

# Decomposing Racial and Ethnic Disparities in the Use of Postacute Rehabilitation Care

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**Objective.** To determine the degree to which racial and ethnic disparities in the use of postacute rehabilitation care (PARC) are explained by observed characteristics.

**Data Sources.** State inpatient databases (SIDs) for 2005 and 2006 from four diverse states were used to identify patients with stays for joint replacement, stroke, or hip fracture.

**Study Design.** Our primary outcomes were use of institutional PARC (versus discharge home) and, conditional on discharge to an institution, skilled nursing facility (versus inpatient rehabilitation facility) care. We modified the Oaxaca–Blinder decomposition method to account for the dichotomous outcome and multilevel nature of the data.

**Data Collection/Extraction Methods.** Discharges from the four SIDs were included if the principal diagnosis (stroke, hip fracture) or procedure (joint replacement) was in the sample inclusion criteria.

**Principal Findings.** Observed characteristics explained roughly half of the unadjusted differences in use of institutional PARC. Patient-level factors (clinical, age) were more explanatory of disparities in institutional PARC use, while hospital-level factors were more explanatory of skilled nursing facility versus inpatient rehabilitation facility care.

**Conclusions.** Adjustment for characteristics influencing PARC use both mitigated and exacerbated racial/ethnic disparities in use. The degree to which the characteristics explained the disparity varied across conditions and outcomes.

**Key Words.** Modeling, multilevel, geographic/spatial factors/small area variations, racial/ethnic differences in health and health care, rehabilitation services

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Postacute rehabilitation care (PARC) is provided by physical therapists, occupational therapists, speech therapists, and/or other rehabilitation professionals to individuals with functional impairments. The primary goals of PARC are to maximize an individual's functional abilities, minimize recovery time, and, if possible, return the individual to the community in his or her

premorbid state. PARC is typically delivered in one or more of the following settings: skilled nursing facility (SNF), inpatient rehabilitation facility (IRF), home, and outpatient setting. The amount and intensity of therapy varies among the different settings with patients admitted to an IRF receiving the most intensive care and those being seen at home or in the outpatient setting receiving the least intensive.

Current evidence generally supports the effectiveness of PARC for stroke, lower extremity joint replacement, and hip fracture, the three most common conditions requiring PARC (Ottenbacher et al. 2004; Buntin et al. 2005). A majority of individuals who are hospitalized for these conditions will use some type of PARC (Kane, Lin, and Blewett 2002). PARC use for these conditions is also expected to increase dramatically over the next few decades with the aging population.

Evidence on racial and ethnic disparities in the use of PARC is mixed. Some studies have found that racial and ethnic minorities tend to receive “less intensive” PARC. In general, there is greater evidence for Hispanics using less intensive PARC than non-Hispanic whites (Ottenbacher et al. 2003; Ganesan et al. 2005) than for differences between African Americans and whites (Kind et al. 2010; Schwamm et al. 2010). Some studies have found *more* intensive use by racial and ethnic minorities (Buntin 2007) with the strongest disparity being with African Americans receiving more intensive care (Harada et al. 2000; Onukwugha and Mullins 2007; Feng, Nietert, and Adams 2009; Sandel et al. 2009; Schwamm et al. 2010). Other studies have found no racial or ethnic disparities in use of PARC (Horner et al. 2003; Bhandari et al. 2005; Gregory et al. 2006). The differences in conditions receiving PARC, the wide variety of covariates and outcomes examined, and differences in study designs, analytical methods, and populations have led to a very mixed picture of racial disparities in the use of PARC. Changes in payment policies for PARC may also explain some differences in findings, as many studies were conducted prior to the implementation of prospective payment systems in all PARC settings. A better and more current understanding of racial disparities in PARC use and the possible explanations for these disparities are needed, particularly considering that minorities often begin PARC in poorer health

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than nonminority patients (Centers for Disease Control and Prevention [CDC] (2005); Feng, Nietert, and Adams 2009; Nwachukwu et al. 2010; Sterling 2011).

Although there are many potential statistical approaches to health disparities research—Cook et al. (2009) discuss several—one common approach is to include a race/ethnicity indicator in a regression. If the indicator is significant, then the analyst concludes there is a race-specific effect on the outcome that cannot be explained by the included covariates. Although the identification of “unexplained” disparities is important, this approach does not easily characterize the proportion of the variation in utilization rates that can be explained by the covariates. The relative contribution of specific characteristics as well as the proportion unexplained provides a more in-depth understanding of disparities that can guide future policy and practice. For example, is there variation due to the difference in “type” of hospitals in which whites and blacks receive their care? Or is there variation due to otherwise unexplainable geographic patterns?

The goal of the present study was to determine the extent to which racial and ethnic differences in the use of PARC can be explained by observed differences in characteristics (i.e., sociodemographics, clinical characteristics, hospital characteristics, community resources, and geography). This inquiry extends the existing literature by considering larger, more representative populations; decomposing the racial and ethnic differences into “explained” and “unexplained” elements; comparing multiple conditions and outcomes; and examining data after PPS implementation in all PARC settings. We depart from the works by Blinder (1973) and Oaxaca (1973) and subsequent extensions and apply the decomposition approach to a mixed logistic model.

