An Administrative Claims Measure Suitable for Profiling Hospital Performance on the Basis of 30-Day All-Cause Readmission Rates Among Patients With Heart Failure

Patricia S. Keenan, PhD, MHS; Sharon-Lise T. Normand, PhD; Zhenqiu Lin, PhD; Elizabeth E. Drye, MD, SM; Kanchana R. Bhat, MPH; Joseph S. Ross, MD, MHS; Jeremiah D. Schuur, MD, MHS; Brett D. Stauffer, MD; Susannah M. Bernheim, MD, MHS; Andrew J. Epstein, PhD, MPP; Yongfei Wang, MSc; Jeph Herrin, PhD; Jersey Chen, MD, MPH; Jessica J. Federer, MPH; Jennifer A. Mattera, MPH; Yun Wang, PhD; Harlan M. Krumholz, MD, SM

Background—Readmission soon after hospital discharge is an expensive and often preventable event for patients with heart failure. We present a model approved by the National Quality Forum for the purpose of public reporting of hospital-level readmission rates by the Centers for Medicare & Medicaid Services.

Methods and Results—We developed a hierarchical logistic regression model to calculate hospital risk-standardized 30-day all-cause readmission rates for patients hospitalized with heart failure. The model was derived with the use of Medicare claims data for a 2004 cohort and validated with the use of claims and medical record data. The unadjusted readmission rate was 23.6%. The final model included 37 variables, had discrimination ranging from 15% observed 30-day readmission rate in the lowest predictive decile to 37% in the upper decile, and had a c statistic of 0.60. The 25th and 75th percentiles of the risk-standardized readmission rates across 4669 hospitals were 23.1% and 24.0%, with 5th and 95th percentiles of 22.2% and 25.1%, respectively. The odds of all-cause readmission for a hospital 1 standard deviation above average was 1.30 times that of a hospital 1 standard deviation below average. State-level adjusted readmission rates developed with the use of the claims model are similar to rates produced for the same cohort with the use of a medical record model (correlation, 0.97; median difference, 0.06 percentage points).

Conclusions—This claims-based model of hospital risk-standardized readmission rates for heart failure patients produces estimates that may serve as surrogates for those derived from a medical record model. (Circ Cardiovasc Qual Outcomes. 2008;1:29-37.)

Key Words: health policy ■ heart failure ■ quality of health care

Readmissions to the hospital shortly after discharge are expensive and often preventable events for heart failure patients.1–3 Heart failure is the most frequent principal discharge diagnosis for hospitalized Medicare beneficiaries4 and is associated with all-cause readmission rates of >40% by 6 months after discharge.1 The Medicare Payment Advisory Commission, an independent federal body that advises the US Congress, has recently called for hospital-specific public reporting of readmission rates, identifying heart failure as a priority condition.2 Readmissions may result from a variety of care deficits, including premature hospital discharge, inadequate preparation of the patient and family for discharge, complications that manifest after discharge, and poor care transitions. Moreover, studies have identified underutilized interventions in and out of the hospital that can decrease readmission risk after a heart failure hospitalization.5–12

Received June 26, 2008; accepted July 7, 2008.

From the Section of Health Policy and Administration, School of Public Health, Yale University School of Medicine, New Haven, Conn (P.S.K., A.J.E., H.M.K.); Department of Health Care Policy, Harvard Medical School and Department of Biostatistics, Harvard School of Public Health, Boston, Mass (S.T.N.); Center for Outcomes Research and Evaluation, Yale–New Haven Hospital, New Haven, Conn (Z.L., E.E.D., K.R.B., J.A.M., Y.W., H.M.K.); Departments of Geriatrics and Adult Development and Medicine, Mount Sinai School of Medicine, New York, NY, and HSR&D Targeted Research Enhancement Program and Geriatrics Research, Education, and Clinical Center, James J. Peters Veterans Administration Medical Center, Bronx, NY (J.S.R.); Department of Emergency Medicine, Brigham and Women’s Hospital and Department of Medicine, Harvard Medical School, Boston, Mass (J.D.S.); Baylor University Medical Hospital System, Dallas, Tex (B.D.S.); Performance Management, Yale–New Haven Health System, New Haven, Conn (S.M.B.); Section of Cardiovascular Medicine, Department of Internal Medicine, Yale University School of Medicine, New Haven, Conn (Y.-F.W., J.H., J.C., H.M.K.); Bayer Healthcare Pharmaceuticals, Wayne, NJ (J.J.F.); and Robert Wood Johnson Clinical Scholars Program, Department of Internal Medicine, Yale University School of Medicine, New Haven, Conn (H.M.K.). Drs Stauffer and Schuur were postdoctoral fellows in the Robert Wood Johnson Clinical Scholars Program at Yale University during the time the work was conducted. Jessica J. Federer was a Masters student at the Yale School of Public Health during the time the work was conducted.

The online-only Data Supplement is available with this article at http://circoutcomes.ahajournals.org/cgi/content/full/1/1/29/DC1.

Correspondence to Dr Harlan M. Krumholz, Yale University School of Medicine, Room I-456 SHM, 333 Cedar St, PO Box 208088, New Haven, CT 06520-8088. E-mail harlan.krumholz@yale.edu

© 2008 American Heart Association, Inc.

