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Methods for Producing Risk-Adjusted, Combined Hospital Admission and Readmission Rates across Post–Acute Care Settings

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Methods for Producing Risk-Adjusted, Combined Hospital Admission and Readmission Rates across Post–Acute Care Settings

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In this brief report, we describe the data and methods used for the Risk-Adjusted, Combined Hospital Admission and Readmission Rates across Post–Acute Care (PAC) Settings project. Hospitalizations are outcomes that are disruptive for patients and caregivers, costly to the health care system, and put patients at additional risk of hospital-acquired infections and complications. Hospitalizations are a major source of patient and family stress and can contribute substantially to loss of functional ability, particularly in older patients.

The project goal is to create uniform, risk-adjusted measures of hospital admissions and readmissions during and after post–acute care, and to use those specifications to calculate provider-level hospitalization rates to assess PAC provider performance. The measure results are based on data from 2015 through 2017 for stays of traditional Medicare adult patients in four PAC settings (home health, skilled nursing facilities, inpatient rehabilitation facilities, and long-term care facilities).

The Centers for Medicare & Medicaid Services (CMS) has developed uniform post-stay readmission measures for PAC providers, but the within-stay measures vary across settings. For home health, the during-stay measure ignores initial admissions to hospitals, even though the majority of home health users are admitted directly from the community. None of the measures consider acute care hospital observation stays, which from the beneficiary's perspective can appear to be an admission. Consistent with its goal to hold PAC providers accountable for their patient outcomes and care they provide "in their walls," the Medicare Payment Advisory Commission (MedPAC) is interested in producing hospitalization-outcome measures that would include hospital observation stays and be uniform across PAC settings for both within- and post-stay measures.

Working with MedPAC staff, we developed eight risk-adjusted hospitalization rates (four all-cause hospitalizations and four avoidable hospitalization measures) defined by whether the hospitalization is measured (1) during or following the stay and (2) over the first 14 days or all of the observation period. The measures use identical definitions of stays to calculate the rates, and a risk-adjustment method that is uniform across the four PAC settings. The measures can be used in a value-based payment system applicable to all PAC providers to align quality improvement incentives. The measures may also allow for direct comparisons of all PAC providers once practice patterns (e.g., length of stay) begin to converge under a unified PAC prospective payment system. We adjusted for differences across providers in their mix of cases using a fixed-effects logit regression model, in which we measure each provider's effect on the probability of hospitalization, controlling for characteristics of the patient and patient condition measured at and before the PAC stay.

Data

We calculate the rates at which adult Medicare fee-for-service patients in PAC facilities are hospitalized during their PAC stay and the subsequent month. The analysis is based on PAC stays beginning between January 2015 and December 2017. The data are from the PAC stay, acute hospital stays, outpatient visits, and hospice claims from the Standard Analytical Files, as well as the Common Medicare Environment enrollment database. Staff at Acumen LLC constructed data files with the subset of variables needed for this work. We use three years of data to increase the number of observations for low-volume providers.

We use PAC claims from the Standard Analytical File to define the beginning and end of PAC stays. In general, the start and discharge dates are used to define when the stay occurred. For PAC stays without a discharge or discharge date (e.g., some skilled nursing facility stays), we use the end date of the last observed claim. We combine back-to-back skilled nursing facility (SNF) claims and back-to-back episodes for home health to form single SNF and HH stays.

To determine whether a hospitalization occurred, we rely on dates from acute hospital and outpatient observation stays, comparing the dates of each PAC stay with the dates of the patient's acute hospital and outpatient observation stays. We use diagnoses from the acute hospital and outpatient stay claims associated with the PAC stay to determine whether these hospitalizations are categorized as avoidable, as we describe more fully below.

Measures of patient condition are based largely on diagnoses reported on the claims from the PAC stay and the most recent acute hospital stay that occurred within 30 days of the start of the PAC stay. With these data, we construct measures of primary reason for treatment, severity of illness, comorbidities, and other patient conditions (see the section on controls for the case mix below). We then supplement these data with demographic and monthly enrollment information from the Common Medicare Environment enrollment database, including birth and death dates, original reason for entitlement, and monthly indicators of whether in a managed-care organization (i.e., Medicare Advantage).

Finally, we use hospice claims to exclude patients in hospice during a PAC stay or the month following discharge.

Definition of Raw Hospitalization Rates

The raw hospitalization rate for a provider is the share of eligible stays resulting in an acute-care hospitalization. We calculate eight measures of hospitalization that vary in their timing (within and following PAC stay; a shorter and longer measurement window) and type of hospitalization (all-cause or avoidable admissions). Hospitalizations include both full hospitalizations and observation stays. We calculate four measures of hospitalization during the PAC stay and four measures within the month following discharge:

Hospitalization during PAC:

- within first 14 days of stay – all-cause
- within first 14 days of stay – avoidable
- within the stay – all-cause
- within the stay – avoidable

Hospitalization following discharge, among those not hospitalized during PAC stay:

- within 14 days – all-cause
- within 14 days – avoidable
- within 30 days – all-cause
- within 30 days – avoidable

We include a measure of hospitalization within the first 14 days of the PAC stay to standardize for differences in length of stay across PAC settings that would likely affect the rates. Though measuring hospitalization over the entire PAC stay will indicate the events that occurred while the beneficiary was directly under the provider's care, it will also result in differences in rates that partly reflect differences in length of stay in the various settings. Restricting to the first 14 days of the stay allows us to assess whether rates vary across settings over a consistent time frame.