## METHODS

### *Data*

We examined 2 years of population-based, hospital discharge data (2005 and 2006) from short-term, acute care hospitals in four demographically and geographically diverse states (AZ, FL, NJ, WI) using the state inpatient databases (SIDs) sponsored by the Agency for Healthcare Research and Quality. Patients were selected based on primary ICD-9-CM diagnosis or procedure codes. Because community and hospital factors affect PARC utilization, we merged discharge data with hospital, ZIP code, and county data.

Hospital characteristics were obtained from the American Hospital Association's *Annual Survey Database* (2006) and the CMS *Provider of Services Files* and *Hospital Cost Reports*. We used the 2006 Demographic Update of the Census 2000 data, conducted annually by Claritas, to obtain ZIP code-level data on household income and the 2006 Area Resource File to obtain county-level measures of PARC supply based on patient residence.

### *Samples*

We limited our samples to individuals 45 years and older who survived their inpatient stay and were not transferred to another short-term acute care hospital, hospice, or other non-PARC facility. Because we only considered disparities between whites and blacks and whites and Hispanics, races and ethnicities other than these were omitted. The final samples for "Institution versus home" analyses consisted of  $N = 164,875$  (joint replacement), 187,188 (stroke), and 71,481 (hip fracture).

### *Dependent Variables or Outcomes*

Our primary outcomes of interest were use of institutional care (versus discharge home) and, conditional on institutional discharge, use of SNF care (versus IRF care).

### *Independent or Explanatory Variables*

In addition to race, explanatory variables included *demographic characteristics*: age, sex, insurance (Medicare/private, Medicaid, or Uninsured), income (median household income by quartiles); *clinical characteristics*: condition-specific measures (e.g., hemorrhagic versus ischemic stroke), Elixhauser's comorbidities, APR-DRG (Averill 2003) severity and mortality measures, emergency department admission, length of stay; *hospital characteristics*: procedure or diagnosis volume, for-profit status, medical school affiliation, RN FTE's/admissions, therapist FTE's/admissions, affiliated rehabilitation hospital, SNF, or HH agency; *PARC supply*: number of PTs and OTs, number of HH agencies, number of SNF beds, and number of IRFs/county population; and *geographic characteristics*: metropolitan status (large metropolitan, medium metropolitan, micro/nonmetropolitan) (Centers for Disease Control and Prevention 2009) and state.

*Decomposition Approach*

The Blinder–Oaxaca approach was originally developed to address wage discrimination. It disaggregates the unadjusted difference into (1) a portion that can be “explained” by observed characteristics and (2) the residual difference that cannot be explained by differences in observed characteristics. One approach is to perform a regression for each subgroup (here *B* for black and *W* for white), store the estimated coefficients, and substitute the means for each variable. Specifically, the difference between the mean dependent variable for whites and blacks can be decomposed as

$$\bar{Y}_W - \bar{Y}_B = \bar{X}_W\beta_W - \bar{X}_B\beta_B = (\bar{X}_W - \bar{X}_B)\beta_W + \bar{X}_B(\beta_W - \beta_B) \quad (1)$$

The final term is the sum of (1) the difference in outcomes due to between-group differences in covariates and (2) the difference in outcomes due to differences in the regression parameters. Typically, the difference is expressed as a percent of the unadjusted difference. The percent “explained” is sensitive to the choice of which coefficient vector (*B* or *W*) is used; various methods have been proposed to address this and other issues (Daymont and Andrisani 1984).

To determine the relative contributions of observed characteristics on disparities in PARC use, we “decompose” the differences in unadjusted rates into portions that are “explained” by observed characteristics and the “unexplained” portion. Our baseline model, with the probability of outcome *Y* as a function of the race/ethnicity of the subject (RACE), a set of individual characteristics (*X*), area (i.e., supply and geographic) (*W*), hospital (*Z*) characteristics, and random hospital-specific intercept (*u<sub>h</sub>*), is

$$\Pr(Y) = f(\text{RACE}\alpha + X\beta + W\gamma + Z\delta + u_h) \quad (2)$$

where *u<sub>h</sub>* is assumed to be distributed normally. We estimated this mixed model using Stata’s `xtnmelogit` command.

Although the Blinder–Oaxaca decomposition method has been applied in numerous analyses of health care disparities, we were unable to identify any previous research applying decomposition techniques to a binary outcome in a mixed model framework. As a point of departure, we used Fairlie (Fairlie 2005), who extended the Oaxaca decomposition framework to binary dependent variables (Stewart Williams 2009). The approach is similar to Oaxaca but addresses the nonlinearities inherent in extensions of the linear model.

Supporting Information Appendix SA2 contains the algorithm for our approach; what follows here is a brief description. The Fairlie approach

involves estimation of a pooled regression model. Predicted probabilities are calculated *ignoring the race coefficient* (i.e., the predicted probabilities assume everyone is white) to isolate the contribution of the differences in covariate values. Thus, the difference in the mean probabilities is the difference due to the covariate values, not to the effect of race per se. Then, the smaller of the two groups (e.g., black) in comparison is “matched” with a random subset of the larger group (e.g., white) where the matching is performed using within-race percentiles of the predicted probability.