Circ Cardiovasc Qual Outcomes is available at http://circoutcomes.ahajournals.org

DOI: 10.1161/CIRCOUTCOMES.108.802686
Despite the clinical and policy importance, a validated, risk-standardized statistical model to accurately profile hospital readmission rates is not available in the published literature.13

---

**Editorial see p 9**
**Clinical Perspective see p 37**

---

This article presents a model, approved by the National Quality Forum,14 to estimate hospital-specific readmission rates for Medicare patients hospitalized with heart failure. We developed and validated the model with Medicare administrative claims data and determined whether estimates from the claims model were good surrogates for the results of a medical record model. We sought to ensure that this model had all the key attributes for publicly reported outcomes measures articulated by an American Heart Association Scientific Statement.15 This approach extends the work that produced National Quality Forum–approved models of 30-day mortality rates for acute myocardial infarction and heart failure, now publicly reported on Hospital Compare by the Centers for Medicare & Medicaid Services (CMS).16–18

### Methods

#### Data

For administrative model derivation and validation for 2003 and 2004 cohorts, we used 2002–2005 claims data from the Medicare inpatient, outpatient, and carrier (physician) Standard Analytic Files. The Medicare Enrollment Database was used to determine Medicare fee-for-service enrollment status and mortality status. For medical record model validation, we analyzed 1998–2001 medical record data from the National Heart Failure (NHF) Project, a CMS quality improvement project.19 The NHF cohorts consisted of 39,477 records in 1998–1999 and 39,405 records in 2000–2001, with up to 800 discharges randomly selected in each state, Washington DC, and Puerto Rico.

#### Study Cohort

We identified hospitalizations of patients ≥65 years of age with a principal discharge diagnosis of heart failure as potential index heart failure hospitalizations (International Classification of Diseases, 9th Revision, Clinical Modification codes 404.01, 404.03, 404.11, 404.13, 404.91, 404.93, or 428.xx). Because our focus was on readmission, we excluded hospitalizations during which the patient died or was transferred to another acute care facility.

To maximize our ability to risk-adjust and to identify readmissions, we restricted the cohort to patients enrolled in fee-for-service Medicare Parts A and B for 12 months before their heart failure hospitalization and who continued in fee-for-service for ≥30 days after their discharge.

Our unit of observation was a heart failure hospitalization. Additional heart failure hospitalizations that occurred within 30 days of discharge of an index hospitalization were classified as an outcome, ie, a readmission, and thus not defined as an index hospitalization.

#### Outcome

The primary outcome was 30-day readmission, defined as the occurrence of at least 1 hospitalization in any US acute care hospital for any cause within 30 days of discharge after an index hospitalization. We identified readmissions from the hospital claims data. Each readmission was attributed to the hospital that dischared the patient.

### Candidate Variables

We developed candidate variables for the model from the claims codes using the aforementioned data sources. To assemble clinically coherent codes into candidate variables, we used the publicly available CMS hierarchical condition categories (CCs) to group codes into 189 CCs.20,21 A CC was indicated as present in any of the hospital inpatient, outpatient, or physician claims data sources in the prior 12 months, including the index admission. Additional candidate variables included 2 demographic variables and procedure codes relevant to heart failure readmission risk. A physician team identified candidate variables and differentiated CC variables that when coded as secondary diagnosis codes during the index hospitalization could represent either comorbid conditions on admission or complications of care (eg, urinary tract infection). To avoid including potential complications as comorbidities, we did not code them as risk factors if they appeared only as secondary diagnosis codes for the index hospitalization and not on claims in the prior year.

#### Model Derivation

A physician team (H.M.K., J.S.R., B.D.S., S.M.B., E.E.D.) selected risk factors for the final model on the basis of their statistical association with and clinical relevance to readmission, with reference to prior research.13 Additional details are provided in the Statistical Appendix in the online-only Data Supplement.

For the derivation of the administrative claims model, we randomly sampled half of the 2004 hospitalizations that met inclusion criteria. We conducted analyses of model performance by using a generalized linear model with a logit link function. To assess model performance at the patient level, we calculated the area under the receiver operating characteristic curve (AUC), explained variation as measured by the generalized $R^2$ statistic, and calculated the observed readmission rates in the lowest and highest deciles on the basis of predicted readmission probabilities.23 We also compared performance with a null model, a model that adjusted for age and sex, and a model that included all of the candidate variables.

#### Risk-Standardized Readmission Rate

Given the clustering of admissions within hospitals and that hospitals were our unit of inference, we estimated risk-standardized readmission rates by using hierarchical generalized linear models.24 This modeling strategy accounts for within-hospital correlation of the observed readmission rates and reflects our assumption that after adjustment for patient risk and sampling variability, the remaining variation is due to hospital quality.

We next calculated risk-standardized hospital-specific readmission rates. These rates are obtained as the ratio of the number of “predicted” to “expected” readmissions, multiplied by the national unadjusted rate. The predicted number of readmissions in each hospital is estimated given its own patient mix and with its own hospital-specific intercept. The expected number of readmissions in each hospital is estimated with its own patient mix and the average hospital-specific intercept based on all hospitals in our sample. (Additional information is available in the Statistical Appendix in the online-only Data Supplement.) This is a form of indirect standardization.

