Thirty-day all-cause hospital readmissions – racial and income disparities and risk factors in a veterans integrated healthcare network

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Abstract: Hospital readmission rate has long been one of the most watched measures for hospital quality of care and possesses significant financial implications. On 1 October 2012, CMS started to reduce payments to the hospitals with excessive readmissions. The penalties implemented by CMS have rekindled extensive research activities centred on the fairness of the penalties owing to racial disparities for hospitals serving disadvantaged populations and on the interventions that can reduce readmissions. In this study, we found that no racial and income disparities exist in the Veterans Integrated Healthcare Network Upstate New York, which could have broader policy implications. We explored demographic and socioeconomic risk factors and found that unmarried patients were 19% more likely to be rehospitalised. Given more than half of the inpatients are unmarried, 19% more readmissions merit greater attention from hospital managers and policymakers alike.

Keywords: hospital readmissions; racial and income disparities; risk factors.

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1 Introduction

Hospital readmission rate has long been regarded as a key measure for hospital quality of care (Hernandez et al., 2010; Jha et al., 2009; Jencks et al., 2009; Luthi et al., 2003; Matthew et al., 2010; Rathore et al., 2003). Moreover, readmissions also possess significant financial implications: in the US, almost 20% of Medicare inpatients are rehospitalised within 30 days, which amounts to a cost of $17 billion (Jencks et al., 2009). On 1 October 2012, the Centers for Medicare & Medicaid Services (CMS) as required by Section 3025 of the Affordable Care Act started to reduce payments to the hospitals with excessive readmissions for three conditions (acute myocardial infarction, heart failure and pneumonia). By 2015 it is expected to expand the list to include chronic obstructive pulmonary disease (COPD), coronary artery bypass graft (CABG), percutaneous coronary interventions and other vascular procedures. The penalty is also expected to increase from 1% of the payment in fiscal year (FY) 2013 to 2% in FY 2014 and to 3% for FY 2015 and beyond (Fontanarosa and McNutt, 2013).

With the strong political wind and many billions of dollars at stake, rates of readmissions have jumped into the centre of spotlight (Bradley et al., 2014; Kansagara et al., 2011; Kripalani et al., 2014). The most recent published literature focuses on two areas: the fairness of the penalties and how readmissions can be reduced. Some studies have raised concerns that hospitals serving disadvantaged populations may be unfairly punished since higher readmission rates have been found pervasive among minority groups (Joynt et al., 2011; Joynt and Jha, 2013; Naylor et al., 2012). Other studies examined the effectiveness of different interventions on readmissions, such as medication safety management and telephone follow-up (Bradley et al., 2014; Jackson et al., 2013; McHugh et al., 2013). Although the literature is extensive, it appears that the most basic risk factors have been understudied: few have attempted to thoroughly examine the effects of demographic and socioeconomic factors on readmissions and to explore specific and readily identifiable information that can be used to reduce readmissions.

In this study, we aim to extend the literature in two fronts:

1 to examine whether racial and income disparities exist in an integrated healthcare network, which could have broader policy implications

2 to identify demographic and socioeconomic risk factors that can be used to reduce readmissions.

2 Method

2.1 Setting and data source

This study analysed FY 2011 and the first month of FY 2012 inpatient data from Veterans Integrated Service Network Upstate New York (VISN 2), which is one of the 21 Networks of US Department of Veterans Affairs Health Administration (VA). VISN 2, with five medical centres and 31 outpatient clinics across Upstate New York, provides healthcare to approximately 140,000 patients each year with an annual budget of over one billion dollars. In FY 2011, 8,718 patients were hospitalised for acute care in VISN 2, which were all included in the analysis.

Since 1997, patient care databases across the VA system have been centralised and hosted at the Austin Information Technology Center (AITC). National Patient Care Database (NPCD) maintained by AITC is the primary data source for this study. We used patient treatment file (PTF), associated census file in FY 2011 and the first 30 days of FY 2012 PTF to identify index hospitalisations and readmissions.

