RACIAL DISPARITIES IN THE HEDIS MEASURES OF HEALTH CARE QUALITY

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Abstract:

The HEDIS® measures of health care quality use health plan administrative records and medical records to estimate rates at which specific clinically-indicated services are provided to patients. Data from Medicare managed care HEDIS provide an opportunity to estimate race-related disparities in care. We analyzed data on four HEDIS measures and found that there were substantial disparities in rates at which services were provided to white and African-American Medicare beneficiaries in managed care. We decomposed these disparities into a component explained by observed differences between white and African-American members on other characteristics, and a residual component. We also decomposed these disparities into a component that was explained by differential enrollment by race in high- and low-performing plans, and another component due to differences by race within the same plan. For one measure (mammography) the differences were largely between plans, while for others the differences were primarily within plan. Health services research commonly encounters such data in which patients are clustered by units (health plan, provider, or geography) that affect the practice of care and the factor of interest cuts across units. The decompositions we illustrated should be a standard part of the analysis of such data.

1. Introduction

Racial differences in health in the United States have been widely documented, with substantially higher rates of morbidity and mortality for minority populations, especially African-Americans. It has also been shown that there are substantial disparities in health care for African-Americans relative to whites. Such disparities might be explained in part by differential access to care, for example due to higher rates of uninsurance for health care for African-Americans. Hence it is particularly interesting to examine disparities in the context of a group with similar insurance coverage, to detect disparities not caused by uninsurance.

One such group consists of beneficiaries of the Medicare program, which covers the vast majority of elderly (over age 65) residents of the United States. Within Medicare, about 14% of beneficiaries are insured through managed care health plans under the Medicare+Choice program. Despite some variations in benefit design, all of these Medicare beneficiaries are entitled to a similar set of basic medical services.

The growth of managed care might tend to reduce disparities, if it standardizes and systematizes care. On the other hand, the incentives to cut costs in managed care could have a negative effect on the the more vulnerable beneficiaries. Thus it is interesting to examine disparities in this context.

Under the Balanced Budget Act of 1997, Medicare+Choice health plans are required to report data on quality of care using a Medicare-specific version of the HEDIS® measures of health care quality, developed by the National Committee for Quality Assurance (NCQA). We analyzed individual-level data from these reports to assess and compare quality of care for African-American and white members of Medicare+Choice health plans. The methods and results of this study are presented by Schneider, Zaslavsky and Epstein (2002), where more detailed information on the measures and extensive references to the literature on health care disparities and quality can be found. In this paper, we extend the previous analysis by decomposing the observed disparities into components attributable to observed characteristics of the beneficiaries other than race, to differential enrollment of whites and African-American beneficiaries in plans of generally lower and higher quality, and to disparities between races within plan. The methods we illustrate are applicable whenever disparities are being examined across a collection of health care units such as hospitals, health plans, or geographic areas that cut across racial lines.

2. Data

Our data are derived from files obtained from the Center for Medicare and Medicaid Services (CMS). Medicare HEDIS data were obtained from 294

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Table 1: Measure definitions and summary eligibility criteria.

Measure	Eligible denominator population
BCS: breast cancer screening	women aged 65–70 years and continuously enrolled
DEE: eye examinations for diabetic patients	continuously enrolled patients at least 65 years old determined to be diabetic by prescriptions or diagnosis codes
BBMI: receipt of beta-blockers after an acute myocardial infarction (AMI)	at least 65 years old, discharged alive after admission for AMI with no recorded contraindications for beta-blockers
FHMI: followup within 30 days after hospitalization for mental illness	at least 65 years old, discharged after admission for mental health diagnosis

health plans, representing services provided in 1998. A total of 415,040 beneficiaries were included for at least one of four measures of quality of care. For each of the measures, an eligible population was defined by HEDIS standards, and each sampled member was determined by some combination of administrative record and medical record review to have received the appropriate service or not. These measures (and the corresponding eligible populations) are shown in Table 1.

