Readmission to the hospital within 30 days of discharge occurs for almost one fifth of Medicare beneficiaries and costs the Centers for Medicare & Medicaid Services (CMS) $26 billion annually (1). One contributor to readmissions is the quality of the transition from hospital to home, which is often inadequate (2–5). Improvements in transitional care have been shown to reduce readmission rates (6–8). Consequently, hospital readmissions have become a key metric for efforts to promote innovations in health care that improve the quality and value of care across settings (9–11).

Rigorous development of a measure that can be used for hospital performance profiling, focused on hospital readmission rates for a broad spectrum of patients, is necessary to support these healthcare innovations. The median hospital risk-standardized unplanned readmission rate was 15.8 (range, 11.6 to 21.9). The 5 specialty cohort models accurately predicted readmission risk in both Medicare and all-payer data sets for average-risk patients but slightly overestimated readmission risk at the extremes. Overall hospital risk-standardized readmission rates did not differ statistically in the split samples ($P = 0.71$ for difference in rank), and 76% of hospitals’ validation-set rankings were within 2 deciles of the development rank (24% were more than 2 deciles). Of hospitals ranking in the top or bottom deciles, 90% remained within 2 deciles (10% were more than 2 deciles) and 82% remained within 1 decile (18% were more than 1 decile).

Limitation: Risk adjustment was limited to that available in claims data.

Conclusion: A claims-based, hospital-wide unplanned readmission measure for profiling hospitals produced reasonably consistent results in different data sets and was similarly calibrated in both Medicare and all-payer data.
wide practices or target different high-risk patients. Single-condition measures may limit hospitals’ abilities to broadly engage physicians, staff, and community members in readmission reduction efforts.

Finally, many hospitals care for few patients with each condition, necessitating multiple years of data to produce stable hospital rankings. This reduces timelines. Thus, it is important to measure all-condition readmission rates in order to capture the majority of hospitalized patients, encourage a focus on high-risk patients regardless of condition, and incentivize system- and community-wide quality improvements.

Constructing an all-condition readmission measure for profiling performance presents several challenges. The measure must account for the diversity of conditions and procedures at different hospitals, to provide a fair assessment of relative hospital performance. It must balance inclusivity (encompassing a wide range of patients) with usability (providing information that hospitals can act upon). A readmission measure should also exclude planned readmissions.

We describe the development of a claims-based, risk-standardized hospital-wide readmission measure that is innovative in several important respects: It includes the great majority of adult inpatients, accounts for diverse conditions and their prevalence at different institutions, excludes planned readmissions, and is a composite of 5 specialty cohort models to make the measure more informative to hospitals. This measure has been endorsed by the National Quality Forum for quality measurement and is publicly reported by CMS (17, 18).

**METHODS**

The Yale University Investigational Review Board approved this study.

**Data Sources**

We developed the measure under contract to CMS by using hospitalizations in Medicare fee-for-service (FFS) Part A claims data. We obtained enrollment and postdischarge mortality status from the Medicare Denominator File. We developed the measure using a random half of the 2007–2008 combined Medicare Provider Analysis and Review (MedPAR) data, and validated the measure using 3 data sets: the second half of the 2007–2008 sample, the 2009 MedPAR data, and 2006 California Patient Discharge data. For each data set, we used 1 prior year of inpatient data for risk adjustment.

**Eligibility Criteria**

Qualifying index admissions must have met the following criteria: The patient was admitted to a short-term acute care or critical access hospital, survived hospitalization, was aged 65 years or older at discharge (≥18 years when applied to the general adult population), and was discharged home or to a non–short-term acute hospital setting. Multiple admissions for the same patient were included.

