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RESEARCH ARTICLE

Community Factors and Hospital Readmission Rates

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Objective. To examine the relationship between community factors and hospital readmission rates.

Data Sources/Study Setting. We examined all hospitals with publicly reported 30-day readmission rates for patients discharged during July 1, 2007, to June 30, 2010, with acute myocardial infarction (AMI), heart failure (HF), or pneumonia (PN). We linked these to publicly available county data from the Area Resource File, the Census, Nursing Home Compare, and the Neilsen PopFacts datasets.

Study Design. We used hierarchical linear models to assess the effect of county demographic, access to care, and nursing home quality characteristics on the pooled 30-day risk-standardized readmission rate.

Data Collection/Extraction Methods. Not applicable.

Principal Findings. The study sample included 4,073 hospitals. Fifty-eight percent of national variation in hospital readmission rates was explained by the county in which the hospital was located. In multivariable analysis, a number of county characteristics were found to be independently associated with higher readmission rates, the strongest associations being for measures of access to care. These county characteristics explained almost half of the total variation across counties.

Conclusions. Community factors, as measured by county characteristics, explain a substantial amount of variation in hospital readmission rates.

Key Words. Readmissions, community, socioeconomic status

Since 2009, the Centers for Medicare & Medicaid Services (CMS) has been publicly reporting hospital risk-standardized 30-day readmission rates for acute myocardial infarction (AMI), heart failure (HF), and pneumonia (PN). Starting in 2013, hospital Medicare reimbursement has been linked to hospital performance on these measures (Axon and Williams 2011). To control costs and improve patient care, hospital leaders across the country are focusing on improving 30-day readmission rates.

Critical to improving these rates is an understanding of the causes for variation in hospital readmission rates. Previous studies have found that some of this variation is explained by hospital characteristics, including ownership, bed size, volume, teaching status, and staffing level (Krumholz et al. 2009; Joynt, Orav, and Jha 2011). Other research has focused on patient-level sociodemographic factors, like race, health literacy, and social support (Arbaje et al. 2008; Foraker et al. 2011; Joynt, Orav, and Jha 2011; Hawkins et al. 2012). However, while it is likely that some contributors to readmissions such as patient social support and community health-system factors are out of the hospital's control, there has been little examination of how such community factors might influence the readmission rates of hospitals in those communities. Thus, we examined the association between community characteristics and 30-day risk-standardized hospital readmission rates. We used county (or county equivalent) as our unit of community; while fairly crude, there is a wide range of data available at the level of the county, making it a useful definition for exploratory analysis. We identified a range of socioeconomic, demographic, and health-system characteristics measurable at the county level that could plausibly influence the likelihood that discharged patients would be readmitted within 30 days. After identifying a large set of county-level characteristics that capture these three types of community attributes, we used conventional techniques to reduce them to a more parsimonious set. We then used hierarchical linear models (HLMs) to evaluate the variation in hospital readmission rates and assess the degree to which these characteristics explain national variation in hospital readmission rates.

METHODS

Overview

In this observational study, we linked publicly reported hospital readmission rates from CMS Hospital Compare (HC) (Hospital Compare 2012) with hospital and county data from a number of data sources. These data sources

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included the 2010 American Hospital Association (AHA) Annual Survey database (AHA Guide 2010), the 2010 Health Resources and Services Administration's Area Resource File (ARF) (Area Resource File 2009–2010), and CMS Nursing Home Compare (NHC) (Nursing Home Compare 2012). Additional county measures were constructed from the 2010 Nielsen PopFacts dataset (Pop-Facts Premier 2010). We used HLMs to examine the variation in hospital readmission rates across counties and to model the bivariate and multivariate relationships between hospital and county factors and hospital readmission rates. Because hospital and community characteristics often correlate (e.g., smaller bed size correlates with rural location), the primary analysis ignored hospital characteristics; these were included in a secondary analysis to determine whether any primary findings might be attenuated.

Conceptual Model

We hypothesized that the likelihood of hospital readmission for a patient residing in a given community would be only partially explained by the hospital discharging the patient, and that in addition to patient-risk factors normally adjusted for in readmission models, there would be contributions from three types of community characteristic.