In addition, we obtained the managed care enrollment database, showing the age, sex, Medicaid eligibility, zip code, and plan membership of each beneficiary. We matched the two files, limited to the over-65 population, and excluded beneficiaries who died or disenrolled from their plan during the year. We also limited our analysis to beneficiaries listed in the enrollment file as either white or black (African-American), since disparities between these two groups were the focus of our analysis.

We also merged into this dataset some characteristics of elderly in the beneficiaries' areas of residence (zip code area) from the 1990 census. Specifically, we defined low income areas as those where over 25% of beneficiaries received public assistance income, and low, medium and high education areas by terciles of the percentage of the elderly with college education. These variables can be interpreted in part as proxies for the corresponding variables measured at the individual level, and in part as measures of the neighborhood context of the beneficiaries. Such variables have been shown in a previous study to be predictive of HEDIS outcomes (Zaslavsky et al. 2000). Thus, including them in our models allowed us to estimate the contribution of some socioeconomic factors that are not available to us at the individual level, although their interpretation is somewhat ambiguous.

In the following sections we concentrate on analyses of the breast cancer screening (BCS) measure. This measure had a large sample size (139,437 cases), was reported by most of the plans (241), and effectively illustrates the methods we applied.

3. Comparisons: unadjusted and adjusted for individual characteristics

We first calculated unadjusted disparities in rates of BCS. While 70.3% of eligible beneficiaries were positive on this measure, 70.9% of whites and only 62.9% of African-Americans were positive, for a disparity of 8.0%. The 95% confidence interval (adjusted for clustering by plan) for the disparity was (4.5%, 11.4%).

A number of characteristics other than race were also associated with disparities in the BCS measure. BCS rates in low-income areas were 62.9% and in other areas 70.8%, a disparity of 7.9%. Similarly the rates by ascending education terciles were 61.9%, 65.4% and 73.2%. Rates for Medicaid-eligible beneficiaries were only 51.3% compared to 70.9% for other beneficiaries. (Medicaid eligibility is perhaps our best measure of poverty at the individual level because only the indigent are eligible, although its interpretation is complicated by rules on "medical indigency" due to high out-of-pocket medical expenses.) All of these disparities are also highly significant.

To decompose the disparity into components interpretable as direct effects of race and indirect effects mediated through other measured variables, we fit a linear multiple regression model. (Although a logistic regression might appear a more obvious choice, the linear model is somewhat easier to interpret and is a good approximation to the logistic regression in the range of probabilities that appear in this analysis.) Coefficients from this model appear in Table 2, for each of the HEDIS outcome variables.

For each variable in the model, we show the white and African-American means, the difference (Δ) between the means, and the regression coefficient (β). Finally, we show an effect representing as the component of the Black-White difference mediated by each variable, defined as the product $\beta\Delta$. Adjustment for individual characteristics reduces the "race disparity" to 3.6%, and it might be tempting to suggest that adjustment explains away much of the disparity.

It would be misleading, however, to interpret this number in isolation from the remaining effects. The largest mediated effect is that of residence in a low education area, reflecting the large difference in socioeconomic status between the elderly of the two race groups. The second largest effect is associated with Medicaid eligibility, also reflecting a difference in poverty rates. The display explains part of the racial disparity, and modifies our previous description of it in purely racial terms. However, it does not make it any less important from a policy standpoint, since the unadjusted effect (shown as "Total" in Table 2) reflects the differences in services received by members of the minority race. Rather, this analysis deepens our understanding of the factors behind such racial effects. It also directs our attention to other groups for whom disparities might be an issue, specifically low-income whites. Whenever a disparities analysis is adjusted for other factors, a similar decomposition of the adjustment is desirable, highlighting the mediating characteristics associated with the disadvantaged group. Such an analysis deepens our understanding of other underlying factors that might contribute to the racial disparity.

