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Contribution of Patient Characteristics to Differences in Readmission Rates

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Abstract

Importance—Medicare penalizes hospitals with higher than expected readmission rates by up to 3% of annual inpatient payments. Expected rates are adjusted only for patients' age, sex, discharge diagnosis, and recent diagnoses.

Objective—To assess the extent to which a comprehensive set of patient characteristics accounts for differences in hospital readmission rates.

Design and Setting—Using survey data from the nationally representative Health and Retirement Study (HRS) and linked Medicare claims, we assessed 29 patient characteristics from survey data and claims as potential predictors of 30-day readmission when added to standard Medicare adjustments of hospital readmission rates. We then compared the distribution of these characteristics between participants admitted to hospitals with higher vs. lower hospital-wide readmission rates reported by Medicare. Finally, we estimated differences in the probability of readmission between these groups of participants before vs. after adjusting for the additional patient characteristics.

Participants—HRS participants enrolled in Medicare who were hospitalized from 2009–2012 (n=8,067 admissions).

Main Outcomes and Measures—All-cause readmission within 30 days of discharge.

Results—Of the additional 29 patient characteristics assessed, 22 significantly predicted readmission beyond standard adjustments, and 17 of these were distributed differently between hospitals in the highest vs. lowest quintiles of publicly reported hospital-wide readmission rates ($p \leq 0.04$ for all). Almost all of these differences (16 of 17) indicated that participants admitted to hospitals in the highest quintile of readmission rates were more likely to have characteristics that were associated with a higher probability of readmission. The difference in the probability of readmission between participants admitted to hospitals in the highest vs. lowest quintile of

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hospital-wide readmission rates was reduced by 48% from 4.41 percentage points with standard adjustments used by Medicare to 2.29 percentage points after adjustment for all patient characteristics assessed (reduction in difference: −2.12, 95% CI −3.33, −0.67; p=0.003).

Conclusions and Relevance—Patient characteristics not included in Medicare's current risk-adjustment methods explained much of the difference in readmission risk between patients admitted to hospitals with higher versus lower readmission rates. Hospitals with high readmission rates may be penalized to a large extent based on the patients they serve.

The Medicare Hospital Readmissions Reduction Program (HRRP) financially penalizes hospitals with higher than expected 30-day readmission rates for Medicare patients by reducing annual reimbursements by up to 3%. In 2014, the second year of the program, 2,610 hospitals were fined a total of $428 million for excess readmissions.[1] In setting an expected readmission rate for each hospital, the Centers for Medicare and Medicaid Services (CMS) adjusts only for patients' age, sex, discharge diagnosis, and diagnoses present in claims during the 12 months prior to admission.[2] This limited adjustment has raised concerns that hospitals may be penalized because they disproportionately serve patients with clinical and social characteristics that predispose them to hospitalization or rehospitalization.[3,4]

Prior research has identified several patient factors that are predictive of readmission and not included in the HRRP's risk-adjustment model.[5] Individual studies have addressed only a sparse set of factors, however, because detailed patient information is typically lacking in databases identifying hospitalizations.[6] Moreover, the most policy-relevant question is not whether patient characteristics omitted from the HRRP's risk-adjustment model predict readmission. Rather, it is whether those characteristics are distributed unevenly across hospitals and thereby account for differences in excess readmissions—and penalties—determined by CMS. Few studies have addressed this question in Medicare directly by examining the effects of adjustment for patient characteristics on differences in hospital readmission rates, and these studies have been restricted to a small number of characteristics.[7–10] Therefore, the extent to which adjustment for a comprehensive set of patient characteristics would account for differences in hospital readmission rates remains unclear.

Using detailed survey data from the Health and Retirement Study (HRS) and linked Medicare claims, we conducted 3 related analyses. First, using data from 2000–2012, we analyzed an extensive set of clinical and social characteristics as potential predictors of all-cause 30-day readmission among hospitalized survey participants, including claims and survey variables not used by CMS in risk adjustment of readmission rates. Second, using data from 2009–2012 to align the study period with the first publicly reported readmission rates, we compared these characteristics between participants admitted to hospitals with high vs. low readmission rates. Third, again using 2009–2012 data, we then compared differences in the probability of readmission between participants admitted to hospitals with high vs. low publicly reported readmission rates before vs. after adjustment for the additional patient characteristics.