#### Model Validation

##### Administrative Claims

We compared the model performance in the derivation sample with its performance in the remaining half of the 2004 claims data and, separately, with the 2003 claims data. The model was recalibrated in each validation set. We calculated indices that quantify overfitting for each validation data set, each time calculating a risk score using the regression estimates from our derivation model.25 A risk score coefficient that is much different from 1 and an intercept different from 0 are indicative of overfitting. We also examined whether model performance varied for important subgroups of patients: older patient age, sex, race/ethnicity, and urban/rural hospital.
Medical Record Model Validation
We developed a separate medical record model of readmission risk on the basis of NHF data (see Statistical Appendix in the online-only Data Supplement). We also linked the patients in the NHF cohort to their Medicare claims data, including claims from 1 year before the index hospitalization, so that we could calculate the risk-standardized state readmission rates in this cohort separately using medical record and claims data models. We conducted this analysis at the state level, for the 50 states plus the District of Columbia and Puerto Rico, because medical record data were only available in sufficient numbers to perform a state-level comparison. To examine the relationship between the risk-standardized rates obtained from medical record and administrative data models, we estimated a linear regression model describing the association between the 2 rates, weighting each state by the number of index hospitalizations, and calculated the intercept and the slope of this equation. A slope close to 1 and an intercept close to 0 would provide evidence that the risk-standardized state readmission rates from the medical record and claims models were similar. We also calculated the difference between the state risk-standardized readmission rates from the 2 models.

Analyses were conducted with the use of SAS version 9.1.3 (SAS Institute Inc, Cary, NC). Models were fitted separately for the NHF cohort and the 2004 cohort. We estimated the hierarchical models using the GLIMMIX procedure in SAS. The Human Investigation Committee at the Yale School of Medicine approved an exemption for the authors to use CMS claims and enrollment data for research analyses and publication.

The authors had full access to the data and take responsibility for the integrity of the data. All authors have read and agree to the manuscript as written.

Results

Model Derivation
After exclusions were applied, the 2004 data included 567,447 heart failure hospitalizations (Table 1). The derivation sample consisted of 283,919 hospitalizations in 4669 hospitals with at least 1 hospitalization, with an unadjusted 30-day readmission rate of 23.6%. The observed readmission rate ranged from 0% to 100% across these hospitals with 25th, 50th, and 75th percentiles of 17.1%, 23.0%, and 28.2%, respectively. The median annual number of Medicare heart failure hospitalizations was 71 (25th, 75th percentile: 27, 166). In 7% of admissions, the patient died within the 30 days after discharge. In 4.4% of admissions, the patient died without being readmitted, and in 2.6% of admissions, the patient was readmitted and died within the 30 days after discharge. Despite an average survival time of 14 days, the readmission rate was 36.9% among the 7% of admissions in which the patient died within 30 days, compared with a readmission rate of 22.7% for admissions in which patients survived the full 30 days.

The claims model included 37 variables (2 demographic, 9 cardiovascular, and 26 comorbidity variables) (Table 2). The mean age of the cohort was 79.9 years, with 57.8% women and 16.3% nonwhite patients. The mean observed readmission rate in the derivation data set ranged from 15% in the lowest decile of predicted readmission rates to 37% in the highest predicted decile, an absolute difference of 22% (Table 3). The AUC was 0.50 for a null model, 0.52 for a model with only age and sex, and 0.60 for a model that included all the candidate variables.

Hospital Risk-Standardized Readmission Rates
Figure 1 displays the distributions of the risk-standardized 30-day readmission rates. The 5th percentile was 22.2%, and the 95th percentile was 25.1%. The 25th and 75th percentiles were 23.1% and 24.0%, respectively. The mean risk-standardized rate was 23.6%. The odds of all-cause readmission for a hospital 1 standard deviation above average was 1.30 times that of a hospital 1 standard deviation below average.

Administrative Model Validation
With the use of the remaining 50% of heart failure index hospitalizations from 2004 and all of the 2003 data, the regression coefficients and SEs were similar to those for the derivation data set. The performance was also similar in the validation data sets (Table 3).

Medical Record Validation
Initial NHF data contained 78,882 hospitalization records. The final NHF validation sample included 64,329 hospitalizations from 4,437 hospitals after exclusions were applied for age <65 years (8.3% of initial sample), in-hospital death (5.1%), transfer to another acute care facility (0.4%), incomplete information in the 12 months before admission (2.7%), incomplete 30-day readmission information (4.1%), and heart failure hospitalizations within 30 days of prior index hospitalizations (1.6%). The crude 30-day readmission rate was 23.7%.

In 6.8% of admissions, the patient died within the 30 days after discharge. In 4.1% of admissions, the patient died without being readmitted, and in 2.7% of admissions the patient was readmitted and died within the 30 days after discharge. The readmission rate was 39.6% among the 6.8% of admissions in which the patient died within 30 days compared with 22.5% for admissions in which patients survived 30 days.