We excluded admissions for patients without at least 30 days of postdischarge enrollment in Medicare FFS (necessary for determining the outcome), admissions for patients not continuously enrolled in Medicare FFS during the 12 months before admission (necessary for risk adjustment), patients discharged against medical advice (because the hospital did not have the opportunity to provide optimal care), admissions to prospective payment system–exempt cancer hospitals (because Medicare has deemed these hospitals not comparable with other institutions), admissions for medical treatment of cancer (because of high competing mortality rates; see Data Supplement 1, available at www.annals.org), and admissions for rehabilitation care. We did not exclude eligible readmissions from serving as index admissions.

**Rationale for the Measure Architecture**

To optimize measure design, we explored trade-offs between estimating risk-standardized rates for one hospital-wide cohort versus a composite measure score of rates for subgroups of patients. One model including all admissions would not be very informative for hospital improvement and would not account for differences in the influence of risk variables across different conditions. However, hospitals did not have sufficient numbers of admissions to support separate models for all conditions. To reconcile these tensions, we tested but rejected an approach of defining 20 to 30 cohorts by using clustering algorithms to group conditions with similar risk variable–outcome relationships; the resulting cohorts were clinically incoherent and sample sizes still small.

Instead, we identified 5 cohorts organized according to service lines that were made up of conditions or procedures with relatively similar readmission and postdischarge mortality rates, were likely to be cared for by similar teams of clinicians, and would generate an adequate sample size for most hospitals. These cohorts were medicine, surgery/gynecology, cardiorespiratory, cardiovascular, and neurology. Cardiorespiratory patients (e.g., heart failure, pneumonia, chronic obstructive pulmonary disease, asthma) were separated from the medicine cohort because they are clinically very similar and have the highest volume and readmission rates. This approach allowed for differential risk adjustment; enabled sufficient sample size for most cohorts at most hospitals; and produced clinically relevant, specialty-specific results, as well as a composite measure score.

To assign admissions to cohorts, we first used the Agency for Healthcare Research and Quality 2009 Clinical Classifications Software (19) to group all International Classification of Diseases, ninth edition (ICD-9)—based principal discharge diagnoses into 1 of 285 mutually exclusive condition categories, and all ICD-9—based procedure codes into 1 of 231 mutually exclusive procedure category.
ries. Next, we identified all procedure categories that would typically result in a patient being cared for by a surgical or gynecologic service (Data Supplement 2, available at www.annals.org), and assigned all admissions that included one of these procedure categories to the surgery/gynecology specialty cohort. We assigned each remaining admission to 1 of the other 4 cohorts on the basis of its principal discharge diagnosis, grouped by condition category (Data Supplement 3, available at www.annals.org).

Outcome

The outcome was all-cause unplanned readmission to any hospital within 30 days of discharge. Because there is no code on administrative claims for identifying planned readmissions, we constructed an algorithm and refined it on the basis of input from 27 clinical experts recommended by 15 specialty societies, and from 3 public comment periods (Data Supplement 4, available at www.annals.org). We defined planned readmissions as either 1) readmissions for a few specific condition or procedure categories (chemotherapy/radiation therapy, organ transplant, rehabilitation, obstetric delivery) or 2) readmissions in which any of a list of typically planned procedures occurred, and in which the principal diagnosis was not an acute condition or a complication of care. Readmissions not meeting either criterion were categorized as unplanned.

Risk Adjustment

We adjusted for both comorbid conditions and principal diagnosis. To define comorbid risk adjustment variables, we grouped ICD-9 codes into 189 CMS condition categories (20) and defined a risk variable as present if it was coded in any inpatient claim in the 12 months before admission or as a secondary diagnosis in the index admission. For practical purposes of data processing, we elected not to include outpatient claims data. To avoid adjusting for potential complications as comorbid conditions, we did not code certain CMS condition categories as risk factors if they only appeared as secondary diagnosis codes in the index admission (Data Supplement 5, available at www.annals.org).

We began with a set of 41 variables that made up 74 CMS condition categories, based on importance in existing risk-standardized readmission models (12–14) or on clinical relevance to an all-condition measure. We ran a separate logistic regression model for each condition category, using the full set of candidate risk-adjustment variables, and examined odds ratios for readmission for each variable across the different condition models. We excluded risk variables that were rarely statistically significant, and those that were not performing consistent with clinical expectations. We then combined risk variables that were clinically coherent and carried similar risks across condition categories.