METHODS

Study Population

We analyzed data from the 2000–2010 biennial waves of the HRS, a nationally representative longitudinal survey of adults over age 50 in the continental US (average response rate 88%), and linked Medicare claims from 2000–2012.[11–13] Our study sample included HRS survey respondents who were eligible for Medicare and provided their Medicare identification numbers for linkage to claims and enrollment files (91% of eligible participants). We excluded participants residing in nursing homes because the HRS samples households and provides sampling weights only for community-dwelling adults. For each survey year, we limited our sample to participants who were hospitalized after survey completion during the survey year or two subsequent years. We analyzed all admissions during this span for each participant (median time between survey and admission, 462 days), using the participant-admission as the unit of analysis. Our study was approved by the Harvard Medical School Committee on Human Studies.

Study Variables

30-day Readmissions—We examined readmissions for all hospitalizations as defined in the hospital-wide readmission rate measure,[14] rather than the condition-specific measures used in the HRRP, to maximize statistical power for analyzing readmissions in the HRS sample; the conditions included in the HRRP (congestive heart failure [CHF], myocardial infarction, and pneumonia) represent <20% of all Medicare admissions.[15] Following CMS specifications for calculating hospital-wide readmission rates,[14,15] we defined index admissions as all admissions to non-federal acute care hospitals without transfer to another acute-care facility or discharge against medical advice, and we excluded admissions for certain primary diagnoses or to certain facilities, using principal discharge diagnoses and procedure codes to define reasons for admission.[14] We also excluded index admissions during which the patient died and admissions for patients without 12 months of enrollment in fee-for-service Medicare prior to admission.[16] Patients who died within 30 days after discharge were not excluded per CMS specifications.

For each index admission, we used Medicare inpatient claims to assess whether the participant had an unplanned readmission within 30 days of discharge, excluding planned readmissions such as scheduled procedures or chemotherapy per CMS specifications.[14] In a sensitivity analysis, we additionally excluded index admissions that were also readmissions; this restriction is applied by CMS in determining readmissions for the HRRP but not in calculating hospital-wide readmission rates.[14,16]

Categorizing Participants by Readmission Rate of Admitting Hospital—For comparisons of participants admitted to hospitals with high vs. low readmission rates, we categorized index admissions in our study sample into quintiles according to the admitting hospital's publicly reported hospital-wide readmission rate from 2011–2012 (the earliest reporting period for this measure).[17] Like the condition-specific readmission rates reported by the HRRP, publicly reported hospital-wide readmission rates are adjusted for age, sex, discharge diagnosis, and specific diagnoses present in claims during the 12 months prior to admission.[16] Among the 1,896 hospitals captured in our study sample, publicly reported hospital-wide readmission rates for 2011–2012 were strongly correlated with case weighted averages of readmission rates reported by the HRRP from 2009–2012 for myocardial infarction, pneumonia and CHF (r=0.70; p<0.001).[17] This strong correlation supports the steps we took to generate adequate statistical power for our research objectives—specifically, considering readmissions for all index hospitalizations and using publicly reported hospital-wide readmission rates from 2011–2012 to categorize participants admitted from 2009–2012.

Because the HRS is a nationally representative sample, participants admitted to hospitals in the highest or lowest quintiles of readmission rates, for example, should constitute representative samples of the national populations of patients admitted to hospitals in the highest or lowest quintile. In a supplementary analysis (eAppendix 1), we confirmed that differences between these quintiles in patient characteristics assessed from claims were largely similar for the HRS study sample and a 20% random sample of all similarly aged fee-for-service Medicare beneficiaries.

Clinical and Social Characteristics—From administrative and survey data for each participant, we assessed a broad range of pre-specified demographic, financial, clinical, and social characteristics, including variables used by CMS for risk adjustment of hospital readmission rates and additional variables not included in those methods (Table 1).

Demographics and Eligibility Categories from Medicare Enrollment Files: From Medicare enrollment files, we determined age, sex, Medicaid enrollment, whether disability was the original reason for Medicare eligibility, and whether the participant had end-stage renal disease.

Clinical Characteristics from Claims: From linked Medicare claims, we assessed the discharge diagnosis and 31 condition indicators used by CMS for adjustment of hospital-wide readmission rates.[14] Consistent with methods employed by the HRRP, we derived these indicators from diagnoses present in inpatient claims for the index admission or in inpatient or outpatient claims during the 12 months prior to admission.[16] We similarly assessed additional condition indicators used for adjusting condition-specific readmission rates in the HRRP but did not include these in our main analyses because they affected our results minimally.

