Health Care Manag Sci (2016) 19:241–248
DOI 10.1007/s10729-014-9316-9

The cost of hospital readmissions: evidence from the VA

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Received: 19 October 2014 / Accepted: 17 December 2014 / Published online: 10 January 2015

Abstract This paper is an examination of hospital 30-day readmission costs using data from 119 acute care hospitals operated by the U.S. Veterans Administration (VA) in fiscal year 2011. We applied a two-part model that linked readmission probability to readmission cost to obtain patient level estimates of expected readmission cost for VA patients overall, and for patients discharged for three prevalent conditions with relatively high readmission rates. Our focus was on the variable component of direct patient cost. Overall, managers could expect to save $2140 for the average 30-day readmission avoided. For heart attack, heart failure, and pneumonia patients, expected readmission cost estimates were $3432, $2488 and $2278. Patient risk of illness was the dominant driver of readmission cost in all cases. The VA experience has implications for private sector hospitals that treat a high proportion of chronically ill and/or low income patients, or that are contemplating adopting bundled payment mechanisms.

Keywords Hospital · Readmission · Cost · VA

1 Introduction

Sustainability of U.S. health care reform is coming up against the reality of high health care costs. One strategy that is drawing increasing policy interest for potential large scale health care cost savings is reduction of hospital inpatient readmissions. Rates of readmission, which are readily measured, have come under intense scrutiny over the last 5–10 years. However there has been little study to date of readmission costs, which are much less easily captured. The notable exception is a comprehensive study of Medicare beneficiaries, which found that approximately 20 % of inpatient discharges in 2003–2004 were readmitted within 30 days at an estimated cost to the Medicare system of $17 billion in 2004 [1].

The Patient Protection and Affordable Care Act of 2010 (ACA) initiated two programs that provide direct incentives for hospitals to reduce readmissions. As of fiscal year (FY) 2013, under the Hospital Readmissions Reduction Program (HRRP), hospitals with "excessive" 30-day readmissions for heart attack, heart failure, or pneumonia incur financial penalties under the Medicare reimbursement system; additional conditions are being penalized as of FY 2015. Moreover, the Bundled Payments for Care Improvement Initiative, currently being launched in many hospital systems by the ACA-established Center for Medicare & Medicaid Innovation, aligns payments across episodes of care. Under a bundled payments model, hospitals receive a single payment for an entire episode of treatment that includes the initial admission and the readmission [2], placing further pressure on hospitals to reduce readmissions.

The study of Medicare beneficiaries cited above [1] demonstrates the scale of the readmission burden on the Medicare system. However, this is a highly aggregated estimate of Medicare payments, which are not the same as costs realized by the hospitals treating those patients. In order to understand the budget implications of avoided readmissions, hospital financial management planners would benefit from knowledge of actual costs incurred when patients are readmitted. Under the current Medicare Prospective Payment System, which is fundamentally a fee-for-service reimbursement system for each admission (or readmission), as well as most other

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payment systems, savings to the hospital realized through readmission reduction is ambiguous. The net benefit has multiple components: incurred cost of the readmission, amount reimbursed for the readmission, and for Medicare patients, any added penalty under the HRRP.

The Veterans Health Administration (VHA), a federal globally-budgeted health care system that operates 119 acute care hospitals across the U.S, is a very good setting for examining readmission costs. There are several reasons for this. First, because readmissions to the hospital within an annual budget period do not result in any additional budgetary allocation to the hospital, managers do not have a financial incentive to readmit patients. Similarly, physicians who treat in VA hospitals are salaried VA employees, therefore do not gain financially when they admit or readmit patients and have no incentive to provide unnecessary care. With its unique role as both payer and provider, VA's incentive structure can provide insights to hospitals and hospital systems that are contemplating implementing bundled payments. Under bundled payment, while the payer and provider are separate entities, their incentives to readmit or not readmit within a short period of time are aligned. Finally, VA has created a comprehensive system of patient level cost accounting that generally is unparalleled outside VA in any large healthcare system. Few hospital accounting systems have good measures of the cost of a unique hospital stay, which can vary according to many factors, especially for complex patients. The VA Decision Support System (DSS) links unique patients over time, and is capable of separating fixed and variable costs at the patient level. Examining the component of cost that varies with a readmission provides a more realistic estimate of how much could be saved through targeted readmission reduction.