In addition to clinical information such as admission/discharge dates and ICD-9 CM codes, PTF also records detailed patient demographic and socioeconomic information such as age, gender, race and income. NPCD, including PTF, is routinely and extensively used for VA operational analyses and research. Most of the variables in NPCD such as admission/discharge dates and ICD-9 CM codes are regularly and rigorously validated with strict business rules; in particular, its patient income information is means tested. One exception is that its racial information is often incomplete because veterans are not required to report their racial status. However, for the last several years, VA has systematically updated its patient racial status by collecting information from other sources such as department of defence (DOD) and Medicare; as a result, the updated racial status information is deemed accurate and reliable (Stroupe et al., 2010; Trivedi et al., 2011).

For case-mix or risk adjustment, we used DxCG risk score (http://www.veriskhealth.com/content/verisk-health-sightlines-dxcg-risk-solutions?gclid). For the last decade, VA has been using DxCG to systematically measure risk and comorbidities of all its 5.7 million patients quarterly on rolling 12-month basis. DxCG algorithm uses ICD-9 CM codes, age and gender as input data to classify patients into hierarchical condition categories (HCCs, which are similar to the HCCs used by CMS) and then produces a risk score for each patient by applying cost-weight for each HCC (Ellis and Ash, 1995; Liu et al., 2003; Sales et al., 2003; Zhao et al., 2005). In addition, we also used decision support system (DSS) files to calculate prior year (FY 2010) patient cost as a risk factor. DSS costs are the primary financial data for internal operations, research, external inquiries from such as congress and general accountability office (GAO). This study used no identifiable patient private information and is therefore exempted from IRB review under VA Title 38, Section 16.101(b)(4).

2.2 Dependent and independent variables

The dependent variable in this study is dichotomous: equals 1 if a patient experienced a hospital readmission, otherwise equals 0. A readmission is defined as a hospitalisation within 30 days after the initial or index discharge. As the convention of other studies, no more than one readmission was counted in this study (Kansagara et al., 2011). Hospitalisations transferred from other medical centres were excluded. To accurately count readmissions, we also included data from the first month of FY 2012 (October 2011) to capture readmissions from the index hospitalisations in the last month of FY 2011 (September 2011).

The independent variables can be grouped into four categories as shown in Table 1:

1 demographic and socioeconomic variables

2 length of stay (LOS) of the index hospitalisation and prior year patient care cost

3 medical centre characteristics (modelled by fixed effect)

4 patient risk score and comorbidities.

Table 1 Descriptive statistics and univariate analysis (n = 8,718)

Variables	*Patients without readmission (n = 7,310) mean or percent (SD)*	*Patients with readmission (n = 1,408) mean or percent (SD)*	*P-value*
Age < 35	4.0% (0.196)	3.7% (0.189)	0.595
Age 35–45	3.8% (0.192)	2.3% (0.151)	0.006
Age 45–55	11.2% (0.315)	10.8% (0.310)	0.688
Age 55–65	29.4% (0.456)	29.3% (0.455)	0.902
Age 65–75	18.7% (0.390)	20.2% (0.401)	0.185
Age > 75	32.9% (0.470)	33.7% (0.473)	0.548
Sex (male = 1)	94.1% (0.235)	96.0% (0.195)	0.005
Race status (black = 1)	11.0% (0.313)	11.6% (0.320)	0.507
Patient income (10k)	2.520 (4.138)	2.463 (3.866)	0.632
Marital status (unmarried = 1)	59.7% (0.491)	62.6% (0.484)	0.044
Number of dependents	0.205 (0.404)	0.197 (0.398)	0.470
Homeless	0.3% (0.057)	0.5% (0.070)	0.330
Disability rating > 70%	20.7% (0.405)	22.0% (0.415)	0.255
No health insurance	27.1% (0.445)	22.4% (0.417)	< 0.001
Enrolled in Medicare	60.4% (0.489)	66.3% (0.473)	< 0.001
Enrolled in Medicaid	1.7% (0.131)	3.0% (0.170)	0.002
Covered by private health insurance	10.7% (0.309)	8.3% (0.276)	0.006
Index hospitalisation length of stay	5.446 (7.925)	6.185 (8.963)	0.002
Prior year patient cost (in logarithm)	8.654 (2.848)	9.326 (2.542)	< 0.001
Medical centre A	20.1% (0.401)	19.5% (0.396)	0.577
Medical centre B	34.6% (0.476)	35.2% (0.478)	0.635