First, prior research has identified a relationship between risk of readmission and a number of patient sociodemographic characteristics, including living alone, employment status, and educational level (Marcantonio et al. 1999; Tsuchihashi et al. 2001; Arbaje et al. 2008; Howie-Esquivel and Spicer 2012). We hypothesized that county measures of these and other sociodemographic factors would explain some of the county-level variation in hospital readmission rates. These "county" characteristics are essentially proxies for individual factors, and don't necessarily reflect county-level attributes as such; however, by including them in the analysis, we are able to account for the individual effects and identify the independent effects of other county-level characteristics.

Second, there is also mixed evidence that access to care is associated with risk of readmission (Weinberger, Oddone, and Henderson 1996; Tsuchihashi et al. 2001), with one study finding a positive relationship and another an inverse relationship; thus, we hypothesized that county measures of access to care would explain some of the county-level variation in hospital readmission rates. We hypothesized that such measures at the county level would include metrics of primary-care access such as numbers of primary care and specialist physicians per capita, and the ratio of primary care to specialist physicians, as well as metrics of hospital access such as number of beds per capita, with increased primary-care access and reduced hospital access both being associated with lower readmissions.

Third, there is evidence that discharge to nursing home care increases the risk of rehospitalizations (Hannan et al. 2003; Konetzka, Polsky, and Werner 2013), and that quality of nursing home care is inversely related to the likelihood that patients at that nursing home will be rehospitalized; thus we hypothesized that the number and quality of nursing homes in a county would explain some of the county-level variation in hospital readmission rates.

This conceptual model—that patient level, access, and nursing home measures influence the likelihood of readmission—was used to identify measures for inclusion in the analysis. This model also informed in analysis, in that the three types of characteristics were considered separately to identify which had the most influence on hospital readmission rates, before these reduced subsets were considered together.

Sample and Outcome

The Centers for Medicare & Medicaid Services publicly reports risk-standardized 30-day readmission rates (RSRRs) for patients with AMI, HF, and PN; these rates are risk-standardized using models that adjust for risk factors, including age, comorbidities, and prior history (Keenan et al. 2008; Krumholz et al. 2011; Lindenauer et al. 2011). We included all hospitals that had publicly reported RSRRs for any of the three conditions for the period July 1, 2007, to June 30, 2010. We calculated Cronbach's α for these three measures and found $\alpha = .689$, indicating substantial homogeneity. Thus, to have more generalized findings, we pooled any reported rates for each hospital; this pooled readmission rate was constructed as the volume-weighted average of the reported condition-specific rates. To account for the differing precision of RSRRs at different hospitals, we also estimated the standard error for this pooled readmission rate; this allowed us to weight all subsequent analyses for the precision of the outcome for each hospital. To estimate the standard error of the pooled RSRR, we used parametric bootstrapping and the interval estimates of the reported rates (Efron and Tibshirani 1993). Specifically, we used the interval estimate to estimate a standard error for each publicly reported RSRR value (AMI, HF, or PN) by dividing the width of the 95 percent confidence interval by twice 1.96 (the 97.5th normal critical value). We then generated for each hospital and each reported RSRR 1,000 random values with mean equal to the RSRR and standard deviation equal to the calculated standard error; for each hospital and each set of random values we calculated the volume-weighted average of the RSRR; the standard deviation of the 1,000 values was used as the estimated standard error for the pooled rate. Since condition-specific rates are reported only for hospitals with at least 25 eligible discharges, not all hospitals had rates for all three conditions.

Community

We used the Federal Information Processing Standard (FIPS) code to define county or county equivalent (depending on the state, county equivalent could mean parish or borough). Hospitals' FIPS county codes were determined by the address reported in the Hospital Compare database.

Data Sources and Variables

Hospitals were linked using Medicare provider numbers or FIPS codes to the following data sources. From the 2010 AHA Annual Survey, we obtained ownership type (public, private not for profit, and private for profit), teaching status (no teaching program, residency program, and Council of Teaching Hospitals designation), bed size (classified as 1–50, 51–100, 101–200, 201–300, and 301 or more), and percentage Medicaid admissions (used to create a safety-net classification, with hospitals classified as "Safety Net" if the Medicaid admission rate was more than one standard deviation above the state average).

From the 2009 ARF, we obtained for each FIPS county code the population (2009 estimated), number of Medicare beneficiaries (2009 estimated), number of general practitioners (GPs) (2008; this included both general practice and family medicine physicians), number of specialists (2008; this included all physician specialists), and number of cardiologists (2008). From these, we constructed variables representing numbers of Medicare beneficiaries, GPs, cardiologists, and specialists *per capita* ($\times$100,000) and the ratio of GPs to specialists (because some counties had no general practitioners or no specialists, 1 was added to each before calculating the ratio). Also from the ARF, we obtained four county classifications made by the Department of Agriculture: retirement community, low employment, persistent poverty classification, and low education.