With matched samples in hand, variable values for members of the control group (e.g., white) are sequentially replaced with values from the comparison group. As each variable is replaced, the average change in probability is calculated due to the control group receiving the comparison group’s characteristics. Formally, the estimated difference in rates explained by a given characteristic  $x_j$  is defined as (3)

$$\Delta(x_j) = \frac{1}{N_b} \sum_i \left[ \Pr \left( x_j^b \beta_j + \sum_{k \neq j} (x_k^w \beta_k) \right) - \Pr \left( x_j^w \beta_j + \sum_{k \neq j} (x_k^w \beta_k) \right) \right] \quad (3)$$

where  $x_j^b$  is the value of  $x_j$  for the black individual matched to the given white individual.

One key aspect of the sequential replacement procedure is that the order in which the variables are “allocated” to the control group can affect the estimated probability differences (Cook et al. 2009). Likewise, the specific sample of “control” observations affects the calculations. Fairlie proposes bootstrapping the calculations by performing many replications, selecting new random control samples and altering the order in which the variables are “allocated” to the control sample.

Although not specifically discussed in his paper, another issue is the sampling variance of the estimates from the underlying logistic regression. Without accounting for the variance of the regression estimates, the decomposition calculations ignore the variance in the decomposition effects due to the imprecision of the underlying regression. In the context of the original work, this imposes minimal cost, as modern computer programs can trivially re-estimate logistic regressions at each replication.

In our case, however, the large sample size, combined with the more intensive estimation procedures inherent in logistic mixed models, means that re-estimating the mixed logistic regression for each replication is time-intensive. To address this issue, we estimate the mixed model once—on the original study sample—but perform parametric bootstraps at each replication yielding

a distribution of parameter estimates equal to the distribution implied by the underlying results. With these new “perturbed” estimates in hand, the procedure proceeds as outlined above—predicted probabilities are calculated, the samples are sorted and matched, etc. At each replication, the estimated decomposition effects are stored, allowing estimates of individual variables and functions of the estimated effects. For example, we may be interested in the aggregated effect of all clinical characteristics.

The departure from Fairlie continues due to the inclusion of random effects in our model. Jacobson, Robinson, and Bluthenthal (2007) outline a mixed model with a continuous dependent variable, but their approach does not translate well into our nonlinear framework. Instead, just like the “slope” parameters, we estimate the hospital-specific random intercepts and consider those another observed variable to contribute to the decomposition. Stata’s `xtmelogit` allows estimation of these effects, and their standard errors, and therefore parametric bootstrapping can simulate the distribution of these hospital-specific intercepts as well.<sup>1</sup> Our final analysis comprised one estimation for each condition-race-outcome triple, or 3 conditions \* 2 outcomes \* 2 race/ethnicities = 12 models. Statistical significance is based on percentiles of the bootstrapped values.

We compare our results with two alternative specifications—specifically (1) a Fairlie logistic regression model ignoring the imprecision of the underlying regression estimates and (2) a Fairlie model that includes the sampling variance. Neither incorporates the hospital-level unobserved intercept.

## RESULTS

Table 1 presents the rates of PARC use: institution (versus home) and SNF (versus IRF) care by race/ethnicity and condition. *P*-values (chi-square analyses) for differences in discharge by race/ethnicity are also presented. Average age and percent with a length of stay of more than 6 days are presented to illustrate differences in the populations; a complete list of summary statistics is available from the authors.

Institutional care varies considerably across the conditions, with 45.63 percent of joint replacement patients, 28.12 percent of stroke patients, and 86.05 percent of hip fracture patients receiving institutional care. Interestingly, there is no clear pattern across conditions in institutional care by race/ethnicity. Although whites are the least likely to receive institutional care for joint replacement, they are the most likely group for hip fracture. For stroke,

Table 1: Rates of PARC Use: Institution versus Home and SNF versus IRF Care, by Race/Ethnicity and Condition

	<i>White</i>	<i>African American</i>	<i>Hispanic</i>	<i>Total</i>
Joint replacement ( <i>N</i> = 164,875)				
% Institutional care (versus home)	44.48	60.68	52.98	45.63
% SNF care (versus IRF)	65.65	59.63*	57.65*	64.88
Mean age	68.4	63.8	66.3	68.1
Percent with acute LOS>6	4.9%	9.4%	7.8%	5.3%
Stroke ( <i>N</i> = 187,188)				
% Institutional care (versus home)	27.93	33.37	23.20	28.12
% SNF care (versus IRF)	69.69	67.84	62.54	68.94
Mean age	73.7	67.1	70.3	72.6
Percent with acute LOS>6	16.5%	27.4%	23.6%	18.4%
Hip fracture ( <i>N</i> = 71,481)				
% Institutional care (versus home)	86.84	81.00	76.72	86.05
% SNF care (versus IRF)	80.18*	81.87*	72.28	79.84
Mean age	80.4	75.2	78.4	80.1
Percent with acute LOS>6	29.4%	41.7%	40.2%	30.4%

*Note.* All variables are statistically significant (1%) between race/ethnicities except for those marked.

