RESEARCH ARTICLE

Community factors and hospital wide readmission rates: Does context matter?

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Abstract

Background

The environment in which a patient lives influences their health outcomes. However, the degree to which community factors are associated with readmissions is uncertain.

Objective

To estimate the influence of community factors on the Centers for Medicare & Medicaid Services risk-standardized hospital-wide readmission measure (HWR)–a quality performance measure in the U.S.

Research design

We assessed 71 community variables in 6 domains related to health outcomes: clinical care; health behaviors; social and economic factors; the physical environment; demographics; and social capital.

Subjects

Medicare fee-for-service patients eligible for the HWR measure between July 2014-June 2015 (n = 6,790,723). Patients were linked to community variables using their 5-digit zip code of residence.

Methods

We used a random forest algorithm to rank variables for their importance in predicting HWR scores. Variables were entered into 6 domain-specific multivariable regression models in order of decreasing importance. Variables with P-values <0.10 were retained for a final model, after eliminating any that were collinear.

Results

Among 71 community variables, 19 were retained in the 6 domain models and in the final model. Domains which explained the most to least variance in HWR were: physical environment (R^2 = 15%); clinical care (R^2 = 12%); demographics (R^2 = 11%); social and economic environment (R^2 = 7%); health behaviors (R^2 = 9%); and social capital (R^2 = 8%). In the final model, the 19 variables explained more than a quarter of the variance in readmission rates (R^2 = 27%).

Conclusions

Readmissions for a wide range of clinical conditions are influenced by factors relating to the communities in which patients reside. These findings can be used to target efforts to keep patients out of the hospital.

Introduction

Readmission following a hospital discharge represents a potentially avoidable outcome and has been a key focus of recent policy, research and quality improvement efforts [1–4] Accordingly, the Centers for Medicare & Medicaid Services (CMS) publicly report a global measure of readmission following an index hospitalization for virtually any condition (hospital-wide readmission [HWR]) [4] This measure is risk-adjusted for patient-level clinical factors which influence the risk of readmission. However, social risk factors may also contribute to readmission, both on an individual level, such as individuals' socioeconomic position, race, ethnicity and culture, gender orientation and sexuality; as well as on a community level, including factors in a patients' home environment. While the relationship between individual-level social risk factors and outcomes has garnered much attention [5–9], less is known about the relative contribution of community-level social, economic and physical factors to outcomes. Communities are multi-dimensional and have attributes that may interact in multiple ways to influence the risk of patients being readmitted soon after discharge [10–20]. Understanding the relative importance of neighborhood characteristics on individual health outcomes will help policymakers identify and prioritize community-based interventions to improve outcomes that might provide benefits beyond purely hospital-focused activities.

Several community factors may influence a patient's risk for readmission. For example, some community factors like accessibility of primary care providers, availability of transportation, healthy foods and places to exercise, density of non-profit organizations, and accessible, high-quality acute rehabilitation centers and skilled nursing facilities may directly support or hinder recovery and thus may contribute to patients' risk of readmission [16, 18, 21]. Additionally, the socioeconomic and social environment, defined by factors such as poverty, unemployment and crime, may exert an indirect effect, as these social ills may result in fewer resources and competing priorities for health [10, 13, 15, 17, 22]. Assessments of the contribution of these and other community factors to hospital readmissions is important for informing health system and community-based efforts to lower readmission rates.

Accordingly, we adapted and expanded the Robert Wood Johnson Foundation (RWJF) County Health Rankings framework to examine how community factors may relate to hospital readmission rates [23]. The original framework consists of 4 domains: clinical care; health behaviors; social and economic factors; and physical environment. We expanded this

