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Variation in readmission rates among hospitals following admission for traumatic injury

Turner Osler[a,*], Dekang Yuan[b], Jeremy Holden[b], Zihao Huang[b], Alan Cook[c], Laurent G. Glance[d], Jeffrey S. Buzas[e], David W. Hosmer[e]

[a] University of Vermont, 789 Orchard Shore Road, Colchester, VT 05446, United States
[b] University of Vermont, United States
[c] Trauma Research Program, Chandler Regional Medical Center, United States
[d] Department of Anesthesiology, University of Rochester, United States
[e] Department of Mathematics and Statistics, University of Vermont, United States

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ABSTRACT

Introduction: Readmission following hospital discharge is both common and costly. The Hospital Readmission Reduction Program (HRRP) financially penalizes hospitals for readmission following admission for some conditions, but this approach may not be appropriate for all conditions. We wished to determine if hospitals differed in their adjusted readmission rates following an index hospital admission for traumatic injury.
Patients and Methods: We extracted from the AHRQ National Readmission Dataset (NRD) all non-elderly adult patients hospitalized following traumatic injury in 2014. We estimated hierarchal logistic regression models to predicted readmission within 30 days. Models included either patient level predictors, hospital level predictors, or both. We quantified the extent of hospital variability in readmissions using the median odds ratio. Additionally, we computed hospital specific risk-adjusted rates of readmission and number of excess readmissions.
Results: Of the 177,322 patients admitted for traumatic injury 11,940 (6.7%) were readmitted within 30 days. Unadjusted hospital readmission rates for the 637 hospitals in our study varied from 0% to 20%. After controlling for sources of variability the range for hospital readmission rates was between 5.5% and 8.5%. Only 2% of hospitals had a random intercept coefficient significantly different from zero, suggesting that their readmission rates differed from the mean level of all hospitals. We also estimated that in 2014 only 11% of hospitals had more than 2 excess readmissions. Our multilevel model discriminated patients who were readmitted from those not readmitted at an acceptable level (C = 0.74).
Conclusions: We found little evidence that hospitals differ in their readmission rates following an index admission for traumatic injury. There is little justification for penalizing hospitals based on readmissions after traumatic injury.

Introduction

Unplanned hospital readmissions are common, as high as 20% of patients for some conditions [1], and seem at face value to acknowledge that the initial hospitalization failed to resolve the patient's presenting complaint. The cost of a readmission stay is high, typically greater than that of the index admission. These two observations suggest that simply decreasing hospital readmission rates could provide an important check on rising health care costs, an observation not lost on policy makers.

In 2012 the Affordable Care Act (ACA) established the Hospital Readmission Reduction Program (HRRP), a program under which hospitals are financially penalized for higher than expected adjusted readmission rates. The penalty began as up to 1% of the total Medicare payments to individual hospitals in 2013, but rose to 2% in 2014 and 3% for 2015. Conditions covered by the HRRP initially included acute myocardial infarction, heart failure and pneumonia, but have since been expanded to include chronic obstructive pulmonary disease (COPD), total joint replacements, and CABG procedures. Although admission following traumatic injury is not currently a part of the HRRP, it is likely that more

* Corresponding author.
E-mail addresses: tosler@uvm.edu (T. Osler), Zhuang12@uvm.edu (Z. Huang).

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conditions, possibly including traumatic injury, will be added to the program as time goes on. Since traumatic injury is a common reason for hospitalization and is often paid for by CMS even for non-elderly Medicare and Medicaid patients [2], it seems likely that traumatic injury will, eventually, be added to the HRRP list of conditions.

The HRRP has already had a significant effect. In 2017 Medicare penalized almost half of the hospitals in the United States, resulting in total collections of just over half a billion dollars. Proponents of the HRRP note that readmission rates have dropped since its introduction by about 1% without increasing length of stay or mortality [3]. Detractors are concerned that the HRRP may have unintended consequences: for example, safety net hospitals may be penalized simply because their patients cannot afford to implement instructions that might prevent readmission [4].