The measures of hospitalization within the stay include hospitalizations or observation stays that occur by day 100 of institutional stays or day 120 of home health episodes. Estimates are based on three years of data to increase the share of facilities with enough stays to obtain sufficiently reliable estimates.

As noted, the measures of hospitalization during PAC are based on stays in PAC settings beginning January 2015 through December 2017. PAC stays are for patients ages 18 and older with fee-for-service coverage for the entire calendar year. Stays must be in facilities in the United States, excluding the territories. We also exclude stays in swing beds for critical access and long-term hospitals, one-day

episodes, and beneficiaries discharged against medical advice (by calendar year), as well as PAC stays that overlap in ways indicating a data error. Finally, we also exclude those who died or used hospice during the PAC stay and those with nonsurgical cancer treatment.

Measures of post-PAC hospitalizations are based on the PAC stays used for the during-PAC measures, excluding patients who had a during-PAC hospitalization, patients discharged from PAC with a planned acute-care hospital stay, patients who die or are in hospice within 30 days of discharge, and patients who had a stay of more than 100 days of institutional care, of 120 days of home health, or with no record of discharge.

Defining All-Cause and Avoidable Hospitalizations

As discussed above, we measure hospitalizations from PAC settings in two ways: all-cause and avoidable. All-cause hospitalizations are comprehensive and include all hospital admissions for the eligible stays, regardless of the hospitalization's relationship to the PAC stay. To the extent possible, we exclude known, planned readmissions from the measures. In particular, for the within-PAC hospitalization measures, we exclude from the calculation patients receiving nonsurgical cancer treatment. For the post-PAC hospitalization measures, we exclude all patients discharged from the PAC setting with a planned acute-care hospitalization.

Avoidable hospitalizations are hospitalizations and observation stays that may have been avoided with appropriate post-acute and primary care meeting current standards of care and care coordination.[1] We sought to develop a uniform definition of avoidable hospitalizations that would allow for comparison of hospitalization rates for both post-acute and community-admitted Medicare beneficiaries across PAC settings, both within a stay and for the 30 days following a stay. We therefore focused on hospitalizations and observation stays that could reasonably be prevented at least some of the time across all settings, including home health care. Our definition is therefore more conservative in deeming conditions avoidable than are definitions of avoidable readmissions used in prior work. This is particularly true for prior measures of hospital readmissions from institutional post-acute care, such as CMS's measures of within-stay readmissions from inpatient rehabilitation facilities (IRFs) and SNFs.[2]

We define avoidable hospitalizations by primary diagnosis. To develop our list of diagnosis codes, we gathered lists of diagnoses considered avoidable in prior work, including the following:

- prior work for MedPAC comparing readmission rates across PAC settings (Kramer et al. 2018)
- CMS measures of readmissions within stay from IRFs and SNFs and readmissions post-stay from long-term care hospitals (LTCHs), IRFs, SNFs, and home health[3]
- Agency for Healthcare Research and Quality prevention quality indicators, which measure for ambulatory care–sensitive condition admissions (AHRQ 2001)

- the Healthcare Effectiveness Data and Information Set hospitalization for potentially preventable complications measure[4]

We grouped ICD-9 and ICD-10 diagnosis codes from these prior definitions of avoidable (re)admissions into condition categories, and we assessed similarities and differences in the condition categories included across measures (table 1). We then engaged two clinical consultants to review the condition categories considered avoidable in prior work and to assess whether each condition category could be considered avoidable across all settings and for both post-acute and community-admitted patients.

TABLE 1

Comparison of Condition Categories Included in Prior Definitions of Avoidable (Re)Admissions

Condition category	Included in all definitions	Included in four definitions	Included in three definitions	Included in two definitions	Included in one definition
Adult asthma	x				
COPD	x				
Congestive heart failure	x				
Diabetes short-term complications	x				
Hypertension/hypotension	x				
Bacterial pneumonia	x				
Urinary tract infection/kidney infection	x				
Skin and subcutaneous tissue infections		x			
Dehydration/electrolyte imbalance		x			
Pressure ulcers		x			
Influenza			x		
Septicemia			x		
Aspiration pneumonitis; food/vomitus			x		
Acute renal failure			x		
Adverse drug events			x		
C. difficile infection				x	
Anticoagulant complications				x	
Acute delirium				x	
Arrhythmia				x	
Intestinal impaction				x	
Head injury				x	
Upper extremity fracture				x	
Lower extremity fracture				x	
Acute bronchitis/bronchiolitis and viral pneumonia					x
Deficiency and other anemia					x
Deep vein thrombosis/pulmonary embolism					x

Source: Urban Institute review of five published measures, including CMS IMPACT Act within-stay and post-stay measures; Kramer et al. (2018)–developed measures for MedPAC; AHRQ prevention quality indicators; and HEDIS hospitalization for potentially preventable complications measure.