\*African American/Hispanic use of SNF versus IRF for joint replacement and white/African American use of SNF versus IRF for hip fracture.

African Americans are the most likely followed by whites and then Hispanics. For all three conditions, African Americans are more likely to receive institutional care than Hispanics. Whites are generally more likely to receive SNF versus IRF care, although there is no difference between whites and blacks with hip fracture.

The differences in utilization patterns may be caused by factors other than race/ethnicity per se. Table 1 also includes sample means for selected variables that may influence PARC use. For example, white patients in the sample tend to be older and appear to have less severe conditions (e.g., shorter length of stay). Adjustment for these factors may alter the disparity magnitude.

For illustration, Table 2 presents the results of the mixed effects logistic model for institutional PARC for joint replacement patients (white and black only). Covariates include a race indicator and other covariates hypothesized to influence utilization. Regression coefficients are presented as odds ratios, and the variation in the hospital-specific random intercept is presented as a median odds ratio (MOR) (Larsen and Merlo 2005). Larger MORs indicate greater variance in the random hospital-specific intercepts. For simplicity, coefficient estimates for some variables, such as comorbidities and hospital characteristics, are not shown.



Table 2: Black–White Decomposition for Institution, Joint Replacement

	<i>Mixed Logistic</i>		<i>Decomposition Estimates</i>	
	<i>OR</i>	<i>CI</i>	<i>Absolute Difference, %</i>	<i>Relative Proportion, %</i>
Black	1.59 <sup>†</sup>	1.49, 1.69	N/A	
Female	2.03 <sup>†</sup>	1.98, 2.08	1.32	8.14
Age/10	2.44 <sup>†</sup>	2.41, 2.48	−6.17	−38.14
Socioeconomic factors (sum)			1.13	6.99
Uninsured	0.35 <sup>†</sup>	0.29, 0.42	−0.13	
Medicaid	1.58 <sup>†</sup>	1.41, 1.77	0.31	
Medicare/private	1.00			
income: lowest quartile	1.33 <sup>†</sup>	1.27, 1.40	1.28	
Income: 2nd lowest quartile	1.21 <sup>†</sup>	1.16, 1.26	−0.12	
Income: 3rd lowest quartile	1.11 <sup>†</sup>	1.07, 1.16	−0.21	
Income: highest quartile	1.00			
Geographic factors (sum)			7.72	47.67
Large metro	1.26 <sup>†</sup>	1.17, 1.37	0.80	
Medium metro	1.05	0.98, 1.13	−0.09	
Small metro	1.00			
State: AZ	1.14	0.78, 1.66	−0.22	
State: FL	2.18 <sup>†</sup>	1.60, 2.97	1.22	
State: NJ	15.29 <sup>†</sup>	10.83, 21.59	6.01	
State: WI	1.00			
Hospital characteristics <sup>‡</sup> (sum)			1.52	9.37
PARC supply (sum)			0.37	2.29
PT and OT/county population	1.02 <sup>†</sup>	1.01, 1.02	0.10	
Home health/county pop	1.00	0.99, 1.01	0.00	
SNF beds/county elderly	1.05 <sup>†</sup>	1.03, 1.07	0.27	
IRFs in county	1.00	1.00, 1.01	0.00	
Clinical factors <sup>§</sup> (sum)			1.59	9.83
Hospital-specific intercept	2.27 <sup>†</sup>	2.13, 2.43	1.53	9.43
Total explained			9.00	55.58
Unexplained			7.19	44.42
Total difference <sup>¶</sup>			16.19	100.00

<sup>†</sup>Statistically different from 1 at 1%.

<sup>‡</sup>“Hospital characteristics (sum)” is the aggregation of all hospital-level variables: PTs per admission, OTs per admission, annual number of joint replacement procedures, and indicators for whether hospital was a teaching hospital, was a for-profit hospital, had a hospital-based rehab unit, had a SNF, and had a home health agency.

<sup>§</sup>“Clinical factors (sum)” is the aggregation of all clinical variables: indicators for a revision, knee (versus hip), severity level, routine/elective (versus emergent), length of stay (4–6 days, >6), and comorbidities.

<sup>¶</sup>Difference between unadjusted black and white rates of institutional use.

Consistent with the unadjusted results, blacks have a higher odds of institutional use. Other factors known to be associated with institutional use, such as female and older age, have the expected signs. The right panel of Table 2 presents the decomposition results, in both absolute (difference in utilization rates) and relative (proportion of the unadjusted difference explained by the characteristics) terms. The final row presents the differences in the unadjusted rate of institutional use between blacks and whites (60.68–44.48 from Table 1).

The absolute difference is interpreted as the change in the average probability of institutional use among whites if they had the same covariates as blacks. For example, because blacks were more likely to be female in the data (71 versus 59 percent) and females were more likely to receive institutional care (OR of 2.03 in Table 2), if whites had a similar gender distribution as blacks, the average probability of institutional use would increase by 1.32 percentage points. This increase represents a change equal to 8.14 percent (relative difference) of the difference in unadjusted utilization rates between blacks and whites. In other words, after adjusting for gender, the black–white disparity in institutional use decreases.