From CMS's NHC (2011) we obtained overall nursing home rating and the following percents: high-risk long-stay residents with pressure sores, low-risk long-stay residents with pressure sores, long-stay residents with flu vaccine, long-stay residents with PN vaccine, short-stay residents with flu vaccine, short-stay residents with PN vaccine, long-stay residents with depression or anxiety, long-stay residents with urinary tract infection, long-stay residents physically restrained, long-stay residents whose need for help with daily activities has increased. From the vaccine measures, we created a single vaccine score (Cronbach's alpha = .77). These values were averaged for each county; for counties with no reported nursing homes in NHC (n = 110), nursing home variables were assigned the median score for inclusion in models.

From the Nielsen Pop-Facts Premier (2010) database, we obtained the following percentages: adults never married, adults 65 or older, families below poverty level. From the same database, we also obtained a ZIP code level measure of socioeconomic status (SES), which we linked to the 2007 Medicare admissions file to create a hospital-level mean SES score based on all Medicare admissions to the hospital during 2007; this SES score has previously been used to create measures of patient SES at the hospital level (Rathore et al. 2006; Bradley et al. 2010).

Finally, to classify each community according to urbanization, we used the 2006 *NCHS Urban-Rural Classification Scheme for Counties*, developed by the National Center for Health Statistics and the Centers for Disease Control and Prevention (Ingram and Franco 2012). The categories are large central metro, large fringe metro, medium metro, small metro, micropolitan, and rural.

Statistical Analysis

We summarized the pooled, risk-standardized, 30-day readmission rate (described above) for all hospitals, as well as by hospital ownership, bed size, teaching status, and safety-net status. All calculations using the pooled RSRR were weighted by the inverse of the square of the estimated standard error. For each county measure, we graphed the distribution of readmission rates for hospitals in each category by decile. We used these figures to combine or collapse categories or deciles according to the patterns of readmission, with all deciles collapsed into quintiles. This produced a final set of candidate variables.

To assess the amount of variance in the pooled hospital readmission rate that could be attributed to the hospital and community, respectively, and to estimate the effect of community and hospital factors on pooled readmission rates, we used HLMs (Snijders and Bosker 1999). HLMs allowed us to partition the total variance in the pooled readmission rate into components at the hospital and county level, respectively, assessing how much could be attributed to each level; such models have been previously used for partitioning variance for nested data in health research (Subramanian, Jones, and Duncan 2003; Haymart et al. 2011). Such models can also be used to assess how much of the variance in readmission across counties is explained by each factor or set of factors. To adjust for the uncertainty in risk-standardized readmission rates, all hospital-level observations in each HLM were weighted for the inverse of the estimated variance of the pooled outcome; in the HLM context this is referred to as a "variance known," or "V-known," model (Bryk and Raudenbush 1992). One characteristic of this model is that the lower level variance (here the hospital) is fixed at exactly 1; this does not affect the interpretation of relative unexplained variance at each level, but it does preclude making inferences about the absolute magnitude of the unexplained variance at each level.

To estimate the proportion of variance due to county, we first estimated an HLM with no covariates, and a random intercept across counties ("the empty model"). Specifically, if RSRR_{ij} is the pooled 30-day readmission rate for the ith hospital in the jth county, with variance V_{ij}, we estimated:

$$\mathrm{RSRR}_{ij}/V_{ij} = \mu + v_j + \varepsilon_{ij} \tag{1}$$

where $v_j \sim N(0,{\sigma_v}^2)$ and $\varepsilon_{ij} \sim N(0,1)$ are the county- and hospital-level effects, respectively. By comparing ${\sigma_v}^2$ to the total variation in RSRRs, ${\sigma_v}^2 + 1$, we are able to assess how much of the national variation in the outcome is attributable to the county, and how much to the hospital. By adding covariates to model (1), we can not only make appropriate inferences about the associations between covariates and outcome but also note the relative degree to which covariates reduce ${\sigma_v}^2$ and ${\sigma_\varepsilon}^2$.

