Supplementary Online Content

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This supplementary material has been provided by the authors to give readers additional information about their work.

eMethods

A. Model specification for estimating difference in probability of readmission between participants admitted to hospitals with HWRRs in highest vs. lowest quintile

To obtain the estimates presented in Table 3 of the manuscript, we estimated the following logistic regression model of 30-day readmission at the respondent-admission level, varying the set of predictors included in the model (β_3-β_5):

$$\text{logit}(E(\text{Readmit}_{i,j,k})) = \beta_0 + \beta_1\text{HWRR\_quintile\_indicators}_k + \beta_2\text{year\_indicators}_j + \beta_3\text{CMS\_variables}_{i,j} + \beta_4\text{Other\_Claims\_variables}_{i,j} + \beta_5\text{HRS\_variables}_{i,j}$$

"$\text{Readmit}_{i,j,k}$" indicates whether participant *i* was readmitted within 30 days of discharge in year j from hospital *k*. "HWRR_quintile_indicators" denotes a vector of indicators for the hospital *k*'s quintile of publicly reported hospital-wide readmission rate*,* "year_indicators" is a vector of year dummies, "CMS_variables" includes the patient characteristics used by CMS for risk adjustment of readmission rates as described in the Methods section(used in models 2-4 in Table 3). "Other_claims_variables" includes other eligibility and diagnostic variables from Medicare enrollment and claims data, as described in the Methods section (used in models 3-4 in Table 3). "HRS_variables" includes the additional 24 clinical and social characteristics assessed from HRS surveys and described in Tables 1 and 2 (used in model 4 in Table 3) as well as the following pre-specified interactions between two key claims-based variables (HCC score and original reason for Medicare enrollment) and the following HRS variables: cognition score, race/ethnicity, prescription insurance coverage, CES-D score, self-rated health, supplemental health insurance, total assets, ADLs with some difficulty, and marital status. Similarly, we included pre-specified interactions between age and self-rated health, CES-D score, and cognition score.

All logistic models were estimated taking account of complex survey design with robust design-based variance estimators to account for clustering within geographic areas, hospitals, or participants (specifying the survey cluster as the ultimate cluster) and HRS survey weights to account for the survey design and survey non-response.

B. Simulation procedure for estimating absolute differences in readmission probabilities

The differences in readmission probabilities presented in Table 3 are retransformations of the b coefficient for the indicator for the highest quintile of publicly reported hospital-wide readmission rates (see section A above). Specifically, to ease interpretation, we used a simulation approach to obtain the three quantities of interest reported in Table 3: 1) the average probability of readmission for a participant admitted to a hospital in the lowest HWRR quintile, 2) the same for participants admitted to a hospital in the highest HWRR quintile, and 3) the average difference in probability of readmission between participants admitted to hospitals in the highest versus lowest quintiles. We took the following steps to estimate these quantities of interest:

1) Fit a logistic regression model predicting 30-day readmission using the specifications described in section A above.
2) Take 10,000 draws of coefficients from the estimated vector of coefficients, β assuming β follows a multivariate normal distribution with a mean of β and a variance-covariance matrix as estimated by the model.
3) For each draw of β coefficients, obtain the model prediction for each observation, alternately setting the highest and lowest HWRR quintile indicator to 1.
4) Retransform the model prediction to a probability by taking the inverse of the logistic function, $\text{logit}^{-1}(\beta X) = e^{\beta X}/(1+e^{\beta X})$
5) For each draw, calculate the mean predicted probability of readmission across observations under each of the two scenarios (HWRR quintile = highest vs. lowest). To

calculate an absolute difference, for each draw, calculate the difference between these mean predicted probabilities under the two scenarios.

6) Estimate the average readmission probability for the lowest or highest HWRR quintiles by taking the mean predicted probability of the 10,000 means in step 5 in each of the two scenarios.
7) Repeat the same procedure in step 6 for the differences to get the average difference in probability of readmission. To get a 95% CI, take the 2.5th and 97.5th percentiles from the distribution of the 10,000 differences from step 5.

C. Estimating Medicare-linkage weights

We repeated the analyses in Table 3 with additional weighting to address potential bias introduced by differences between participants who provided their Medicare identification numbers for linkage to claims data and those who did not. Among participants otherwise eligible for study inclusion, we fitted a logistic regression model predicting successful linkage to Medicare claims data as a function of baseline sociodemographic characteristics (age, sex, race/ethnicity, education, marital status, need for proxy response) and weighted this analysis by survey sampling weights. From this model we derived weights equal to the inverse of the probability of linkage and combined these weights with sampling weights by taking the product of the two sets. We then repeated the analyses in Table 3 using these combination weights and found no substantial change to the results reported in Table 3.