framework to also include the domains of demographics and social capital. We viewed these 6 domains as representing different 'spheres' of influence with different effect sizes and implications for causality and intervention. Specifically, clinical care features of a community can influence readmissions through both quality and access to care; the RWJF County Health Rankings framework captures measures of both. Community healthy behaviors, measured at the population level, capture residents' healthy activities as well as the availability of open spaces, fresh fruits and vegetables–reflecting the dominant culture towards health and available health resources that may make it more or less easy for a patient returning home from the hospital to engage in health-promoting activities. The social and economic domain includes metrics of education, income, and employment which may directly or indirectly influence patient risk wherein a person has less available resources or the community is deprived of resources which are necessary for recovery and health (e.g., available funds to pay for transportation to appointments; caregiver who can take time off of work; community support groups). The physical environment–including variables such as housing density and air and water quality– is known to affect individual health—impacting respiratory and cardiovascular physiology and increasing people's risk for admission. To these four domains from the RWJF County Health Rankings framework we added two additional community domains which we hypothesized would influence the risk of readmission. One was a demographic domain, which includes age and race/ethnicity characteristics of the community; we hypothesized that communities with greater percentages of minority residents have more limited access to care and poorer quality of care, beyond what is already captured in the HWR measure, because of historical disparities [24]. and that other socioeconomic factors (e.g., employment; income; education) have different effects in minority populations [25–27]. The other additional domain was social capital, which includes metrics on voter turnout and the number of active non-profits and religious organizations [28]; we hypothesized that communities with greater social cohesion and citizen involvement would also provide additional support to patients who might otherwise return to the hospital.

We had 2 primary objectives: to identify variables most associated with hospital readmission rates and to estimate the relative contribution of distinct spheres or domains of influence as well as specific community variables within each domain hypothesized to impact hospital readmission rates. Importantly, and distinct from prior work, we focus on patients admitted for a broad range of different clinical conditions; additionally, we measure the attributes of the communities where patients reside, not where the hospital is located [18], which may be more relevant to patient outcomes [29]. Ultimately, a better understanding of the community factors that have an impact on post-discharge outcomes is essential to promote the development of effective, safe and patient-centered healthcare environments.

Methods

Design and setting

The context for this study was the United States. Medicare is a federal program, providing insurance coverage to people aged 65 years and older and who are on long-term disability. The Centers for Medicare and Medicaid Services, through which the Medicare program is administered, also generates hospital quality performance metrics which are publicly reported, and which are tied to value-based care programs. We assessed U.S. based community factors, as described below, in relation to a hospital quality measure of readmissions.

Specifically, we assessed the contribution of community-level variables to performance on the measure of HWR, a measure of 30-day readmissions among Medicare fee-for-service patients hospitalized for all but a few conditions or procedures. This measure was previously

developed by members of our group and is currently publicly-reported by CMS [4]. We identified a wide range of community variables which we linked to zip code of patient residence, and applied a machine learning approach, random forest, to identify which variables had the most 'importance' (a parameter assigned by random forest to each variable) for predicting hospital readmission rates. Since variables from different domains may correlate with each other (e.g., poverty and smoking), which may impact statistical significance though not necessarily clinical significance, we first organized all top ranked variables into their respective domains and assessed the relative importance of variables within each domain; the most important variables from each domain were then retained for final comprehensive assessment.

Participants. Patients included in the hospital measure of all-cause readmissions are Medicare fee-for-service beneficiaries aged 65 years and older who are hospitalized for a condition in one of the following specialty cohorts: medicine, surgery/gynecology, cardiorespiratory, cardiovascular, and neurology. Among these patients, we assessed the hospital risk-standardized readmission rate, as described below. We also assessed patients' community context, based on the patients' 5-digit zip code; also described in more detail below.

Independent study variables: Community factors. The variables for each domain were selected based on the RWJF County Health Rankings, prior literature and/or face validity, and were drawn from several sources, including the U.S. Census Bureau, Bureau of Health Professions Area Health Resources File, Northeast Regional Center for Rural Development Social Capital Index, Nursing Home Compare and Home Health Compare [23, 30]. Each variable was assessed at the smallest unit for which there were data, ranging from Census block to county. See Table 1 for a list of the 71 community variables assessed for this analysis, and the level of measurement.