After estimating the empty model (1), we used a set of sequential analyses to reduce the set of factors to a parsimonious set of independent community factors most strongly associated with hospital readmission rates. Because of collinearity between many characteristics that were not conceptually related (e.g., proportion Medicare beneficiaries *per capita* and proportion of the population never married), we used an approach that was both mechanical and conceptual to reduce the number of factors. First we looked at all of the bivariate relationships between county factors and hospital rates, calculating p-values and the proportions of variance explained at the county level (Bryk and Raudenbush 1992). We grouped those that were significant ($p < .05$) into county demographic factors, county access to care factors, and nursing home factors, as being conceptually distinct; within each of these three groups, we examined the variance decomposition matrix (Belsley, Kuh, and Welsch

1980) to determine which were collinear; when two or more variables had variance decomposition portion more than 50 percent, we retained the one with the greatest percent variation explained at the county level in the bivariate analysis. We did this for all sets of variables in the three groups with singular values greater than 20 (Belsley, Kuh, and Welsch 1980). This method has been previously used in the context of health services research to reduce larger numbers of related factors to a parsimonious set (Bradley et al. 2012). All retained variables were then included in a single multivariable HLM with a random intercept across counties; all county variables with Wald $p < .05$ in this intermediate model were retained for a final multivariable HLM.

Because hospital characteristics and community factors often correlate (e.g., smaller bed size correlates with rural location), the primary analysis did not include hospital characteristics. However, as a secondary analysis to assess whether any community effects were attenuated by hospital characteristics, we included hospital ownership, bed size, teaching status, and safety-net status in a secondary model. For interpretation, we report the adjusted rates from each model.

All analyses were performed using Stata version 12.1 (StataCorp, College Station, TX, USA) and HLM version 7 (Scientific Software International, Lincolnwood, IL, USA) statistical software.

RESULTS

A total of 4,079 hospitals had publicly reported readmission rates for at least one condition (AMI, HF, or PN) during the study period. Six hospitals could not be matched to the AHA database, leaving 4,073 in the final sample (see Table 1 for a description of the hospitals and their readmission rates). The study hospitals were located in 2,254 counties. Cronbach's α for the three readmission measures was 0.69; the weighted average AMI, HF, and PN readmission rate had a mean (standard deviation) of 20.8 percent (1.8 percent) and an interquartile range of [19.6, 21.9].

Before accounting for any hospital or county characteristics, the empty model found that 58 percent of the national variation in hospital pooled readmission rates was at the county level. Full bivariate results are reported in the Appendix; the characteristics that explained the greatest proportion of variation across counties were number of GPs *per capita* (11.9 percent of county variance explained), NCHS urban rural continuum classification (13.3 percent), and the average percentage of high-risk long-stay nursing home patients with

Table 1: Characteristics of the Hospitals Included in the Study

Characteristic	*N (%)*	*Readmission Rate* Mean (SD)*
N	4,073 (100.0)	20.9 (1.8)
Control		
Public	882 (21.7)	20.6 (1.8)
Private not for profit	2,545 (62.5)	20.9 (1.8)
Private for profit	646 (15.9)	21.2 (1.7)
Teaching		
Neither	3,296 (80.9)	20.8 (1.7)
Residency	505 (12.4)	20.9 (1.8)
Council of Teaching Hospital	272 (6.7)	21.9 (1.9)
Beds		
≤50	1,131 (27.8)	20.1 (1.6)
51–100	713 (17.5)	20.5 (1.6)
101–200	919 (22.6)	21.0 (1.7)
201–300	531 (13.0)	21.1 (1.7)
301+	779 (19.1)	21.2 (1.8)
Safety-net hospital		
No	3,513 (86.3)	20.8 (1.7)
Yes	560 (13.7)	21.4 (2.0)

*Pooled risk-standardized 30-day readmission rate for acute myocardial infarction, heart failure, and pneumonia.

pressure sores (20.3 percent). After reduction of the set of significant factors by variance decomposition, the following county characteristics were retained for multivariable analysis. Demographics and socioeconomic factors: percentage of residents never married; percentage of household below poverty line; number of Medicare beneficiaries per capita; low education designation of county; low employment designation; retirement destination designation, persistent poverty designation, and NCH Rural/Urban continuum. Access to care factors: number of nursing homes *per capita*; number of GPs *per capita*; number of specialists *per capita*; ratio of GPs to specialists; hospital beds *per capita*. Nursing home quality factors: NH vaccine score; percent of high-risk long-stay NH patients with pressure sores; percent of long-stay NH patients who are depressed or anxious; percent long-stay NH residents with UTI; percent of long-stay NH patients who are physically restrained; percent of long-stay NH patients whose need for help has increased. In the initial multivariable model, the following were not significant and excluded from the final model: percent of households below poverty line, low employment, and persistent poverty, NH vaccine score, NH patients with UTI, NH patients restrained.