D. Multilevel model estimating variation in hospital readmission rates

To estimate the change in between-hospital variation in readmission rates after accounting for each successive set of variables described in Table 3, we fitted a multilevel linear model predicting readmission as a function of these variables and hospital random effects. Since many hospitals captured by our study sample had only a few admissions in the 2009-2012 study period, we expanded the study sample to include admissions from 2008-2012 and only included admissions to hospitals with at least 20 admissions from 2008-2012 (108 out of 1,377 hospitals, accounting for 44% of admissions in the study sample). We specified the multilevel model as below, with a hospital-level random intercept:

$$\text{Readmit}_{i,j,k} = \beta_0 + \beta_1\text{year\_indicators}_j + \beta_2\text{CMS\_variables}_{i,j} + \beta_3\text{Other\_Claims\_variables}_{i,j} + \beta_4\text{HRS\_variables}_{i,j} + u_{0k}$$

$$u_{0k} \sim N(0, \sigma^2)$$

Where the terms are the same as in the model described in section A above, with the addition of random intercepts for hospital readmission rates, u_{0k}, normally distributed with a mean of 0 and variance σ^2. We present the estimated between-hospital standard deviation, σ, for each of the 4 models in Table 3 (Table S3) and also plotted the hospital random effects after adding each set of characteristics (Figure S1). Multilevel models were fitted using the *lme4* package, v1.1-7 in R v3.1.2.[1,2]

E. Multiple imputation of missing data

In the 2009-2012 sample, approximately 9.9% of admissions had missing data for at least one survey item due to item non-response. In the manuscript, we present an analysis accounting for this missing data by carrying the last survey observation with a response forward, reducing the missingness to 1.5% of admissions. To test the validity of this approach, we performed a sensitivity analysis using multiple imputation instead of carrying the last observation forward.

Using the R package *Amelia*, we generated 5 multiply imputed datasets using a bootstrap EM algorithm based on all HRS clinical and social variables present in Tables 1 and 2.[3] We then fit the 4 logistic regression models specified in part A and reported in Table 3 using these 5 multiply imputed datasets. We obtain an estimate for the coefficient indicator for hospital membership in the highest HWRR quintile using Rubin's method for combining estimates from several multiply imputed datasets.[4] We compared these coefficient estimates to those used to generate the results for Table 3 and found no substantial difference.

eAppendix 1: Comparison of patient characteristics available in Medicare claims between 20% Medicare sample and analytic sample

Using Medicare enrollment information and claims data from 2009-2012 for a 20% random sample of fee-for-service Medicare beneficiaries, we replicated the analysis we present in Table 2 for inpatients from the 20% sample, comparing patient characteristics assessed from Medicare and enrollment and claims files between patients admitted to hospitals in the highest vs. lowest quintile of publicly reported readmission rates. In this table, we focus on comparing the between-quintile differences between the two samples rather than comparing the samples within a given quintile, because we expect the two samples to differ somewhat due to differences in inclusion criteria. For example, we excluded nursing home residents from the HRS sample based on reports from respondents and respondents' families collected by HRS investigators, whereas we had to rely on a claims-based algorithm for excluding nursing home residents from the 20% sample to improve comparability.[5]

We find that the distribution of patient characteristics differs between the quintiles similarly for the HRS and 20% samples. The only exceptions are gender and ESRD status, neither of which differed significantly between the quintiles in our study sample in Table 2 (and therefore did not contribute to our results), and "other" race. Since we used the HRS race and ethnicity variables in our analyses rather than the race and ethnicity variables in the Medicare enrollment files, this minor discrepancy could be due to differences in how race and ethnicity were measured in each sample. The rest of the between-quintile differences estimated using the 20% sample (including differences in age, HCC score, white race, disability as the original reason for eligibility, and Medicaid eligibility) are very similar in the two samples in magnitude and direction, with estimates from the 20% sample comfortably within the 95% confidence interval of estimates from our study sample.

Comparison of patient characteristics available in Medicare claims between 20% Medicare sample and analytic sample