For each admission of each participant, we additionally determined a hierarchical condition category (HCC) risk score from the 12 months of claims prior to admission, and we determined at the start of the year the presence of 26 conditions from the Chronic Condition Data Warehouse (CCW), which uses claims since 1999 to describe Medicare beneficiaries' accumulated chronic disease burden.[18,19]

Clinical and Social Characteristics from HRS Surveys: From HRS surveys, we selected 24 variables potentially predictive of readmission in the elderly according to previously developed conceptual models.[6,20] As listed in Table 1, these variables included race/ethnicity, education, labor force status, household income and assets, supplemental and prescription drug coverage, smoking status, alcohol consumption, general health status, physical functioning, difficulties with activities of daily living (ADLs) and instrumental ADLs (IADLs), work limitations due to health, depressive symptoms based on the Center for Epidemiologic Studies Depression Scale,[21] cognition based on the Telephone Interview for Cognitive Status,[22] whether participants required a proxy to respond on their behalf, and measures of household structure and social supports (eAppendix 2).

Missing Data: Linked survey data were missing for at least one item of interest for 9.9% of admissions in our study sample. In our main analysis, we carried values forward from prior surveys to reduce this proportion to 1.5% and excluded these remaining 1.5% of admissions.

Statistical Analysis

In unadjusted analyses of 2000–2012 data, we compared the proportion of admissions that were followed by readmission across different categories of each patient characteristic. We then fitted a logistic regression model predicting 30-day readmission as a function of the variables used by CMS for risk adjustment of hospital readmission rates (age, sex, discharge diagnosis, and condition indicators), alternately adding each additional characteristic to test whether it independently predicted readmission after standard adjustments by CMS. In these models, we also included indicators for the quintile of the admitting hospital's publicly reported hospital-wide readmission rate to hold hospital performance constant, as the focus of this analysis was the within-quintile association between each additional characteristic and readmission. That is, if a characteristic were more common among hospitals with readmission rates that are high because of poor quality of care, we would not want to conclude from such clustering that the characteristic is a consistent predictor of readmission for which CMS might consider adjustment. In a sensitivity analysis, we modeled the interaction between these characteristics and the hospital quintile to test whether the association between each characteristic and readmission was similar across quintiles (eAppendix 3). We assumed similarity across quintiles when subsequently examining the effects of additional adjustments on between-quintile differences in the probability of readmission.

In unadjusted analyses focusing on admissions from 2009–2012, we then compared the distribution of patient characteristics between hospitals in the highest versus lowest quintile of publicly reported hospital-wide readmission rates. Finally, we estimated the difference in the probability of readmission between participants admitted to hospitals with higher vs. lower hospital-wide readmission rates by including indicators for the admitting hospital's quintile in a logistic regression model of readmission. To examine how this difference was affected by adjustment for additional patient characteristics, we sequentially added to this model subsets of characteristics as covariates (see eMethods for model specification). We report differences in the probability of readmission between participants admitted to hospitals in the highest vs. lowest quintile of readmission rates (eMethods) because we expected small differences in readmission probabilities among the middle quintiles based on publicly reported rates and because hospitals in the highest quintile were substantially more likely to receive a high penalty than other hospitals (eAppendix 4).[23] We also report the reduction in the between-quintile difference in the probability of readmission due to each successive subset of characteristics, using bootstrap methods to estimate 95% confidence intervals for the reductions.

We performed several sensitivity analyses (eMethods). First, we weighted analyses to address the lack of linkage of some participants to Medicare data. Second, we repeated our analyses without survey weights, alternately including and excluding nursing home residents to assess their impact on results. Third, for hospitals with ≥20 admissions in our sample, we estimated a multilevel model of readmission with hospital random effects to estimate changes in hospital variation in readmission rates associated with adjustment for additional patient characteristics (eMethods).[24] Fourth, using publicly available data from CMS,[25] we assessed the distribution of HRRP penalties in 2014 (which use data from 2009–2012) across quintiles of hospitals (defined by hospital-wide readmission rates) for all U.S. hospitals vs. the hospitals captured in our study sample (eAppendix 4). Finally, we repeated analyses using multiple imputation instead of carrying the last observation forward to handle missing data.[26]