Table 1 Descriptive statistics and univariate analysis (n = 8,718) (continued)

Variables	*Patients without readmission (n = 7,310) mean or percent (SD)*	*Patients with readmission (n = 1,408) mean or percent (SD)*	*P-value*
Medical centre C	40.2% (0.490)	41.3% (0.493)	0.446
Medical centre D	5.1% (0.220)	4.0% (0.196)	0.080
DxCG risk score	2.851 (2.404)	4.592 (3.247)	< 0.001
Hypertension	46.8% (0.499)	39.9% (0.490)	< 0.001
Diabetes	16.3% (0.370)	22.3% (0.416)	< 0.001
Congestive heart failure	21.1% (0.408)	34.2% (0.475)	< 0.001
Chronic obstructive pulmonary disease	28.0% (0.449)	38.1% (0.486)	< 0.001
Cancer	22.5% (0.418)	26.6% (0.442)	0.001
Depression	31.7% (0.465)	37.4% (0.484)	< 0.001

2.3 Modelling

In this study, we first conducted univariate analysis by using ANOVA to compare the independent variables of the patients with and without readmissions. However, univariate analysis could produce misleading results since confounders such as case-mix are not controlled for. For multivariate analyses, as in most studies, we adopted logistic regression to assess the main effects and to control for the confounding factors. Logistic regression has been the most robust and the most extensively used model in modelling readmissions or other outcomes where the dependent variable is binary, i.e., equals 1 if the event happened, otherwise equals 0 (Bewick et al., 2005; Maddala, 1983; McFadden, 1980). However, proper model selection is only a necessary, not a sufficient, condition for unbiased coefficient estimates. The accuracy of the estimates heavily relies on how the confounding factors are controlled for.

To ensure reliable results, in this study we pay particular attention to patient case-mix or risk adjustment. The selection and use of case-mix or comorbidities in the literature has been rather ad hoc. Some studies only used a priori coexisting conditions ranging from a few to a couple of dozens (Joynt et al., 2011; Jencks et al., 2009; Jha et al., 2009) while others included a comprehensive measure (e.g., Charlson comorbidity index, Medicare mortality prediction system score) and a number of coexisting conditions (Luthi et al., 2003; Rathore et al., 2003). We chose DxCG risk score as the aggregated case-mix or comorbidity measure. DxCG is a well validated case-mix algorithm; most studies found DxCG is superior to other algorithms in predicting resources use (Ellis and Ash, 1995; Liu et al., 2003; Sales et al., 2003; Zhao et al., 2005). Despite its superiority, we configured a separated model that supplemented DxCG with a set of most prevalent and/or expensive chronic conditions (hypertension, diabetes, congestive heart failure, COPD cancer and depression) to ensure the results are not due to insufficient risk adjustment.

In addition, veterans also seek care from non-VA providers, especially Medicare. To rule out any potential bias due to the dual-users, in addition to the Medicare enrolment, we also created and used age groups rather than age as a continuous variable in the regression. Further, we separately analysed the data with only patients aged 65 or younger to verify the consistency of the results. Finally, we controlled for medical centre characteristics such as teaching or rural status with fixed effects by creating four indicator variables for each medical centre (four medical centres offer inpatient services and one is omitted in the regression as the reference).

3 Results

The univariate analysis results are presented in Table 1. For the multivariate analyses, Table 2 reports the coefficient estimates of model 1 which used DxCG score as the aggregated patient case-mix; Table 3 displays the estimates of model 2 that augmented DxCG score with a set of chronic conditions.

Table 2 Logistic regression parameter estimate and odds ratio (model 1)