Notes: COPD = chronic obstructive pulmonary disease.

Drawing on the feedback from our clinical consultants, we developed a final list of condition categories to include in our avoidable admissions measure (table 2). For each condition category, we include the individual ICD-9 and ICD-10 codes developed by CMS for its within- and/or post-stay readmission measures in our definition where possible. We use CMS code lists because the CMS measures have been translated into both ICD-9 and ICD-10 codes. We include one category, acute bronchitis/viral pneumonia, not used by CMS in its definitions of potentially avoidable admissions. For that category, we rely on ICD-9 codes from prior MedPAC work (Kramer et al. 2018), translating those codes into ICD-10 codes using a crosswalk.[5]

TABLE 2

List of Condition Categories Included in Our Definition of Avoidable Hospitalizations and Source of Code List

Condition category	Source of diagnosis code list
Acute bronchitis/bronchiolitis and viral pneumonia	Kramer et al. measure
Acute delirium	CMS within-stay measure
Adult asthma	CMS post-stay measure
Adverse drug events	CMS post-stay measure
Anticoagulant complications	CMS within-stay measure
Bacterial pneumonia	CMS post-stay measure
C. difficile infection	CMS post-stay measure
Chronic obstructive pulmonary disease	CMS post-stay measure
Congestive heart failure	CMS post-stay measure
Dehydration/electrolyte imbalance	CMS post-stay measure
Diabetes short-term complications	CMS post-stay measure
Head injury	CMS within-stay measure
Hypertension/hypotension	CMS post-stay measure
Influenza	CMS post-stay measure
Intestinal impaction	CMS post-stay measure
Lower extremity fracture	CMS within-stay measure
Septicemia (except in labor)	CMS post-stay measure
Skin and subcutaneous tissue infections	CMS post-stay measure
Upper extremity fracture	CMS within-stay measure
Urinary tract infection/kidney infection	CMS post-stay measure

Source: Urban Institute analysis based on past studies, discussions with MedPAC staff, and input from clinical consultants.
Note: CMS = Centers for Medicare & Medicaid Services.

Our final list of diagnosis groups includes the condition categories that are included in all five of the following: CMS IMPACT Act within-stay and post-stay measures;[2] Kramer and colleagues–developed measures for MedPAC (Kramer et al. 2018); Agency for Healthcare Research and Quality prevention quality indicators (AHRQ 2001), and the Healthcare Effectiveness Data and Information Set hospitalization for potentially preventable complications measure.[4] We also include some condition categories that are in one or more of the existing measures. As shown in table 3, our definition omits several commonly included condition categories. In general, we omit these condition categories because of our goal to develop uniform PAC measures and hospitalizations for these conditions that are avoidable across all PAC settings. Also, including some condition categories in a quality measure could increase use of services that are not evidence-based (for example, see the

discussion below on aspiration pneumonitis due to food/vomitus) Excluding these condition categories from our definition of avoidable admissions lowers our estimated rates of avoidable admissions relative to other definitions that include these condition categories.

TABLE 3

Condition Categories Excluded from Our Definition of Avoidable Hospitalizations

Condition category	Number of prior measures including condition category	Reviewer rationale for exclusion
Pressure ulcers	4	Home health agencies are not able to turn patients every two hours, so they likely cannot prevent new events. Similarly, new pressure ulcers cannot be prevented post-stay.
Aspiration pneumonitis; food/vomitus	3	Inclusion as avoidable may increase use of non-evidence-based prescriptions for speech therapy, supplements, swallowing studies, and feeding tube placement.
Acute renal failure	3	Condition may occur for multiple reasons, many of which are not related to quality of post-acute care.
Arrhythmia	2	Medication review and QT interval monitoring can potentially prevent drug-induced arrhythmia,[a] but continuous monitoring is not possible in home health or after discharge.
Deficiency and other anemia	1	Quite prevalent and may reflect comorbidities rather than quality of care.
Deep vein thrombosis/ pulmonary embolism	1	Use of prophylaxis in SNF, IRF, and HH is not the standard of care yet.

Source: Urban Institute analysis of past studies, discussions with MedPAC staff, and input from clinical consultants.
Notes: SNF = skilled nursing facility. IRF = inpatient rehabilitation facility. HH = home health.
[a] See Schwartz and Woosley (2016).

First, on the advice of one of our clinical consultants, we do not consider hospitalizations due to pressure ulcers to be necessarily avoidable. In the home health setting, patients cannot be turned every two hours to prevent new pressure ulcers from forming unless a caregiver is present, and new pressure ulcers also cannot be prevented post-stay through appropriate patient hand-off. Our dataset does not allow us to clearly distinguish between hospitalizations for new pressure ulcers and hospitalizations for existing pressure ulcers, so we therefore exclude this condition category from our list of avoidable admissions. However, development and progression of pressure ulcers remain important quality measures for post-acute care, particularly in institutional settings.