Dependent study variable: Hospital wide readmission measure. The HWR measure, previously described [4], was used as the main outcome for this analysis, since this measure captures the broadest range of patients who are hospitalized and at-risk for readmission. Briefly, the HWR measure is a volume-weighted logarithmic mean of the standardized readmission rates (SRRs) of 5 specialty cohorts: surgical, medical, cardiovascular, cardiorespiratory and neurological. The readmission risk ratio of each cohort is calculated as the ratio of the predicted readmissions divided by the expected readmissions. The numerator is the sum of the predicted probability of readmission for all readmissions, estimated using a hierarchical logistic regression model that includes a hospital-specific effect estimated for each hospital as well as covariates for age, principal diagnosis and comorbidity. The denominator is the same as the numerator but replaces the hospital-specific effect in the model with the average hospital-specific effect of all hospitals in the sample. Only readmissions that are deemed as unplanned are included in the outcome. To exclude planned readmissions, the HWR uses a "planned readmission" algorithm which identifies procedures that are: 1) "always" or "potentially" planned procedures; and 2) not associated with an acute medical discharge diagnosis code; we used version 4.0 of this algorithm [31]. For analyses we used the logarithmic mean SRR. We used 2015–2016 Medicare Part A to identify the cohort and to assess the outcome for the measurement period July 1, 2015 through June 30, 2016.

Analysis. We linked all variables to Medicare FFS patients included in the HWR measure using their 5-digit zip code of residence. For zip codes that crossed more than one county, if only county-level data were available we used the value for the county with the greatest population. For each hospital we then averaged the factor value over all patients discharged from that hospital and categorized these means into quintiles based on their distribution across hospitals. We then summarized hospital HWR SRR for each factor quintile, reporting mean and standard deviation.

Our analytic approach focused on identifying key variables both within each domain and across all domains. Therefore, we used a multi-step analysis. First, because of the large number

Table 1. Variables included in study, by domain.

Domain	Variable	Source	Level	P-value	R2
Demographic					
	2011 population estimate Value	RWJF County Health Rankings	FIPS	<0.001	0.0355
	% below 18 years of age	RWJF County Health Rankings	FIPS	<0.001	0.0159
	% aged 65 years and older	RWJF County Health Rankings	FIPS	<0.001	0.0050
	% non-Hispanic African American	RWJF County Health Rankings	FIPS	<0.001	0.0801
	% Am Indian or AK Native	RWJF County Health Rankings	FIPS	<0.001	0.0320
	% Asian	RWJF County Health Rankings	FIPS	<0.001	0.0197
	% Hawaiian/Pacific Islander	RWJF County Health Rankings	FIPS	<0.001	0.0301
	% Hispanic	RWJF County Health Rankings	FIPS	0.005	0.0029
	% non-Hispanic White	RWJF County Health Rankings	FIPS	<0.001	0.0234
	% non-English Value	RWJF County Health Rankings	FIPS	<0.001	0.0122
Health Behaviors					
	Adult smoking Value	RWJF County Health Rankings	FIPS	<0.001	0.0060
	Adult obesity Value	RWJF County Health Rankings	FIPS	<0.001	0.0151
	Food environment index Value	RWJF County Health Rankings	FIPS	<0.001	0.0097
	Physical inactivity Value	RWJF County Health Rankings	FIPS	<0.001	0.0298
	Access to exercise opportunities Value	RWJF County Health Rankings	FIPS	<0.001	0.0511
	Excessive drinking Value	RWJF County Health Rankings	FIPS	0.060	0.0014
	Alcohol-impaired driving deaths Value	RWJF County Health Rankings	FIPS	<0.001	0.0344
	Sexually transmitted infections Value	RWJF County Health Rankings	FIPS	<0.001	0.0117
	Teen births Value	RWJF County Health Rankings	FIPS	0.001	0.0037
	Food insecurity Value	RWJF County Health Rankings	FIPS	<0.001	0.0214
	Limited access to healthy foods Value	RWJF County Health Rankings	FIPS	<0.001	0.0181
	Motor vehicle crash deaths Value	RWJF County Health Rankings	FIPS	<0.001	0.0228
	Drug poisoning deaths Value	RWJF County Health Rankings	FIPS	0.003	0.0033
Clinical Care					
	Uninsured Value	RWJF County Health Rankings	FIPS	<0.001	0.0060
	Primary care physicians Value	RWJF County Health Rankings	FIPS	0.026	0.0019
	Dentists Value	RWJF County Health Rankings	FIPS	0.017	0.0021
	Mental health providers Value	RWJF County Health Rankings	FIPS	0.954	-0.0009
	Diabetic screening Value	RWJF County Health Rankings	FIPS	<0.001	0.0078
	Mammography screening Value	RWJF County Health Rankings	FIPS	<0.001	0.0075
	Nursing Home Quality: Vaccines	Nursing Home Compare	ZIP	<0.001	0.0058
	Nursing Home Quality: Pain	Nursing Home Compare	ZIP	<0.001	0.0645
	HHA Quality: Improvement	Home Health Compare	ZIP	<0.001	0.0160
	HHA Quality: Pain, bedsores	Home Health Compare	ZIP	<0.001	0.0072
	HHA Quality: Vaccines	Home Health Compare	ZIP	<0.001	0.0826
	# Nursing Home beds	Area Health Resources File	FIPS	<0.001	0.0444
	# Hospital Beds	Area Health Resources File	FIPS	<0.001	0.0388
	GPs/100k	Area Health Resources File	FIPS	<0.001	0.0669
	Med Specialists/100k	Area Health Resources File	FIPS	<0.001	0.0410
	Surg Specialists/100k	Area Health Resources File	FIPS	<0.001	0.0156
	Other Specialists/100k	Area Health Resources File	FIPS	<0.001	0.0153
	GPs/Specialists	Area Health Resources File	FIPS	<0.001	0.0535
	# Fed Qual Health Centers	Area Health Resources File	FIPS	<0.001	0.0242
Social & Economic Environment					
	High school graduation Value	RWJF County Health Rankings	FIPS	<0.001	0.0238