		HRS Sample				**20% Sample of Fee-for-Service Medicare Beneficiaries**			
		Lowest HWRR Quintile (n = 1,629)	Highest HWRR Quintile (n = 1,495)	Difference (95% CI)	p-value	Lowest HWRR Quintile (n = 1,828,379)	Highest HWRR Quintile (n = 1,816,639)	Difference (95% CI)	p-value
		Mean				Mean			
	Age	75.6	75.1	-0.48 (-1.34, 0.39)	<0.001	74.9	74.1	-0.76 (-0.78, -0.74)	<0.001
	HCC Score	2.1	2.4	0.25 (0.12, 0.38)	<0.001	1.7	2.0	0.23 (0.22, 0.23)	<0.001
		Percent				Percent			
Gender	Female	53.4	56.4	3.0 (-1.1, 7.1)	0.16	55.2	55.8	0.63 (0.53, 0.73)	<0.001
Race/Ethnicity	White	86.4	72.4	-14.1 (-17.0, -11.1)	<0.001	85.7	69.5	-16.2 (-16.3, -16.1)	<0.001
	Black	6.3	16.0	9.7 (7.7, 11.8)		6.9	19.0	12.1 (12.0,12.2)	
	Hispanic	5.7	7.2	1.5 (-0.4, 3.4)		4.4	8.7	4.3 (4.2, 4.4)	
	Other	1.6	4.4	2.8 (1.3, 4.3)		3.0	2.8	-0.2 (-0.2, -0.1)	
Original Reason for Medicare Eligibility	Age≥65	82.3	74.8	-5.7 (-9.6, -1.9)	<0.001	77.1	71.1	-6.0 (-6.1, -5.9)	<0.001
	Disability or ESRD	17.7	25.2	5.7 (1.9, 9.6)		23.0	29.0	6.0 (5.9, 6.1)	
Current End-Stage Renal Disease		5.2	4.1	-1.1 (-3.1, 0.9)	0.28	4.2	5.7	1.5 (1.4, 1.6)	<0.001
	Medicaid	17.8	27.0	9.2 (5.6, 12.7)	<0.001	16.3	26.6	10.3 (10.2, 10.4)	<0.001

Abbreviations: hospital-wide readmission rate (HWRR), Hierarchical Condition Category (HCC), end-stage renal disease (ESRD).
[a] Percentages and differences were calculated using survey weights and P values using design-based variance estimators for the analytic sample. and without weights for the 20% sample since it is not a survey.
[b] P-values are from χ^2 or t-tests as appropriate.

eAppendix 2: Description of Health and Retirement Study survey variables

Variable Name	Raw data categories	Analytic categories	Comment
Race/Ethnicity	White, black and other, with separate variable for ethnicity: hispanic or not hispanic	White (non-hispanic), black, hispanic (non-white) and other	Combines two variables, race and ethnicity
Marital Status	married, married, spouse absent, partnered, separated, divorced, separated/divorced, widowed or never married	Married = married or partnered, Divorce/never married = separated, divorced or never married, and Widowed = widowed	
Education	Less than high school, GED, High school graduate, Some college, College any beyond	Less than high school, High school graduate/GED, Some college, College any beyond	
Labor Force Status	Works full time, works part time, unemployed, partly retired, retired, disabled, not in labor force, combined with whether health problems limit work, yes or no	Retired (any), disabled, not in labor force, Working, no health limits (full or part time), Working, with health limits (full or part time)	Combines two variables, labor force status and whether health problems limit work since work limitations of health problems only assessed among those working full or part time
Total Assets (quartiles)	Continuous variable, excludes secondary residences	Recoded in quartiles	
Household Income (quartiles)	Continuous variable	Recoded in quartiles	
Household Debt (tertiles)	Continuous variable	Recoded into tertiles	
Supplemental Health Insurance	Yes or no	Yes or no	Indicates if respondent has any supplemental health insurance other than government, employer or long term care.

Prescription Drug Coverage	If using drugs: fully covered, mostly covered, partially covered, not covered at all or no drugs	full/most coverage, partial coverage, not covered or no drugs	Combines two variables, drug costs covered by insurance and whether taking drugs or not
Smoking Status	Ever smoker: yes or no, current smoker: yes or no	Never, past, current	Combines two variables, ever smoker and current smoker.
Number of Drinks Daily	Continuous integer variable	0, 1, and 2+	Number of drinks a day when drinking
CES-D Quartile‡	Integer from 0-8, higher score corresponding to worse mood	Recoded in quartiles	
Cognition Score‡	Integer from 0-35, high score corresponding to better cognition	Recoded in quartiles	Some respondents not eligible due to age and prior response to portion of cognition score module
Self-rated Health	Excellent, very good, good, fair, or poor	Same	
Proxy Respondent	Yes or no	Same	Indicator for whether respondent needed another household member to do the interview
Number of difficulties with ADLs	Integer 0-5 of ADLs with at least some difficulty	Same	ADLs = bathing, dressing, eating, walking across a room, getting in/out of bed
Number of difficulties with IADLs	Integer 0-5 of IADLs with at least some difficulty	Same	IADLs = using a phone, managing money, take medications, grocery shopping, prepare hot meal
Number of difficulties with activities requiring mobility	Integer 0-5 of activities with at least some difficulty that require mobility. Mobility activities = walking one block, walking several blocks, walking across a room, climbing one flight of stairs, and climbing several flights of stairs	Same	