Second, we do not include hospitalizations for aspiration pneumonitis due to food/vomitus in our definition of avoidable admissions. Our clinical consultants indicated that inclusion of this condition category in a quality measure could encourage the use of non-evidence-based therapies to attempt to prevent aspiration, such as speech therapy, supplements, swallowing studies, and feeding tube

placement. These therapies, particularly feeding tube placement, may also negatively affect a patient's quality of life.

We also exclude hospitalizations for acute renal failure, arrhythmia, deep vein thrombosis/pulmonary embolism, and deficiency or other anemia from our definition of avoidable admissions. Acute renal failure and deficiency or other anemia have many causes that may be unrelated to the quality of post-acute care received. Drug-induced arrhythmia may be avoidable with medication review and by monitoring heart rhythm via echocardiogram (QT interval monitoring), but continuous QT interval monitoring is not the standard of care in home health settings or after discharge. Finally, we exclude hospitalizations for deep vein thrombosis and pulmonary embolism from our definition of avoidable admissions because our clinical consultants indicated that use of prophylactic garments, like compression stockings, is not yet the standard of care in institutional post-acute care or home health.

Risk-Adjustment Model

To obtain hospitalization rates that can be used to assess the relative performance of PAC providers, we adjust the raw provider hospitalization rates for differences in case mix. The risk-adjusted rates better reflect a provider's contribution to the likelihood of hospitalization, separating the provider effect from the need for hospitalization that would be expected given the provider's patient mix. For each measure of hospitalization, a common risk-adjustment model is used across the four post-acute settings to allow comparability of estimates for providers within and across settings.

We estimate risk-adjusted relative hospitalization rates for facilities using unconditional fixed-effect logit regression models.[6] We model hospitalization as a function of beneficiary characteristics and diagnoses from the current stay and the preceding hospitalization if one occurred. The unconditional fixed-effects logit model allows us to estimate an intercept (i.e., fixed effect) for each provider, controlling for beneficiary characteristics and diagnoses.

Each provider intercept measures how much higher or lower that provider's odds of patient hospitalization are than the odds expected based on their patient mix. The intercepts are used to calculate risk-adjusted hospitalization rates, as described below. A comparison of the intercepts across providers gives an estimate of how the odds of hospitalization would differ if providers faced the same patient mix.

We decided to use the fixed-effects logit model after considering a number of alternatives. We selected a logit regression approach because, unlike linear regression models, it appropriately accounts for the binary nature of hospitalization outcomes (hospitalization/no hospitalization) and ensures that all predicted probabilities fall between zero and one. We decided against using a logit model without any form of provider effects because we expect provider effects to be important and likely correlated with other individual-level risk factors. The logit model with fixed effects provides estimated intercepts for each provider, which are estimated jointly with the coefficients describing the risk associated with the characteristics of beneficiaries and stays.

We strongly considered adopting the hierarchical (random-effects) logit model CMS uses, but we chose not to for two reasons. First, the random-effects model assumes provider effects are uncorrelated with the beneficiary and stay controls. We expect that the provider effects would very likely be correlated with these factors. In contrast, the fixed-effects model does not make this assumption, as it allows potential correlation between the provider effects and individual-level control variables.

Second, the random-effects logit model uses shrinkage, which MedPAC prefers to avoid, to improve the estimates for low-volume providers. Unlike the fixed-effects approach, the random-effects model does not estimate the provider effects directly. Instead, it estimates the variance of the provider effects and obtains posterior estimates of effects, which are used together with a shrinkage method to reduce extreme estimates. Shrinkage can improve estimates, particularly for small providers, by averaging the individual provider estimate with the average for the population. It has the downside, however, of attributing to the provider hospitalizations that did not necessarily occur (and discounting hospitalizations that did occur) by shrinking low (and high) rates toward the average. This approach may dampen a provider's incentive to improve because their rate does not depend entirely on their own performance. For this reason, MedPAC generally prefers to avoid shrinkage approaches in favor of other approaches to improve estimates for low-volume providers such as combining multiple years of data and setting minimum size thresholds to achieve an acceptable level of reliability (MedPAC 2013).

Estimating unconditional fixed-effects logit models of readmission, with an intercept for each of more than 25,000 providers, is computationally difficult with standard logit regression routines. The model, however, can be estimated using the bife package in R, which produces both hospital-specific intercepts and corresponding standard errors.

Estimation of Risk-Adjusted Readmission Rates

In the unconditional fixed-effect logit model, the log of the odds of hospitalization (i.e., the probability of hospitalization divided by the probability of nonhospitalization) is a linear function of patient and stay characteristics (x_i) and α_j, an indicator for each PAC provider. The logit model takes the form

$$\ln\left(\frac{\Pr(Hospitalization_{ij})}{1-\Pr(Hospitalization_{ij})}\right) = x_i\beta + \alpha_j, \quad (1)$$

where *i* indicates the ith stay and *j* indicates the jth provider. This equation can be solved for the probability of hospitalization to obtain the formula to predict the probability of hospitalization for a stay:

$$\Pr\left(Hospitalization_{ij}\right) = \frac{e^{(x_i\beta+\alpha_j)}}{1+e^{(x_i\beta+\alpha_j)}}. \quad (2)$$

As seen in the equation, the logit specification ensures that the predicted probability falls between zero and one.