(Continued)

Table 1. (Continued)

Domain	Variable	Source	Level	P-value	R2
	Some college Value	RWJF County Health Rankings	FIPS	0.020	0.0020
	Unemployment Value	RWJF County Health Rankings	FIPS	<0.001	0.0507
	Children in poverty Value	RWJF County Health Rankings	FIPS	<0.001	0.0237
	Income inequality Value	RWJF County Health Rankings	FIPS	<0.001	0.0679
	Children of single parents Value	RWJF County Health Rankings	FIPS	<0.001	0.0397
	Violent crime Value	RWJF County Health Rankings	FIPS	<0.001	0.0392
	Injury deaths Value	RWJF County Health Rankings	FIPS	<0.001	0.0195
	% Commute car	American Community Survey	FIPS	<0.001	0.0345
	% Commute bike	American Community Survey	FIPS	<0.001	0.0144
	% Commute work at home	American Community Survey	FIPS	<0.001	0.0265
	% Commute public	American Community Survey	FIPS	<0.001	0.0316
	% Preschool	American Community Survey	FIPS	<0.001	0.0186
	% Kindergarten	American Community Survey	FIPS	<0.001	0.0342
	Median Home Value	American Community Survey	FIPS	<0.001	0.0060
Physical Environment					
	Particulate air population Value	RWJF County Health Rankings	FIPS	<0.001	0.0224
	Drinking water violations Value	RWJF County Health Rankings	FIPS	<0.001	0.0087
	Severe housing problems Value	RWJF County Health Rankings	FIPS	<0.001	0.0449
	Driving alone to work Value	RWJF County Health Rankings	FIPS	<0.001	0.0181
	Long commute—driving alone Value	RWJF County Health Rankings	FIPS	<0.001	0.0711
	Housing Density	Area Health Resources File	FIPS	<0.001	0.0532
	Good Air Days	Area Health Resources File	FIPS	0.001	0.0038
	Daily Fine Particulate Matter	Area Health Resources File	FIPS	<0.001	0.0222
	Toxic Sites	Area Health Resources File	FIPS	<0.001	0.0099
	Housing Units	American Community Survey	FIPS	<0.001	0.0413
Social Capital					
	Social Capital: Associations	Social Capital Index	FIPS	<0.001	0.0388
	Social Capital: Voter turnout	Social Capital Index	FIPS	<0.001	0.0277
	Social Capital: Census response	Social Capital Index	FIPS	<0.001	0.0257
	Social Capital: Non-profits	Social Capital Index	FIPS	<0.001	0.0312