Number of difficulties with activities requiring agility	Integer 0-4 of activities with at least some difficulty that require agility. Agility activities = sitting for 2 hours, getting up from a chair, stooping/kneeling/crouching, and pushing or pulling large objects	Same	
Number of Household Residents	Continuous integer variable	1, 2, 3, and 4+	
Have living children	Continuous integer variable	Yes or no	
Number of living siblings	Continuous integer variable	0, 1, and 2+	
Friends Live Nearby	Yes or no	Same	
Frequency of Contact with Friends	Day, week, every two weeks, month, year, almost never	Daily, weekly, bimonthly/monthly, less than monthly	

eAppendix 3: Interactions testing whether differences in readmission rates associated with patient characteristics differed across quintiles of hospital-wide readmission rates

To explore whether disparities in probability of readmission by patient characteristics were constant across quintiles of hospitals' publicly reported readmission rates, we examined the interaction between each of the 22 patient characteristics which were significantly associated with readmission in the adjusted and unadjusted analyses in Table 1 in the main text. See eAppendix 7 for why these tests are important.

Specifically, for each of the 22 patient characteristics, we added to the models described in the first step of our analysis (assessing whether each characteristic predicted readmission) an interaction between the additional characteristic and the hospital readmission rate quintile.

Exploring these interactions, we found that for 21 of the 22 characteristics which were significantly associated with readmission probability in unadjusted and adjusted analyses in Table 1, differences in the probability of readmission between patients that differ in a characteristic did not significantly vary across quintiles of hospital readmission rates. The interaction between readmission rate quintile and patient characteristic was significant for only 1 of 22 variables: prescription drug insurance. Prescription drug insurance was significantly predictive of readmission and differentially distributed across hospital quintiles, but the negative coefficient on the interaction term indicates that the disparity in readmission rates narrowed in higher readmission hospitals—the reverse of the relationship that might cause underestimation of quality differences as a consequence of risk adjustment. Overall, these supplementary findings are consistent with previous research finding that quality of care and disparities are largely uncorrelated.[6–8] These findings also indicate that our results in Table 3 are not due to poorer quality at some hospitals (e.g., poorer discharge planning) leading to higher readmission rates in some groups but not others (i.e., greater disparities at higher readmission hospitals).

Interactions testing whether differences in readmission rates associated with patient characteristics differed across quintiles of hospital-wide readmission rates

Patient Characteristic	HWRR Quintile Interaction Coefficient Estimate	P-value
Education Status	0.029	0.29
Total Assets	-0.028	0.25
Total Income	-0.014	0.58
Original Reason for Medicare Enrollment	0.070	0.33
Medicaid Status	0.021	0.73
Supplemental Health Insurance	-0.034	0.60
Prescription Drug Insurance	**-0.103**	**0.01**
Smoking Status	-0.054	0.23
Drinking	0.007	0.87
HCC Score	-0.008	0.54
Number of CCW Conditions	-0.004	0.64
CES-D Score	-0.020	0.42
Cognition Score	0.015	0.40
Self-Rated Health	0.041	0.15
Proxy Status	-0.071	0.48
ADLs	-0.023	0.22
IADLs	-0.011	0.58
Mobility	-0.017	0.28
Agility	-0.010	0.63
Number of Living Siblings	-0.008	0.65
Friends Live Nearby	0.049	0.37
Frequency of Contact with Friends	-0.031	0.20

Abbreviations: hospital-wide readmission rate (HWRR), Chronic Condition Warehouse (CCW), Hierarchical Condition Category (HCC), Center for Epidemiologic Studies Depression (CES-D), activities of daily living (ADLs), instrumental activities of daily living (IADLs).

eAppendix 4: Comparison of 2014 HRRP penalties stratified by publicly reported readmission rate quintiles in study sample vs. all US hospitals

We used Hospital Compare data from CMS on HRRP penalties assessed in 2014 (which use data from 2009 to 2012) to compare the distribution of penalties across all hospitals nationally, categorized into quintiles according to hospital-wide readmission rates, with the distribution of penalties across the quintiles of hospitals captured in our study sample.[9] The maximum possible penalty in 2014 was 2% of inpatient payments.

Quintiles were derived separately for the hospitals in our study and the full set of hospitals nationally. We weighted each hospital in the Hospital Compare data by its admissions volume before determining the quintiles to match the methods of our analysis (which categorized admissions into quintiles based on the admitting hospital's readmission rate).

These similarities, along with the comparisons presented in eAppendix 1, support our conclusion that the differences in patient characteristics we identified between hospitals in the highest and lowest quintiles of readmission rates likely contribute to the penalties levied on hospitals in the highest quintile nationally, not just those in the highest quintile in our study sample. In other words, our findings generalize to all hospitals with high readmission rates that are disproportionately penalized by the HRRP. Of note, in the table below, some hospitals in the lowest quintile of hospital-wide readmission rates were penalized and some hospitals in the highest quintile were not because the hospital-wide readmission rates we used to categorize hospitals were not perfectly correlated with the condition-specific readmission rates used by the HRRP to calculate penalties.