Independent of the merits of the HRRP program, it is possible that for some conditions readmission rates may simply not be influenced, or influenced only slightly, by hospital performance. Because such conditions would not conform to the underlying premise of the HRRP they would be poor metrics upon which to compare or penalize hospitals. We chose to examine readmission rates following traumatic injury to discover if hospitals differ significantly on their adjusted readmission rates for this condition.

Methods

Data and cohort

The National Readmission Database (2014) [5] (NRD) included a total of 14,894,613 admissions. We extracted all patients whose index hospital admission met the following criteria: the admission had at least one ICD-9-CM code in the trauma range of 800–959.5 as the primary diagnosis (excluding diagnosis codes for burns, late effects of trauma, foreign bodies or complications of traumatic injury). Additionally the admission had to be coded as an emergency admission and have a valid External Causes of Injury and Poisoning (E-Code) (excluding E-Codes for drowning/submersion, bites/stings, overexertion, poisoning, suffocation, adverse effects of medical and surgical interventions or medications). Patients were excluded if they died during their index admission, were younger than 18 years old or over the age of 64, or were admitted to a combined hospital and rehabilitation facility.

Table 1
Characteristics of Patients That Were and Were Not Readmitted Within 30 Days.

Factor	Level	Not Readmitted	Readmitted	p-value
N		165382	11940	
Age, mean (SD)		41.2 (14.1)	44.5 (13.3)	<0.001
Predicted mortality (TMPM[a]), mean (SD)		−4.2 (1.4)	−4.1 (1.3)	<0.001
Number chronic conditions, median (IQR)		2.0 (0.0, 3.0)	3.0 (1.0, 5.0)	<0.001
Total charges, median (IQR)		40,839.5 (22,729.0, 75,887.0)	47,105.0 (25,152.0, 91,712.0)	<0.001
Sex	Male	114090 (69.0%)	8175 (68.5%)	0.24
	Female	51292 (31.0%)	3765 (31.5%)	
Disposition of patient	Routine	140462 (85.0%)	8988 (75.3%)	<0.001
	Home Health Care	21663 (13.1%)	2342 (19.6%)	
	AMA[b]	3070 (1.9%)	602 (5.0%)	
Median household income for ZIP Code	$1-$37,999	51533 (31.8%)	4125 (35.3%)	<0.001
	$38,000-$47,999	42281 (26.1%)	3021 (25.8%)	
	$48,000-$63,999	36223 (22.4%)	2509 (21.5%)	
	64,000 & up	31831 (19.7%)	2036 (17.4%)	
Congestive Heart Failure		2014 (1.2%)	442 (3.7%)	<0.001
AIDS		311 (0.2%)	55 (0.5%)	<0.001
Alcohol Abuse		28293 (17.1%)	2701 (22.6%)	<0.001
Anemia		10171 (6.2%)	1335 (11.2%)	<0.001
Rheumatoid Arthritis		1910 (1.2%)	216 (1.8%)	<0.001
Blood Loss Anemia		839 (0.5%)	90 (0.8%)	<0.001
CHF		2014 (1.2%)	442 (3.7%)	<0.001
Chronic Pulmonary Diseases		14709 (8.9%)	1590 (13.3%)	<0.001
Coagulopathy		4685 (2.8%)	644 (5.4%)	<0.001
Depression		11775 (7.1%)	1306 (10.9%)	<0.001
Diabetes Uncomplicated		12007 (7.3%)	1363 (11.4%)	<0.001
Diabetes with Complications		2343 (1.4%)	466 (3.9%)	<0.001
Drug Abuse		17188 (10.4%)	1736 (14.5%)	<0.001
Hypertension		38022 (23.0%)	4063 (34.0%)	<0.001
Hypothyroid		5938 (3.6%)	588 (4.9%)	<0.001
Liver Disease		3724 (2.3%)	664 (5.6%)	<0.001
Lymphoma		270 (0.2%)	52 (0.4%)	<0.001
Fluid/Electrolyte Disorder		22064 (13.3%)	2442 (20.5%)	<0.001
Metastatic Cancer		342 (0.2%)	71 (0.6%)	<0.001
Other Neuro Disorder		6427 (3.9%)	761 (6.4%)	<0.001
Obesity		11012 (6.7%)	1075 (9.0%)	<0.001
Paralysis		2584 (1.6%)	293 (2.5%)	<0.001
Peripheral Vascular Disease		2319 (1.4%)	313 (2.6%)	<0.001
Psychosis		7745 (4.7%)	1083 (9.1%)	<0.001
Pulmonary Circulatory Disorder		1081 (0.7%)	161 (1.3%)	<0.001
Renal Failure		2961 (1.8%)	654 (5.5%)	<0.001
Solid Tumor		511 (0.3%)	114 (1.0%)	<0.001
Valvular Heart Disease		1468 (0.9%)	171 (1.4%)	<0.001
Weight Loss		2900 (1.8%)	399 (3.3%)	<0.001