We also created indicator variables for each discharge condition category with at least 1000 admissions yearly. All conditions with fewer than 1000 admissions in a given specialty cohort were grouped into a single “low-frequency” indicator variable. When using the California validation set, we respecified the conditions belonging to the low-frequency condition groups.

Measure Calculation

Using PROC GLIMMIX, we estimated a separate mixed-effects logistic regression model with hospital as a random intercept for each of the 5 cohorts and used the results to calculate the predicted and expected numbers of readmissions at each hospital (21, 22). The predicted number of readmissions in each cohort was calculated as the sum of the predicted probability of readmission for all admissions, estimated using each hospital’s patient mix and a hospital-specific effect estimated for each hospital. The hospital-specific effect, also called the empirical Bayes estimator, is an estimate of each hospital’s outcome rate; this estimate is stabilized, or “shrunk,” by pooling the adjusted rate at that hospital with the adjusted rate for all hospitals. The pooling is weighted by volume, so low-volume hospitals are shifted toward the national mean more than high-volume hospitals (23).

The expected number of readmissions in each cohort for each hospital was similarly calculated as the sum of the predicted probability of readmission for all admissions, using each hospital’s patient mix and the average hospital-specific effect of all hospitals. We divided the predicted number of readmissions by the expected number of readmissions to obtain a standardized readmission ratio for each specialty cohort for each hospital (21). We determined the hospital-wide composite ratio by calculating the volume-weighted logarithmic mean of the 5 specialty cohort ratios. The logarithmic mean is the mathematically appropriate method of averaging ratios (24). Specialty cohorts with no eligible admissions at a hospital were not included in the hospital’s composite.

To aid in interpretation, we multiplied the composite standardized ratios by the national observed readmission rate to produce the hospital-wide RSRR. We used bootstrapping to derive an interval estimate for the final rates for each hospital (25–28) (Data Supplement 6, available at www.annals.org).

Statistical Analysis

To assess the discrimination of the models, we constructed calibration curves plotting observed and predicted readmission rates for patients in each decile of predicted probability on the basis of ordinary logistic regression models without hospital random effects, and assessed the degree of overlap (29).

Reliability is defined by the National Quality Forum as the extent to which the measure produces consistent results (30). To assess reliability of model parameters, we compared regression coefficients and SEs of risk variables in each specialty cohort model between the development sample and each of the 3 validation sets. To assess the consistency of the composite hospital-wide measure, we
The 2 within-hospital rates against the average of the 2 within-hospital rates (32). Data on model c-statistics, correlation of specialty ratios with each other, and internal consistency of the composite rate appear in the technical report (18).

We used SAS software, version 9.2 (SAS Institute), for analyses.

**Role of the Funding Source**

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**RESULTS**

**Study Cohort**

The development data set included 8 018 949 discharges from 4821 hospitals (approximately 93% of all Medicare FFS acute care hospitalizations of patients aged ≥65 years). Figure 1 shows 2008 data. The mean age of the cohort was 78 years, with 58.2% women and 13.3% nonwhite patients. The median annual hospital volume of index admissions was 702 (interquartile range, 239 to 2246).

Specialty cohort volume ranged from 464 776 (neurology) to 3 157 943 (medicine) (Table 1). A total of 83.1% of hospitals accounting for 98.6% of admissions had at least 1 index admission in all 5 specialty cohorts.

The data set included 1 276 165 (90.8%) unplanned and 129 436 (9.2%) planned readmissions, for an overall unplanned 30-day readmission rate of 15.9%, ranging from a minimum of 11.8% (surgery/gynecology) to a maximum of 20.7% (cardiorespiratory). In 3.9% of admissions, the patient died after discharge without being readmitted. The median RSRR was 15.8% (range, 11.6 to 21.9). Table 2 shows the distributions of rates.