### *Institution versus Home*

Table 3 presents the estimated decomposition effects (absolute differences) along with 95 percent bootstrapped confidence intervals for the institution versus home outcome. The top portion of the table contains the estimated absolute decomposition effects. The row “total explained” is the sum of the effects, and “total difference” refers to the unadjusted difference. The second portion of the table presents the observed rates for the racial/ethnic minority, the predicted rates for whites based on the distribution of the covariates of the minority group, and the observed rate for whites. The difference between the “predicted rate” and the “observed white” is the explained difference; the difference between the “observed minority” and the “predicted rate” is the unexplained difference. Finally, the relative percent of unadjusted disparity explained and unexplained is presented.

For all six models, the clinical effect is statistically significant. Although it only explains 5 percent of the white-Hispanic disparity (0.004/0.085) and 10 percent of the white–black disparity (0.016/0.162) for joint replacement, it explains much more of the disparity for stroke and hip fracture, particularly in regard to the white–black disparity. Age is another important contributor to the racial/ethnic differences seen in all models, allocating the ages of blacks or

Table 3: Institution versus Home

	Joint Replacement		Stroke		Hip Fracture	
	Black	Hispanic	Black	Hispanic	Black	Hispanic
Decomposition effects						
Comorbidities						
Age	0.016* (0.011, 0.020)	0.004* (0.000, 0.009)	0.069* (0.051, 0.092)	0.034* (0.020, 0.053)	-0.046* (-0.060, -0.032)	-0.017* (-0.029, -0.005)
Gender	-0.062* (-0.082, -0.042)	-0.026* (-0.043, -0.009)	-0.040* (-0.059, -0.028)	-0.021* (-0.035, -0.012)	-0.055* (-0.072, -0.039)	-0.017* (-0.031, -0.004)
Geography	0.013* (0.010, 0.016)	0.006* (0.002, 0.010)	0.001* (0.001, 0.001)	-0.000 (-0.001, 0.000)	-0.003* (-0.004, -0.002)	-0.000 (-0.001, 0.000)
Hospital	0.077* (0.052, 0.102)	0.031* (0.006, 0.056)	-0.009* (-0.015, -0.004)	-0.013* (-0.019, -0.008)	0.011* (0.003, 0.020)	-0.005 (-0.012, 0.002)
Hosp random effect	0.015* (0.006, 0.025)	0.003 (-0.005, 0.011)	-0.001 (-0.003, 0.001)	-0.004* (-0.007, -0.001)	-0.002 (-0.005, 0.001)	0.000 (-0.003, 0.004)
PARC supply	0.004* (0.002, 0.006)	0.027* (0.012, 0.041)	-0.007* (-0.013, -0.002)	-0.011* (-0.018, -0.005)	-0.007 (-0.018, 0.005)	-0.018* (-0.031, -0.005)
Socioeconomics	0.011* (0.009, 0.014)	-0.005* (-0.009, -0.001)	0.002* (0.000, 0.003)	-0.008* (-0.012, -0.004)	0.001 (-0.001, 0.003)	-0.007* (-0.013, -0.000)
Total explained	0.090* (0.078, 0.103)	0.050* (0.037, 0.064)	0.016* (0.010, 0.023)	-0.020* (-0.027, -0.013)	-0.002 (-0.005, 0.002)	-0.005* (-0.008, -0.002)
Total difference	0.162	0.085	0.054	-0.047	-0.047* (-0.058, -0.036)	-0.101 (-0.063, -0.040)
Predicted rates						
Observed minority	60.68	52.98	33.37	23.20	81.00	76.72
Predicted	53.48	49.48	29.53	25.93	82.84	81.84
Observed white	44.48	44.48	27.93	27.93	86.84	86.84
Percent of unadjusted gap						
Explained, %	56	59	29	42	68	49
Unexplained, %	44	41	71	58	32	51

\*Statistically different from 0 at 5%.

Hispanics to whites *lowers* the probability of institutional use. In some models where whites have a lower observed rate of institutional use (e.g., joint replacement), this adjustment exacerbates the difference. Although often statistically significant, differences in gender explain 1.3 percentage points or less of the white-minority disparities. These effects are also small on a relative basis, less than 10 percent of the total difference in unadjusted rates. Geography (state and metropolitan status) is an important explanatory factor in the joint replacement models, contributing the greatest percentage change, but is less important for stroke and hip fracture. Generally, observable acute hospital characteristics have little effect on the disparities, but differences in the otherwise unobserved tendency of the hospital to discharge to institution are important; whites tend to be discharged from acute hospitals that have an otherwise lower unobserved tendency to discharge to institution. For Hispanics, this difference is particularly important, explaining 30 percent of the relative differences for joint replacement (i.e.,  $0.027/0.085$ ) and 23 and 17 percent, respectively, for stroke and hip fracture. The supply of PARC resources in the community and socioeconomics is statistically significant in half the models, but relatively small in importance, explaining less than 10 percent of the differences. With the exception of the white–black model for hip fracture (68 percent) and stroke (29 percent), the set of observed characteristics explains roughly 50 percent of the difference between institutional care use by whites and racial and ethnic minorities.