This paper examines the cost of 30-day readmissions to acute care hospitals operated by the VA during FY 2011. It links readmission probabilities to readmission variable costs at the patient level to obtain the average expected cost saving owing to an avoided readmission. A main finding was a substantial increase in expected readmission cost for patients with high risk of illness.

2 Empirical model

We used a two-part model (2PM) to estimate the expected cost of 30-day readmissions at the patient level. We estimated a model for readmissions overall and also models for each of three high volume/high cost conditions: heart attack, heart failure, and pneumonia. The 2PM linked a readmission probability model to a readmission cost model. The 2PM estimates the probability of nonzero costs separately from the level of costs conditional on nonzero costs. This model is appropriate for estimations involving individual patient hospitalization cost data, which tend to be characterized by presence of a large number of zeros, and by a skewed distribution on nonzero values of cost [3]. The 2PM produces the expected cost of readmission for an individual patient by taking the product of the predictions obtained from estimating each part of the model.

We estimated the 2PMs using generalized linear modeling (GLM), which provides appropriate estimators of mean values when the distribution of the data is non-normal [4]. GLM takes a variety of forms, each of which is characterized by a link function that describes the scale on which the independent variables in the model are related to the dependent variable. Part one of a 2PM generally uses either the probit or logit link function for binary distribution to estimate probabilities.[1] We followed the general literature on hospital readmissions and applied the logistic model for binary distribution of the response variable:

$$Pr(\mathbf{R} = 1|\mathbf{X}) = \exp(X\beta)\Big/[1 + \exp(X\beta)] \tag{1}$$

where Pr is the probability of readmission R and exp is the exponential function. Applying the logit link function:

$$G = \log(Pr/(1\text{-}Pr)) \tag{2}$$

and substituting (1) into (2), gives the estimating equation:

$$G\Big(Pr\Big(R_i = 1\Big|X_{ik}\Big)\Big) = \sum\beta_k{}^*X_{ik} + \varepsilon_{1i} \tag{3}$$

where i indexes patient, X_k are k explanatory variables of interest, and the β_ks are parameters to be estimated. We calculated the probability of readmission for each patient i from the expression in Eq. (1), using the parameters obtained from estimating Eq. (3), and the values of the independent variables for patient i.

Part two of the 2PM was a cost regression estimated on those patients who were readmitted (conditional on readmission). We followed previous study of VA DSS patient costs and used the natural log link function, assuming a gamma distribution for the response variable [5], based on application of the modified Park Test [6]. GLM has the practical advantage of providing estimates of the expected value of log transformed dependent variables directly, without requirement of

[1] Both of these models are drawn from the GLM class. The logistic distribution has heavier tails than the normal distribution on which the probit model is based; however, the two models produce very similar results in practice over a very wide range of values.

retransformation.[2] The GLM expression for cost is:

$$E\left(C\middle|\mathbf{X}\right) = \exp(X\delta) \tag{4}$$

or

$$\ln\left(E\left(C\middle|\mathbf{X}\right)\right) = (X\delta). \tag{5}$$

The estimating equation is:

$$\ln\left(C^{R}{}_{i}\right) = \sum\delta_j{*}X_{ij} + \varepsilon_{2i} \tag{6}$$

where C_i^R is the cost of readmission for patient *i*, and the δ_j are parameters to be estimated. The parameters of interest can be consistently estimated on the subset of patients for which the binary variable for readmissions is nonzero [3].