The results of the final multivariable models are shown in Table 2. A number of county characteristics were found to be independently associated with increased rates of readmission. Of the demographic factors, proportion of the population never married, number of Medicare beneficiaries *per capita*, and low education area status were all associated with significantly higher readmission rates; rural areas and retirement areas were associated with lower readmission. Among the access to care factors, the strongest effect was of higher numbers of general practitioners *per capita* (adjusted difference in RSRR between highest and lowest quartile [95 percent Confidence Interval]: −0.80 percent [−1.09 percent, −0.51 percent]; $p < .001$); more nursing homes per capita were also associated with lower readmission rates; in contrast, higher numbers of specialists per capita (0.70 percent [0.22 percent, 1.17 percent]; $p < .001$), and hospital beds *per capita* were all independently associated with higher readmission rates. One factor had a non-linear relationship with readmissions: while the ratio of general practitioners to specialists was significant overall, the association was complex: a ratio in the middle quintile rather than high or low was associated with decreased readmission rates relative to the lowest quintile, but readmission rates in the highest quintile of communities were higher than those in the lowest quintile (see coefficients in Table 2). Among the nursing home measures considered, the percentage of high-risk long-stay patients with pressure sores (0.92 percent [0.71, 1.13]; $p < .001$) and percentage of long-stay residents with increased need for help (0.33 percent [0.12, 0.53]; $p = .002$) were positively associated with increased readmission rates; however, the percentage of long-stay residents depressed or anxious was associated with decreased readmission rates (−0.53 percent [−0.75 percent, −0.32 percent]). Taken together, the county characteristics explained 47.5 percent of the total variation in rates across counties; that is, the unexplained variance at the county level reduced from 1.37 (empty model) to 0.72 (final model) relative to the hospital-level unexplained variance of exactly 1. Accounting for hospital ownership, bed size, teaching status, safety-net status, and patient SES status did not substantially affect these results, with only number of hospital beds per capita no longer significant and unexplained variance at the county level further reduced only from 0.72 to 0.71.

The overall range in pooled readmission rate was (15.0, 28.9); after adjusting for county factors (including county random effect), the range was (17.6, 25.7); and after adjusting also for hospital characteristics it was (18.1, 25.1).

Table 2: Results of Multivariable Models of Pooled Thirty-Day Risk-Standardized Readmission Rates for 4,073 Hospitals in 2,244 Counties; Main Results (without Hospital Characteristics) and Sensitivity Analysis (with Hospital Characteristics)

	Without Hospital Characteristics			With Hospital Characteristics		
	Coefficient* (95% CI)	p	Wald $p^{\dagger}$	Coefficient* (95% CI)	p	Wald $p^{\dagger}$
Intercept	20.11 (19.56, 20.65)			20.35 (19.78, 20.92)		
Demographic factors						
% Residents never married			<.001			<.001
1st quintile	ref[‡]			ref		
2nd quintile	−0.11 (−0.32, 0.11)	.33		−0.14 (−0.35, 0.08)	.22	
3rd quintile	0.05 (−0.17, 0.27)	.67		0.09 (−0.13, 0.31)	.44	
4th quintile	0.16 (−0.07, 0.38)	.17		0.18 (−0.04, 0.41)	.11	
5th quintile	0.42 (0.18, 0.66)	<.001		0.50 (0.26, 0.74)	<.001	
Medicare beneficiaries/100k			<.001			<.001
1st quintile	ref			ref		
2nd quintile	0.10 (−0.08, 0.29)	.27		0.15 (−0.04, 0.33)	.12	
3rd quintile	0.37 (0.16, 0.58)	<.001		0.35 (0.13, 0.56)	.00	
4th quintile	0.58 (0.36, 0.81)	<.001		0.52 (0.30, 0.75)	<.001	
5th quintile	0.56 (0.30, 0.82)	<.001		0.53 (0.27, 0.79)	<.001	
Low education[§]						
No	ref			ref		
Yes	0.72 (0.54, 0.91)	<.001.		0.41 (0.21, 0.61)	<.001	
Retirement destination[§]						
No	ref			ref		
Yes	−0.32 (−0.51, −0.13)	<.001		−0.25 (−0.44, −0.06)	.01	
Rural/urban continuum						
Large central metro	ref		<.001	ref		<.001
Large fringe metro	0.16 (−0.14, 0.47)	.29		0.15 (−0.15, 0.46)	.33	
Medium metro	−0.58 (−0.88, −0.28)	<.001		−0.68 (−0.98, −0.38)	<.001	
Small metro	−0.72 (−1.04, −0.41)	<.001		−0.89 (−1.21, −0.58)	<.001	
Micropolitan	−0.52 (−0.84, −0.19)	.002		−0.70 (−1.02, −0.37)	<.001	
Rural	−0.58 (−0.94, −0.22)	.002		−0.64 (−1.01, −0.28)	<.001	
Access to care						
Nursing homes/100k			.001			
1st quintile	ref			ref		.011
2nd quintile	0.08 (−0.10, 0.25)	.39		0.10 (−0.08, 0.27)	.27	
3rd quintile	−0.04 (−0.23, 0.16)	.71		−0.04 (−0.24, 0.15)	.67	
4th quintile	−0.15 (−0.38, 0.07)	.18		−0.13 (−0.36, 0.10)	.26	
5th quintile	−0.48 (−0.75, −0.20)	<.001		−0.37 (−0.65, −0.09)	.01	