We use the model estimates of the provider-specific effect α_j to compute risk-adjusted hospitalization rates for provider *j*. For this computation, we replace the individual-varying patient and stay characteristics in estimated equation (2) with a constant parameter, *c*, to obtain an estimate that treats each provider as though they face the same patient mix. The parameter *c* is chosen to ensure that for all facilities larger than a minimum size, the average risk-adjusted rate equals the average hospitalization rate. The risk-adjusted hospitalization rate is calculated as follows:

$$\text{Risk-adjusted hospitalization rate for provider } j = \frac{e^{(\alpha_j - c)}}{1+e^{(\alpha_j - c)}}. \qquad (3)$$

The risk-adjusted estimates maintain the relative rankings of facilities estimated from the fixed-effects logit, imposing only that the average risk-adjusted hospitalization rate equal the average unadjusted hospitalization rate.

The fixed-effects logit cannot calculate an intercept for any providers without any hospitalizations. (This would require an intercept of minus infinity, and the model would not converge.) These providers are therefore excluded from the logit regression model and assigned a risk-adjusted hospitalization rate of zero.

We estimate unconditional fixed-effects logit models for each hospitalization measure with version 0.6 of the bife package in R.[7] The package, designed for large data files, uses a demeaning procedure to estimate the model without excessive computation time. Output from the model includes both provider fixed effects and the corresponding standard errors.

Controls for Case Mix

We use case-mix variables (health conditions and other patient-level risk factors) expected to be correlated with hospitalization as controls in the fixed-effects logit models. The variables are based on the enrollment files, PAC claims, and acute hospital stay claims.

The control variables fall into three groups: patient, stay, and hospitalization history. The patient control variables are indicators of sex, age, and original reason for Medicare entitlement obtained from the enrollment files. Stay control variables are measures of condition at the time of the stay based on diagnosis codes in the PAC stay or the most recent hospital stay occurring in the 30 days before PAC admission. The stay control variables include

- primary reason for treatment based on Medicare Severity-Diagnosis Related Group from the prior hospital stay if available, else imputed from PAC diagnoses;
- severity of illness from the prior hospital stay if available, else from the post-acute stay;
- comorbidities based on 22 groupings of hierarchical condition categories based on secondary diagnoses in the hospital and PAC;
- indicator of the patient having conditions within at least 5 of the 22 groupings of hierarchical condition categories;

- dementia in hospital or PAC;
- dialysis in hospital or PAC; and
- PAC services/condition (ventilator, dysphagia, bowel incontinence, presence of various wounds).

Finally, we include the following indicators of hospitalization history: whether the patient was hospitalized in the previous month, the length and number of intensive care unit days in the most recent hospitalization in the previous month, and the number of hospitalizations over the prior year (excluding previous month). We expect these measures to be particularly strong predictors of future hospitalization.

Consistent with MedPAC's principles for quality measurement, we did not include any social risk factors in the risk-adjustment model to avoid masking disparities. To reduce the computational difficulty of estimation, we excluded some conditions that were either rare or had weak relationships to within-PAC avoidable hospitalizations. Though we generally sought to avoid including indicators of service use in the control variables, we include dialysis and ventilator use (both also included in CMS's SNF and LTCH systems), given their strong relationship to hospitalizations and because they are not considered to be easily manipulated by providers.

Predictive Performance of Stay-Level Risk Models

By controlling for patient-level health condition indicators and other patient characteristics within the fixed-effects logit models, the fixed effects capture provider differences in hospitalization rates after adjusting (controlling) for observable characteristics of the patients they treat. After this adjustment for differences attributable to patient characteristics, remaining differences in hospitalizations across providers may be interpreted as differences in provider performance, with the always-present caveat that the risk models do not and cannot control for unobservable patient characteristics, except to the extent they are correlated with the included variables. The models also do not control for potentially observable patient characteristics that are outside the scope of what may be used for administrative purposes (i.e., medical record data) or for variables that are intentionally excluded from the model (i.e., social factors and gameable service use measures).

Here we examine the degree to which the patient-level case-mix variables can predict hospitalization outcomes (i.e., statistically discriminate between stays at higher and lower risk of hospitalization), using two measures of model performance. We report model performance statistics for patient-level logistic regression models of hospitalization outcomes that include as explanatory variables all the patient risk measures used in our final models. We base these performance statistics on standard logistic regression models that do not include the provider fixed-effects. This allows us to gauge the predictive ability of the patient case-mix variables before adding the provider-level fixed effects to the models. When the fixed effects are added for the final models, the coefficients on the patient variables can change somewhat, particularly if the provider effects and patient characteristics

are correlated. Performance statistics for the models including the fixed effects in the predictions would gauge the total model predictability, including the provider effects, and therefore would overstate the predictability of the patient-level risk factors alone. And there is no standard way to produce comparable statistics for the final models with the fixed effects that only accounts for the predictive ability of the patient-level factors. Examining the predictive ability of the patient case-mix factors with standard logistic regression models also allows us to compare performance statistics with those obtained in other settings where similar models were used.