*All variables were stratified into quintiles.

**P-values and R^2 are from a bivariate regression model, weighted for volume.

of candidate community variables and potential for interaction effects, we used a random forest (RF) algorithm to identify the variables with greatest influence on risk standardized readmissions. The RF approach is robust to interactions, missing data, and collinearity, using an ensemble of small classification trees to construct a 'forest' which best predicts the outcome [32]. It is also self-validating in that each tree is trained on a new random half sample and validated on the second half. Our RF incorporated a linear regression model with hospital standardized risk ratio as the outcome to classify variables; we constructed 10,000 trees, each using 3 randomly selected variables. The final RF was used to assign an importance score to each variable, representing the proportion of decision paths which ran through that variable.

Though the random forest algorithm can rank variables on importance, it cannot provide estimates of independent effects for each variable. Therefore, in the second step, for each domain we identified the most important factor from the RF results and estimated a domain specific model using that variable. We then sequentially added the next most important

variables in that domain, assessing the change in adjusted R^2, and retaining additional variables that increased the R^2 by a (relative) 10% or more. The rationale for estimating separate domain models is to identify key variables within each domain which may have less relative importance when assessing effects across all domains. Because variables from different domains might be highly correlated, we assessed the variance decomposition matrix for all retained variables, in order to eliminate any variables that were redundant (as indicated by a condition number of at least 20 and a common variance portion greater than 0.50) [33] These retained variables were entered into a final multivariable model, which collectively assessed the key variables from each domain for an overall assessment of the relative contribution of community variables to readmission rates. All regression models were hospital level models, weighted for the readmission denominator volume, and for each we report the proportion of variance explained R^2 and the overall Wald P-value for each variable.

The Institutional Review Boards of Yale School of Medicine and New York University School of Medicine approved the study. All analysis was performed using SAS 9.3 (SAS Institute Inc, Cary NC, USA), Stata 15.1 (StataCorp, College Station TX, USA), R 3.5.2 (R Foundation for Statistical Computing, Vienna, Austria), and the R package *randomForestSRC*.

Ethical considerations. This study was conducted with de-identified data of the patients and the hospitals.

Results

After excluding patients with a planned index admission, who were transferred to another hospital, or who died, enrolled in hospice or left against medical advice during the index admission, the final cohort was 6,790,723 discharges from 4,711 hospitals. The mean (SD) risk standardized readmission rate was 15.3% (0.81%) and the median (interquartile range) was 15.3% (14.8%– 15.8%). Among the 71 community variables, the RF algorithm and sequential model selection identified 19 variables for inclusion in the domain specific models. The 10 most important factors associated with higher readmissions in the random forest model were (in descending order of importance): increasing percent of population that is non-Hispanic African American; lower rate of vaccination by home health agencies; poorer nursing home quality related to pain management; severe housing problems; greater physical inactivity; lower density of social associations; greater income inequality; children living in poverty; lower Census response rates; and greater housing density (Fig 1).

The domains that explained the most to least variation were: physical environment (R^2 for the domain specific model = 15%); clinical care (R^2 = 12%); demographic (R^2 = 11%); social and economic environment (R^2 = 7%); health behaviors (R^2 = 9%); and social capital (R^2 = 8%). Of the 19 variables, none were eliminated by the variance decomposition assessment. Thus all 19 variables were included in the final model (Table 2); all variables except voting participation were significant; together these contextual factors explained more than a quarter of the variance in hospital HWR readmission rate (R^2 = 27%).

