	<.0001

(*Continued*)

Table 2 (*Continued*)

Independent variables	Total number of patients who meet medical criteria to use antiobesity drugs, N = 65,886,625 (100%)	Patients who are taking antiobesity medications, N = 40,190,841 (0.61%)	Bivariate OR (95% CI)	*P* value
Comorbidity				
No	27,890,133	0.68	Reference	
Yes	37,996,493	0.56	0.82 (0.61-1.10)	.185
ADL				
No	378,893,696	0.58	Reference	
Yes	16,380,482	1.26	2.18 (1.29-3.66)	.003
IADL				
No	63,148,949	0.58	Reference	
Yes	2,730,080	0.99	1.73 (1.09-2.74)	.020
General health status				
Excellent/very good/good	51,900,314	0.56	Reference	
Fair/poor	13,986,311	0.81	1.46 (1.04-2.05)	.028
Survey year				
2002	9,849,781	0.63	Reference	
2003	10,163,788	0.72	1.15 (0.82-1.62)	.417
2004	10,907,284	0.69	1.11 (0.75-1.64)	.615
2005	11,288,644	0.43	0.69 (0.41-1.15)	.153
2006	11,539,459	0.45	0.71 (0.41-1.23)	.224
2007	12,137,670	0.75	1.19 (0.76-1.87)	.446

[a] Age (Patients who are not taking antiobesity medications) = 50.41 ± 0.17.
[b] BMI (Patients who are not taking antiobesity medications) = 33.65 ± 0.05.

Nonlinear BO decomposition results

Because a statistically significant difference exists only between the non-Hispanic Whites and non-Hispanic Blacks, the decomposition was only performed for these 2 categories. The results are presented in Table 4.

Before the decomposition, logistic regressions on antiobesity medication use were estimated separately for Blacks and Whites (results not presented here). These analyses provided evidence of interaction effects for each independent variable with race. Only 1 variable had a statistically different effect for Blacks versus Whites; being insured had no effect on medication use for overall population and whites, but it had a borderline significant positive effect on medication use for blacks (OR 7.6; 95% CI: 0.98-59.1; *P* value, .05).

Predicted probability of antiobesity medication use was 0.0066 for non-Hispanic White and 0.0044 for non-Hispanic Black people. Therefore, a difference of 0.0022, or 0.22 percentage points, exists between the 2 groups. The decomposition estimated a negative coefficient (−0.0013) for racial disparity. This indicates that observed characteristics did not successfully explain disparity in antiobesity medication use. In other words, had non-Hispanic Blacks had a similar distribution of observed characteristics as non-Hispanic whites, observed disparity in antiobesity medication use (0.22 percentage points) will be 58% higher (calculated as 0.0013/0.0022). Age, gender, marital status, region, and BMI were significant factors in the decomposition model; only marital status explained the racial/ethnic disparity among all observed characteristics. If a higher number of non-Hispanic Black people were married, then the likelihood of using antiobesity medication would have increased by 42%, which would have reduced the disparity. In addition, observed characteristics such as age, gender, region, and BMI had an opposite effect in explaining the disparity. Based on the previous bivariate and multivariable analysis, younger individuals, females, individuals living in south, and individuals having a higher BMI had a higher probability of antiobesity medication use. Although non-Hispanic Blacks were younger, had a higher proportion of females, lived in south, and

Table 3
Multivariable logistic regression model results for antiobesity medication use

Independent variables	Model with predisposing characteristics (model I)	Model with predisposing + enabling characteristics (model II)	Model with predisposing + enabling + need characteristics (model III)
Predisposing characteristics			
Race/ethnicity			
Whites	Reference	Reference	Reference
Blacks	0.57 (0.40-0.87)	0.55 (0.36-0.85)	0.54 (0.35-0.83)
Hispanics	0.64 (0.34-1.20)	0.74 (0.39-1.42)	0.77 (0.41-1.45)
Others	1.42 (0.83-2.45)	1.47 (0.84-2.56)	1.46 (0.83-2.56)
Age	0.98 (0.97-0.99)	0.97 (0.96-0.98)	0.97 (0.96-0.98)
Gender (female)	2.40 (1.73-3.35)	2.26 (1.62-3.13)	2.12 (1.53-2.99)
Marital status			
Unmarried	Reference	Reference	Reference
Married	1.42 (1.03-1.97)	1.34 (0.96-1.86)	1.39 (0.99-1.95)
Education (yr)			
<12	Reference	Reference	Reference
12-15	1.61 (1.02-2.52)	1.60 (1.00-2.54)	1.75 (1.08-2.83)
>15	1.31 (0.71-2.40)	1.28 (0.67-2.43)	1.48 (0.75-2.90)
Enabling characteristics			
Income			
<100% FPL		Reference	Reference
100-200% FPL		0.94 (0.55-1.61)	1.04 (0.60-1.78)
>200% FPL		1.12 (0.71-1.78)	1.32 (0.80-2.16)
Health insurance coverage		1.94 (0.96-3.92)	1.73 (0.85-3.56)
Prescription insurance coverage		0.76 (0.51-1.14)	0.83 (0.56-1.23)
Usual source of health care		2.15 (1.19-3.89)	2.13 (1.17-3.88)
Urban residence		0.87 (0.61-1.23)	0.87 (0.60-1.24)
Region			
Northeast		Reference	Reference
Midwest		0.88 (0.53-1.49)	0.88 (0.52-1.48)
South		1.84 (0.96-2.28)	1.43 (0.92-2.23)
West		0.97 (0.56-1.70)	0.94 (0.54-1.65)
Need characteristics			
BMI			1.02 (1.01-1.03)
Comorbidity			0.92 (0.64-1.32)
ADL			1.81 (0.77-4.24)
IADL			1.33 (0.61-2.92)
General health status			
Excellent/very good/good			Reference
Fair/poor			1.46 (0.98-2.18)
Survey year			
2002			Reference
2003			1.14 (0.81-1.61)
2004			1.12 (0.76-1.65)
2005			0.70 (0.42-1.18)
2006			0.71 (0.41-1.23)
2007			1.27 (0.81-1.92)