Figures 1–3 (Appendix SA3) outline the cumulative effect of these various adjustments for the three diagnoses. The left  $x$ -axis is the unadjusted rate of institutional use. Moving right along the  $x$ -axis, the estimated probability of institutional use for whites changes as the characteristics of blacks (dotted line) and Hispanics (dashed line) are allocated to whites. The joint replacement and stroke figures demonstrate that the net effect of adjustment for the characteristics narrows the unexplained racial and ethnic differences. For hip fracture, the adjustment narrows the unexplained white-Hispanic difference, but it widens the white-African American difference. The figures underscore the relative contributions of the various factors. For example, in the joint replacement model, clinical factors make a small contribution with larger effects for age and geography.

#### *SNF versus IRF Care*

The decomposition results show a different pattern for the SNF versus IRF care models (Table 4). Clinical factors do not explain the disparities

Table 4: SNF versus IRF

	Joint Replacement		Stroke		Hip Fracture	
	Black	Hispanic	Black	Hispanic	Black	Hispanic
Decomposition effects						
Comorbidities	0.000 (-0.001, 0.002)	-0.000 (-0.002, 0.002)	0.002 (-0.009, 0.013)	-0.001 (-0.012, 0.009)	-0.016* (-0.026, -0.007)	-0.008* (-0.015, -0.002)
Age	-0.003* (-0.005, -0.002)	-0.002* (-0.003, -0.001)	-0.048* (-0.056, -0.041)	-0.024* (-0.030, -0.018)	-0.021* (-0.029, -0.014)	-0.008* (-0.013, -0.004)
Gender	0.001* (0.001, 0.002)	0.000* (0.000, 0.001)	-0.000 (-0.001, 0.000)	-0.002* (-0.003, -0.001)	-0.002* (-0.003, -0.001)	-0.000 (-0.001, 0.000)
Geography	-0.059* (-0.092, -0.027)	0.004 (-0.043, 0.043)	-0.007 (-0.028, 0.012)	0.013 (-0.007, 0.033)	0.003* (0.000, 0.007)	0.004* (0.001, 0.008)
Hospital	0.012 (-0.021, 0.049)	-0.044* (-0.078, -0.006)	0.004 (-0.010, 0.019)	-0.031* (-0.048, -0.016)	0.010 (-0.020, 0.042)	-0.028* (-0.062, -0.001)
Hosp rand effect	-0.052* (-0.071, -0.033)	-0.065* (-0.087, -0.040)	0.006 (-0.016, 0.026)	-0.037* (-0.057, -0.018)	-0.016 (-0.057, 0.024)	-0.100* (-0.138, -0.065)
PARC supply	0.001 (-0.002, 0.004)	-0.008* (-0.016, -0.002)	0.000 (-0.001, 0.002)	-0.002 (-0.009, 0.005)	0.006* (0.002, 0.011)	-0.000 (-0.014, 0.013)
Socioeconomics	0.003* (0.001, 0.005)	0.003* (0.001, 0.006)	0.014* (0.010, 0.017)	0.013* (0.010, 0.016)	0.004* (0.002, 0.008)	0.005* (0.002, 0.008)
Total explained	-0.097* (-0.124, -0.068)	-0.111* (-0.139, -0.084)	-0.028* (-0.046, -0.011)	-0.071* (-0.092, -0.051)	-0.046* (-0.074, -0.019)	-0.128* (-0.159, -0.099)
Total difference	-0.060	-0.080	-0.018	-0.072	0.017	-0.079
Predicted rates						
Observed minority	59.63	57.65	67.84	62.54	81.87	72.28
Predicted	56.65	54.65	67.69	62.69	76.18	68.18
Observed white	65.65	65.65	69.69	69.69	80.18	80.18
Percent of unadjusted gap						
Explained, %	150	138	108	98	-237	152
Unexplained, %	-50	-37	-8	2	337	-52

\*Statistically different from 0 at 5%.

for joint replacement and stroke (although they are important for hip fracture, especially for blacks). Age is significant in all models and is particularly important in explaining differences in whites versus blacks rate of SNF care use for stroke and hip fracture. Gender is significant in many models, but it makes a relatively small contribution to differences in use of SNF care.

Geography is significant in the white–black comparison for joint replacement, having a large effect of 6 percentage points (although statistically significant for hip fracture, the effect size is small). The hospital random effect is also generally large in these models, with some at 5–10 percentage points. Hospital characteristics and random effects were significant contributors in explaining the white-Hispanic disparity in all three models. For joint replacement, the net effect of the acute hospital (i.e., characteristics and random intercept) for Hispanics was to increase the probability of SNF use by 10.9 percentage points, 36 percent of the total unadjusted effect. Socioeconomic factors were significant in all models but had minimal effect, with the exception of the stroke models, where its effect was modest. PARC supply was significant in two of the six models but only minimally explained differences.