Discussion

In this comprehensive examination of a range of contextual factors and their association with all-cause clinically risk-adjusted hospital readmission rates we found that a range of community variables across 6 distinct domains were independently associated with readmission rates; the 19 community variables which were most associated with readmission rates explained 27% of the variation in hospital-wide readmissions. Importantly, among the variables most accounting for this variation, many could be modifiable by local, state and federal governments, community organizations, hospitals, and health care systems. For example, these findings
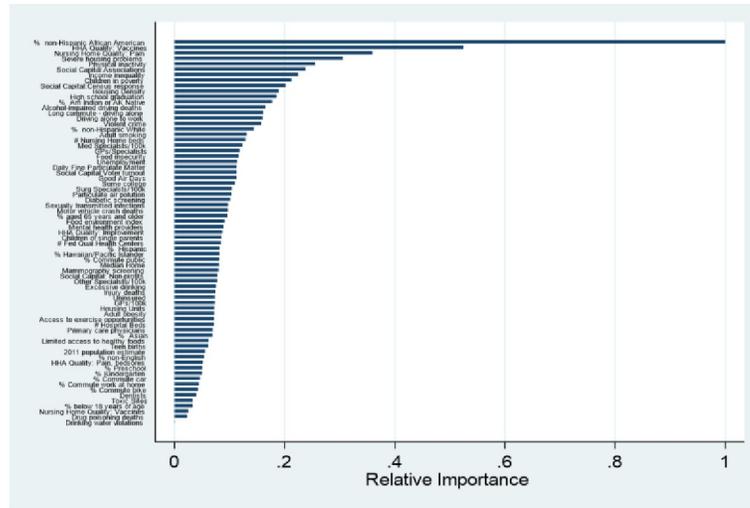
Fig 1. Results of random forest analysis, showing relative importance of each factor for predicting hospital overall Standardized Readmission Ratio (SRR).

could give impetus for healthcare delivery systems to partner with community agencies to improve the quality of home care, or to partner with local community health centers to improve vaccination rates. Next, as previously demonstrated, demographics and social and economic factors independently contributed to outcomes, including the proportion of the community that was African American or Native American or Alaskan, as well as the unemployment rate, the level of income inequality and the percent of children living in poverty. These associations amplify known racial and economic disparities–each of which needs to be separately considered. While race is associated with lower socioeconomic status, it is also the case that racial minorities derive less benefits from higher socioeconomic status; i.e., racial disparities in health outcomes persist even among high income and highly educated groups [25, 34, 35]. This is known as the Minorities' Diminished Return (MDR) theory, which can serve as a compass for addressing racial and ethnic disparities in health outcomes [27].

We also found that housing density and commuting, and people's social connectedness and engagement were significant. This finding provides evidence to support investments in social services by health payors. Payors, such as Medicaid, are increasingly allowing waivers that encourage patients to use premiums towards social issues; hospitals could lobby for such waivers [36]. Moreover, hospitals are becoming more involved in the composition and quality of the medical community in which their patients live [21, 37, 38]. For example, some hospitals are partnering with nursing homes with a track record of high-quality performance and quality improvement initiatives [39]. Whether these efforts will result in reduced readmission rates should be a focus of future study.

Finally, we found that 3 variables indicating communities' social capital (Census response rates, voter turnout and density of social associations) explained 8% of the variation in readmission rates. Unfortunately, we do not have detailed data available about the types of social supports existing in these communities. However, in extrapolating these findings we might infer that in communities where residents have limited family or friend support, and limited engagement with religious institutions and community centers, there may be a need for hospitals or other health entities to furnish outpatient supports. Patients discharged from the hospital are weak and convalescing–and providing assistance with basic meals and shopping, transportation to appointments, along with emotional support needs to be considered.

Table 2. Final multivariable model.