The expected cost of readmission for an individual patient, *ECR*, is determined by combining both parts of the 2PM: the product of the predicted readmission probability for the patient multiplied by the predicted cost of readmission for the patient:

$$\begin{aligned} ECR &= Pr_{predicted}(R = 1){*}C^{R}{}_{predicted} \\ &= \left[\exp\left(\sum \beta_k{*}X_{ik}\right)\Big/1 + \exp\left(\sum\delta_k{*}X_{ik}\right)\right]{*}\exp\left(\sum\delta_j{*}X_{ij}\right) \end{aligned} \tag{7}$$

We estimated the GLM equations for the 2PM using PROC GENMOD in SAS v9.3.[3]

[2] Retransformation from the log scale to the natural scale requires exponentiating the log scale error term. This usually does not exponentiate to one, so that the exponentiated predicted values are misleading [21]. Suitable retransformation techniques have been developed [22]; however, serious bias results in subsequent inference unless heteroscedasticity is properly characterized and applied to the retransformation process [3, 21, 23]. This process is generally not practical when there are continuous variables or there is heteroscedasticity across multiple factors.

[3] In order to account for hospital-level clustering, we used the generalized estimating equation (GEE) technique [24] to estimate the GLM parameters for both parts of the 2PM. GEE focuses on estimating the average response over the population rather than predictions for individual patients.

3 Data

3.1 Overview

There were 619,479 acute care patients discharged from VA hospitals during FY 2011. From these, we defined an initial admission or "index" hospitalization as a stay in which no inpatient discharge had occurred within the previous 30 days (hence a hospitalization could not be both an index hospitalization and a readmission). From the 514,041 index stays we excluded cases in which 1) the patient was discharged and readmitted to a different facility on the same day (transfer patient), 2) the patient died during the index stay and 3) the index stay was greater than 25 days.[4] We also excluded 18,277 patients identified as chronically mentally ill, a population which is more specific to VA, has substantially higher readmission rates, and also differs according to the nature of the disease and patient health care needs. These patients were identified from the Chronic Mental Illness Registry that is maintained by the VA Allocation Resource Center. We performed analyses on observations corresponding to the remaining 466,348 index stays. We also separately examined subgroups corresponding to three high-volume, high-cost conditions targeted by the Medicare HRRP: acute myocardial infarction – heart attack (AMI), heart failure (HF), and pneumonia (PNE). Data were extracted from a number of VA administrative sources: National Data Extract, Inpatient, Veterans Equitable Resource Allocation, and Outpatient files.

3.2 Dependent variables

Readmission is measured as a dichotomous indicator (0/1) of whether the patient was readmitted to a VA acute care hospital within 30 days of discharge from the index stay. The 30-day post discharge period is the most frequently studied readmissions window, and is the window of interest in the Medicare HRRP as well as in most bundled payment designs. We included readmissions for all causes because it not possible to determine which readmissions are preventable and which are not. From the patient perspective, readmission for any cause is an adverse event. Moreover, in the interest of simultaneous quality improvement and cost savings, hospitals can act to reduce readmissions from all causes.

We measured patient level readmission cost using the VA DSS, an accounting system which applies activity-based costing (ABC), a bottom-up approach that sums the cost of intermediate products and services provided during a hospital stay. ABC systems are considered to be the best estimates of the

[4] Hospitalizations with length of stay longer than 25 days generally are considered to be long-term stays. In particular, Medicare classifies acute care hospitals with average length of stay of more than 25 days as long-term care hospitals [25, 26].

true economic costs of the production of health services [7]. DSS disaggregates total cost of each hospitalization into direct (patient cost) and indirect (overhead and administration cost) components. Direct patient costs are disaggregated into fixed and variable components according to whether or not they vary with volume of services. Variable costs consist of supplies and labor expenses that might be released if workload decreased. Hospital managers are aware that if readmissions are reduced, the total readmission cost will not be recuperated in the short term (i.e. one fiscal year), because indirect and fixed direct costs cannot be recovered except over longer periods of time. For these reasons, we focus on measures of variable direct cost.

3.3 Independent variables

Demographic variables included five age categories: (18–39), (40–59), (60–69), (70–79), and 80+, and binary variables for race (Caucasian=1), gender (Female=1), and marital status (Married=1). A recent study highlighted the importance of neighborhood socioeconomic factors in predicting readmissions for heart failure patients [8]; failure to account for socioeconomic status also has been voiced recently as a criticism of the HRRP [9, 10]. We included income as a continuous variable measured in dollars.