In a supplementary analysis, we assessed the extent to which a ZIP code-level composite index of 17 sociodemographic indicators of deprivation reduced the difference in the probability of readmission between participants admitted to hospitals in the highest vs. lowest quintile of readmission rates, when added to standard CMS adjustments.[27–29] In all analyses, we used robust design-based variance estimators to account for clustering within geographic areas, hospitals, or participants and HRS survey weights to account for the survey design and survey non-response.[30] All analyses were performed with the *survey* package (v. 3.30–3) in R (v. 3.1.2, Vienna, Austria). [31,32]

RESULTS

Our study sample included 33,158 index admissions from 2000–2012 for 8,767 Medicare beneficiaries in the HRS and 8,067 index admissions from 2009–2012 for 3,470 beneficiaries in the HRS. In unadjusted analyses of the 2000–2012 sample (Table 1, eAppendix 5), the proportion of admissions followed by readmission significantly differed across categories for 27 of the 29 patient characteristics not included in CMS adjustments (all p≤0.02). Of these characteristics, 22 remained significantly predictive of readmission after standard CMS adjustments (p≤0.04). Associations between these characteristics and readmission were similar across quintiles of the admitting hospital's publicly reported readmission rate (eAppendix 3).

In unadjusted analyses of admissions from 2009–2012, the characteristics of participants with index admissions to hospitals in the highest quintile of publicly reported readmission rates differed substantially from those with index admissions to hospitals in the lowest quintile of readmission rates (Table 2). Of the 22 characteristics significantly predictive of readmission after standard CMS adjustments, 17 were distributed differently between the highest and lowest quintiles (p≤0.04), with almost all of these differences (16 of 17) indicating that participants admitted to hospitals in the highest quintile of readmission rates were more likely to have characteristics associated with a higher probability of readmission. For example, participants admitted to hospitals in the highest quintile had higher HCC scores, more chronic conditions, less education, fewer assets, worse self-reported health status, more depressive symptoms, worse cognition, worse physical functioning, and more difficulties with ADLs and IADLs than participants admitted to hospitals in the lowest quintile. Differences between quintiles in patient characteristics assessed from Medicare enrollment and claims data were similar when estimated using a 20% sample of Medicare beneficiaries from 2009–2012 (eAppendix 1).

Table 3 describes the effects of successive adjustments for patient characteristics on the difference in the probability of readmission between participants admitted to hospitals in the highest vs. lowest quintile of readmission rates. This difference decreased from 5.86 percentage points without any adjustment to 4.41 percentage points after standard CMS adjustments (reduction in difference: −1.45 percentage points, 95% CI −2.63,−0.48), to 3.50 percentage points after adjustment for additional variables from Medicare enrollment and claims data (additional reduction: −0.91, 95% CI −1.78,−0.04), to 2.29 after additional adjustment for variables from HRS surveys (additional reduction: −1.21, 95% CI −2.07,−0.21). The fully adjusted difference constituted a 61% reduction relative to the unadjusted difference and a 48% reduction relative to the difference adjusted for variables already used by CMS for risk adjustment of readmission rates, or an absolute reduction of −2.12 percentage points (95% CI −3.33,−0.67, P=0.003). Similar reductions were observed in a sensitivity analysis excluding index admissions that were also readmissions. Adding the area deprivation index to the model with standard CMS adjustments reduced the between-quintile difference minimally.

A multilevel model estimating between-hospital variation in readmission rates in the sample similarly demonstrated a substantial reduction in between-hospital variation in readmission rates after adjustment for more patient characteristics (eAppendix 6, eFigure 1). The distribution of penalties assessed by the HRRP in 2014 across all U.S. hospitals, when categorized into quintiles based on hospital-wide readmission rates, was similar to the distribution of penalties across quintiles of hospitals in our study sample (eAppendix 4). Weighting analyses to account for incomplete linkage to Medicare claims, including nursing home residents in analyses without survey weights, and use of multiple imputation to address item non-response did not substantively alter our conclusions.