### Table 1. Admissions, Readmissions, and Mortality for the 5 Cohorts (2007–2008 Data Set)

<table>
<thead>
<tr>
<th>Specialty Cohort</th>
<th>Admissions, n</th>
<th>30-d Unplanned Readmissions, n</th>
<th>30-d Unplanned Readmission Rate, %*</th>
<th>30-d Postdischarge Mortality Without Readmission, n</th>
<th>30-d Postdischarge Mortality Rate Without Readmission, %†</th>
<th>Planned Readmissions, n</th>
<th>Unadjusted Planned 30-Day Readmission Rate, %‡</th>
<th>Proportion of All Readmissions That Are Planned, %§</th>
</tr>
</thead>
<tbody>
<tr>
<td>Medicine</td>
<td>3 157 943</td>
<td>549 345</td>
<td>17.4</td>
<td>154 855</td>
<td>4.9</td>
<td>51 408</td>
<td>1.6</td>
<td>8.6</td>
</tr>
<tr>
<td>Surgery/gynecology</td>
<td>1 889 282</td>
<td>223 071</td>
<td>11.8</td>
<td>32 875</td>
<td>1.7</td>
<td>22 269</td>
<td>1.2</td>
<td>9.1</td>
</tr>
<tr>
<td>Cardiorespiratory</td>
<td>1 413 209</td>
<td>292 606</td>
<td>20.7</td>
<td>74 753</td>
<td>5.3</td>
<td>14 347</td>
<td>1.0</td>
<td>4.7</td>
</tr>
<tr>
<td>Cardiovascular</td>
<td>1 093 739</td>
<td>145 201</td>
<td>13.3</td>
<td>23 568</td>
<td>2.2</td>
<td>35 367</td>
<td>3.2</td>
<td>19.6</td>
</tr>
<tr>
<td>Neurology</td>
<td>464 776</td>
<td>65 942</td>
<td>14.2</td>
<td>29 986</td>
<td>6.5</td>
<td>5995</td>
<td>1.3</td>
<td>8.3</td>
</tr>
<tr>
<td>Total</td>
<td>8 018 949</td>
<td>1 276 165</td>
<td>15.9</td>
<td>316 037</td>
<td>3.9</td>
<td>129 436</td>
<td>1.6</td>
<td>9.2</td>
</tr>
</tbody>
</table>

* 30-d unplanned readmissions divided by total admissions.
† 30-d postdischarge mortality without readmission divided by total admissions.
‡ Planned readmissions divided by total admissions.
§ Planned readmissions divided by 30-d unplanned readmissions.
### Table 2. Hospital-Level Unadjusted and Risk-Standardized Readmission Rates (Development Data Set)

<table>
<thead>
<tr>
<th>Cohort</th>
<th>Readmissions, n</th>
<th>Unadjusted Mean Readmission Rate (SD)</th>
<th>Unadjusted Median Readmission Rate (IQR)</th>
<th>Mean RSRR (SD)</th>
<th>Median RSRR (IQR)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Medicine</td>
<td>4942</td>
<td>16.4 (6.5)</td>
<td>16.4 (13.9, 18.8)</td>
<td>17.5 (1.6)</td>
<td>17.3 (16.5, 18.3)</td>
</tr>
<tr>
<td>Surgery/gynecology</td>
<td>4343</td>
<td>11.7 (9.3)</td>
<td>11.1 (8.1, 14.1)</td>
<td>11.8 (1.0)</td>
<td>11.8 (11.3, 12.3)</td>
</tr>
<tr>
<td>Cardiovascular</td>
<td>4711</td>
<td>14.2 (8.4)</td>
<td>13.5 (10.5, 17.1)</td>
<td>13.3 (0.8)</td>
<td>13.3 (12.9, 13.7)</td>
</tr>
<tr>
<td>Cardiorespiratory</td>
<td>4808</td>
<td>19.4 (6.9)</td>
<td>19.5 (16.1, 22.7)</td>
<td>20.8 (1.7)</td>
<td>20.6 (19.7, 21.7)</td>
</tr>
<tr>
<td>Neurology</td>
<td>4691</td>
<td>13.7 (10.3)</td>
<td>13.1 (9.1, 17.1)</td>
<td>14.2 (1.0)</td>
<td>14.1 (13.7, 14.6)</td>
</tr>
<tr>
<td>Hospital-wide</td>
<td>4997</td>
<td>15.6 (5.6)</td>
<td>15.5 (13.2, 18.0)</td>
<td>15.9 (1.1)</td>
<td>15.8 (15.2, 16.4)</td>
</tr>
</tbody>
</table>