Comparison of 2014 HRRP penalties stratified by publicly reported readmission rate quintiles in study sample vs. all US hospitals

Analytic Sample				
HWRR Quintile	Number of Hospitals	Percent of Hospitals with Any HRRP Penalty	Percent of Hospitals with 1-2% Penalty (2% maximum possible penalty)	Average % Penalty
1 (Lowest)	278	37.8	0.4	0.06
2	250	66.8	0.4	0.14
3	279	86.7	2.5	0.26
4	212	88.7	3.3	0.34
5 (Highest)	187	98.9	17.6	0.65
All US Hospitals				
HWRR Quintile	Number of Hospitals	Percent of Hospitals with Any HRRP Penalty	Percent of Hospitals with 1-2% Penalty (2% maximum possible penalty)	Average % Penalty
1 (Lowest)	791	35.4	0.3	0.06
2	617	61.4	0.8	0.14
3	519	68.4	2.7	0.20
4	663	77.7	5.3	0.29
5 (Highest)	713	90.2	15.4	0.55

Abbreviations: hospital-wide readmission rate (HWRR), hospital readmissions reduction program (HRRP)

eAppendix 5: Distribution of patient characteristics by discharge without and with readmissions, 2000-2012[a]

		Discharges without Readmission (N = 25,395) Percent	Discharges with Readmission (N = 4,699) Percent
Age	≤64	11.2	12.1
	65-74	34.9	32.1
	75-84	37.1	36.6
	≥85	16.8	19.2
Gender	Male	41.9	43.6
	Female	58.1	56.4
Race/Ethnicity	White	83.0	80.1
	Black	10.1	12.8
	Hispanic	4.7	5.0
	Other	2.2	2.1
Marital Status	Married	49.7	45.5
	Divorced/Never Married	14.3	16.8
	Widowed	35.9	37.7
Education	Less than HS	30.5	35.9
	HS graduate/GED	36.9	35.8
	Some college	17.6	14.6
	College and above	15.0	13.8
Labor Force Status	Retired	80.2	80.4
	Disabled	4.5	5.9
	Not in labor force	11.2	11.1
	Working, no limits	3.1	1.8
	Working, health limits	0.9	0.8
Total Assets (quartiles)	1 (Low)	28.8	35.4
	2	22.9	25.1
	3	22.9	20.4
	4 (High)	25.4	19.1

		Discharges without Readmission (N = 25,395) Percent	Discharges with Readmission (N = 4,699) Percent
Number of CCW Chronic Conditions[b]	0-7	29.7	13.9
	8-12	18.4	30.7
	13+	51.9	55.4
HCC Score Quartile[c]	1 (Low)	28.4	16.5
	2	26.8	21.1
	3	24.4	27.0
	4 (High)	20.3	35.3
CES-D Quartile[d]	1 (Least Depressed)	28.8	22.6
	2	34.1	33.6
	3	16.4	20.0
	4 (Most Depressed)	15.5	17.3
Cognition Score[d]	1 (Worse)	32.6	36.3
	2	24.3	22.8
	3	15.7	12.2
	4 (Best)	8.8	6.7
	Not eligible	9.9	10.8
Self-rated Health	1 (Best)	3.8	2.0
	2	16.4	9.5
	3	29.4	24.5
	4	29.6	33.5
	5 (Worst)	20.9	30.5
Proxy Interview	No	91.3	88.7
	Yes	8.7	11.3
Number of difficulties with ADLs	None	64.8	55.6
	1-2	23.7	29.2
	3+	11.5	15.3

Household Income (quartiles)	1 (Low)	34.1	40.1	Number of difficulties with IADLs	None	68.3	58.0
	2	30.8	30.5		1-2	21.8	28.9
	3	21.4	18.7		3+	9.9	13.2
	4 (High)	13.7	10.6	Number of difficulties with activities requiring mobility[e]	None	25.5	17.1
Household Debt (tertiles)	1 (Low)	76.5	75.3		1-2	34.1	31.0
	2	5.0	5.5		3+	40.4	51.9
	3 (High)	18.5	19.2	Number of difficulties with activities requiring agility[e]	None	21.1	16.5
Original Reason for Medicare Enrollment	Age≥65	79.5	74.2		1-2	42.0	40.0
	Disability/ESRD	20.5	25.8		3+	36.9	43.5
End-Stage Renal Disease	No	97.2	94.3	Household Residents	1	33.3	33.9
	Yes	2.8	5.7		2	49.6	46.6
Medicaid	No	79.9	72.5		3	10.3	11.9
	Yes	20.1	27.5		4+	6.7	7.6
Supplemental Health Insurance	No	71.0	73.2	Have living children	No	7.8	8.7
	Yes	29.0	26.8		Yes	92.2	91.3
Prescription Insurance	Full/Most coverage	45.4	50.2	Number of living siblings	0	23.1	25.2
	Partial coverage	29.8	28.2		1	25.1	24.4
	No coverage	19.1	17.5		2+	51.8	50.4
	No medications	5.7	4.1	Friends Live Nearby	No	31.3	34.2
Smoking Status	Never	38.6	34.8		Yes	68.7	65.8
	Past	49.9	52.3	Frequency of Contact with Friends	Daily	16.1	14.7
	Current	11.5	12.9		Weekly	36.7	35.4
Number of Drinks Daily	0	78.4	81.5		Biweekly/Monthly	14.1	13.1
	1	11.8	10.7		Less than monthly	33.2	36.8
	2+	9.8	7.8				