The medical record comparison model included 30 variables (Table 4). In the medical record model, the AUC was...
Table 2. Heart Failure Readmission Administrative Logistic Regression Model (Based on 2004 Derivation Sample)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean (SD or Percent)</th>
<th>Estimate</th>
<th>SE</th>
<th>Odds Ratio</th>
<th>95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>. . .</td>
<td>-1.89</td>
<td>0.02</td>
<td>. . .</td>
<td>. . .</td>
</tr>
<tr>
<td>Age 65 (years ≥65, continuous)</td>
<td>14.9 (7.8)</td>
<td>0.00</td>
<td>0.00</td>
<td>1.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Male</td>
<td>42.21</td>
<td>0.01</td>
<td>0.01</td>
<td>1.01</td>
<td>0.99</td>
</tr>
<tr>
<td>History of coronary artery bypass graft surgery</td>
<td>13.45</td>
<td>-0.07</td>
<td>0.01</td>
<td>0.93</td>
<td>0.91</td>
</tr>
<tr>
<td>Congestive heart failure (CC 80)</td>
<td>75.59</td>
<td>0.09</td>
<td>0.01</td>
<td>1.09</td>
<td>1.07</td>
</tr>
<tr>
<td>Acute coronary syndrome (CC 81, 82)</td>
<td>20.85</td>
<td>0.12</td>
<td>0.01</td>
<td>1.12</td>
<td>1.10</td>
</tr>
<tr>
<td>Arrhythmias (CC 92, 93)</td>
<td>59.65</td>
<td>0.06</td>
<td>0.01</td>
<td>1.06</td>
<td>1.04</td>
</tr>
<tr>
<td>Cardiorespiratory failure and shock (CC 79)</td>
<td>18.54</td>
<td>0.08</td>
<td>0.01</td>
<td>1.08</td>
<td>1.06</td>
</tr>
<tr>
<td>Valvular and rheumatic heart disease (CC 86)</td>
<td>47.05</td>
<td>0.08</td>
<td>0.01</td>
<td>1.08</td>
<td>1.06</td>
</tr>
<tr>
<td>Vascular or circulatory disease (CC 104–106)</td>
<td>45.39</td>
<td>0.07</td>
<td>0.01</td>
<td>1.07</td>
<td>1.05</td>
</tr>
<tr>
<td>Chronic atherosclerosis (CC 83, 84)</td>
<td>73.71</td>
<td>0.08</td>
<td>0.01</td>
<td>1.09</td>
<td>1.06</td>
</tr>
<tr>
<td>Other and unspecified heart disease (CC 94)</td>
<td>35.71</td>
<td>0.05</td>
<td>0.01</td>
<td>1.05</td>
<td>1.03</td>
</tr>
<tr>
<td>Hemiplegia, paraplegia, paralysis, functional disability (CC 67–69, 100–102, 177, 178)</td>
<td>6.69</td>
<td>0.04</td>
<td>0.02</td>
<td>1.04</td>
<td>1.01</td>
</tr>
<tr>
<td>Stroke (CC 95, 96)</td>
<td>10.66</td>
<td>0.03</td>
<td>0.01</td>
<td>1.03</td>
<td>1.00</td>
</tr>
<tr>
<td>Renal failure (CC 131)</td>
<td>26.15</td>
<td>0.14</td>
<td>0.01</td>
<td>1.15</td>
<td>1.13</td>
</tr>
<tr>
<td>Chronic obstructive pulmonary disease (CC 108)</td>
<td>46.87</td>
<td>0.15</td>
<td>0.01</td>
<td>1.17</td>
<td>1.14</td>
</tr>
<tr>
<td>Diabetes and diabetes mellitus complications (CC 15–20, 119, 120)</td>
<td>49.40</td>
<td>0.08</td>
<td>0.01</td>
<td>1.08</td>
<td>1.06</td>
</tr>
<tr>
<td>Disorders of fluid/electrolyte/acid-base (CC 22, 23)</td>
<td>36.28</td>
<td>0.11</td>
<td>0.01</td>
<td>1.12</td>
<td>1.09</td>
</tr>
<tr>
<td>Other urinary tract disorders (CC 136)</td>
<td>40.61</td>
<td>0.12</td>
<td>0.01</td>
<td>1.12</td>
<td>1.10</td>
</tr>
<tr>
<td>Decubitus ulcer or chronic skin ulcer (CC 148, 149)</td>
<td>11.86</td>
<td>0.10</td>
<td>0.01</td>
<td>1.10</td>
<td>1.07</td>
</tr>
<tr>
<td>Other gastrointestinal disorders (CC 36)</td>
<td>51.12</td>
<td>0.06</td>
<td>0.01</td>
<td>1.06</td>
<td>1.04</td>
</tr>
<tr>
<td>Peptic ulcer, hemorrhage, other specified gastrointestinal disorders (CC 34)</td>
<td>15.94</td>
<td>0.07</td>
<td>0.01</td>
<td>1.07</td>
<td>1.05</td>
</tr>
<tr>
<td>Severe hematologic disorders (CC 44)</td>
<td>3.28</td>
<td>0.14</td>
<td>0.02</td>
<td>1.15</td>
<td>1.10</td>
</tr>
<tr>
<td>Nephritis (CC 132)</td>
<td>3.88</td>
<td>0.07</td>
<td>0.02</td>
<td>1.08</td>
<td>1.03</td>
</tr>
<tr>
<td>Dementia and senility (CC 49, 50)</td>
<td>18.94</td>
<td>0.01</td>
<td>0.01</td>
<td>1.01</td>
<td>0.99</td>
</tr>
<tr>
<td>Metastatic cancer and acute leukemia (CC 7)</td>
<td>2.13</td>
<td>0.13</td>
<td>0.03</td>
<td>1.14</td>
<td>1.07</td>
</tr>
<tr>
<td>Cancer (nonmetastatic) (CC 8–12)</td>
<td>19.58</td>
<td>0.01</td>
<td>0.01</td>
<td>1.01</td>
<td>0.99</td>
</tr>
<tr>
<td>Liver and biliary disease (CC 25–30)</td>
<td>7.64</td>
<td>0.06</td>
<td>0.02</td>
<td>1.06</td>
<td>1.02</td>
</tr>
<tr>
<td>End-stage renal disease or dialysis (CC 129, 130)</td>
<td>2.98</td>
<td>0.15</td>
<td>0.03</td>
<td>1.16</td>
<td>1.11</td>
</tr>
<tr>
<td>Asthma (CC 110)</td>
<td>8.15</td>
<td>0.06</td>
<td>0.02</td>
<td>1.06</td>
<td>1.03</td>
</tr>
<tr>
<td>Iron deficiency and other/unspecified anemias and blood disease (CC 47)</td>
<td>45.43</td>
<td>0.08</td>
<td>0.01</td>
<td>1.09</td>
<td>1.06</td>
</tr>
<tr>
<td>Pneumonia (CC 111–113)</td>
<td>37.49</td>
<td>0.09</td>
<td>0.01</td>
<td>1.09</td>
<td>1.07</td>
</tr>
<tr>
<td>Drug/alcohol abuse/dependence/psychosis (CC 51–53)</td>
<td>8.68</td>
<td>0.07</td>
<td>0.02</td>
<td>1.07</td>
<td>1.04</td>
</tr>
<tr>
<td>Major psychiatric disorders (CC 54–56)</td>
<td>8.48</td>
<td>0.02</td>
<td>0.02</td>
<td>1.02</td>
<td>0.99</td>
</tr>
<tr>
<td>Depression (CC 58)</td>
<td>13.03</td>
<td>0.02</td>
<td>0.01</td>
<td>1.02</td>
<td>0.99</td>
</tr>
<tr>
<td>Other psychiatric disorders (CC 60)</td>
<td>9.31</td>
<td>0.08</td>
<td>0.02</td>
<td>1.08</td>
<td>1.05</td>
</tr>
<tr>
<td>Fibrosis of lung and other chronic lung disorders (CC 109)</td>
<td>13.03</td>
<td>0.05</td>
<td>0.01</td>
<td>1.05</td>
<td>1.02</td>
</tr>
<tr>
<td>Protein-calorie malnutrition (CC 21)</td>
<td>4.52</td>
<td>0.05</td>
<td>0.02</td>
<td>1.05</td>
<td>1.01</td>
</tr>
</tbody>
</table>