4. Within- and between-plan effects on disparities

The lower performance of the health care system for African-Americans, after adjustment for other variables, could reflect two mechanisms. African-Americans could be enrolled in worse (poorer-performing) plans, possibly due to location, and also they could be receiving worse services within each plan. These two mechanisms have different policy implications. The first mechanism, related to plan selection, would suggest examination of the reasons why the underserved group is enrolled in worse plans. Do higher quality plans selectively enroll fewer minorities, or are minorities simply located in market areas with poorer quality of care? The second mechanism would suggest a focus on the ways that care is provided to the various groups, which might reflect characteristics of the health care system that interfere with equitable service delivery to minorities but are not consequences of the policies of any plan in particular.

To address this issue, we first correlated the percent African-American in plans with their BCS rates. The correlation was -0.147 with BCS rates overall, -0.115 with BCS rates for African-Americans, and -0.148 with BCS rates for whites. Thus, African-Americans appear to be concentrated in plans with lower BCS rates for both racial groups.

It is noteworthy that ecological correlation between BCS rates for white and African-American members by plan is 0.880 (downweighting the plans with few African-American members, for which the corresponding estimated BCS rate is noisiest). Using a hierarchical model to remove the attenuation of the correlation due to independent sampling error, we obtain an even higher correlation of 0.928. Thus, as might be expected, plans that do well tend to do well for both groups. In fact the gap between white and black rates is almost uncorrelated with the racial composition of the plan.

To understand the implications of the these correlations, we can write an analytical decomposition of the differences (assuming that there are no individual effects, or that as in this analysis we have adjusted them away first and are analyzing the residuals). Let y_{cdk} be the outcome for person k in cluster c and domain d. Here c is the health plan and d the race group. The mean for domain d is $\bar{y}_d = \sum_c \left(\frac{N_{cd}}{N_{+d}}\right) \bar{y}_{cd}$, where $+$ represents summation over the corresponding index, N is population size, and $\bar{y}$ represents a population mean. Then the difference between the domain means is

$$\bar{y}_1 - \bar{y}_0 = \sum_c \left[\left(\frac{N_{c1}}{N_{+1}}\right) \bar{y}_{c1} - \left(\frac{N_{c0}}{N_{+0}}\right) \bar{y}_{c0} \right].$$

If we assume a constant within-cluster difference $\bar{y}_{c1} - \bar{y}_{c0} = \delta$, then

$$\begin{aligned}\bar{y}_1 - \bar{y}_0 &= \delta + \sum_c \left[\left(\frac{N_{c1}}{N_{+1}}\right) - \left(\frac{N_{c0}}{N_{+0}}\right) \right] \bar{y}_{c0} \\ &= \delta + \mathrm{Cov}(D_c, \bar{y}_{c0}),\end{aligned}$$

where D_c is the difference in shares of total population in the two domains that falls into the cluster. Thus the overall difference depends on the *within* difference and the *covariance* of the difference in shares with the overall level for the cluster (for one group; by our hypothesis of constant differences, it doesn't matter which is chosen).

This neatly symmetrical result breaks down when the difference $\bar{y}_{c1} - \bar{y}_{c0}$ is not assumed to be constant.

Table 2: Regression decomposition of individual-level effects.
Notes: all entries are percentages; Δ = Black-white difference; * indicates coefficients significantly different from 0 ($p < .05$).

BCS: Breast cancer screening ($n = 121,423$)

	White mean	Black mean	Δ	β	Effect
Black	0.0	100.0	100.0	−3.6*	−3.6
Urban	95.3	99.1	3.8	−2.5	−0.1
Medicaid eligible	2.6	10.0	7.4	−17.1*	−1.3
Age 70—80	0.6	2.9	2.3	−11.6	−0.3
Age > 80	0.2	0.8	0.6	−16.5	−0.1
Poverty area	3.5	16.4	12.9	−1.7	−0.2
Low education area	6.8	28.2	21.4	−9.5*	−2.0
Medium education area	22.8	30.6	7.8	−7.3*	−0.6
Total					−8.1

BBMI: Beta-blockers after AMI ($n = 10,161$)