DISCUSSION

In this nationally representative study of readmissions in the Medicare population, many patient characteristics not currently included in risk adjustment of hospital readmission rates were significantly predictive of readmission and more prevalent at hospitals with higher publicly reported readmission rates. In our study sample, additional adjustment for these characteristics accounted for approximately half of the observed difference in the probability of readmission between patients admitted to hospitals in the highest versus lowest quintiles of publicly reported readmission rates. These findings suggest that differences in patient characteristics between hospitals may contribute substantially to the penalties levied by Medicare on hospitals with high readmission rates.

The higher prevalence of clinical and social predictors of readmission among patients admitted to hospitals with higher readmission rates is likely driven by factors largely outside of a hospital's influence. Our findings therefore call into question the extent to which variation in hospital readmission rates reflects quality of care and, by extension, the extent to which this variation should serve as the basis for financial penalties.[33,34] The differences in patient characteristics between hospitals with high vs. low readmission rates also suggest that the HRRP imposes substantially greater costs on hospitals disproportionately serving patients more likely to be readmitted. Hospitals serving healthier, more socially advantaged patients may not have to devote any resources to achieving a penalty-free readmission rate, whereas hospitals serving sicker, more socially disadvantage patients may have to devote considerable resources to avoid a penalty. By selectively increasing costs or lowering revenue for hospitals serving patients at greater risk of readmission, the HRRP therefore threatens to deplete hospital resources available to improve overall quality for populations at high risk of poor outcomes.

More detailed risk adjustment by CMS could help mitigate this risk of exacerbating disparities. Arguments against additional adjustments contend that adjusting for some risk factors—such as race/ethnicity or income—would hold hospitals serving more disadvantaged patients to a lower standard of quality or obscure the poorer quality they might provide.[35,36] Appropriate case mix adjustment for more clinical and social factors, however, should not raise these concerns as it would only help to isolate the portion of between-hospital variation in readmissions that is due to differences in hospital quality.[33,34,37] After adjustment for income, for example, hypothetically poorer quality provided by a hospital disproportionately serving low-income patients would still be evident (see hypothetical example in eAppendix 7).

In response to the prospect of penalties, a hospital may target patients at highest risk in its efforts to reduce readmissions, for example through better discharge planning, thereby potentially reducing disparities to some extent while lowering its overall readmission rate.[38] Incentives to reduce readmission rates and within-hospital disparities, however, need not be at cross purposes with the goals of risk adjustment.[34] Thus, our findings support legislation calling for the adjustment of readmission rates and other quality measures for patients' socioeconomic status and more health-related variables.[39,40]

Because the detailed risk adjustment available for HRS respondents may not be feasible for CMS on a large scale, alternative payment models may be required to preserve strong incentives to lower readmissions without unfairly penalizing hospitals based on the populations they serve and consequently risking deterioration in quality for patients at high risk of readmission. For example, a hospital's expected readmission rate could be set at its historical average, with financial rewards for achieving a rate below the historical average and penalties for exceeding it. The expected rate would have to be held constant or constrained gradually over time, since incentives to reduce readmissions would be diminished by a policy requiring continual improvement over the prior year's performance.[41] Alternatively, growth in similarly designed payment models that cover the full spectrum of care and allow providers discretion in identifying avoidable care to target, such as accountable care organization programs, might obviate the need for payment incentives wedded specifically to readmissions.[42]

Our study had several limitations. Because our study sample was limited to HRS participants, we were unable to assess the impact of additional risk adjustment on readmission rates for individual hospitals. Because the HRS sample is nationally representative, however, we were able to compare samples of patients admitted to hospitals with high versus low readmission rates, and we confirmed that differences between these groups of patients were reflected in the full population of fee-for-service Medicare beneficiaries (eAppendix 1). In addition, our conclusions were supported by a multilevel model of hospital-level variation in our study sample. The size of the HRS sample also limited the precision with which we could estimate differences in the probability of readmission between participants admitted to hospitals with high vs. low readmission rates or the reduction in this difference due to adjustment for additional patient characteristics. We would not expect the survey design, however, to cause sampling of systematically sicker and more disadvantaged patients when admitted to a hospital with a high readmission rate.