Table 4
Nonlinear decomposition of antiobesity medication use between non-Hispanic Whites and non-Hispanic Blacks

Probability of receiving antiobesity medications for Whites				0.00660993
Probability of receiving antiobesity medications for Blacks				0.00438918
Difference in antiobesity medication use				0.00222075
Independent variables	Decomposition	Standard error	*P* value	% Contribution
Predisposing characteristics				
Age	−0.0011	0.0004	.012	−50.3148
Gender	−0.0006	0.0002	.008	−25.6670
Marital status	0.0009	0.0004	.023	41.6852
Education	0.0000	0.0001	.818	1.3364
Enabling characteristics				
Income	0.0004	0.0003	.248	17.7214
Health insurance coverage	0.0001	0.0002	.417	5.7576
Prescription insurance coverage	−0.0002	0.0003	.348	−10.7497
Usual source of health care	0.0002	0.0002	.202	9.2639
Urban residence	0.0001	0.0002	.680	3.0351
Region	−0.0006	0.0003	.049	−26.8539
Need characteristics				
BMI	−0.0004	0.0001	.003	−18.4462
Comorbidity	−0.0000	0.0001	.961	−0.3031
ADL	−0.0000	0.0001	.903	−0.6931
IADL	−0.0000	0.0002	.927	−0.7928
General health status	−0.0001	0.0001	.579	−3.3024
Total explained by measurable characteristics	−0.0013			−58.32%

had a higher BMI, they had lower drug utilization. If the characteristics of these non-Hispanic Blacks were similar to Whites, the disparity will be wider.

Discussion

The linear BO decomposition methods are available since 1973 and are widely used in the field of labor economics for continuous outcomes such as income or expenditure. The nonlinear BO methods developed recently for categorical variables are being used increasingly in health services research. A few applications of the nonlinear BO method include examination of racial/ethnic (eg, Blacks vs Whites), gender (males vs females), and insurance (insured vs uninsured) disparities for categorical outcomes such as access to care, prescription drug use, and treatment.[16-25] The nonlinear BO method is usually performed as a postmultivariable logistic regression technique. If significant disparity is observed in multivariable logistic regression, then the decomposition method can be used to identify individual contribution of observed characteristics. This study particularly demonstrates application of nonlinear BO method to study racial/ethnic disparity in antiobesity medication use.

Results of the multivariable analysis show that non-Hispanic Blacks were significantly less likely and Hispanics were equally likely to use antiobesity medications compared with non-Hispanic Whites. Younger adults, females, and adults with higher education (12-15 years), higher BMI, and those with a usual source of health care were more likely to use antiobesity medications.

Khan et al[11] reported that utilization of antiobesity drugs was one-third higher among Hispanics than Whites or Blacks and there was no difference between Blacks and Whites. Whereas, Cawley and Rizzo reported that drug use was significantly lower in Blacks compared with Whites, and there was no difference between Hispanics and Whites.[12] It should be noted that Khan et al used descriptive statistics to derive their conclusions; they did not control for any confounders. The study by Cawley and Rizzo was methodologically stronger because it controlled for several confounders in multivariable logistic regression.

The present study, guided by Andersen's behavioral model, used multivariable regression models to control for predisposing, enabling, and need factors while assessing racial/ethnic disparity in antiobesity medication use; the results are consistent with Cawley and Rizzo's demonstrating significantly lower use in Non-Hispanic Blacks. The present study provides further evidence to fill the gap in current knowledge about racial/ethnic disparity in antiobesity medication use.

The study results demonstrated that antiobesity medication use was 2-fold higher in women, which is supported by previous studies.[11,12,31] This might be partially explained by women's attitude toward body size, body weight, and self-image.[31,32] Other studies have also shown that the use of nonprescription antiobesity drugs is higher among women when compared with men.[13,33,34] A reduction in likelihood of antiobesity medication use with age could be because of the increase in prevalence of other life-threatening chronic conditions requiring medications. Hence, older people may not consume, or their physician may not prefer to prescribe antiobesity medications along with numerous other required medications.[35,36] Age is also an indicator for life-stage factors and older adults might be less concerned about their body image and might not typically invest in medical interventions to reduce weight unless medically required. Usual source of health care is an indicator for consistent health care access and thus it is not surprising that individuals with higher access have higher medication use.