Models were also adjusted for 253 ICD-9 diagnosis codes (e.g. ICD-9 3004: Dysrhymic disorder) and 92 ICD-9 procedure codes (e.g. ICD-9 4671: Duodenal suture).
[a] TMPM: Trauma Mortality Prediction Model (logit transform).
[b] AMA: Left against medical advice.

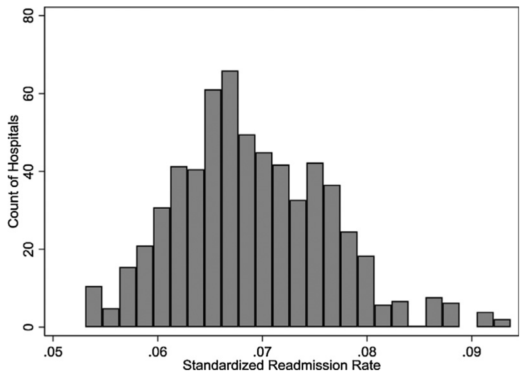

Fig. 1. Distribution of Standardized Readmission Rates for 637 Hospitals.

Additionally, only a patient's first admission for trauma and the first readmission following the trauma admission, if any, were retained as the study dataset. Finally, only patients admitted to hospitals with at least 50 trauma admissions in 2014 were retained for analysis. After applying these exclusions a total of 177,322 patients admitted to one of 637 different hospitals were available for analysis, 11,940 (6.8%) were readmitted within 30 days. By construction, the NRD has no missing data elements.

Variables available for analysis for each patient included age, gender, and income level [ZIP Code income quartile]. Additionally, baseline health information recorded as number of chronic disease and the presence or absence of 29 individual conditions was available. The NRD provides ICD-9-CM codes, and we parsed the 922 different codes into binary descriptors (present/absent), 171 of which represented traumatic injuries. We retained the 253 parsed ICD-9 codes that were individually significant predictors of readmission at the 0.05 level; 56 of these codes represented traumatic injuries associated with readmission (e.g. crushing injury of foot, open ankle fracture, biliary tract injury-closed, bladder/urethra injury-closed, etc.). The remaining 197 ICD-9 codes represented chronic medical conditions (e.g. morbid obesity, depressive disorder, diabetes, atrial fibrillation, alcoholic cirrhosis, various malignancies, etc.), acute medical conditions (e.g. alcohol withdrawal, acute kidney failure, etc.) and a few acquired medical conditions likely representing complications (e.g. septicemia, disruption external operative wound, pneumonia, etc.). Finally, 341 unique ICD-9 procedure codes were available in the dataset, 92 of which were individually associated with readmission at the 0.05 level (e.g. transfusion packed red cells, vertebral fracture repair, percutaneous cystostomy, suture kidney laceration, suture large bowl laceration, external fixator application, etc.) Hospital level predictors included hospital size (number of beds) and volume of trauma admissions (trauma patients/year).