Figures 4–6 (Appendix SA3) present the decomposition results for SNF versus IRF care in a graphical format. Contrary to the results of institutional care (versus home), the bulk of the difference is attributable to three factors: hospital random effects (for blacks receiving joint replacement and Hispanics for all three conditions), hospital characteristics (for Hispanics for all three conditions), and geography (for blacks receiving joint replacement). With the exception of the white-Hispanic comparison for stroke and white–black comparison for hip fracture, the net effect of the adjustments is a reversal in the differences—although whites were more likely to be discharged to SNF than the other groups in the unadjusted results, after adjustment they are *less* likely. Because of these reversals, greater than 100 percent of the unadjusted disparities for these four models are explained. While whites were slightly less likely to be discharged to a SNF after hip fracture, the net effect of the adjustment is a large decrease in the likelihood of whites to use SNF care. Thus, the conclusion for the SNF versus IRF models is that racial and ethnic minorities are more likely (not less likely) to be discharged to SNFs and whites are more likely to receive IRF care. With the exception of age in the white–black comparison for stroke, clinical factors, age, gender, and PARC supply explained little of the disparities.

### Comparison of Techniques

Table 5 presents differences in results between the presented results and two alternative techniques: both use logistic regression (ignoring the hospital random effect) and one does not account for the variance in the parameter estimates. Results are presented for the “Institution versus Home, Joint replacement” model. Overall, the results are largely consistent across the three models. Notably, the addition of the sampling variance adds little to the confidence intervals, likely due to the large sample in our specific application.

Comparing the multilevel decomposition with the logistic O-B model, the conclusions for the African American sample are largely consistent. Although the estimated decomposed effect due to clinical, for example, is 25 percent higher in the logistic model, the qualitative conclusions are identical between the two models. Only the multilevel model allows the identification of the role of the hospital intercept, an important element in this application, but conclusions are similar between the two models.

The Hispanic population yields much different effects. First, some factors are insignificant in the logit yet significant in the multilevel (e.g., clinical factors and PARC supply), while the converse is also true (hospital characteristics). Despite having similar sample sizes (7,793 versus 7,335), the relative comparability of the decomposition varies between the two populations.

## DISCUSSION

The decomposition approach used here demonstrated a number of important findings. First, one-quarter to two-thirds of the racial/ethnic differences in institutional PARC use were explained by differences in observed (including hospital-specific random intercepts) characteristics. Racial and ethnic disparities in institutional PARC use due to unexplainable factors, therefore, remain for these conditions. For the SNF versus IRF models the explained portion was much larger and in most instances led to a widening of the disparity. For example, the unadjusted rate of SNF use for whites with joint replacement was 65.65 percent, higher than the rate of SNF use for blacks (59.63), suggesting blacks are less likely to be discharged to SNF. But after adjusting for the difference in observed characteristics, the disparity is increased—blacks have an unexplained *increased* tendency to use SNF care (actual 59.63 versus predicted 56.65). These findings were fairly consistent in all of the SNF-IRF models and, in most instances, were driven by hospital factors (both observed

Table 5: Comparison of Results across Methods for Institution versus Home, Joint Replacement

	<i>Logit, No V-COV</i>	<i>Logit, with V-COV</i>	<i>Multilevel</i>
Black			
Clinical			
Age	0.020* (0.012, 0.029)	0.020* (0.012, 0.029)	0.016* (0.011, 0.020)
Gender	-0.061* (-0.081, -0.041)	-0.061* (-0.081, -0.040)	-0.062* (-0.082, -0.042)
Geography	0.014* (0.010, 0.022)	0.014* (0.010, 0.022)	0.013* (0.010, 0.016)
Hospital	0.080* (0.058, 0.103)	0.080* (0.058, 0.102)	0.077* (0.052, 0.102)
Hospital RE	0.018* (0.014, 0.027)	0.018* (0.014, 0.027)	0.015* (0.006, 0.025)
PARC supply	-	-	0.015* (0.002, 0.028)
Socioeconomics	0.004* (0.002, 0.011)	0.004* (0.002, 0.011)	0.004* (0.002, 0.006)
Total	0.011* (0.009, 0.018)	0.011* (0.009, 0.018)	0.011* (0.009, 0.014)
Hispanic	0.086* (0.080, 0.092)	0.086* (0.079, 0.092)	0.090* (0.078, 0.103)
Clinical			
Age	0.005 (-0.002, 0.013)	0.005 (-0.002, 0.014)	0.004* (0.000, 0.009)
Gender	-0.027* (-0.042, -0.014)	-0.027* (-0.042, -0.014)	-0.026* (-0.043, -0.009)
Geography	0.006* (0.002, 0.014)	0.006* (0.002, 0.014)	0.006* (0.002, 0.010)
Hospital	0.026* (0.009, 0.045)	0.026* (0.008, 0.045)	0.031* (0.006, 0.056)
Hospital RE	0.009* (0.004, 0.017)	0.009* (0.004, 0.017)	0.003 (-0.005, 0.011)
PARC supply	-	-	0.027* (0.012, 0.041)
Socioeconomics	0.000 (-0.001, 0.007)	0.000 (-0.003, 0.008)	-0.005* (-0.009, -0.001)
Total	0.009* (0.007, 0.017)	0.009* (0.006, 0.017)	0.010* (0.007, 0.012)
	0.029* (0.023, 0.035)	0.029* (0.022, 0.036)	0.050* (0.037, 0.064)

*Note.* Cells contain mean absolute differences in probability due to the given set of characteristics, with 95 percent confidence interval. “Logit-No V-COV” uses the Fairlie model without accounting for the imprecision in the underlying logistic model, “Logit-With V-COV” uses the Fairlie model and accounts for the imprecision in the underlying logistic model by bootstrapping, and Multilevel is the model specified in equation (2) and used throughout the manuscript.