We included three clinical variables to adjust for patient risk. First is a patient specific risk score generated according to the Diagnostic Cost Group (DCG)/Hierarchical Coexisting Conditions (RISKSMART) model. [5] The DCG model is prominent within the growing application of risk adjustment that is informing health care delivery systems for purposes of budget allocation or rate setting [11, 12]. We employed concurrent modeling in which diagnoses presently treated are directly related to costs in the year of observation. Estimated risk is measured relative to an average Medicare patient risk value of one. Second is the number of chronic conditions. We followed previous literature and used a count of the number of VA chronic conditions to measure complexity and burden of chronic illness [13, 14].[6] Third is clinical severity. We used the MS-DRG classification system and categorized each index hospitalization as high, medium, or low severity depending on whether the patient's MS-DRG designation was with major complications/comorbidities, complications/comorbidities, or no complications/comorbidities.

We also included factors that are potentially modifiable. Among these, length of stay has potentially interesting consequences. If in response to financial incentives of payers or providers, patients are discharged too soon, many may need to return to the hospital for additional inpatient care within a short period of time. This association has important cost implications owing to the trade-off between cost savings from shorter stays and potential savings from avoided readmission. Study of a previous period in VA did not find an inverse relationship between length of stay of an index hospitalization and readmission [15]. However, a private sector study of a more recent period found a negative association between length of stay and 30-day readmission for AMI patients [16]. We included a measure of length of stay, calculated as the difference in number of days between index admission date and discharge date.

The Medicare readmission study noted that half the patients readmitted within 30 days had not received ambulatory care between discharge and readmission, suggesting that failure to provide close follow-up on an outpatient basis may be a contributor to readmission rates [1]. We examined this issue in VA by including a binary measure of whether the patient received a follow up outpatient visit during the 30-day readmission window.

Finally, improved communication with patients and with other providers at discharge have been found to result in lower readmission rates in a wide range of settings [17, 18]. Analyses of readmission as it relates to the discharge process have been small observational settings, and broad studies that use large administrative databases are limited in what can be measured. We included a binary variable for day of the week of discharge occurring during the period Friday to Sunday as a proxy for comprehensiveness of discharge planning, which may be lower on Friday because of high density of discharged patients, and on Saturday or Sunday because of lower numbers of clinical personnel relative to the number of discharges.

4 Results

4.1 Descriptive

Table 1 exhibits descriptive statistics for the variables used in estimating the 2PMs. Salient features of this population are that it is primarily male, only 42 % married, moderately low income, and affected by a relatively high level of chronic disease. Overall, 13.74 % of VA index hospitalizations resulted in a readmission to acute care within 30 days. For the high cost/high volume subgroups, the rates were higher, ranging up to 21.18 % for

[5] The DCG approach maps 15,000 ICD-9-CM codes to clinically homogeneous diagnostic groups which are further aggregated into 184 clinically and expenditure-similar categories. It then places the groups into body system/clinical condition specific hierarchies called Hierarchical Condition Categories (HCCs). Patients are classified into multiple HCCs based on their respective ICD-9 codes. Each HCC is weighted and aggregated into a patient specific risk score.

[6] The number of chronic conditions is limited to one per category as defined by the AHRQ Clinical Classifications Software (CCS), a tool for clustering ICD-9-CM diagnosis and procedure codes into a manageable number of clinically meaningful categories.

Table 1 Descriptive statistics: mean (Standard Deviation)

Variable	Overall	Heart attack	Heart failure	Pneumonia
30-Day readmission rate	13.74	21.18	19.74	14.49
Readmission cost ($)	7,280 (8,630)	8,345 (9,088)	6,089 (5,979)	6,077 (6,073)
Age 18-39	0.056	0.004	0.003	0.014
Age 40-59	0.290	0.164	0.131	0.148
Age 60-69	0.352	0.359	0.325	0.313
Age 70-79	0.152	0.215	0.230	0.213
Age 80+	0.150	0.259	0.312	0.313
Caucasian	0.721	0.759	0.694	0.803
Female	0.055	0.021	0.017	0.030
Married	0.416	0.479	0.441	0.491
Income (0,000$)	2.385 (4.38)	2.602 (5.14)	2.386 (4.04)	2.515 (4.37)
DCG risk score	3.014 (2.63)	4.855 (2.65)	3.788 (2.67)	3.703 (2.77)
# of chronic conditions	5.214 (2.66)	7.286 (2.38)	7.594 (2.38)	5.361 (2.45)
High severity	0.104	0.210	0.140	0.141
Medium severity	0.203	0.377	0.496	0.552
Low severity	0.694	0.413	0.363	0.307
Length of stay (Days)	4.777 (4.40)	4.417 (3.91)	4.659 (3.75)	4.686 (3.67)
Outpatient w/in 30 days	0.909	0.903	0.926	0.883
Weekend discharge	0.165	0.171	0.185	0.170
Number of observations	466,348	4,486	15,975	14,351