In table 4, we report two measures of the stay-level models' ability to discriminate between stays at high versus low risk of hospitalization: the C-statistic and the difference in mean predicted probabilities between the top and bottom deciles of the predicted values. Studies of logit model predictability in the medical and risk-adjustment literature typically focus on C-statistics. The C-statistics for our within-stay measures range from 0.672 to 0.697. The C-statistics for the post-stay measures are higher, ranging from 0.710 to 0.722. For comparison, in the technical report for CMS's hospital-wide all-cause hospitalization measure, the C-statistic is 0.658.[8] Thus, the ability of the risk factors in our models to discriminate low- from high-risk cases is similar to that of CMS's measure.

Another way to measure the models' discrimination ability is examining the range of predicted hospitalization rates. A model with little variability in predicted values would have little ability to discriminate between stays at higher and lower risk of hospitalization. For all within-stay hospitalizations, the mean prediction in the bottom decile is 0.058, and the mean prediction in the top decile is 0.359, where lower rates reflect better performance. For the 30-day post-stay hospitalization measure, predictions range from 0.049 to 0.397. In both examples, the range of predicted values is substantial and comparable with what CMS reports for its hospital readmission models.[9]

TABLE 4

Predictive Performance of Stay-Level Logistic Regression Models of Hospitalization Risk

	Within-Stay Measures			
	14-day all hospitalizations	**14-day all avoidable hospitalizations**	**All hospitalizations**	**Avoidable hospitalizations**
C-statistic	0.672	0.696	0.679	0.697
Range of bottom decile mean predicted rate to top decile mean predicted rate	0.028–0.172	0.008–0.078	0.058–0.359	0.017–0.172
	Post-Stay Measures			
	14-day all hospitalizations	**14-day all avoidable hospitalizations**	**30-day all hospitalizations**	**30-day all avoidable hospitalizations**
C-statistic	0.710	0.725	0.710	0.722
Range of bottom decile mean predicted rate to top decile mean predicted rate	0.031–0.288	0.009–0.116	0.049–0.397	0.014–0.168

Source: Urban Institute analysis of Medicare claims data from the Standard Analytical Files and the Common Medicare Environment enrollment database.

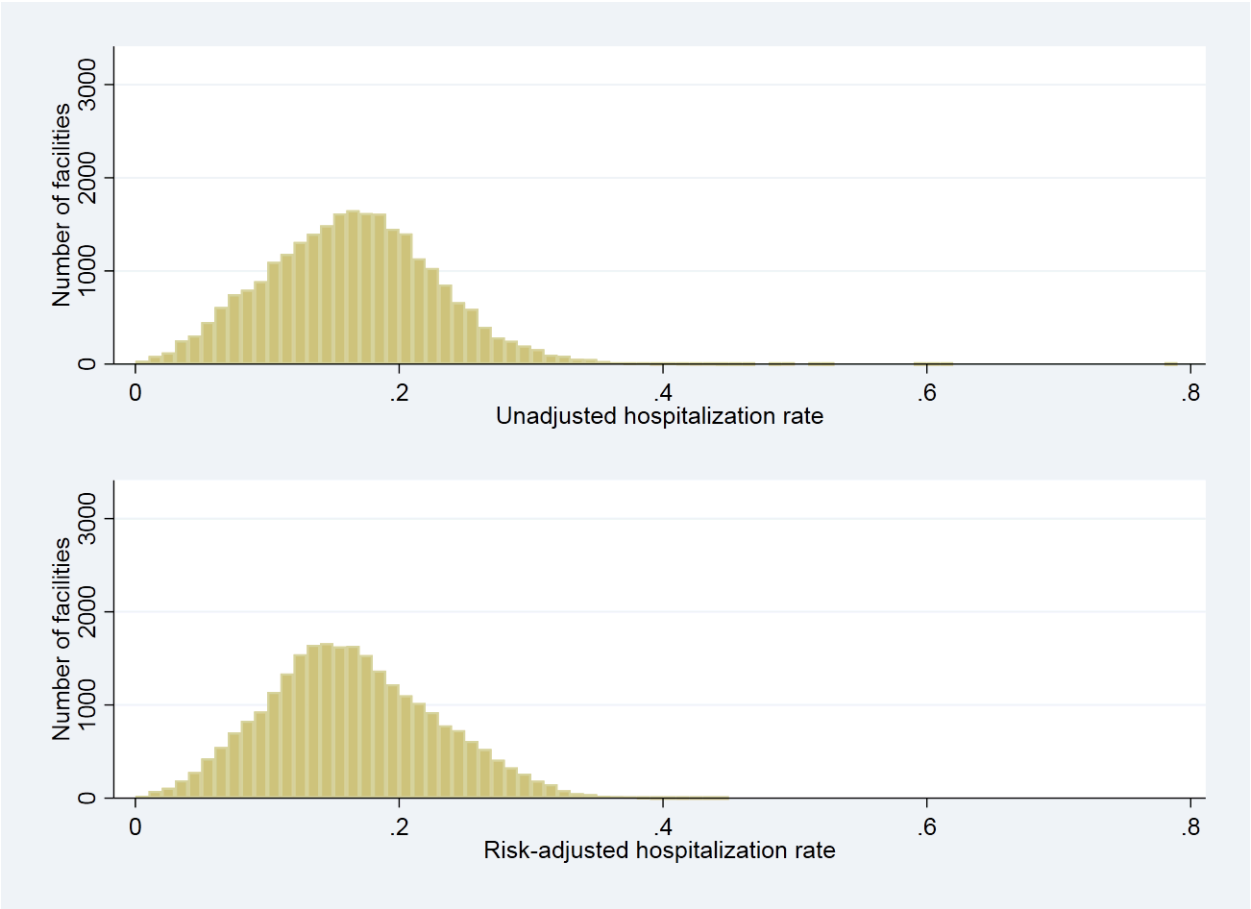
Notes: Statistics are reported for standard logistic regression models that exclude the provider fixed effects included in the final models used to compute risk-adjusted hospitalization rates. Lower hospitalization rates generally indicate better performance. A wider range in predicted rates indicates better ability to distinguish between patients at higher and lower risk.