\*Statistically different from 0 at 5%.



characteristics and random intercepts). This contributes to the existing literature by identifying the relative importance of various characteristics in differences in PARC use. Understanding the source of the disparities can lead to more effective efforts to decrease them. For example, identifying the importance of the acute hospital suggests interventions targeted there may be more fruitful than examining the role of PARC supply in the community (which had little effect in most models). The estimated effects of geography suggest that local/regional efforts to decrease disparities may be most useful. One limitation of most decomposition research is that the source of the remaining “unexplained” difference cannot be identified. Such findings are, nevertheless, important particularly if the proportion of the disparity that is unexplained is large. The unexplained differences in our models could be due to cultural difference in preferences for care, unobserved social differences (e.g., social support enabling discharge to home), differences in condition severity not captured by our measures, or discrimination. These factors should be considered in future research.

Second, although certain characteristics that explained the differences may drive *indicated* variation in the use of PARC, the clinical justification for other characteristics is not clear. For example, the variation due to geography while controlling for PARC resources in the community is difficult to understand. Geography—primarily resulting from metro status for hip and joint and state for stroke (not shown)—was important in explaining racial/ethnic differences in use of institutional care for all three conditions, and use of SNF care for joint replacement. The source of the interstate variability is unknown—is it legal or regulatory (such as incentives inherent in certificate of need laws), cultural (such as the availability of informal care), market-driven (such as reimbursement policies in the commercial insurance market), provider-driven (such as practice patterns), or something else entirely?

Third, there were general findings that tended to hold across conditions, despite the differences in their “planned” nature and care guidelines. For example, clinical factors, age, and geography were important characteristics for some of the racial/ethnic differences in use of institutional PARC; hospital random effects and/or characteristics were important in explaining some of the racial/ethnic differences in use of SNF care. Overall, observable characteristics tended to explain less of the racial variation in PARC use for stroke, but the unadjusted differences were smaller as well. The source of the inter-condition variation is unknown and could reflect the differences in the nature of the conditions (i.e., joint replacement being elective, while stroke and hip fracture are more urgent). We generally found that adjusting for comorbidities, age,

and gender had a small effect on the disparity among patients with joint replacement, but larger effects for stroke or hip fracture. These findings suggest that the inter-racial/ethnic variation in health among joint replacement patients may be smaller than among stroke or hip fracture patients. Further study on the causal pathways behind the differences across conditions would be useful.

Finally, in contrast to our expectations, socioeconomic factors and PARC supply were, in most cases, only modest explanations of the racial/ethnic disparities. The Institute of Medicine definition of a racial disparity is any difference not explained by clinical factors or patient preferences (Smedley et al. 2003). Given that definition, PARC disparities are quite pronounced.

Limitations of the study include the selection of specific states. New Jersey, in particular, had a higher referral rate to institutions and IRFs than the other three states; if New Jersey is an outlier, this may limit the generalizability of the findings. We performed sensitivity analyses by omitting New Jersey; results were qualitatively similar. The data contained only limited information on functional status, which is an important determinant of PARC; “length of stay” may be confounded by condition severity or reflect time waiting for institutional PARC. Some variables were measured with error (e.g., therapist supply in the hospital was standardized by admission, not by patients with a “rehab” condition). Future work should exploit the spatial nature of the data, specifically in the spatial autocorrelation that may be present (although mixed logistic models with spatial autocorrelation represents a methodological frontier). Finally, our measures of PARC supply were somewhat crude.

## CONCLUSION

Adjustment for characteristics influencing PARC use both mitigated and exacerbated racial/ethnic disparities in use. The degree to which the characteristics explained the disparity varied across conditions and outcomes. Generally, patient-level factors (clinical factors and age) were more explanatory of disparities in use of institutional PARC, whereas hospital-level factors were more explanatory of SNF versus IRF care. Geography was an important factor in the joint replacement models for both use of institutional PARC and SNF versus IRF care. A better understanding of the sources of hospital and geographic variation in PARC use are topics for future research.

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## NOTE

1. Unlike the slope parameters, however, covariances are not readily available, so we assume independence of the random intercepts when performing the replications.

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## SUPPORTING INFORMATION

Additional supporting information may be found in the online version of this article:

Appendix SA1: Author Matrix.

Appendix SA2: Details of Estimation Procedure.

Appendix SA3: Graphical Representation of Results.

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