Independent variable	*Parameter estimate*	*P-value*	*Odds-ratio*	*Confidence interval (95%)*
Intercept	–2.922	< 0.001		
Age 35–45	–0.535	0.027	0.586	0.365–0.940
Age 45–55	–0.349	0.055	0.706	0.494–1.008
Age 55–65	–0.482	0.004	0.617	0.443–0.859
Age 65–75	–0.557	0.003	0.573	0.399–0.822
Age > 75	–0.700	< 0.001	0.497	0.347–0.711
Sex (male = 1)	0.280	0.064	1.323	0.984–1.779
Race status (black = 1)	–0.093	0.346	0.911	0.750–1.106
Patient income (10k)	–0.001	0.912	0.999	0.984–1.015
Marital status (unmarried = 1)	0.170	0.019	1.186	1.028–1.367
Number of dependents	0.060	0.507	1.062	0.889–1.269
Homeless	0.377	0.402	1.457	0.604–3.518
Disability rating > 70%	–0.064	0.438	0.938	0.797–1.103
No health insurance	0.134	0.284	1.143	0.895–1.460
Enrolled in Medicare	0.332	0.004	1.394	1.115–1.743
Enrolled in Medicaid	0.781	< 0.001	2.184	1.432–3.330
Index hospitalisation length of stay	–0.009	0.010	0.991	0.983–0.998
Prior year patient cost (in logarithm)	0.052	< 0.001	1.053	1.027–1.081
Medical centre A	0.088	0.590	1.091	0.794–1.500
Medical centre B	0.280	0.072	1.323	0.975–1.795
Medical centre C	0.204	0.187	1.227	0.906–1.661
DxCG risk score	0.210	< 0.001	1.234	1.208–1.261

Table 3 Logistic regression parameter estimate and odds ratio (model 2)

Independent variable	*Parameter estimate*	*P-value*	*Odds-ratio*	*Confidence interval (95%)*
Intercept	–3.161	<0.001		
Age 35–45	–0.561	0.021	0.571	0.355–0.918
Age 45–55	–0.370	0.046	0.691	0.480–0.993
Age 55–65	–0.543	0.002	0.581	0.411–0.820
Age 65–75	–0.600	0.002	0.549	0.375–0.803
Age >75	–0.751	<0.001	0.472	0.323–0.689
Sex (male = 1)	0.316	0.037	1.372	1.019–1.847
Race status (black = 1)	–0.046	0.645	0.955	0.786–1.161
Patient income (10k)	0.003	0.746	1.003	0.987–1.018
Marital status (unmarried = 1)	0.172	0.019	1.188	1.029–1.371
Number of dependents	0.063	0.487	1.065	0.891–1.274
Homeless	0.310	0.494	1.364	0.561–3.317
Disability rating > 70%	–0.077	0.358	0.926	0.787–1.091
No health insurance	0.132	0.290	1.141	0.894–1.458
Enrolled in Medicare	0.302	0.008	1.353	1.082–1.692
Enrolled in Medicaid	0.754	<0.001	2.125	1.393–3.242
Index hospitalisation length of stay	–0.009	0.019	0.991	0.984–0.999
Prior year patient cost (in logarithm)	0.040	0.002	1.041	1.014–1.068
Medical centre A	0.193	0.238	1.213	0.880–1.671
Medical centre B	0.382	0.015	1.465	1.077–1.993
Medical centre C	0.288	0.064	1.334	0.983–1.809
DxCG risk score	0.198	<0.001	1.218	1.190–1.247
Hypertension	0.065	0.401	1.068	0.917–1.243
Diabetes	–0.005	0.950	0.995	0.851–1.163
Congestive heart failure	0.357	<0.001	1.429	1.201–1.700
Chronic obstructive pulmonary disease	0.276	<0.001	1.317	1.156–1.501
Cancer	–0.011	0.883	0.989	0.857–1.142
Depression	0.307	<0.001	1.360	1.192–1.551

Interestingly, in the univariate analysis, all age groups except for the age group 35–45 showed no difference in propensity of readmissions. However, in the multivariate analyses, both models demonstrated older patients (compared with the youngest group omitted in the regression as the reference) were less likely to be rehospitalised given all other factors equal. Furthermore, there appeared to be a linear trend after age 45: the older, the less likely to be rehospitalised. On the other hand, both univariate and multivariate analyses showed that male patients were more likely to experience rehospitalisations ($p = 0.005$, 0.064 and 0.037 respectively).

Of particular importance, both the univariate and multivariate analyses revealed no racial disparity in hospital readmissions (p = 0.507, 0.346 and 0.645 respectively). Equally important, no income disparity was found either (p = 0.632, 0.912 and 0.746 respectively). Rather interestingly, both univariate and multivariate analyses demonstrated that unmarried patients were more likely rehospitalised. In the univariate analysis, among the patients without readmissions, 59.7% were unmarried while it was 62.6% among the rehospitalised patients (p = 0.044). After adjusting the confounders, both models confirmed that unmarried patients were 19% more likely to be readmitted into hospitals within 30 days of the index hospitalisation (p = 0.019).