Comparison of Distributions of Unadjusted and Risk-Adjusted Hospitalization Rates at the Provider Level

From the provider fixed effects included in the patient-level logit regression models, we estimate adjusted hospitalization rates at the provider level (as described above) to evaluate provider performance. The unadjusted rates are simply the proportion of the eligible PAC stays hospitalized within the time frame. In figures 1 and 2, we show how the variability in hospitalization rates across all PAC providers changes after risk adjustment for two main outcomes: all-cause within-stay hospitalizations and all-cause hospitalizations 30 days post-stay.

FIGURE 1

Distribution of Unadjusted and Adjusted Provider-Level Within-Stay All-Cause Hospitalization Rates across All PAC Settings

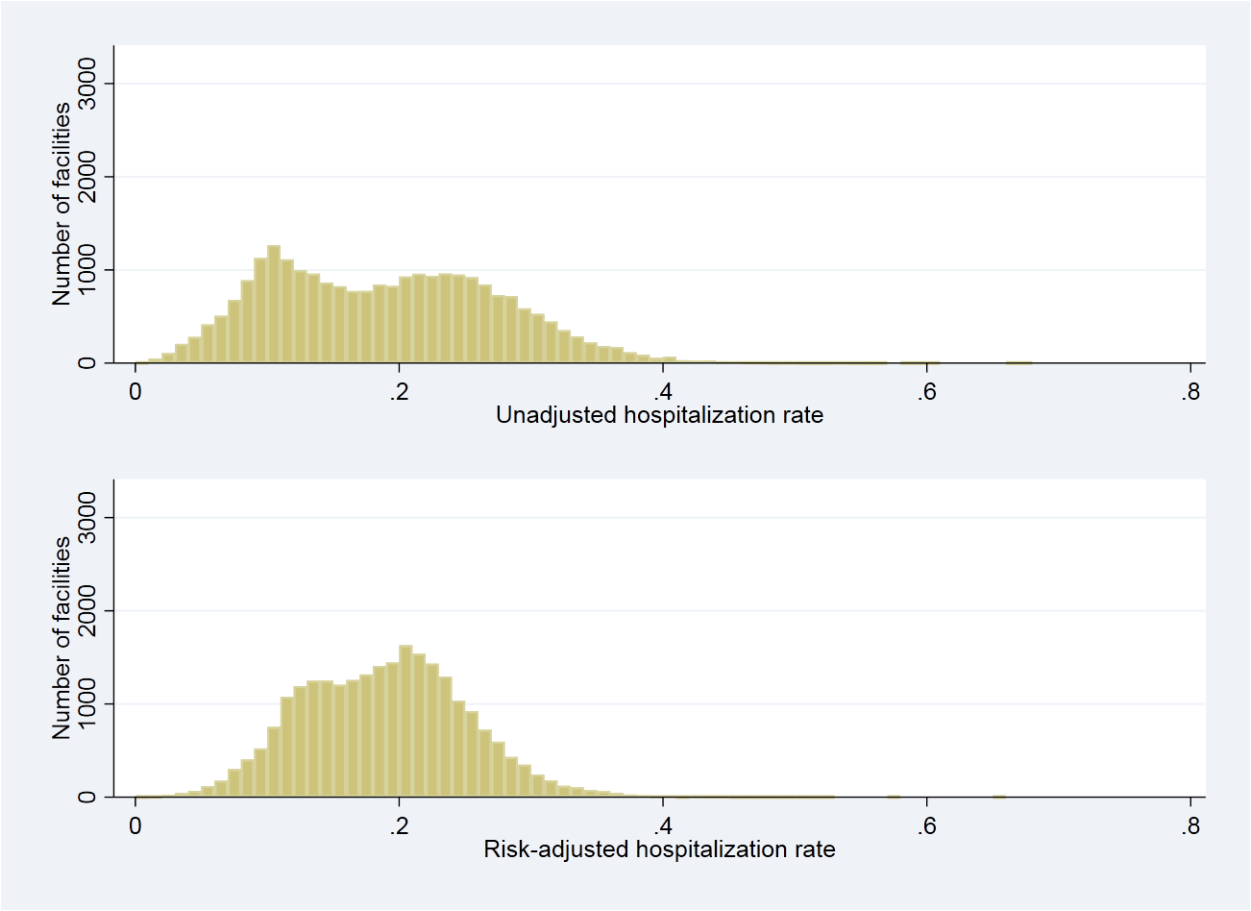


Source: Urban Institute analysis of Medicare claims data from the Standard Analytical Files and the Common Medicare Environment enrollment database.
Note: PAC = post-acute care.