IQR = interquartile range; RSRR = risk-standardized readmission rate.

### Measure Performance

The final 31 comorbidity variables are listed in [Supplement 7](#). Parameter estimates varied in magnitude but not direction across specialty cohorts ([Data Supplements 8 to 12](#), available at www.annals.org).

Model calibration plots for the 2007–2008 Medicare split-sample development data set, the 2009 Medicare data set, and the 2006 California all-payer data set are shown in Figure 2. This figure shows that at the patient level, the models slightly overestimate readmission risk at the highest and lowest risks. Figure 2 also demonstrates consistent calibration of the models in 2009 Medicare data and in all-payer data. The RSRR rank for each hospital did not significantly differ between the 2007–2008 derivation and validation sets ($P = 0.71$).

When ranked by standardized readmission rate, 76% of hospitals shifted 2 deciles or less between development and validation sets; put another way, 24% shifted by more than 2 deciles. Model performance was most stable at the extremes: 90% of hospitals starting in the top or bottom deciles in the derivation set shifted by 2 deciles or less in the validation set (10% shifted more than 2 deciles), and 82% shifted 1 decile or less (18% shifted more than 1 decile). The difference in standardized rates between the 9th and 10th deciles is 1.2 percentage points, compared with a difference of 0.63 percentage point between the central 4th and 7th deciles.

Figure 3 cross-classifies the within-hospital differences in RSRRs between the derivation and validation sets against the within-hospital means. Ninety-five percent of hospitals have a difference of less than 1.4 percentage points, and outlier differences are nearly all among hospitals of average performance, indicated by the 2 vertical 95% CI lines. Hospitals falling in or near areas I, III, VII, and IX are those with extreme rates that varied more than average between the data sets.

### Discussion

We developed a hospital-wide, 30-day unplanned readmission measure that is risk-standardized to account for differences in comorbidity and in the distribution of diagnoses within each hospital, and can be used to measure hospital performance. It had reasonable split-sample consistency in Medicare data and performed well in subsequent years of data, as well as in the full adult (aged ≥18 years) patient population.

The measure broadens the scope of readmission outcome measurement from a minority of primarily medical patients to the vast majority of a hospital’s patients, including those cared for by surgeons, neurologists, gynecologists, and others, thus providing a more comprehensive view of readmissions. Unlike other all-condition readmission measures, it excludes planned readmissions and is composed of multiple clinically distinct rates to increase usability. In addition, the measure conforms to standards for publicly reported outcome measures ([33](#)). The CMS began publicly reporting this measure in December 2013.

The simultaneous all-condition and specialty-specific nature of this measure makes it particularly suitable for helping institutions identify areas needing improvement. The hospital-wide rates apply to over 90% of admissions, making the measure broadly applicable. This global rate can be publicly reported and benchmarked against national averages, enabling patients, payers, and clinicians to select hospitals on the basis of results and incentivizing poorly performing hospitals to improve ([34–36](#)). In addition, the measure produces specialty-specific rates that can be provided to hospitals confidentially to help them identify care teams or patient populations for particular focus. In this way, the measure takes a unique approach of providing both an overall incentive for change and more specific data to target change efforts.