Final Model*				
Variable	**Value***	**Mean (SD)**	**P-value**	**R2**
				0.2658
Housing Density			0.012	
	Q1	ref		
	Q 2	-0.202 (0.100)		
	Q 3	-0.266 (0.104)		
	Q 4	-0.359 (0.111)		
	Q 5	-0.296 (0.120)		
Daily Fine Particulate Matter			<0.001	
	Q 1	ref		
	Q 2	0.192 (0.056)		
	Q 3	0.159 (0.060)		
	Q 4	0.018 (0.064)		
	Q 5	-0.126 (0.066)		
# Nursing Home beds			<0.001	
	Q 1	ref		
	Q 2	0.076 (0.060)		
	Q 3	0.177 (0.060)		
	Q 4	0.074 (0.062)		
	Q 5	0.270 (0.064)		
HHA Quality: Vaccines			<0.001	
	Q 1	ref		
	Q 2	-0.153 (0.047)		
	Q 3	-0.195 (0.050)		
	Q 4	-0.250 (0.056)		
	Q 5	-0.333 (0.062)		
Nursing Home Quality: Pain			0.004	
	Q 1	ref		
	Q 2	0.053 (0.049)		
	Q 3	-0.097 (0.055)		
	Q 4	-0.002 (0.060)		
	Q 5	0.057 (0.069)		
% non-Hispanic White			<0.001	
	Q 1	ref		
	Q 2	0.011 (0.052)		
	Q 3	0.182 (0.064)		
	Q 4	0.293 (0.079)		
	Q 5	0.588 (0.104)		
Alcohol-impaired driving deaths			<0.001	
	Q 1	ref		
	Q 2	0.107 (0.049)		
	Q 3	0.067 (0.050)		
	Q 4	0.022 (0.051)		
	Q 5	-0.123 (0.057)		
Severe housing problems			0.015	
	Q 1	ref		
	Q 2	0.090 (0.069)		

(*Continued*)

Table 2. (Continued)

Final Model[*]				
Variable	**Value**[*]	**Mean (SD)**	**P-value**	**R2**
	Q 3	0.108 (0.077)		
	Q 4	0.238 (0.087)		
	Q 5	0.300 (0.102)		
Long commute—driving alone			<0.001	
	Q 1	ref		
	Q 2	0.142 (0.062)		
	Q 3	0.250 (0.065)		
	Q 4	0.344 (0.068)		
	Q 5	0.298 (0.076)		
Food insecurity			<0.001	
	Q 1	ref		
	Q 2	-0.175 (0.051)		
	Q 3	-0.311 (0.053)		
	Q 4	-0.273 (0.059)		
	Q 5	-0.067 (0.072)		
Income inequality			<0.001	
	Q 1	ref		
	Q 2	0.070 (0.054)		
	Q 3	0.085 (0.057)		
	Q 4	0.265 (0.061)		
	Q 5	0.232 (0.071)		
% non-Hispanic African American			<0.001	
	Q 1	ref		
	Q 2	0.159 (0.077)		
	Q 3	0.347 (0.086)		
	Q 4	0.587 (0.095)		
	Q 5	0.537 (0.108)		
% American Indian or Alaskan Native			0.014	
	Q 1	ref		
	Q 2	-0.022 (0.048)		
	Q 3	-0.149 (0.051)		
	Q 4	-0.135 (0.063)		
	Q 5	-0.113 (0.076)		
Driving alone to work			0.004	
	Q 1	ref		
	Q 2	-0.132 (0.055)		
	Q 3	-0.075 (0.062)		
	Q 4	-0.038 (0.067)		
	Q 5	0.074 (0.075)		
Physical inactivity			<0.001	
	Q 1	ref		
	Q 2	0.219 (0.053)		
	Q 3	0.396 (0.062)		
	Q 4	0.343 (0.076)		
	Q 5	0.434 (0.093)		
Adult smoking			0.004	

(*Continued*)

Table 2. (Continued)