heart attack patient discharges. The variation in variable costs among the subgroups was lower than for readmission rates, ranging from $6077 for pneumonia to $8345 for heart attack.

4.2 Probability

Table 2 displays the results of the probability model for the overall group of patients. The overall diagnostic accuracy (fit)

Table 2 Logistic regression results for 30-Day readmissions

Variable	Estimate	$Pr > \chi^2$	Odds ratio	OR lower limit 95 % level	OR upper limit 95 % level
Intercept	−2.7600	<0.0001	–	–	–
Age 18–39	Reference category				
Age 40–59	0.0110	0.6426	1.011	0.965	1.059
Age 60–69	−0.0955	<0.0001	0.909	0.867	0.952
Age 70–79	−0.0586	0.0205	0.943	0.897	0.991
Age 80+	0.0355	0.1594	0.965	0.919	1.014
Caucasian	0.0953	<0.0001	1.100	1.077	1.124
Female	−0.1385	<0.0001	0.871	0.834	0.909
Married	−0.1120	<0.0001	0.894	0.878	0.910
Income (000$)	−0.00565	<0.0001	0.976	0.971	0.981
DCG risk score	0.2265	<0.0001	1.814	1.806	1.822
# Chronic conditions	0.0287	<0.0001	1.079	1.074	1.084
High severity	−0.1468	<0.0001	0.863	0.839	0.889
Medium severity	0.1082	<0.0001	1.114	1.091	1.138
Low severity	Reference category				
Length of stay (Days)	−0.00542	<0.0001	0.976	0.972	0.980
c-statistic = 0.716					

of the regression is characterized by the c-statistic, which has a value of 0.716, indicating that the model predicted moderately well.[7] In general, the coefficients exhibit the expected signs and are highly statistically significant. [8] The logistic regression coefficients in themselves are not intuitive, but they can be used to obtain predicted values, which are the natural logarithms of odds ratios [Pr/(1-Pr)]. Exponentiating the predicted values, we obtained odds ratios, listed in column four of Table 2. For the most part these are not very different from 1.00 (even odds), as indicated by the lower and upper 95 % confidence level limits. However, among binary variables, being Caucasian carries a 10 % higher odds of being readmitted; for females the odds of being readmitted are 87.1 % that of male patients.

For the continuous variables, a one unit change in the independent variable does not have the same straightforward interpretation as for binary variables. For the continuous variables we calculated standardized odds ratios, using one standard deviation of the distribution of the continuous variable as the unit change. The strongest predictor was DCG risk score: for a unit change of one standard deviation (2.63), the standardized odds ratio is calculated using the estimated coefficient: exp (0.2265*2.63)=1.814. The interpretation is that a patient with a risk score of 5.64 (one standard deviation above the mean) is 1.814 times more likely to be readmitted within 30 days than a patient with average risk. For income, a unit change of one standard deviation is 4.38 ($43,800). The standardized odds ratio is exp (−0.00565*4.38)=0.976. Here the interpretation is that a veteran with an income of $67,650 ($43,800+$23,850) is 2.4 % less likely to be readmitted than a veteran with an income at the mean of $23,850.

We also applied the logistic regression model to the three subgroups. Results were largely similar to the overall group; the c-statistics were in the same general range, women less likely to be readmitted, and the strongest predictor was DCG risk. Unlike the overall group, length of stay was not a significant predictor of readmissions in any of the subgroup regressions.