CONCLUSIONS

Accounting for a comprehensive array of clinical and social characteristics substantially decreased the difference in patients' probability of readmission between hospitals with higher versus lower readmission rates. This finding suggests that Medicare is penalizing hospitals to a large extent based on the patients they serve.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Table 1

Readmission Rates by Patient Characteristics[a]

		Readmission Rate (n = 33,158)	p-value[b]				Readmission Rate (n = 33,158)	p-value[b]	
		Percent	Unadj.	Adjusted			Percent	Unadj.	Adjusted
Age	≤64	16.6	0.09	0.01	Number of CCW Conditions[c]	0–7	7.9	<0.001	<0.001
	65–74	14.4				8–12	16.4		
	75–84	15.4				13+	23.4		
	≥85	17.3			HCC Score Quartile[d]	1 (Low)	9.7	<0.001	0.002
Gender	Male	16.1	0.06	0.52		2	12.6		
	Female	15.1				3	16.9		
Race/Ethnicity	White	15.1	<0.001	0.50		4 (High)	24.2		
	Black	18.8			CES-D Quartile[e]	1 (Least Depressed)	12.6	<0.001	0.008
	Hispanic	16.4				2	15.3		
	Other	14.9				3	18.3		
Marital Status	Married	14.4	<0.001	0.082		4 (Most Depressed)	16.9		
	Divorced/Never Married	17.7			Cognition Score[e]	1 (Worst)	17.0	<0.001	0.04
	Widowed	16.2				2	14.7		
Education	Less than HS	17.8	<0.001	0.033		3	12.5		
	HS graduate/GED	15.1				4 (Best)	12.2		
	Some college	13.3				Not assessed	16.7		
	College and above	14.4			Self-rated Health	1 (Best)	8.8	<0.001	<0.001
Labor Force Status	Retired	15.5	<0.001	0.22		2	9.6		
	Disabled	19.3				3	13.3		
	Not in labor force	15.3				4	17.2		
	Working, no limits	9.8				5 (Worst)	21.2		

		Readmission Rate (n = 33,158)	p-value[b]	
		Percent	Unadj.	Adjusted
	Working, health limits	13.9		
Total Assets (quartiles)	1 (Low)	18.4	<0.001	<0.001
	2	16.7		
	3	14.1		
	4 (High)	12.1		
Household Income (quartiles)	1 (Low)	17.8	<0.001	0.02
	2	15.4		
	3	13.9		
	4 (High)	12.4		
Household Debt (tertiles)	1 (Low)	15.3	0.27	0.68
	2	16.9		
	3 (High)	16.0		
Original Reason for Medicare Eligibility	Age≥65	14.6	<0.001	<0.001
	Disability or ESRD	18.8		
Current End-Stage Renal Disease	No	15.1	<0.001	0.72
	Yes	27.3		
Medicaid	No	14.3	<0.001	<0.001
	Yes	20.1		
Supplemental Health Insurance	No	15.9	0.007	<0.001
	Yes	14.5		
Prescription Drug Coverage	Full/Most coverage	16.9	<0.001	<0.001
	Partial coverage	14.8		
	No coverage	14.4		

		Readmission Rate (n = 33,158)	p-value[b]	
		Percent	Unadj.	Adjusted
Proxy Respondent	No	15.1	<0.001	0.02
	Yes	19.2		
Number of difficulties with ADLs	None	13.6	<0.001	<0.001
	1–2	18.4		
	3+	19.6		
Number of difficulties with IADLs	None	13.5	<0.001	<0.001
	1–2	19.5		
	3+	19.7		
Number of difficulties with activities requiring mobility[f]	None	11.0	<0.001	<0.001
	1–2	14.3		
	3+	19.1		
Number of difficulties with activities requiring agility[f]	None	12.6	<0.001	<0.001
	1–2	14.9		
	3+	17.8		
Number of Household Residents	1	15.8	0.002	0.63
	2	14.7		
	3	17.4		
	4+	17.2		
Have living children	No	16.9	0.13	<0.001
	Yes	15.3		
Number of living siblings	0	16.6	0.02	<0.001
	1	15.1		
	2+	15.1		

		Readmission Rate (n = 33,158)	p-value[b]				Readmission Rate (n = 33,158)	p-value[b]	
		Percent	Unadj.	Adjusted			Percent	Unadj.	Adjusted
	No medications	11.6			Friends Live Nearby	No	16.7	<0.001	<0.001
Smoking Status	Never	14.2	<0.001	<0.001		Yes	15.0		
	Past	16.1			Frequency of Contact with Friends	Daily	14.3	<0.001	<0.001
	Current	17.1				Weekly	15.1		
Number of Drinks Daily	0	16.0	0.003	0.005		Biweekly/Monthly	14.6		
	1	14.3				Less than monthly	16.9		
	2+	12.7							

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]Unadjusted p-values are from χ^2 tests. For each characteristic, the adjusted p-value is from a likelihood ratio test comparing the fit of a logistic model predicting 30-day readmission as a function of variables used by CMS for risk adjustment of readmission rates (age, sex, discharge diagnosis, and 31 clinical indicators) and admitting hospital's quintile of publicly reported hospital-wide readmission rate vs. the fit of a model additionally including that characteristic as a predictor.