An additional novel feature of this measure is the planned readmission algorithm, vetted through extensive expert consultations and public comment ([37](#)), which enabled us to exclude planned readmissions. Some measures have attempted to count only readmissions that are “preventable” or “related to” the index admission, on the assumption that any “unrelated” readmission is necessarily unpreventable ([38–40](#)). However, “unrelated” readmissions may be consequences of stressors during hospitalization ([41](#)) or low quality of care provided during the index admission ([3](#)); conversely, some “related” readmissions are unavoidable, owing to natural progression of disease. Furthermore, there is little evidence to suggest that relatedness can reliably be determined, even with detailed chart review ([42, 43](#)).
Figure 2. Calibration plots, by cohort, for development data set (2007–2008 split sample), Medicare 2009 data, and California 2006 all-payer data.

Boxes represent predicted probability, and diamonds represent observed predictability.
As such, it may catalyze improvement activities and can be
none use models appropriate for clustered data as recom-
Nearly all of the other measures use risk adjustment, but
Some measures exclude planned readmissions (44, 45, 47).
ours, also exclude patients admitted for cancer treatment
frame. Some include virtually all patients (45) and others
should be similar across hospitals given similar care quality,
sumes that the proportion of unavoidable readmissions
patients will unavoidably be readmitted. The measure as-
edge that the ideal readmission rate is not zero; many pa-
theses; of these, 3 have been used in the United States
in this area.
established and will be an important focus for future work
replicated by individual hospitals, which lack access to na-
tional data. It was not designed to track internal improve-
ments (for which risk standardization against national data
nor as a tool to predict individual patient readmission risk.
We deliberately did not include such covariates as race,
income, previous admission, complications during hospi-
talization, or length of stay, even though they may improve
variation in the outcome due to hospital practice that the
measure is intended to capture. We did not want to adjust
For example, adjustment for complications would perversely give
credit to hospitals with more readmissions caused by com-
lications of care. We did not adjust for previous admis-
sion because repeated admissions may be an indicator of
failed transitions, inadequate attention to goals of care, or
other gaps in hospital- and community-level care. Adjust-
ment for race or income might obscure differences in care
provided to these patients. Notably, only 1 of the 8 other
all-condition readmission measures includes race as a cova-
rariate (47), and none includes income, education, previous
admission, or length of stay.
When benchmarking hospitals, it is important to en-
sure that results are reproducible and not unduly subject to
random differences in patient mix, variation in measure-
ment or patient coding, or unexplained random variation.
We found no statistical difference in rank-ordering of hos-
pitals between randomly split development and validation
sets, and three quarters of hospitals moved fewer than 3
deciles between the development and validation data sets.
Nonetheless, 24% of hospitals moved 3 deciles or more.
In this regard, it is important to consider the limita-
tions of a rank-order analysis. First, moves among middle
deciles are small and may not be as clinically meaningful as
moves in extreme deciles. Moves among middle deciles
occurred more frequently than among outlier deciles. We
found that outlier ranks were more consistent, with 90% of
hospitals in the top or bottom deciles remaining in the top
or bottom 3 deciles in the validation set. These findings
should be considered in using the measure score in profil-
ing. In addition, the number of hospitals changing ranks
depends on the number of ranks selected; we chose a con-
servative decile approach. Furthermore, because deciles are
divided on the basis of single points on a continuous scale,
hospitals close to the dividing lines will naturally move
decile ranks even with virtually identical results. Most im-
portant, a simple rank order ignores sampling error because
it does not incorporate CIs. For these reasons, the measure
is publicly reported on the basis of statistical outlier status,
not ranks. The stability of outlier status has not yet been
established and will be an important focus for future work
in this area.
Our measure has several limitations. First, there is no
gold standard against which to compare this measure to