[7] We conducted exploratory analysis to examine the extent of collinearity in our data. The Belsley Kuh Welsch diagnostics [27] indicated a very weak collinear relationship between DCG risk and high severity.

[8] We dropped outpatient visits and weekend discharge based on unstable coefficient signs on these variables, a classic symptom of multicollinearity.

[9] The GEE method is not a likelihood based method, hence the AIC (Akaike's Information Criterion) statistic is not supported. Rather, we used the QIC (Quasi-likelihood under the Independence model Criterion) statistic [28] to compare models using different working correlation structures. Our results are based on the exchangeability structure, which implies that all distinct members of a cluster are equally correlated with each other.

4.3 Cost

Table 3 lists the parameter estimates for the GLM cost regressions estimated on the readmitted patients.[9] The model exhibits a very good fit to the data; with the exception of female, all coefficients are higly signficiant. The coefficients on the number of chronic conditions is negative, although the magnitude of the coefficients is very small.

The coefficients represent the change in the log of cost expected with an increase in one unit of the independent variable, and can be interpreted as the multiplicative effects on the dependent variable. A high severity patient relative to a low severity patient is predicted to have readmission cost that is exp (0.1611) higher, or approximately 17 %, if readmitted within 30-days. A typical patient aged 70–79 is predicted to have readmission cost of exp (0.2833) or approximately 33 % higher than a typical patient of age 18–39. For risk score, the predicted difference is relatively small: exp (0.0173), or approximately 2 % higher. This means that compared with a patient of average risk (score=3.0), a patient with a risk score of 4 would have 2 % higher expected readmission cost. We entered length of stay in natural logarithms, following previous literature [19]. The coefficient can be interpreted as the elasticity of length of stay; 0.889 indicates that for a 10 % increase in length of stay, the cost is predicted to increase by 0.889*10, or 8.9 %. The coefficients in the cost regressions for the three subgroups followed the same general pattern as for the cost regression for the overall group.

4.4 Expected cost of readmission

Table 4 exhibits the results of the 2PM for the overall group of patients and for the three subgroups of interest. The third

Table 3 Readmission cost function estimates[a]

Variable	Estimate	Pr > |Z|
Intercept	7.1727	<0.0001
Age 18–39	Reference category	
Age 40–59	0.1733	<0.0001
Age 60–69	0.3024	<0.0001
Age 70–79	0.2833	<0.0001
Age 80+	0.2113	<0.0001
Female	0.0309	0.3541
DCG risk score	0.0173	<0.0001
# Chronic conditions	−0.0116	<0.0001
High severity	0.1611	<0.0001
Medium severity	0.0626	<0.0001
Low severity	Reference category	
Log length of stay	0.8894	<0.0001
Number of observations 64,073		

[a] From gamma distributed GLM regression with log link

Table 4 Mean values of predicted estimates from the 2PM

Group	Number of observations	Predicted probability	Predicted cost ($)	Expected cost of readmission ($)
Overall	63,961	19.6 %	8940	2140
Heart attack	949	29.3 %	10,814	3432
Heart failure	3149	24.9 %	8607	2488
Pneumonia	2075	21.2 %	9047	2278

column shows the mean values of the predicted probabilities. The fourth column shows the mean value of predicted costs, or those costs that would actually be incurred, adjusting for age, gender, risk, and length of stay. The fifth column shows the mean values of the expected readmission costs, which are calculated at the patient level as the product of the predicted probability and the predicted cost. The expected readmission costs differ from the predicted costs by accounting for the likelihood that the patient will be readmitted. Both predicted and expected variable direct costs are shown for those patients who were actually readmitted.

There is considerable variation in the predicted and expected readmission costs across groups and subgroups. The highest costs are for the AMI group which has an average predicted readmission cost of $10,814 and an expected readmission cost of $3432. The lowest costs are for heart failure, which has a mean predicted readmission cost of $8607 and expected readmission cost of $2488.

Table 5 indicates how expected readmission cost varies across level of risk, the high impact factor in explaining readmission likelihood. For the bottom quartile of DCG risk, the mean value of expected readmission cost varies from a low of $625 for the overall group, to $1287 for the heart attack subgroup. At the top quartile, the mean value is $5281 and ranges from $5216 for pneumonia to $7392 for heart attack.