To the authors' best knowledge, this is the first study to decompose antiobesity medication use disparity between observable and unobserved characteristics. The decomposition revealed interesting but disconcerting findings. None of the differences in observed sociodemographic and health characteristics (except marital status) successfully explained racial/ethnic disparity. However, results indicated that disparity would have been larger if non-Hispanic Blacks had similar observed characteristics as non-Hispanic Whites. As observed characteristics were not able to explain the disparity, other factors may be responsible for causing disparity in antiobesity medication use. Such factors could be as follows:

1. Variation in provider preferences and prescribing patterns by specialty or geographic location;
2. Differences in choice of (or access to) providers by different racial/ethnic minorities;
3. Differences in use of obesity-related counseling, which is usually associated with an increased use of antiobesity medication; and
4. Differences in individuals' beliefs, behavioral patterns, motivational factors, and cultural factors.

Elimination of disparity was set as one of the nation's top priority in HP 2010 goals and it is again one of the priorities for HP 2020. The study results have important implications for policymakers and health care professionals. Commonly suspected contributors to racial/ethnic disparities such as income, education, baseline health status, and source of care are not the main determinants of the racial/ethnic disparity in antiobesity medication use. Thus, policies and interventions targeted at these factors may not necessarily help reduce the disparity. Further exploratory studies examining racial differences in individual beliefs, behavioral patterns, and provider prescription patterns are vital to understand these disparities, and it will provide useful information to policymakers to achieve the goal of eliminating disparities. Nevertheless, subgroup analyses before decomposition in this study established that being insured increases medication use among non-Hispanic Blacks although the effect was nonsignificant for the entire population. Thus, improving access to care by improving insurance coverage for non-Hispanic Blacks may help reduce the disparity. Future research is needed to address the important question of antiobesity medication use disparity.

This study had several strengths: this is the first study to decompose antiobesity medication use disparity using a nonlinear BO method. The study used MEPS data, a nationally representative data, which provides precise prescribing information. Also, oversampling of minority population in MEPS makes it an ideal database to study racial/ethnic disparity.

The study is not without its limitations. In MEPS, BMI was calculated using self-reported height and weight measurements, so the possibility of reporting/measurement errors cannot be ruled out. The database did not capture any information regarding nonprescription medications for obesity treatment. Hence, nonprescription medications were not included in the analysis. Various characteristics such as physician specialty, weight reduction-related counseling, diet intake, exercise, and motivation for weight reduction are significant factors determining antiobesity medication use. However, these characteristics were not controlled

for due to their absence in the data set, thereby leading to possible omitted variable bias.[37,38] The omitted variable bias is particularly problematic during decomposition because contribution of these omitted factors to the disparity becomes a part of the unexplained component of disparity and cannot be quantified. If these characteristics were included in the model, they might be able to explain some of the disparity. For instance, weight-related counseling is a major predictor of antiobesity medication use. This factor was not recorded in the database; hence, its possible contribution to the disparity could not be estimated.

The nonlinear BO decomposition method is vulnerable to the following problems[16]:

1. Ordering of variables in the decomposition model: Results from Fairlie's nonlinear BO method are sensitive to the order of covariates in the regression, and can produce different estimates based on the order.
2. Index problem: The decomposition can be performed with coefficients from Equations 3, 4 or a pooled regression (using a pooled Blacks and Whites sample). Choice of the coefficients can result in different decomposition estimates.
3. Observations matching problem: As mentioned earlier, Fairlie's method requires a 1-to-1 matching of observations between Blacks and Whites to estimate racial disparity. Restricting the decomposition to just 1 subsample can bias the estimates or lead to different results every time a new subsample is picked.
4. Choice of sample weights: Sample weights for Whites or Blacks can be used for the decomposition, and results can change based on the choice of weights.

As proposed by Fairlie[16] to overcome the above issues, variables were randomly ordered in the decomposition model and 1000 random subsamples were selected from white population to match with black population. The final decomposition estimate was an average of these 1000 samples. Also, the model was estimated multiple times using the different beta coefficients and sample weights. The results were robust to these modifications.

Conclusion

The nonlinear BO methods for categorical variables are potentially useful for evaluating disparities in health services research. Using the nonlinear BO method, this study found that although the prevalence of obesity is higher among Non-Hispanic Blacks, they were significantly less likely to use antiobesity medications compared with Non-Hispanic Whites. Observable characteristics were unable to explain racial/ethnic disparity in antiobesity medication use. Unobserved cultural and behavioral factors or regional variations and differences in provider prescribing patterns could play a major role in explaining the disparity. Any intervention targeted to reduce this disparity might be ineffective if they focus on observable characteristics mentioned in the present study. Nevertheless, improving insurance coverage specifically among Blacks may help reduce medication use disparity.

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