Instead, we counted all readmissions except those that
were likely to have been planned. In doing so, we acknowl-
edge that the ideal readmission rate is not zero; many pa-
tients will unavoidably be readmitted. The measure as-
sumes that the proportion of unavoidable readmissions
should be similar across hospitals given similar care quality,
one case mix and principal diagnoses are accounted for.
Excluding planned readmissions from the measure creates
an opportunity for gaming; however, because the planned
readmissions are largely identified through procedures that
are performed during the readmission, we anticipate that
the opportunity for gaming will be limited. The CMS con-
ducts routine surveillance for evidence of unintended con-
sequences, and if necessary, measure specifications can be
altered in response.
We have identified 8 other all-condition readmission
measures; of these, 3 have been used in the United States
or Canada, though none currently on a national scale (38–
40, 44–50). All but 2 use a similar 28- or 30-day time
frame. Some include virtually all patients (45) and others
include only a narrow spectrum (40), but all exclude trans-
fers to acute settings and hospitalizations in which the pa-
tient died, as does this measure. Three of the measures, like
ours, also exclude patients admitted for cancer treatment
and those who left against medical advice (39, 40, 47).
Some measures exclude planned readmissions (44, 45, 47).
Nearly all of the other measures use risk adjustment, but
none use models appropriate for clustered data as recom-
manded by outcome measure guidelines (33, 51).
This measure was designed to profile hospital quality
by benchmarking hospitals against national performance.
As such, it may catalyze improvement activities and can be
used to track national trends over time, but it cannot be
replicated by individual hospitals, which lack access to na-
tional data. It was not designed to track internal improve-
ments (for which risk standardization against national data
is not necessary), nor as a tool to predict individual patient
readmission risk.

Figure 3. Difference between the development and
validation RSRRs, plotted against the average of the two.
Horizontal and vertical lines show the bounds of 95% of the hospitals.
The center box is area V. Hospitals in or near areas I, III, VII, and IX
had extreme rates that tended to vary substantially between the 2 data
sets. RSRR = risk-standardized readmission rate.
assess validity. Second, it is based on administrative data, which are known to contain errors and do not include specific information on disease severity. However, claims data are more complete and easily obtained than chart data, and prior readmission measures based on claims data were shown to have good agreement with measures based on chart data (25–27).

Third, the measure has only fair patient-level predictive capacity, although our assessment of patient-level discrimination may be hampered by clustering within hospitals. Fourth, using a 1-year look-back for comorbid conditions may artificially make patients at high-intensity hospitals appear sicker (53); on the other hand, using only comorbid conditions identified during the index admission would undercount risk for truly sicker patients.

Fifth, planned readmissions are not explicitly flagged in administrative data, requiring us to develop an algorithm to identify them. Although it is not possible to perfectly identify planned readmissions by using claims data, we used input from many surgical experts and the public to improve the algorithm and adequately trade off precision versus usability. Sixth, competing mortality is always a concern in readmission measures, although we minimized this risk by excluding conditions with the highest competing mortality.

Finally, readmission risk is also influenced by community factors, such as access to care, local practice patterns, and sociodemographic characteristics. Therefore, this measure should be considered in conjunction with complementary measures, such as community-level admission and readmission rates, and mortality. Nonetheless, it will remain critically important to measure hospital performance both to identify problems and to catalyze hospital-community partnerships.

In conclusion, our measure reports RSRRs for over 90% of admissions to acute care hospitals. It performs well in both Medicare and all-payer data and has reasonably stable performance over time. The structure of the measure, which includes separate models for specialty cohorts, increases its usability for hospital quality improvement while still producing summary results for consumers. Ultimately, the utility of the measure will depend on the degree to which hospitals and communities can work together to reduce unnecessary hospital readmission.

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Note: Dr. Lin had full access to all of the data in the study and takes responsibility for the integrity of the data and the accuracy of the data analysis.

Disclaimer: The content is solely the responsibility of the authors and does not necessarily represent the official views or policies of the U.S. Department of Health and Human Services, the National Institute on Aging, the National Heart, Lung, and Blood Institute, or the American Federation for Aging Research.

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