Statistical analysis

We fit three hierarchal logistic models to estimate the probability of hospital readmission within 30 days: (1) conditional on only hospital as a random level two effect, (2) conditional on patient-level fixed effects and (3) conditional of patient level and hospital level fixed effects. Model based estimated random intercepts were used evaluate the effect of individual hospitals. We also computed the observed-to expected (OE) ratio and risk-standardized readmission rate for each hospital using the CMS algorithm [6]. Hospitals with an OE ratio significantly different from 1 were considered quality outliers. We also calculated the number of excess readmission for each hospital in 2014 [7]. We calculated the median odds ratio (MOR) to quantify the hospital-level variability in performance after controlling for patient risk. Data manipulation and statistical analysis was performed using Stata (Version 15/MP). The observed-to-expected ratio (OE) was computed for each hospital using empirical Bayes' outcome predictions as the basis for the observed rates of readmission. These results were independently confirmed using the James Stein estimators as well as using fully Bayesian models implemented in the Stan probabilistic programming language [8], with samples drawn using the NUTS algorithm (see supplemental appendix).

Results

As noted above all analyses were based on 177,322 injured patients cared for at one of 637 hospitals in 2014. A total of 11,940 (6.8%) patients were readmitted within 30 days. We extracted from the NRD a total of 1299 predictors, 627 of which were individually significantly associated with readmission at the 0.05 level. Table 1 presents a sample of the variables in our dataset (see supplemental appendix for complete Table 1 as well as fitted results of our models). Hospital readmission rates were compared using a single multilevel model that retained only the 381 predictors that were jointly statistically significant. No attempt was made to search for interactions. The final model discriminated readmitted from non-readmitted patients at an acceptable level (C = 0.74), and a calibration plot suggested that our model was well calibrated. Following most other authors who have modeled hospital readmission we computed the C statistic for our model using the same data that we used to construct our models, so it is likely that the C statistic we report is slightly inflated.

Although the unadjusted rates of readmission varied widely (0%–20%), after controlling for case mix and accounting for the small numbers of readmissions at many hospitals using a hierarchal logistic model we find 95% of hospitals have readmission rates between 6.5% and 8.5%. (Fig. 1). Moreover, when we compute the number of excess readmissions for each hospital (by multiplying the OE ratio by the number of cases at a given hospital and then subtracting the actual number of readmissions) we find that in 2014 only 11% of hospitals had more than 2 excess readmissions, and only 5% of hospitals had more than 5 excess readmissions.

We also examined the sources of variation in readmission rates. Random intercept terms and their standard errors estimated from our random effects model were examined to compare individual hospital's performance graphically and are shown in Fig. 2. Only 13 of the 637 hospitals (2.00%) had 95% confidence intervals that failed to include 0 (no effect), 8 hospitals estimated to be performing worse than expected and 5 hospitals to be performing better than expected. Fig. 2. Results were confirmed with Bayesian methods (see Supplemental Appendix).

Finally, we computed the median odds ratio for each of our models. If one samples at random two subjects with exactly the same clinical situation from two different hospitals, the median odds ratio reports the odds ratio for readmission between the patient at the hospital with higher risk of readmission compared with the identical patient at the hospital with a lower risk of readmission. Thus, the median odds ratio of 0.067 (Table 2) asserts that, after controlling for case mix and hospital factors, of two hospitals selected at random the hospital with the higher readmission rate will have a median odds of readmitting a patient that is 1.067 compared to another randomly selected hospital. In half of such comparisons the probability of readmission at the higher readmission hospital would be less than 7% greater.

Discussion

Hospital care currently represents one third of the total yearly cost of health care in the United States [9] and continues to grow.