Between-hospital variance estimate when using the hierarchical model is 0.02 (SE = 0.002).

Generalized linear model (GLM) estimates.
0.58, and the observed readmission rate ranged from 16% in the lowest predicted decile to 34% in the highest (Table 5). In the same cohort of 64,329 hospitalizations, the administrative model had an AUC of 0.61 and observed readmission rates ranging from 15% in the lowest predicted decile to 38% in the highest predicted decile.

The estimated state-specific standardized readmission rates derived from each model are displayed in Figure 2. The slope of the weighted regression line between chart- and claims-based state readmission rates was 0.81 (SE=0.0008), and the intercept was 0.04 (SE=0.0002). The correlation coefficient of the standardized readmission rates from the 2 models was 0.97 (SE=0.03). The median difference between the models in the state-specific risk-standardized readmission rates was 0.06 percentage points (25th percentile=0.5; 75th percentile=0.8; 10th percentile=0.9; 90th percentile=0.5 percentage points). The odds of all-cause readmission for a hospital 1 standard deviation above average was 1.34 times that of a hospital 1 standard deviation below average.

**Subgroup Analysis**

The claims model shows comparable discrimination by patient age, sex, and race/ethnicity, as well as by hospital urban/rural status (Figure 3). Compared with the overall AUC of 0.60, the AUCs are comparable when the sample is restricted to male patients (0.60), female patients (0.60), white patients (0.62), nonwhite patients (0.60), rural hospitals (0.60), nonrural hospitals (0.60), patients ≥85 years of age (0.58), and patients <85 years of age (0.61).

**Discussion**

We present a hospital 30-day risk-standardized all-cause readmission model for heart failure patients that can be used in performance measurement and quality improvement. The model uses administrative claims data from Medicare fee-for-service patients and produces results that are very similar to a model based on medical record data. The model reveals a clinically meaningful range of 30-day readmission rates among the nation’s hospitals.