Abbreviations: unadjusted analysis (Unadj.), Chronic Condition Warehouse (CCW), Hierarchical Condition Category (HCC), high school (HS), general educational development (GED) exam, end-stage renal disease (ESRD), Center for Epidemiologic Studies Depression (CES-D), activities of daily living (ADLs), instrumental activities of daily living (IADLs).

[a] Percentages were calculated using survey weights and P values using design-based variance estimators.

[b] Chronic conditions from the CCW include the following 26 conditions: acute myocardial infarction, Alzheimer's disease, Alzheimer's disease and related disorders or senile dementia, anemia, atrial fibrillation, benign prostatic hyperplasia, cataract, chronic kidney disease, chronic obstructive pulmonary disease, depression, diabetes, glaucoma, heart failure, hip or pelvic fracture, hyperlipidemia, hypertension, hypothyroidism, ischemic heart disease, osteoporosis, rheumatoid arthritis or osteoarthritis, stroke or transient ischemic attack, breast cancer, colorectal cancer, endometrial cancer, lung cancer, and prostate cancer.

[c] HCC risk scores are derived from demographic and diagnostic data in Medicare enrollment and claims files, with higher scores indicating higher predicted Medicare spending. In our study, HCC risk scores ranged from 0.16 to 14.0, with 75% of the study sample having a score of 2.7 or less.
[d] The CES-D and cognition scores were not assessed for 1,875 and 3,237 participants, respectively, who had a proxy survey respondent.
[e] For mobility, the 5 activities are: walking one block, walking several blocks, walking across a room, climbing one flight of stairs, and climbing several flights of stairs. For agility, the 4 activities are: sitting for 2 hours, getting up from a chair, stooping/kneeling/crouching, and pushing or pulling large objects.

eAppendix 6: Impact of adjustment for patient characteristics on hospital-level variation in readmission rates

Model	Description	Hospital-level variation in readmission rates (Std. Dev.)
1	Unadjusted[a]	0.061
2	Variables used by CMS to adjust readmission rates[b]	0.038
3	Model 2 + additional claims data on eligibility categories and diagnoses[c]	0.034
4	Model 3 + additional clinical and social characteristics from the HRS [d]	0.023

[a] Model 1 adjusted for year fixed effects alone.

[b] Model 2 includes age, sex, principal diagnosis condition and 31 additional condition indicators included in the publicly reported HWRR measure.[10]

[c] Model 3 includes all variables in model 2 as well as indicators for Medicaid eligibility, disability as the original reason for Medicare enrollment, end-stage renal disease, HCC score, and 26 CCW condition indicators.[11]

[d] Model 4 includes all variables in model 3 as well as 24 social and clinical characteristics from the HRS (variables listed in Tables 1 and 2 that were not already present in model 3) and selected interaction terms (see eMethods above).

eAppendix 7: Hypothetical scenarios illustrating the effects of adjustment for income on hospital readmission rates

In this hypothetical example shown in the table below, adapted from Jha and Zaslavsky,[12] 50% of patients admitted to Hospital A are low-income, whereas 20% of patients admitted to Hospital B are low-income.

In scenario 1, there is a disparity in readmission rates between low-income and high-income patients, and the disparity is the same in both hospitals, but there is no difference in quality between the hospitals, as evidenced by equivalent readmission rates for each income group in each of the two hospitals. The unadjusted readmission rate is 3 percentage points higher at Hospital A than Hospital B because Hospital A disproportionately serves low-income patients, but the adjusted rates (calculated via direct standardization to a hypothetical national distribution of income that is similar to Hospital B's patient population—20% low-income) are equal, reflecting the equivalent readmission rates in each income group.