continued

Table 2. *Continued*

	Without Hospital Characteristics			With Hospital Characteristics		
	Coefficient* (95% CI)	*p*	Wald *p*†	Coefficient* (95% CI)	*p*	Wald *p*†
GPs/100k			<.001			<.001
1st quintile	ref			ref		
2nd quintile	−0.39 (−0.58, −0.19)	<.001		−0.34 (−0.54, −0.15)	<.001	
3rd quintile	−0.49 (−0.71, −0.28)	<.001		−0.43 (−0.64, −0.21)	<.001	
4th quintile	−0.72 (−0.96, −0.48)	<.001		−0.59 (−0.83, −0.35)	<.001	
5th quintile	−0.80 (−1.09, −0.51)	<.001		−0.63 (−0.92, −0.34)	<.001	
Specialists/100k			.006			
1st quintile	ref			ref		.004
2nd quintile	0.46 (0.18, 0.73)	.001		0.37 (0.09, 0.65)	.01	
3rd quintile	0.76 (0.41, 1.11)	<.001		0.71 (0.35, 1.06)	<.001	
4th quintile	0.78 (0.37, 1.19)	<.001		0.76 (0.35, 1.17)	<.001	
5th quintile	0.70 (0.22, 1.17)	.004		0.77 (0.29, 1.25)	.002	
GPS/specialist			<.001			<.001
1st quintile	ref			ref		
2nd quintile	−0.26 (−0.46, −0.06)	.009		−0.27 (−0.47, −0.07)	.01	
3rd quintile	−0.27 (−0.54, −0.01)	.04		−0.26 (−0.53, 0.00)	.05	
4th quintile	−0.05 (−0.42, 0.31)	.77		−0.02 (−0.38, 0.35)	.93	
5th quintile	0.30 (−0.20, 0.80)	.23		0.33 (−0.17, 0.84)	.19	
Beds/100k			<.001			.240
1st quintile	ref			ref		
2nd quintile	0.07 (−0.13, 0.27)	.52		−0.04 (−0.24, 0.17)	.72	
3rd quintile	0.11 (−0.10, 0.32)	.31		−0.11 (−0.33, 0.10)	.31	
4th quintile	0.41 (0.19, 0.63)	<.001		0.09 (−0.14, 0.32)	.46	
5th quintile	0.51 (0.27, 0.74)	<.001		0.05 (−0.20, 0.31)	.68	
Nursing home quality						
% High-risk long-stay patients with pressure sores			<.001			<.001
1st quintile	ref			ref		
2nd quintile	0.17 (−0.03, 0.37)	.10		0.11 (−0.09, 0.31)	.29	
3rd quintile	0.24 (0.04, 0.44)	.02		0.17 (−0.03, 0.37)	.09	
4th quintile	0.48 (0.28, 0.69)	<.001		0.40 (0.19, 0.61)	<.001	
5th quintile	0.92 (0.71, 1.13)	<.001		0.83 (0.61, 1.04)	<.001	
% Long-stay patients depressed or anxious			<.001			.013
1st quintile	ref			ref		
2nd quintile	−0.17 (−0.36, 0.01)	.07		−0.11 (−0.30, 0.07)	.24	
3rd quintile	−0.24 (−0.43, −0.05)	.02		−0.14 (−0.33, 0.06)	.16	
4th quintile	−0.31 (−0.51, −0.11)	.002		−0.21 (−0.41, −0.01)	.04	
5th quintile	−0.53 (−0.75, −0.32)	<.001		−0.38 (−0.60, −0.17)	<.001	