Readmission after a hospitalization for heart failure is an important target for quality improvement. Heart failure accounts for approximately 800,000 hospitalizations of Medicare fee-for-service patients annually. The risk of readmission is remarkably high within a short time after discharge. Our study shows that 1 in 4 patients returns to the hospital within 30 days. Many studies have demonstrated the effectiveness of in-hospital and postdischarge interventions in reducing the risk of readmission, suggesting that hospitals and their partners have the ability to lower readmission rates.5–7,9–12,25 A 25% reduction in the readmission rate (ie, from 23.6% to 17.7%) could result in approximately 50,000 fewer readmissions annually. Incentives for hospitals to reduce readmission rates are currently limited. In fact, hospitals that reduce readmissions could lower their Medicare revenues. Even institutions that participated in studies of successful interventions to reduce readmission often abandoned them soon after the study was over.26 Measuring readmission could promote sustained efforts to reduce readmission rates.

This model is consistent with the American Heart Association standards for models suitable for public reporting of outcomes in that it is transparent, excludes potential complications, uses an analysis appropriate for the organization of the data, and is validated against clinical data.15 It is patient oriented in that it includes readmissions to any acute care hospital, not just the discharging hospital, and minimizes the incentives for gaming readmission etiology as being unrelated to the index heart failure hospitalization. Inpatient and outpatient comorbidity information from the year before the index hospitalization captures the patients’ clinical conditions. The hierarchical model takes into account the structure of the data, with discharges clustered within hospitals, isolates variations due to quality differences, and accommodates hospitals with small volumes by appropriately reflecting their limited data in the estimates.
The agreement between the estimates from the claims model and from the medical record model suggests that despite the known limitations of administrative codes, the proposed model can stand in place of a model with more detailed clinical information for hospital-level profiling. The AUC and the explained variation of the model are modest, but the use of the model is to profile hospital performance on the basis of patient status at admission, not to develop a model with the best ability to predict outcomes for individual patients. In addition, the performance at the patient level is consistent with previously published models developed to predict readmission after a heart failure hospitalization, which also show modest c statistics for models based on administrative27 and medical record28 data. Furthermore, we excluded covariates that we would not want to adjust for in a quality measure, such as potential complications, patient race and socioeconomic status, and discharge disposition (eg, discharge to a skilled nursing facility). These characteristics may be associated with readmission and thus could increase the model performance to predict patient readmissions.13,29 However, they may reflect quality or system factors that should not be included in an adjustment that seeks to control for patient clinical characteristics while illuminating important quality differences.

Discrimination is lower in the heart failure readmission administrative and medical record models than in the heart failure mortality models.17 The risk of readmission may be much more dependent on the quality-of-care and system
characteristics than on patient severity and comorbidity characteristics. The readiness for discharge, the proper medications, and the proper transition to the outpatient setting may be even more important for readmission than death. Intervention studies underscore this potential, finding substantial decreases in readmissions.5–7,9–12,25 Furthermore, some heart failure admissions may be discretionary, with higher rates in geographic areas with a greater supply of hospital beds.29

The approach has several limitations. The approach to calculating risk-standardized readmission rates is only validated with Medicare data. However, 75% of the patients hospitalized with heart failure are ≥65 years of age.30 In addition, we were unable to test the model with a Medicare managed care population because data are not currently available on those patients. Furthermore, the chart validation was conducted by state-level analysis because sample size was insufficient for hospital-level analysis. In addition, our modeling approach does not account for within-patient correlation of multiple index heart failure hospitalizations per patient because of computational limitations. However, a relatively small share of patients (9.1%) had multiple index heart failure hospitalizations. Although it is important to include all admissions for these patients so that hospital efforts to reduce readmissions among patients with multiple heart failure hospitalizations are fully reflected in the measure, we may have overstated the precision of individual covariates’ association with the risk of readmission. Furthermore, although not every readmission may be preventable, the all-cause readmission outcome minimizes incentives for gaming and best captures outcomes that are important to patients and amenable to quality improvement because interventions have generally shown reductions in non–heart failure as well as heart failure readmissions.

Finally, our approach focuses on 30-day readmission and not death. If a patient died within 30 days after discharge without a readmission, we coded the outcome as no readmission. We recognize that this has the effect of counting such a death as a “no event” readmission outcome. In addition, such patients have a shorter length of follow-up during which they are eligible to experience the readmission outcome. This approach is thus intended to be used in conjunction with the publicly reported heart failure mortality measure to reflect performance on readmission and death. We believe that it is important to retain these admissions in the measure as opposed to excluding them because they provide a more complete picture of quality of care and resource use, including for individuals at the end of life. Despite the shorter average survival time of 14 days, the readmission rate was higher for these admissions, at 36.9%, compared with the readmission rate of 22.7% for admissions in which the patient survived the full 30 days. Another possible approach to handling the competing outcome of death is to use a composite outcome of readmission or death. However, we believe that it is important to show the outcomes separately because the factors that predict readmission and death may differ and because, from a quality improvement perspective, it would not be possible to assess whether hospital performance was driven by readmission rates or mortality rates if a combined outcome were utilized.