[c]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.

[d]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.

[e]The CES-D and cognition scores were not assessed for 1,875 and 3,237 participants, respectively, who had a proxy survey respondent.

[f]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.

Table 2

Differences in Patient Characteristics between Admissions to Hospitals in the Highest vs. Lowest Quintile of Hospital-wide Readmission Rates[a]

		Lowest HWRR Quintile (n = 1,629)	Highest HWRR Quintile (n = 1,495)	p-value[b]			Lowest HWRR Quintile (n = 1,629)	Highest HWRR Quintile (n = 1,495)	p-value[b]
		Percent	Percent				Mean	Mean	
Age	≤64	9.4	13.8	<0.001	Number of CCW Conditions[c]		10.1	10.8	<0.001
	65–74	36.1	32.3		HCC Score[d]		2.1	2.4	<0.001
	75–84	36.0	36.1				Percent	Percent	
	≥85	18.5	17.8		Medicaid Enrollment		17.8	27.0	<0.001
Gender	Male	46.6	43.6	0.16	Supplemental Health Insurance		28.3	20.9	<0.001
Race/Ethnicity	White	86.4	72.4	<0.001	CES-D Quartile[e]	1 (Least Depressed)	36.7	27.1	<0.001
	Black	6.3	16.0			2	34.5	38.1	
	Hispanic	5.7	7.2			3	14.8	18.6	
	Other	1.6	4.4			4 (Most Depressed)	12.8	15.0	
Marital Status	Married	54.4	45.8	<0.001	Cognition Score[e]	1 (Worst)	31.6	37.9	<0.001
	Divorced/Never Married	15.1	21.0			2	27.4	24.4	
	Widowed	30.5	33.2			3	17.7	13.1	
Education	Less than HS	20.9	30.4	<0.001		4 (Best)	10.1	6.5	
	HS graduate/GED	33.4	36.3			Not assessed	7.7	12.0	
	Some college	22.0	17.2		Self-rated Health	1 (Best)	3.6	3.7	<0.001
	College and above	23.8	16.1			2	17.5	13.3	
Labor Force Status	Retired	85.8	87.1	0.005		3	31.7	25.6	
	Disabled	2.4	3.0			4	31.0	35.6	
	Not in labor force	6.4	6.5			5 (Worst)	16.2	21.9	
	Working, no limits	3.5	2.9		Proxy Respondent (%)		5.4	6.1	0.39

		Lowest HWRR Quintile (n = 1,629)	Highest HWRR Quintile (n = 1,495)	p-value[b]			Lowest HWRR Quintile (n = 1,629)	Highest HWRR Quintile (n = 1,495)	p-value[b]
		Percent	Percent				Mean	Mean	
	Working, health limits	1.9	0.6		Number of difficulties with ADLs	None	67.5	57.6	<0.001
Total Assets (quartiles)	1 (Low)	23.9	36.2	<0.001		1–2	24.2	31.5	
	2	18.0	23.2			3+	8.3	10.9	
	3	21.0	20.8		Number of difficulties With IADLs	None	74.8	65.2	<0.001
	4 (High)	37.1	19.8			1–2	16.5	23.1	
Household Income (quartiles)	1 (Low)	23.4	37.1	<0.001		3+	8.6	11.7	
	2	27.0	29.6		Number of difficulties with activities requiring mobility[f]	None	24.0	19.5	0.04
	3	24.3	22.6			1–2	33.1	32.9	
	4 (High)	25.3	10.7			3+	42.9	47.7	
Household Debt (tertiles)	1 (Low)	70.3	69.4	0.27	Number of difficulties with activities requiring agility[f]	None	18.9	22.5	0.01
	2	5.3	4.2			1–2	44.4	37.5	
	3 (High)	24.4	26.5			3+	36.7	40.0	
Original Reason for Medicare Eligibility	Age≥65	82.3	74.8	<0.001	Number of Household Residents	1	32.5	34.8	0.004
	Disability or ESRD	17.7	25.2			2	53.2	46.7	
Current End-Stage Renal Disease		5.2	4.1	0.28		3	9.1	11.0	
Prescription Drug Coverage	Full/Most coverage	59.6	67.2	<0.001		4+	5.2	7.5	
	Partial coverage	28.9	24.5		Have living children	Yes	91.2	89.9	0.42
	No coverage	6.4	5.4		Number of living siblings	0	20.5	19.6	0.56
	No medications	5.1	2.9			1	25.7	24.4	
Smoking Status	Never	38.2	38.7	0.06		2+	53.8	56.0	
	Past	51.0	47.2		Friends Live Nearby	Yes	61.6	67.5	0.004
	Current	10.8	14.1		Frequency of Contact With Friends	Daily	11.3	10.5	0.28