The number of dependents, disability rating (> 70%) and homeless were not correlated with rehospitalisations (all p-values > 0.255).

The univariate analysis indicated that patients who were not covered by any health insurance were less likely to be rehospitalised: among the patients without rehospitalisations, 27.1% had no health insurance, while it was 22.4% among the patients with rehospitalisations (p < 0.001). However, upon controlling for confounders, both models showed that having no insurance did not affect readmissions compared to the patients covered with private insurance which was omitted in the regressions as the reference (p = 0.284 and 0.290). Further, both univariate and multivariate analyses demonstrated patient enrolled in Medicaid or Medicare were more likely to be rehospitalised (all p values < 0.008).

Interestingly, the univariate analysis showed rehospitalised patients had longer index LOS (9.0 days) compared to the patients without rehospitalisations (7.9 days; p = 0.002); after controlling for the confounding factors, both models demonstrated that shorter LOS was associated with more readmissions (p = 0.010 and 0.019). Not surprisingly, higher prior year patient costs were associated with more readmissions in both univariate and multivariate analyses (p < 0.001 and p = 0.002). Regarding medical centre characteristics captured by the fixed effect, only medical centre B seemed to have more readmissions compared with medical centre D (omitted in the regression as the reference) after controlling for the confounders (p = 0.072 and 0.015 respectively).

As expected, DxCG risk score was positively associated with readmissions (all p-values < 0.001). In the univariate analysis, except for hypertension, all other five chronic conditions were associated with more readmissions. Upon controlling for the aggregated risk score and other confounders in model 2, hypertension, diabetes and cancer were not correlated with readmissions (p = 0.401, 0.950 and 0.883 respectively), while CHF, COPD and depression were associated with more readmissions (all p-values < 0.001).

Finally, we conducted extensive sensitivity analyses. For example, we refitted the models with age as continuous variable and with different groupings; we broke down income into categorical variables and tested prior year patient income to rule out endogeneity bias; we also regrouped non-black minorities into black and white separately for reanalysis. Virtually none of these sensitivity analyses altered the results. More importantly, we refitted model 2 with patients aged 65 or younger: no racial and income disparities were found either (p = 0.496 and 0.393); interestingly, married patients were found 22% less likely to experience rehospitalisations (OR = 0.781; 95% CI: 0.633-0.964).

4 Discussion

The rate of hospital readmissions has long been one of the most watched hospital quality measures; recently, the financial penalties implemented by CMS on hospitals with excessive readmissions ignited renewed attention among hospital managers, researchers and policymakers alike. Some focus on the fact that hospitals serving disadvantaged populations could be unfairly punished because minorities have consistently had high readmission rates, while others explore mechanisms that can reduce readmissions. Although racial disparities have been extensively examined and found pervasive, other patient demographic and socioeconomic factors in relation to readmissions seemed to be understudied in the literature. In this study, we explored two issues: are racial and income disparities universal or can be avoided in an integrated healthcare network? Can any demographic or socioeconomic information be used to help reduce readmissions?

After comprehensively controlling for confounders, we found no racial disparities in readmissions in an integrated healthcare network, which suggests that racial disparities are not necessarily universal and may be dependent on how patient care is paid for and delivered. Contrary to most of the US healthcare systems, patients in the VA system have little financial barriers; the salaried VA clinicians have no financial incentive to over or under treat patients. More importantly, VA has reformed itself to focus on patient-centred care since the inception of integrated healthcare networks in 1995 (Kizer et al., 2000). These might be among the factors that could help to eliminate the racial disparities.

No income disparity in readmissions was found either in this study. Income disparity has not been well studied in the literature compared to racial disparity, which may be due to the fact that income data are often unavailable. Apart from the importance of income disparity itself, analysing racial disparity without controlling for income can yield misleading results since race and income are often correlated (Yu and Zhang, 2005). As a result, what appears to be a racial issue could actually be an income issue. VA is a unique institution that collects and means-tests patient income, which enables us to analyse reliable patient income data.