In conclusion, this article presents an instrument to produce hospital-specific risk-standardized estimates of 30-day readmission rates after discharge for heart failure. These estimates can bring to light a perspective on the health system’s performance and facilitate tracking of improvement over time.

### Table 5. Heart Failure Readmission Administrative Model and Medical Record Model Performance

<table>
<thead>
<tr>
<th>Model</th>
<th>n</th>
<th>Heart Failure Admissions With at Least 1 Readmission Within 30 Days</th>
<th>Overfitting Indices (Intercept, Slope)</th>
<th>Predictive Ability† (Lowest Decile, Highest Decile)</th>
<th>AUC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Medical record model derivation sample (NHF)</td>
<td>64 329</td>
<td>15 223</td>
<td>(0.1)</td>
<td>0.02</td>
<td>0.16–0.34</td>
</tr>
<tr>
<td>Linked administrative model validation sample</td>
<td>64 329</td>
<td>15 223</td>
<td>(0.1)</td>
<td>0.04</td>
<td>0.15–0.38</td>
</tr>
</tbody>
</table>

Between-state estimate for hierarchical generalized linear models medical record model, 0.022 (SE=0.005); hierarchical generalized linear models claims model, 0.017 (SE=0.004).

*Max-rescaled $R^2$.

†Observed rates.

![Figure 2](http://circoutcomes.ahajournals.org/). Comparison of the state-level risk-standardized readmission rates from the medical record and administrative models. Circles are weighted by the number of admissions. HGLM indicates hierarchical generalized linear model.
Acknowledgments

The authors thank Dima Turkmani, Maureen O’Brien, and Debra Chromik at the Colorado Foundation for Medical Care; Geoffrey Schreiner from the Center for Outcomes Research and Evaluation, Yale–New Haven Hospital; Angela Merrill and Eric Schone from Mathematica Policy Research; and Lein Han and Michael Rapp at CMS for their contributions to this work. CMS reviewed and approved the use of its data for this work and approved submission of the manuscript.

Sources of Funding

Drs Stauffer and Schuur were funded by the Department of Veterans Affairs during the time the work was conducted. The analyses on which this publication is based were performed under contract No. HHSM-500–2005-C0001C, entitled “Utilization and Quality Control Quality Improvement Organization for the State (Commonwealth) of Colorado,” funded by the CMS, an agency of the US Department of Health and Human Services. The content of this publication does not necessarily reflect the views or policies of the Department of Health and Human Services, nor does mention of trade names, commercial products, or organizations imply endorsement by the US government. The authors assume full responsibility for the accuracy and completeness of the ideas presented.

Disclosures

Dr Krumholz reports that he is a consultant to United Healthcare. Dr Normand reports that she is funded by the Massachusetts Department of Public Health to monitor the quality of care after cardiac surgery or percutaneous coronary intervention. The other authors report no conflicts.

References


Readmission soon after hospital discharge is an expensive and often preventable event for patients with heart failure. We present a model approved by the National Quality Forum for the purpose of public reporting of hospital-level readmission rates by the Centers for Medicare & Medicaid Services. We developed a hierarchical logistic regression model to calculate hospital risk-standardized 30-day all-cause readmission rates for patients hospitalized with heart failure. The model was derived with the use of Medicare claims data for a 2004 cohort and validated with the use of claims and medical record data. The unadjusted readmission rate was 23.6%. The final model included 37 variables, had discrimination ranging from 0.60. The 25th and 75th percentiles of the risk-standardized readmission rates across 4669 hospitals were 23.1% and 24.0%, respectively. State-level adjusted readmission rates developed with the use of the claims model are similar to rates produced by the CMS-HCC model. Health Care Financ Rev. 2004;25:119–141.

Deletion in proof.


An Administrative Claims Measure Suitable for Profiling Hospital Performance on the Basis of 30-Day All-Cause Readmission Rates Among Patients With Heart Failure


doi: 10.1161/CIRCOUTCOMES.108.802686

Circulation: Cardiovascular Quality and Outcomes is published by the American Heart Association, 7272 Greenville Avenue, Dallas, TX 75231
Copyright © 2008 American Heart Association, Inc. All rights reserved.
Print ISSN: 1941-7705. Online ISSN: 1941-7713

The online version of this article, along with updated information and services, is located on the World Wide Web at:
http://circoutcomes.ahajournals.org/content/1/1/29

Data Supplement (unedited) at:
http://circoutcomes.ahajournals.org/content/suppl/2008/09/24/1.1.29.DC1

Permissions: Requests for permissions to reproduce figures, tables, or portions of articles originally published in Circulation: Cardiovascular Quality and Outcomes can be obtained via RightsLink, a service of the Copyright Clearance Center, not the Editorial Office. Once the online version of the published article for which permission is being requested is located, click Request Permissions in the middle column of the Web page under Services. Further information about this process is available in the Permissions and Rights Question and Answer document.