		Lowest HWRR Quintile (n = 1,629)	Highest HWRR Quintile (n = 1,495)	p-value[b]		Lowest HWRR Quintile (n = 1,629)	Highest HWRR Quintile (n = 1,495)	p-value[b]
		Percent	Percent			Mean	Mean	
Number of Drinks Daily	0	72.7	75.7	0.31	Weekly	38.1	38.7	
	1	13.8	12.3		Biweekly/Monthly	15.4	13.0	
	2+	13.5	12.1		Less than monthly	35.1	37.9	

Abbreviations: unadjusted analysis (Unadj.), hospital-wide readmission rate (HWRR), 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] P-values are from χ^2 tests.

[c] 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.

[d] 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.

[e] The CES-D and cognition scores exclude 121 and 599 respondents, respectively with a proxy survey respondent who were not eligible for this survey item. Some proxy respondents were able to perform the CES-D questionnaire, so the number not eligible is not the same across the two scores.

[f] 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.

Table 3

Impact of Patient Characteristics on Difference in Probability of Readmission between Participants Admitted to Hospitals with Higher vs. Lower Readmission Rates[a]

Model	Description	Probability of Readmission[b] (%)		Difference in Probability of Readmission[b] (%) (95% CI)	Reduction in Difference from Previous Model[c] (%) (95% CI)
		Admitting Hospital in Lowest HWRR Quintile	Admitting Hospital in Highest HWRR Quintile		
1	Unadjusted[d]	14.53	20.39	5.86 (2.61, 9.21)	-
2	Variables used by CMS to adjust readmission rates[e]	15.04	19.45	4.41 (1.19, 7.54)	−1.45 (−2.63, −0.48)
3	Model 2 + additional claims data on eligibility categories and diagnoses[f]	15.74	19.24	3.50 (0.31, 6.67)	−0.91 (−1.78, −0.04)
4	Model 3 + additional clinical and social characteristics from the HRS [g]	16.06	18.36	2.29 (−0.77, 5.31)	−1.21 (−2.07, −0.21)

[a]Abbreviations: Hospital Wide Readmission Rate (HWRR) measure, Health and Retirement Study (HRS), Center for Medicare and Medicaid Services (CMS), 95% confidence interval (95% CI).

[b]From logistic regression estimates, we simulated probabilities of readmission and differences in readmission probabilities (see eMethods in Supplement for details). For each of the 4 models, we took 10,000 draws of model coefficients, assuming a multivariate normal distribution. For each draw of coefficients, we obtained the model prediction for each observation, alternately setting the highest and lowest HWRR quintile indicator to 1. Then for each draw, we calculated the mean predicted probability of readmission across observations under each of the two scenarios (HWRR quintile = highest vs. lowest). We calculated the absolute difference between these mean predicted probabilities under the two scenarios for each draw and then took the mean of these probabilities and absolute differences across draws and report these means in the table, along with 95% CIs derived from the 2.5th and 97.5th percentiles of the distribution across draws.

[c]The average reduction and 95% confidence interval are estimated comparing each model to the one in the row above using bootstrap methods.

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

[e]Model 2 includes age, sex, discharge diagnosis and 31 additional condition indicators included in the publicly reported HWRR measure.[14]

[f]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.[18]

[g]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 pre-specified interaction terms (see eMethods in Supplement for details).