Of meaningful practical value, we found that unmarried patients were 19% more likely to experience rehospitalisations compared to their married counterparts after controlling for the confounding factors. Given 60% of the patients in this study were not married (Rosenthal et al., 2003, reported 54% for non-VA patients), 19% more readmissions merits more focused attention from hospital managers, policymakers and researchers alike. Although marital status may be a mirror of other factors such as lack of post-discharge caregiver support which could result in low medication adherence and hinder timely outpatient follow-up, it is easy to identify and use for proper proactive interventions.

The univariate analysis showed that patients who had no other health insurance and thereby almost solely relied on VA for their care were less likely to experience readmissions ($p < 0.001$). However, the association disappeared after controlling for the confounders such as case-mix, which seemed to suggest that uninsured patients were relatively younger or healthier. On the other hand, patients enrolled in Medicare or Medicaid were more likely to be rehospitalised compared to those who had private insurance (omitted in the regression as the reference group). This could be attributed to the fact that patients with private insurance may also be different in other aspects such as more likely being employed and paying closer attention to their health; however, further study may be warranted.

In addition, some of the confounders in the model entail further elaboration. Paradoxically, both models demonstrated that older patients were less likely to be rehospitalised after controlling for disease severity and other confounders. Although older patients suffer more chronic diseases and incur higher healthcare expenditures as they age, it is possible that older patients are less likely to seek intensive treatments for the same disease compared to younger patients given all other factors equal. Studies have consistently found that medical care costs at the end of life are inversely correlated with age (Felder et al., 2000; Levinsky et al., 2001).

Similarly, the univariate analysis showed that the longer index LOS was associated with more readmissions. However, after controlling for patient risk and other confounders, both models revealed that the longer LOS was associated with fewer readmissions. These seemingly inconsistent results suggest that sicker patients experienced longer LOS and more readmissions; but after controlling for confounding variables, it appeared longer LOS may reduce readmissions. In other words, for the same disease severity, short LOS may result in more readmissions, which is consistent with the finding by Carey and Lin (2014).

As reported in the Dartmouth Atlas and numerous journals, outcomes such as readmissions may vary greatly across geographic areas. Our finding indicates that patients in medical centre B experienced more readmissions compared to patients in medical centre D (omitted in the regression as the reference). But this study was not designed to assess and thus cannot conclude if the high readmission rate was due to practice or management patterns because many hospital characteristics such as teaching mission and referral centre were absorbed into the fixed effect.

Despite our effort, this study is not without limitations. First, patients in this study could be rehospitalised in non-VA hospitals paid by Medicare, Medicaid, or private health plans. As a result, lack of concurrent actual non-VA hospitalisation data could affect the accuracy of our results. To keep this potential bias at minimum, we fitted the model with age groups, Medicare/Medicaid enrolment and insurance status. Further, we also gained more confidence on our results that, for the patients aged 65 and younger, no racial/income disparities were found either and the effect of marital status on rehospitalisations was even larger. In addition, a study funded by VA Health Services Research and Development Service (HSR&D) concluded that Medicare data has little effect on measuring VA readmissions (only 1–2%; O'Brien et al., 2013). Second, the study population was from one geographic area (i.e., upstate New York) which may not resemble the whole VA system or other non-VA healthcare systems well. Third, all other non-black minority patients count for less than 1% of the study population which cannot not be analysed separately in any reliable way. Fourth, only 5% of the study population was female; thus, the finding of fewer readmissions with female patients may not be replicable to non-VA populations. Finally, as in most studies, all-cause readmissions were analysed, which inevitably includes some readmissions that are not related to the initial hospitalisations. However, same-cause readmissions are even more problematic: some readmissions due to inadequate care during and after the initial hospitalisation may be inadvertently excluded. For example, readmissions for hypertension or renal failure may be due to poor care associated with the initial hospitalisation for diabetes. Clearly, more research is needed.

In spite of the limitations, the extensive sensitivity analyses demonstrate our results are robust. Our findings may have meaningful policy implications: racial and income disparities are not unavoidable; how care is delivered and paid may make a difference.

Further, given more than half of the hospitalised patients are unmarried, 19% more readmissions warrants greater attention on discharge planning and post-discharge care support from the discharge planners at hospital level and policymakers at national as well as local levels.

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