5 Discussion

In this study, we examined the variable costs of hospital readmissions in order to inform hospitals on potential savings associated with readmission reduction. Results showed that risk was the most important factor in driving costs; however,

Table 5 mean values of expected cost of readmission ($) by risk level

	Lowest 25 %	Interquartile range	Highest 25 %
Overall	625	1327	5281
Heart attack	1287	2847	7392
Heart failure	937	1803	5409
Pneumonia	704	1597	5216

the demographic factors of male gender and Caucasian race also were modestly predictive. We demonstrated that the costs incurred when patients are readmitted are considerable, particularly for the high volume patient subgroup conditions which we examined. Furthermore, our estimations showed the substantial costs savings that managers could expect, after accounting for the likelihood of the event of readmission.

A key finding was the significant and substantial increase in readmission cost among patients with high risk of illness. This is an important finding for managers, because even though risk is a factor that cannot be controlled, it can be expected that these patients will have higher readmissions after accounting for other factors. The DCG metric that we used is a fine-tuned measure of patient risk; non-VA studies of readmission generally have not had this adjuster available for prediction models. While we found a negative association between length of stay and readmission probability for the overall population, the practical effects on cost saving associated with longer length of stay was negligible. Hence we found no evidence that VA efforts at improved hospital flow and shorter inpatient stays had the unintended consequence of more readmissions. We also found that socioeconomic status matters in likelihood of readmission, which is of general interest due to controversy around failure to account for this factor under the Medicare HRRP and the corresponding impact on safety net hospitals.

Our results regarding readmission costs also can inform policy outside of VA. Among health care systems in the U.S, VA is distinct as it is the largest integrated delivery system, operates under a global budget, and serves a patient population that is relatively low income and more chronically ill. As such, VA has processes of care that may differ from other health care systems. However, the VA experience is relevant to policy-making for safety net hospitals or for those that serve high numbers of Medicare and/or Medicaid patients. We found the singular factor that had high impact on readmission cost was high risk of illness. This is an important finding for managers. Even though risk is a factor over which providers have no control, these patients may be good candidates for targeted intervention, since they can be expected to add significantly to the readmission cost burden after controlling for other factors. Our results also have special relevance for hospital systems that are contemplating adopting bundled payment mechanisms because they measure the pure readmission cost effect without the mixed incentives to readmit or not readmit that presently exist in most health care systems.

While our study is comprehensive, the drawback to a broad study that relies on administrative data is that measures for many important factors are not available for inclusion in the analyses. In particular, the quality and comprehensiveness of discharge planning was not easily measured in our study. Information on the amount and quality of follow-up care administered during the post-discharge period was minimal.

Another qualification is that we did not account for the veterans who received acute inpatient care in VA hospitals and were subsequently readmitted to private sector hospitals within 30 days. We do not know what portion or which types of VA patients were readmitted within the readmission window outside of the VA system [20]. This limitation does not affect our estimates of unadjusted and adjusted readmission cost, but does affect our estimates of expected readmission costs, which rely on the results of the two-part model.

Finally, it should be noted that this is an observational study. Absent a randomized controlled experiment, examination of the effect of variables of interest on outcome variables is subject to parameter estimate bias to the extent of correlation between measured variables of interest and omitted variables that are significantly associated with the outcomes variables. No method can completely identify causality from observational data, and the associations uncovered as part of this study should be interpreted in that respect.

Chronic health conditions are having a growing impact on the utilization of health care services, both inside and outside of VA, and the vast majority of hospital readmissions are chronically ill patients. Improving the management of high cost patients, especially those with chronic conditions, is an increasingly important strategy for improving patient health outcomes and controlling healthcare expenditures.

Acknowledgments Funding for this study was provided by the VA Office of Quality, Safety and Value. The authors also acknowledge Eileen Moran, Peter Almenoff, and the efforts of the VA Office of Productivity, Efficiency and Staffing in support of this work. The opinions are solely those of the authors, and do not necessarily reflect those of the U.S. Department of Veterans Affairs or Boston University.

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