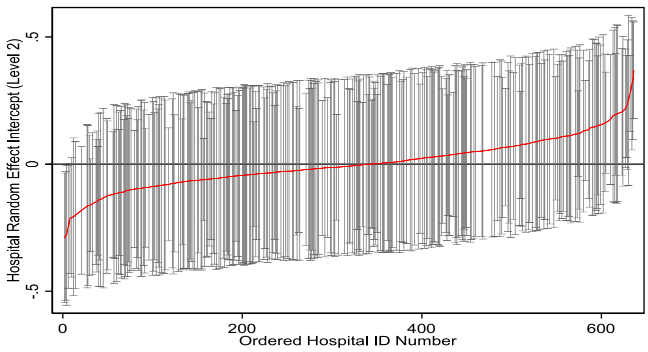

Fig. 2. Hospital Effect Ordered by Estimated Effect Size Adjusted for Patient Factors but not for Hospital Factors.

Interest in hospital performance is therefore keen, and the demand for hospital performance measures understandable. One measure of hospital performance recently introduced is readmission rate, and it seems unarguable that hospitals with lower readmission rates are providing better, or at least better organized, care and save money as a result. However, before comparing hospitals on a metric it is important to have a clear understanding of the proposed measure. In particular, it is essential that hospitals actually differ on the metric of interest; if hospitals do not differ there is little to be learned by comparing them. Indeed, inappropriate decisions may result if policy is based on comparisons that cannot be informative.

Although several authors have reported on readmission following traumatic injury, most of these studies are based on single institution [10] or regional [11] experiences. Recently the AHRQ has made available the National Readmission Database (NRD), a research dataset with approximately 17 million hospital discharges per year. Importantly, the NRD captures all readmission events, regardless of whether the readmission is to the index hospital or a different hospital. Parreco et al. have use this resource to examine readmission following traumatic injury and they report that, over all age groups, 9.4% of trauma patients were readmitted within 30 days at a median cost of over $8000. Using an omnibus logistic regression model they find that a dozen different factors that contribute to the likelihood of readmission (i.e. age, ISS, discharge against medical advice.) We recommend this paper to those interested in a broad overview of readmission following traumatic injury.

We used the same dataset as Parreco et al. (NRD) to examine a very specific research question: Do hospitals vary in their readmission rates following an index admission for traumatic injury? We restricted our study population to patients between the ages of 18 and 65 to reduce the likelihood of readmission for medical conditions unrelated to the index admission for trauma. We find that about 98% of hospitals in the US had 30-day adjusted readmission rates that were no different than other hospitals for non-elderly trauma patients. It is noteworthy that the CMS Hospital Readmission Reduction Program penalizes approximately 50% of hospitals for “excessive” readmissions.

We conclude that readmission rates following an index admission for traumatic injury are not a useful performance measure for hospitals, and thus should not be used as the basis for pay-for-performance. Our conclusion may seem counterintuitive because the 637 hospitals in the NRD differed dramatically in their unadjusted readmission rates, from a low of 0% to a high of 20%. Perhaps surprisingly, however, an individual hospital’s observed rate of readmission is not the best estimate of that hospital’s readmission rate. This indisputable mathematical fact has been known to statisticians for over sixty years [12], but has only gradually been incorporated into the evaluation of hospital performance through the use of so called shrinkage estimators, estimators that borrow strength from the entire dataset to better estimate individual hospital’s performance. Using these more precise methods of estimation our analysis finds that readmission rates for hospitals actually vary much less, roughly between 5.5% and 8.5%. Moreover, uncertainty in the measurement of each of these rates for individual hospitals is so great that we find no evidence that hospitals differ meaningfully in their readmission rates. It might be objected that our methods might miss real differences among hospitals because of the substantial uncertainty surrounding our estimates of individual hospital readmission rates. However, performance measures of our statistical model show it to be among the best proposed for predicting hospital readmission [13]; the wide confidence intervals that we find stem from a combination of the typically small number of readmissions following admission for traumatic injury for each hospital and the inherent uncertainty in predicting readmission, an outcome that necessarily includes many factors outside of hospital control (i.e. outpatient follow-up), as well as some element of chance.