continued

Table 2. *Continued*

	Without Hospital Characteristics			With Hospital Characteristics		
	Coefficient* (95% CI)	p	Wald $p^{\dagger}$	Coefficient* (95% CI)	p	Wald $p^{\dagger}$
% Long-stay patients whose need for help has increased						
1st quintile	ref		.002	ref		.001
2nd quintile	0.28 (0.09, 0.47)	.003		0.32 (0.13, 0.51)	<.001	
3rd quintile	0.07 (−0.12, 0.25)	.50		0.08 (−0.11, 0.27)	.40	
4th quintile	0.08 (−0.11, 0.27)	.42		0.08 (−0.11, 0.27)	.43	
5th quintile	0.33 (0.12, 0.53)	.002		0.32 (0.11, 0.52)	.002	
Hospital characteristics						
Ownership						
Public				ref		<.001
Private not for profit				0.08 (−0.04, 0.21)	.20	
Private for profit				0.54 (0.38, 0.70)	<.001	
Teaching status						
None				ref		<.001
Residency				−0.20 (−0.33, −0.07)	.002	
COTH				0.34 (0.17, 0.50)	<.001	
Beds						
≤50				ref		<.001
51–100				0.28 (0.10, 0.45)	.003	
101–200				0.51 (0.32, 0.69)	<.001	
201–300				0.48 (0.28, 0.69)	<.001	
301+				0.37 (0.15, 0.58)	<.001	
Safety-net hospital						
No				ref		
Yes				0.14 (0.01, 0.27)	.04	
Patient socioeconomic status						
1st quintile				ref		<.001
2nd quintile				−0.26 (−0.43, −0.10)	.001	
3rd quintile				−0.66 (−0.83, −0.50)	<.001	
4th quintile				−0.73 (−0.91, −0.55)	<.001	
5th quintile				−0.99 (−1.19, −0.80)	<.001	

*Change in pooled risk-standardized readmission rate.
†Overall p-value based on Wald-test.
‡Ref = Reference category, omitted from model.
§County classification from the Department of Agriculture.

DISCUSSION

In this examination of the relationship between community factors and hospital risk-standardized readmission rates, we found that a substantial amount of the variation is explained by the county where a hospital is located: 58 percent of the total variation in publicly reported hospital 30-day readmission rates was attributable to the county where the hospital was located. Expressed differently, the results suggest that individual hospital performance accounts for only 42 percent of the variation in pooled readmission rates across the United States.

Several demographic and socioeconomic characteristics were found to explain county-level variation in hospital readmission rates: higher percentage of residents who never married, the number of Medicare beneficiaries per 100,000 residents, and a low employment designation were all associated with higher hospital readmission rates, while designation as a retirement destination was associated with lower readmission rates. The first two are consistent with prior findings; individuals who live alone, who are unemployed, or who have challenges affording health care are more likely to be readmitted (Jasti et al. 2008; Murphy et al. 2008). These findings are also consistent with a study that established a correlation between lower county income level and increased hospital readmission rate (Joynt and Jha 2011). What is surprising is the positive relationship between density of Medicare beneficiaries and readmission rates. While higher density of Medicare beneficiaries may reflect an older population, the readmission rates were adjusted for age so it is likely there is an additional effect, perhaps related to health-system variables. Designation as a retirement destination may indicate both higher socioeconomic status among the Medicare population and a community that is oriented toward the care of older residents, though it is notable that these effects persisted even after adjusting for the hospital patient population SES.

It is worth emphasizing that while they are constructed at the county level, our analysis does not allow us to interpret these demographic and socioeconomic as true county effects. As noted above in our description of the conceptual model, we interpret them instead as proxies for patient-level attributes. For example, the effect of the percentage of residents never married on hospital readmission rates is likely through the married status of individual patients, not the aggregate effect of having higher numbers of unmarried individuals in the community. More critically, there is some evidence that using such "area based measures" to make inferences about individuals leads to incorrect or inflated estimates of effect (Soobader et al. 2001; Geronimus 2006). A related limitation is that while there may also be indirect ecological effects (e.g., living in a lower income community may have otherwise unmeasured effects on the health of individuals), it is not possible to identify them without patient-level data and corresponding analysis.