	White mean	Black mean	Δ	β	Effect
Black	0.0	100.0	100.0	−7.3*	−7.3
Urban	93.8	99.1	5.3	1.6	0.1
Medicaid eligible	2.8	11.9	9.1	−10.8*	−1.0
Age 70—80	53.0	46.0	−7.1	0.4	0.0
Age > 80	19.2	15.8	−3.4	−1.1	0.0
Poverty area	2.0	17.2	15.2	−3.0	−0.5
Low education area	9.1	28.1	18.9	−4.2	−0.8
Medium education area	27.1	34.0	7.0	−1.8	−0.1
Total					−9.6

DEE: Diabetic eye exams ($n = 140,534$)

	White mean	Black mean	Δ	β	Effect
Black	0.0	100.0	100.0	−3.9	−3.9
Urban	95.3	98.7	3.3	−1.0	0.0
Medicaid eligible	4.4	11.3	6.9	−11.9*	−0.8
Age 70—80	53.3	51.6	−1.7	2.3*	0.0
Age > 80	13.4	9.4	−4.0	−1.1	0.0
Poverty area	3.6	17.6	14.0	−1.7	−0.2
Low education area	8.9	28.9	20.0	−9.1*	−1.8
Medium education area	25.9	31.1	5.2	−5.2*	−0.3
Total					−7.1

FFMI: Followup for mental illness after hospitalization ($n = 3279$)

	White mean	Black mean	Δ	β	Effect
Black	0.0	100.0	100.0	−18.4*	−18.4
Urban	95.8	98.7	3.0	−7.2	−0.2
Medicaid eligible	10.1	26.8	16.8	−11.0*	−1.8
Age 70—80	52.2	51.1	−1.2	−4.8*	0.1
Age > 80	19.6	11.9	−7.7	−17.5*	1.3
Poverty area	1.9	13.6	11.7	−2.6	−0.3
Low education area	9.6	28.1	18.5	−6.4	−1.2
Medium education area	25.5	26.8	1.3	−2.4	0.0
Total					−20.6

In that case a slightly different formula is obtained, in which δ is a weighted average of the within-plan disparities. The second term is the covariance with the mean for the group used to define the weighting. Typically this reference group would be taken to be whites, in a disparities analysis, because plan performance for whites is taken as a target that might be obtained for both groups in the absence of the factors causing disparities.

When disparities are not equal across plans, another approach to summarizing the disparity is to calculated a weighted mean of within-plan disparities (or rather of estimated disparities, the within-plan difference in rates $\bar{y}_{c1} - \bar{y}_{c0}$). Various weightings are possible, such as equal by plan, by number of African-American members, etc., and the choice among them is somewhat arbitrary. The optimal weighting based on sample sizes alone, in the sense of minimizing the variance of the weighted mean, is proportional to the *effective sample size* for the comparison in the cluster, $N_{c,\text{eff}} = N_{c1}N_{c2}/Nc+$. This weighting gives more weight, for a given overall sample size, to plans with comparable numbers of members from each group than those where there is a great disproportion, and obviously no weight to those where one group is unrepresented.

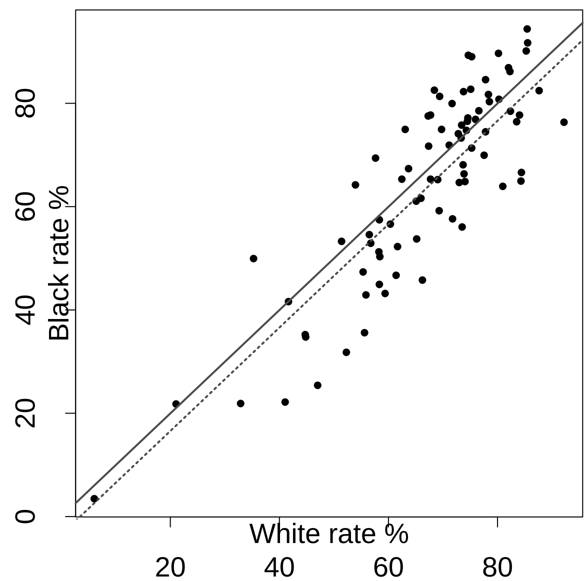
We calculated the mean disparity for breast cancer screening with equal weights per plan (excluding those with no African-Americans), weighted by enrollment, and with the optimal weighting, in both cases without adjusting for other individual effects. The mean disparities were 3.5%, 2.4% and 3.4% respectively. Using a linear hierarchical model, which implicitly weights the plans in yet another way, the estimated mean disparity was even smaller (1.3%). Thus less than half of the overall disparity for this measure is due to to within-plan effects. Corresponding results for other measures appear in Table 3. (Population estimates of disparities differ slightly between tables due to varying exclusions for missing data.)