Reprints: Information about reprints can be found online at:
http://www.lww.com/reprints

Subscriptions: Information about subscribing to Circulation: Cardiovascular Quality and Outcomes is online at:
http://circoutcomes.ahajournals.org//subscriptions/
Statistical Appendix

An administrative claims measure suitable for profiling hospital performance based on 30-day all-cause readmission rates among patients with heart failure

Patricia S. Keenan, PhD, MHS, Sharon-Lise T. Normand, PhD, Zhenqiu Lin, PhD, Elizabeth E. Drye, MD, SM, Kanchana R. Bhat, MPH, Joseph S. Ross, MD, MHS, Jeremiah D. Schuur, MD, MHS, Brett D. Stauffer, MD, Susannah M. Bernheim, MD, MHS, Andrew J. Epstein, PhD, MPP, Yongfei Wang, MSc, Jeph Herrin, PhD, Jersey Chen, MD, MPH, Jessica J. Federer, MPH, Jennifer A. Mattera, MPH, Yun Wang, PhD, Harlan M. Krumholz, MD, SM
Methods

Data

For administrative model derivation and validation for 2003 and 2004 cohorts, we used 2002-2005 claims data from the Medicare inpatient, outpatient, and carrier (physician) Standard Analytical Files (SAF). For example, for the 2004 cohort, we identified index hospitalizations using 2004 inpatient SAF data, then derived model candidate variables (risk factors within 1 year prior to index hospitalization) using 2003 and 2004 inpatient SAF data, outpatient SAF data, and carrier (physician) SAF data; and we derived readmissions using 2004 and 2005 inpatient SAF data.

Candidate variables

To identify candidate variables, 3 physicians (HMK, JDS, BDS) with experience in clinical medicine and epidemiology reviewed the 189 CC variables, excluded those deemed to be irrelevant (e.g., ectopic pregnancy) and combined related categories to produce 95 potential covariates for the model.

Model derivation

We evaluated candidate variables by estimating a logistic regression model with stepwise selection using an exit criterion of P value <0.001. We repeated this process 200 times by implementing a bootstrap re-sampling procedure. Each bootstrap sample was created by randomly selecting 283,919 index heart failure admissions with replacement from the derivation sample (n=283,919). We selected 200 samples to provide sufficient accuracy for determining variable inclusion in the final model. Over the 200 bootstrap samples we calculated the number of times that each candidate variable was selected into the model. A physician team (HMK, JSR, BDS, SMB, EED) selected risk-adjustment variables for the final model based on their statistical association (based on the frequency of times
the candidate variable was selected via the stepwise procedure) with and clinical relevance
to readmission, with reference to prior research examining predictors of readmission.22

**Risk-standardized readmission rate**

We estimated models using hierarchical generalized linear models (HGLM)24 in order
to address 3 specific features of the data: (1) patients are clustered within hospitals; (2) the
number of admissions vary across hospitals; and (3) our “experimental” unit (or unit of
main interest) is the hospital. We modeled the log-odds of readmission within 30 days of an
index hospitalization as a function of the selected variables in the best-performing model
determined above, and a random hospital-specific intercept. The hospital-specific intercepts
were assumed to arise from a Normal distribution reflecting our assumption that some
hospitals’ baseline risks could be larger than the national average and some baseline risk
could be below the national average. The variance of this Normal distribution provides a
quantitative estimate of the between-hospital variation in the sample after accounting for
observed patient differences and sampling variability.

Risk-standardized hospital-specific readmission rates were calculated as the ratio of
the number of “predicted” to “expected” readmissions, multiplied by the national unadjusted
rate. Operationally, we obtained the expected number of readmissions for each hospital by
regressing the risk factors on readmission using all hospitals in our sample, applying the
subsequent estimated regression coefficients to the patient characteristics observed in the
hospital, adding the average of the hospital-specific intercepts, and after transformation,
summing over all patients in the hospital to get a count. The predicted number of
readmissions (technically called a shrinkage estimate) is calculated by adding the hospital-
specific intercept, representing baseline readmission risk, to the sum of the estimated
regression coefficients applied to the patient characteristics in the hospital, and after
transformation, summing over all patients in the hospital.
Model Validation

Medical record model validation. A separate medical record model of readmission risk using NHF data was developed. A physician team (HMK, JDS) selected covariates for the medical record model based on the medical literature, clinical experience, and statistical association with readmission using the same modified approach to stepwise logistic regression used for the administrative model and computed similar measures of model fit and discrimination. Unlike the administrative claims data, some covariates could be missing for patients in this sample. This typically occurred for measurements based on laboratory or diagnostic tests that were not conducted. In such cases, we categorized continuous variables into categories using the clinically meaningful cut points and added a category for missing values where applicable. For discrete-valued variables, we included an additional category that indicated if the variable was missing. This method of modeling missing data assumes data are missing at random and permits inclusion of all available hospitalizations. It does have the limitation of understating the standard error associated with covariates with missing data. The share with 1 or more covariates missing is 7% excluding left ventricular ejection fraction (LVEF), 8.6% including those with LVEF measured but missing, and increases to 40% including all with LVEF unknown (including unmeasured and measured yet missing). We retained LVEF due to its clinical importance, although including LVEF as a covariate does not appreciably change the AUC of the medical record model or the results of the comparison of medical record and claims model results.