Regarding community-level health-system variables, a number of measures of the local health care system were independently associated with the readmission rates of hospitals. The supply of general practitioners and specialists and the ratio of general practitioners to specialists were all independently associated with the outcome. The number of general practitioners per capita is a measure of access to primary care; patients who are discharged into areas with smaller numbers of general practitioners may have fewer options other than returning to the hospital following postdischarge events. For both GP density and specialist density, the adjusted difference in readmission rates between the lowest and highest quintile was at least 0.7 percent; because these are independent effects, counties with high numbers of GPs and low numbers of specialists would have risk-standardized readmission rates 1.5 percentage points higher than those with the opposite characteristics. This is greater than the difference between teaching and nonteaching or smallest and largest hospitals (Table 1).

We examined several county factors related to nursing homes. Prior research has found no link between the rate of discharge to nursing homes and the rate of readmission (Chen et al. 2012). However, our results suggest that the number and quality of nursing homes in a community could affect the rate of readmission.

Finally, and perhaps most critically, it is notable that 58 percent of the variance in hospital readmission rates was at the county level; a model incorporating only county variables explained nearly half of that 58 percent, and when hospital ownership, teaching status, bed size, safety-net status, and patient SES were added, only slightly more variance was explained, suggesting that these particular hospital factors contribute relatively little to the variation in rates of readmission. That the majority of the unexplained variation in hospital readmission rates can be attributed to counties rather than hospitals suggests that narrowly targeting hospitals with reimbursement adjustments and other incentives can lead at best to marginal improvements in readmission rates; more effective policies might be directed at the wider system of care, including primary care and nursing home quality.

There are a number of limitations to consider when assessing these results. First, since this is an observational study, associations cannot be interpreted as causal. However, the examination of variance reflects a true partitioning of the readmission-rate variance, and the observed effects provide insights into patterns of readmission. In addition, while unmeasured confounding is an important concern with any observational study, it is not likely that one or more unmeasured confounders would be associated with both the entire set of identified community characteristics and with patient-level risk of readmission. Second, our outcome of pooled readmission comprises readmissions for only three conditions, HF, AMI, and PN; and while it is plausible that the same factors would influence readmission after discharge for other conditions, further research would be necessary to establish this. Another limitation is that of our data: the use of county as a measure of community is one of convenience, in that measures were available at the county level; in reality, counties in urban areas rarely serve as isolated communities or markets, and several of our factors might vary considerably within urban counties, and across hospitals within those counties. Similarly, the AHA survey file may sometimes contains a single record for hospitals that have several facilities; those facilities may not all lie within the same county as the primary facility, leading to misclassification of the outcome by county. However, both of these limitations are more likely to bias our results toward the null, if at all, in that they introduce measurement noise.

In summary, this study is one of the most thorough looks to date at how hospital readmission rates are explained by community-level factors. The evidence shows that after accounting for patient-risk factors (done by the risk-standardization of the publicly reported rates) and community socioeconomic factors (such as income and employment levels), as well as accounting for hospital characteristics and location, a substantial amount of the variation in readmission rates is explained by local health-system characteristics related to primary care access and the quality of nursing homes. These findings have significant implications on how health care leaders, payers, and policy makers should conceptualize the level of accountability for excess readmissions. The current readmission reduction program that aims to penalize hospitals whose readmissions are above a certain threshold may not be appropriate (Centers 2012). Instead, other payment methods such as those being tested in the Community-based Care Transitions Program (Community 2012), where community-based organizations receive a bundle payment to cover the costs of services required in the postacute care transition period, might be more effective.

Conclusion

We found that nearly 60 percent of the variation in hospital pooled AMI, HF, and PN risk-standardized 30-day readmission rates is explained by the county where the hospital is located, and that county measures, including socioeconomic status, physician mix, and nursing home quality, explain nearly half of this county-level variation. Thus, hospital readmission rates might be more effectively reduced if community-based readmission reduction strategies are added to ongoing, hospital-focused improvement efforts.

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Supporting Information

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

Appendix SA1: Author Matrix.

Appendix SA2: Bivariate Results for All County Factors Evaluated in Study. R^2 is percent of County-Level Variance Explained. $N = 4{,}079$ Hospitals.