In scenario 2, there remains the same within-hospital disparity of 10 percentage points in both hospitals, but quality is better at Hospital B, as evidenced by the readmission rate being 5 percentage points lower for each income group. In this scenario, the unadjusted difference in readmission rates is 8 percentage points and the adjusted difference is 5 percentage points. Thus, adjusting for income does not conceal the fact that Hospital B provides better quality care, and the adjustment more appropriately quantifies that difference in quality as 5 percentage points better for each income group. Similarly, the adjustment for income leads to the same reduction in the difference in readmission rates between the two hospitals (3 percentage points) whether or not there is a between-hospital quality difference. The key point is that the adjustment is driven only by the differences in the income distribution between the hospitals and the within-hospital disparity in readmission rates between income groups.

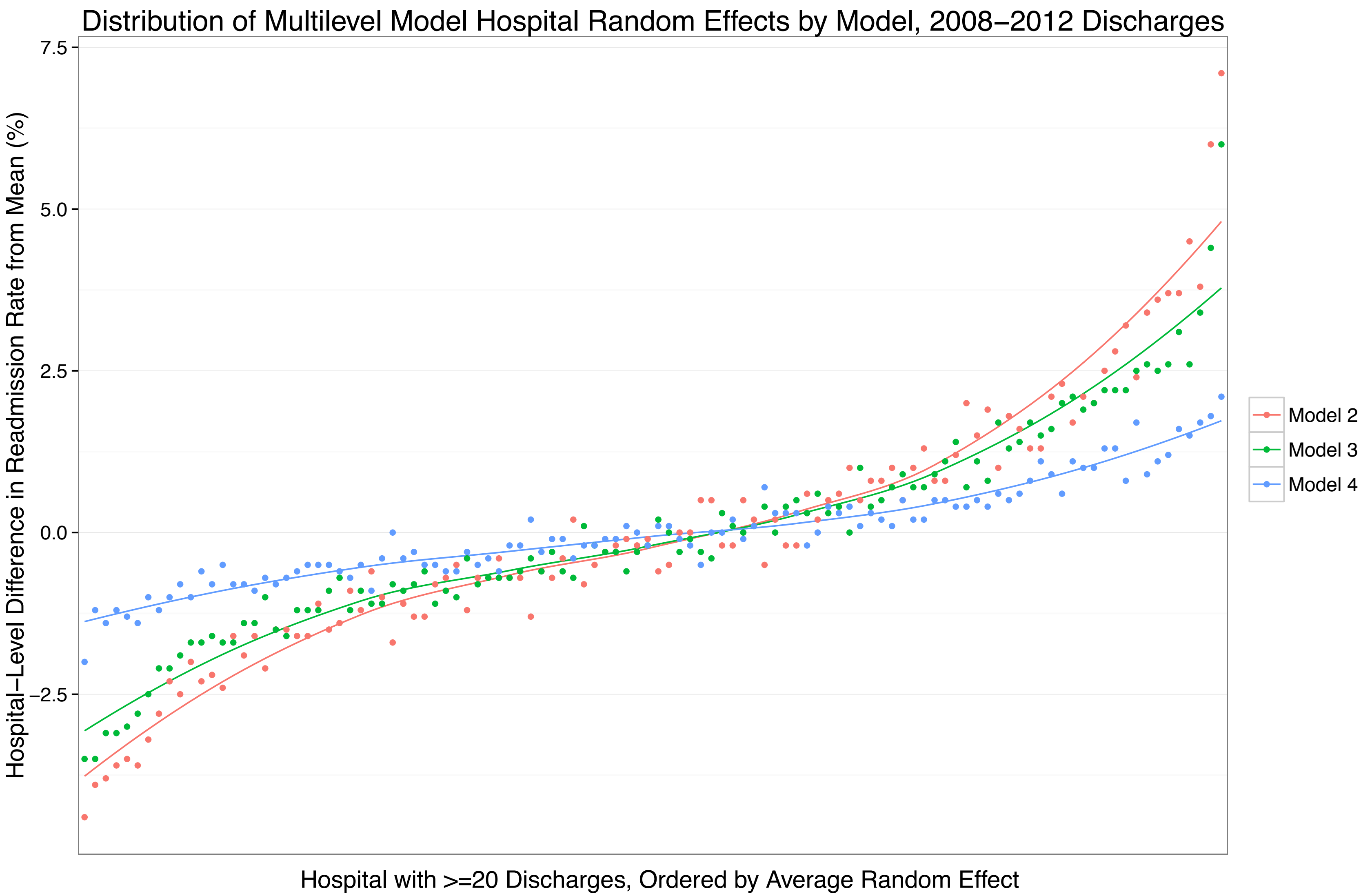
In other words, hospitals serving more disadvantaged patients may have worse quality than other hospitals, but adjusting for the differences in the populations they serve does not obscure the quality difference between the hospitals. On the contrary, the adjustment isolates it. This conclusion is upheld as long as within-hospital differences in readmission rates between patients that differ along a particular dimension are similar across hospitals; that is, as long as disparities in readmission rates within hospitals are not correlated with hospital readmission rates. As demonstrated in eAppendix 5, we explored this assumption and found that, for almost all of the characteristics we assessed, differences in the probability of readmission between patients that differ in a characteristic did not significantly vary across quintiles of hospital readmission rates. This is consistent with other studies finding that quality of care and disparities are largely uncorrelated.[6–8]