5. Variation in disparities

It is interesting, in a disparities analysis, to compare the overall mean disparity to the variation in both disparities and overall rates across plans. Figure 1 is a scatterplot of BCS rates, restricted to plans with at least 20 cases in each race group. Disparities appear to be very variable, but even more notably, the variation in rates among plans is much larger than the disparities within any plan.

The figure might be greatly affected by sampling error. To examine this same issue more systematically, we fit a hierarchical model. The hierarchical linear probability model included random effects for the plan intercept (the plan effect for whites) and the African-American-white difference. Under this model, the mean difference is -1.2%, the SD of the intercept is 16.5%, and the SD of the difference is 11.2%. Thus even after correcting for sampling error, the variation in both overall plan quality and in disparities is much larger than the mean disparity. This suggests that there is potential for improvement for both groups, and especially for African-Americans (concentrated in the worse plans), if plans can be brought up to the performance now realized by the better-performing plans. Similar results are seen for the other measures (Table 3). Note that for FHMI, the racial disparity is fairly constant across plans (SD= 5.5%) relative to the large variation in overall performance (SD= 13.2%).

Figure 1: White and African-American BCS rates, by plan. The solid line represents equality and the dashed line the average disparity. Plans with fewer than 20 cases in either race are excluded.



6. Conclusions

We draw several methodological conclusions from these illustrative examples. First, it is essential to think about what "adjustments" are appropriate to the research and policy questions at hand. Adjusting away mediated effects might tend to underestimate real differences in performance.

Second, the clustered structure of the data gives us another way to look at disparities. Sampling

Table 3: Means, correlations and variation across plans for HEDIS measures.

	BCS	DEE	BBMI	FHMI
White population rate	70.9%	50.4%	73.8%	54.0%
Black population rate	62.9%	43.6%	64.1%	33.2%
Population delta	7.9%	6.8%	9.7%	20.8%
Mean plan delta (plan-weighted)	3.5%	3.6%	5.7%	12.6%
Mean plan delta (enrollment-weighted)	2.4%	3.3%	4.6%	13.8%
Mean plan delta (comparison-weighted)	3.4%	2.9%	5.1%	15.0%
Mean plan delta (linear hierarchical model)	1.3%	3.0%	6.8%	17.4%
Correlation of % black with overall rate	-0.147	-0.292	-0.245	-0.476
Correlation of % black with white rate	-0.148	-0.288	-0.201	-0.412
Correlation of % black with black rate	-0.115	-0.248	-0.141	-0.315
Correlation of % black with delta	-0.006	0.029	-0.003	0.003
Correlation of white and black rates (empirical, comparison-weighted)	0.880	0.914	0.705	0.457
Correlation of white and black rates (hierarchical model)	0.928	0.873	0.947	0.989
SD across plans of white rate (hierarchical model)	16.5%	17.4%	18.2%	13.2%
SD across plans of delta (hierarchical model)	11.2%	12.0%	7.9%	5.5%

variation assumes greater importance as analysis is brought down to the cluster level, and formal use of hierarchical models may be essential.

Finally, variation both in overall quality and in disparities across the units of analysis might be as important as the mean level of the disparity. Once variation is found, further research and case studies can seek out the mechanisms by which equitable performance is obtained and seek to disseminate best practices.

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