Final Model*				
Variable	**Value***	**Mean (SD)**	**P-value**	**R2**
	Q 1	ref		
	Q 2	-0.050 (0.051)		
	Q 3	0.080 (0.061)		
	Q 4	0.079 (0.072)		
	Q 5	0.211 (0.084)		
Social Capital: Associations			<0.001	
	Q 1	ref		
	Q 2	-0.278 (0.049)		
	Q 3	-0.460 (0.062)		
	Q 4	-0.403 (0.070)		
	Q 5	-0.361 (0.088)		
Social Capital: Voter turnout			0.354	
	Q 1	ref		
	Q 2	0.047 (0.051)		
	Q 3	0.007 (0.054)		
	Q 4	0.013 (0.055)		
	Q 5	-0.061 (0.062)		
Social Capital: Census response			0.046	
	Q 1	ref		
	Q 2	-0.101 (0.064)		
	Q 3	0.018 (0.067)		
	Q 4	-0.074 (0.073)		
	Q 5	-0.085 (0.084)		

*Values represent quintiles for each variable.

The observation that social risk factors contribute to readmission rates is not new, but prior studies have not assessed the range of factors explored in this study and the differential effects of their impact on readmission. In a national study of hospital readmission rates, Herrin et al assessed 3 community contextual domains: socioeconomic status; access to care; and nursing home status [18]. They found that 58% of the variation in performance was explained by these factors, with the most potent factor being access to care. Other studies have examined singular domains. For example, a study by Pandolfi et al also found that a community's nursing home quality is associated with hospital readmission rates [20] and a study by Brewster et al found that social capital was associated with readmission rates [10]. Our study attempts to offer a fuller picture of how a community's well-being can impact health outcomes.

As part of its implementation of the IMPACT Act of 2014, the U.S. Department of Health and Human Services is charged with providing analyses and recommendations on considering social risk within CMS payment programs. Moreover, as of 2019, CMS is applying differential penalties in reimbursement based on poor hospital performance on quality measures, according to the proportion of low SES patients at hospitals. Global measures of community-level SES are being considered in value-based care programs, including the Accountable Care Organization program and the Merit-based Incentive Payment System program. Indeed many accountable care organizations are already working to address community factors such as housing quality and transportation, with the goal of reducing health care costs and improving quality outcomes [40, 41]. Understanding the effects of a comprehensive set of contextual

factors across a range of healthcare environments and settings is important for coordinating efforts to address these factors and reducing readmissions [42].

These findings have several limitations. Community level variables may not represent the reality of an individual's living situation or community. We selected the most granular level of variable collection, though we still expect there to be heterogeneity within each unit. Still, these variables are intended to inform a hospital's readmission rates, and not to predict the readmission rate for any one individual. Having an understanding of the community's characteristics can inform broader strategies to reduce readmission rates among patients from "vulnerable communities." Second, we lacked data to fully describe the domains conceptualized as impacting readmission rates. For example, in the domain of social support, several factors known to impact outcomes, including community cohesion and resilience, have not been assessed in this population, which may have underestimated the effect of social support in the model. Third, it is unknown whether these variables would also have the same effect on the readmission rates of other populations, for example, younger or commercially insured patients, or on other outcomes, such as mortality. Finally, we are largely unable to determine the degree to which community factors are contributing above and beyond individual factors because many of these factors (e.g., income, commute to work, health behaviors such as exercise and diet) are not known to us on an individual patient level. As such, it is possible that we are measuring factors that are a proxy for individual risk rather than identifying some intrinsic characteristics of communities that are inherently meaningful. Hopefully, attention to contextual factors will drive more individual and community-level data so that we can best understand patient risk and implement and study strategies to reduce that risk.

Conclusion

This comprehensive examination of publicly available contextual factors, centered on patient residence, identified community level variables across a number of domains which explained almost a quarter of the variation in hospital-wide readmission rates. These findings provide a number of targets that policymakers, payers, community organizations and hospitals can and should engage with in order to reduce readmission rates and provide safer, more efficient, patient-centered care.

Acknowledgments

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