Table 2
Estimated Variance Components.

Model Covariates	MOR	AUC
Fixed Effects (FE: Patient level) only		0.7412
Random Effects (RE: Hospital Identification) only	1.234	0.5843
FE and RE	1.193	0.7499
FE and RE and Hosp Variables (Bed Size, Patient Volume)	1.067	0.7472

MOR: Median odds ratio.
AUC: Area under the receiver operating characteristic curve.

A few researchers have noted that the HRRP approach may simply not be appropriate for some conditions leading to hospital admission. Clapp et al. [14]. note that readmissions are not only rare after admission for childbirth but further that hospital quality contributes far less than 1% of the variability in readmission rates. This less than 1% contribution of hospital is similar to our findings regarding patients admitted following traumatic injury. It is possible, even likely, that readmission rates may not be appropriate for evaluating hospital performance for other conditions as well. We suggest that the HRRP should not be extended to other conditions until there is clear evidence that such penalties are meaningful, fair, and would have the intended effect of improving hospital performance. At a minimum, it seems necessary to demonstrate that hospital performance is a significant determinant of unplanned readmissions before readmissions are used as the basis for penalizing hospitals based on their performance.

Conclusions

We find little evidence that hospitals vary significantly in their readmission rates for patients admitted because of traumatic injuries. Therefore hospitals cannot be evaluated on this metric, and certainly should not be penalized on it.

Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.injury.2018.08.021.

References

[1] K. Fingar, R. Washington. Trends in hospital readmissions for four high-volume conditions, 2009–2013 (Statistical Brief #196). 2015; Healthcare Cost and Utilization Project. Accessed 2/6/2018

[2] Osler T., Glance LG, Li W, Buzas JS, Wetzel ML, Hosmer DW. Trauma care does not discriminate: the association of race and health insurance with mortality following traumatic injury. J Trauma Acute Care Surg 2015;78(5):1026–33.
[3] Zuckerman RB, Sheingold SH, Orav EJ, Ruhter J, Epstein AM. Readmissions, observation, and the hospital readmissions reduction program. N Engl J Med 2016;374(16):1543–51.
[4] Fonarow GC, Konstam MA, Yancy CW. The hospital readmission reduction program is associated with fewer readmissions, more deaths: time to reconsider. J Am Coll Cardiol 2017;70(15):1931–4.
[5] Centers for Medicare & Medicaid Services. Readmissions Reduction Program (HRRP). Last modified 11/30/2017. Accessed 2/5/2018.
[6] McIlvennan CK, Eapen ZJ, Allen LA. Hospital readmissions reduction program. Circulation 2015;131(20):1796–803.
[7] Normand SLT, Shahian DM. Statistical and clinical aspects of hospital outcomes profiling. Stat Sci 2007;2007(1):206–26.
[8] Stan Development Team. Stan modeling language users guide and reference manual, version. 2015.
[9] National Health Expenditures, 2016. Highlights. Accessed 2/6/2018.
[10] Morris DS, Rohrbach J, Sundaram LMT, Sonnad S, Sarani B, Pascual J, et al. Early hospital readmission in the trauma population: are the risk factors different? Injury 2014;45(1):56–60.
[11] Moore L, Stelfox HT, Turgeon AF, Nathens AB, Lavoie A, Bourgeois G, et al. Derivation and validation of a quality indicator for 30-day unplanned hospital readmission to evaluate trauma care. J Trauma Acute Care Surg 2014;76(5):1310–6.
[12] Efron B, Morris C. Stein's paradox in statistics. Sci Am 1977;236(5):119–27.
[13] Kansagara D, Englander H, Salanitro A, Kagen D, Theobald C, Freeman M, et al. Risk prediction models for hospital readmission: a systematic review. JAMA 2011;306(15):1688–98.
[14] Clapp MA, Little SE, Zheng J, Kaimal AJ, Robinson JN. Hospital-level variation in postpartum readmissions. JAMA 2017;317(20):2128–9.