In addition, case-mix adjustment does not conceal within-hospital disparities that might arise as a result of unequal treatment. Those can still be easily calculated and monitored. In the scenarios described in the table below, one concern might be that the standardization of Hospital A's readmission rate applies less weight to low-income patients than high-income patients, thereby potentially diminishing incentives for hospitals serving more low-income patients to lower readmission rates for low-income patients specifically (relative to incentives to lower readmission rates for high-income patients), because lowering the rates for low-income patients would contribute less to lowering the overall rate. This concern, however, could be addressed by using alternate weighting schemes (e.g., standardizing to Hospital B's population) or through other interventions or incentives to reduce disparities.

Hypothetical scenarios illustrating the effects of adjustment for income on hospital readmission rates

		Hospital A (50% Low-Income Patients)			Hospital B (20% Low-Income Patients)			Difference in Rate between Hospitals A and B, %	
		Stratified Readmission Rate, %	Readmission Rate, %		Stratified Readmission Rate, %	Readmission Rate, %			
			Unadjusted	Adjusted		Unadjusted	Adjusted	Unadjusted	Adjusted
Scenario 1: Within-hospital disparity, no difference in quality	Low-Income	20	15	12	20	12	12	3	0
	High-Income	10			10				
Scenario 2: Within hospital-disparity, hospital B has better quality	Low-Income	20	15	12	15	7	7	8	5
	High-Income	10			5				

eFigure 1: Distribution of hospital random effects after adjustment for patient characteristics



References

1. Bates D, Mächler M, Bolker B, Walker S. Fitting Linear Mixed-Effects Models using lme4. *ArXiv StatCO*. June 2014. http://arxiv.org/abs/1406.5823. Accessed March 24, 2015.

2. R Core Team. *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing; 2014. http://www.R-project.org/. Accessed March 25, 2015.

3. Honaker J, King G, Blackwell M. Amelia II: A Program for Missing Data. 2010. http://CRAN.R-project.org/package=Amelia. Accessed March 25, 2015.

4. Rubin DB. *Multiple Imputation for Nonresponse in Surveys*. Vol 81. John Wiley & Sons; 2004.

5. Yun H, Kilgore ML, Curtis JR, et al. Identifying types of nursing facility stays using medicare claims data: an algorithm and validation. *Health Serv Outcomes Res Methodol*. 2010;10(1-2):100-110. doi:10.1007/s10742-010-0060-4.

6. Anderson RE, Ayanian JZ, Zaslavsky AM, McWilliams JM. Quality of Care and Racial Disparities in Medicare Among Potential ACOs. *J Gen Intern Med*. 2014;29(9):1296-1304. doi:10.1007/s11606-014-2900-3.

7. McWilliams JM, Meara E, Zaslavsky AM, Ayanian JZ. Differences in Control of Cardiovascular Disease and Diabetes by Race, Ethnicity, and Education: U.S. Trends From 1999 to 2006 and Effects of Medicare Coverage. *Ann Intern Med*. 2009;150(8):505-515. doi:10.7326/0003-4819-150-8-200904210-00005.

8. Trivedi AN, Zaslavsky AM, Schneider EC, Ayanian JZ. Relationship between quality of care and racial disparities in medicare health plans. *JAMA*. 2006;296(16):1998-2004. doi:10.1001/jama.296.16.1998.

9. Data available at Readmissions Reduction Program. August 2014. http://www.cms.gov/Medicare/medicare-fee-for-service-payment/acuteinpatientPPS/readmissions-reduction-program.html. Accessed July 3, 2015.

10. Yale New Haven Health Services Corporation/Center for Outcomes Research & Evaluation (YNHHSC/CORE). 2014 Measure Updates and Specifications Report Hospital-Wide All-Cause Unplanned Readmission – Version 3.0. July 2014. http://www.qualitynet.org/dcs/ContentServer?cid=1228774371008&pagename=QnetPublic%2FPage%2FQnetTier4&c=Page Accessed February 4, 2015.

11. Center for Medicare and Medicaid Services. Chronic Conditions Data Warehouse. 2014. https://www.ccwdata.org/. Accessed March 25, 2015.

12. Jha AK, Zaslavsky AM. Quality reporting that addresses disparities in health care. *JAMA*. 2014;312(3):225-226. doi:10.1001/jama.2014.7204.