Figure 1 shows that the distributions of unadjusted and adjusted provider-level rates for the all-cause within-stay hospitalizations outcome are similar. This is somewhat surprising, because, normally, the variability that remains after removing the risk component is expected to be less than the total variability. We discuss the reason for this result below. In figure 2, showing the all-cause 30-day post-stay provider-level hospitalization rates, we see the more typical pattern, in which the distribution of adjusted rates is substantially narrower than that of the unadjusted rates.

FIGURE 2

Distribution of Unadjusted and Adjusted Provider-Level 30-Day Post-Stay All-Cause Hospitalization Rates across All PAC Settings



Source: Urban Institute analysis of Medicare claims data from the Standard Analytical Files and the Common Medicare Environment enrollment database.
Note: PAC = post-acute care.

Variation in Risk-Adjusted Hospitalization Rates across Settings at the Provider Level

Table 5 reports the standard deviation and mean of unadjusted and adjusted provider-level hospitalization rates by setting for the two outcomes shown in figures 1 and 2. The first panel of table 5 confirms numerically that risk adjustment does not reduce the overall variability of within-stay hospitalization rates overall. Both unadjusted and adjusted rates have a standard deviation of 0.064. Within the SNF, IRF, and LTCH settings, we see less variation in the risk-adjusted rates than in the unadjusted rates, as indicated by the smaller standard deviation of the adjusted rate. Among home health agencies, however, the standard deviation of adjusted rates (0.059) is larger than that of the corresponding unadjusted rates (0.057).

Focusing on the average provider rates for within-stay total hospitalizations, we observe a substantially wider gap of average provider rates across settings after risk adjustment than before risk adjustment. Before adjustment, SNFs have the highest average hospitalization rates (17.0 percent) and IRFs have the lowest (8.0 percent), producing a range across settings of 9.0 percentage points. Risk adjustment changes the rates meaningfully, altering the ranking of settings with the most to least hospitalizations. After risk adjustment, home health providers have the highest mean rate (20.7 percent) and long-term care hospitals have the lowest (5.6 percent). The range in average adjusted rates over settings is 15.1 percentage points, compared with a 9.0 percentage-point range for unadjusted rates.

The increased spread between home health and long-term care hospitals that we see on average can also be seen when examining hospitalization rates by provider. In other tabulations (data not shown), we find that nearly all home health agencies (97 percent) have risk-adjusted hospitalization rates within the PAC stay that are higher than their unadjusted rates. Nearly all long-term care hospitals (99 percent) have risk-adjusted hospitalization rates within the PAC stay that are lower than their unadjusted rates. This means that the pattern of differences we see by setting between adjusted and unadjusted rates is occurring broadly and is unlikely to be altered by the minor changes to the risk models, such as inclusion of additional patient case-mix factors.

TABLE 5

Variability of Provider-Level Unadjusted and Risk-Adjusted Hospitalization Rates, by PAC Setting

	All Within-Stay Hospitalizations				
	All	**HH**	**IRF**	**LTCH**	**SNF**
Unadjusted standard deviation	0.064	0.057	0.025	0.061	0.066
Unadjusted mean rate	0.164	0.167	0.080	0.128	0.170
Adjusted standard deviation	0.064	0.059	0.022	0.033	0.048
Adjusted mean rate	0.164	0.207	0.078	0.056	0.144
	All Post-Stay Hospitalizations				
	All	**HH**	**IRF**	**LTCH**	**SNF**
Unadjusted standard deviation	0.086	0.042	0.037	0.054	0.066
Unadjusted mean rate	0.189	0.109	0.164	0.304	0.241
Adjusted standard deviation	0.062	0.044	0.032	0.031	0.052
Adjusted mean rate	0.189	0.139	0.183	0.203	0.223

Source: Urban Institute analysis of Medicare claims data from the Standard Analytical Files and the Common Medicare Environment enrollment database.

Notes: PAC = post-acute care. HH = home health. IRF = inpatient rehabilitation facility. LTCH = long-term care hospital. SNF = skilled nursing facility.

It might seem counterintuitive that risk adjustment would widen the spread in average hospitalization rates across settings. But consider what differences we should expect risk adjustment to make. In general, we would expect home health patients to have less acute health conditions than institutional PAC cases and therefore be at lower risk for hospitalization. We would expect patients in long-term care hospitals to have the most acute conditions and be at higher risk of hospitalization. We should therefore expect risk adjustment to increase rates for home health agencies and reduce rates for LTCHs. As just noted, this is observed for nearly all home health agencies and LTCHs. On both of these counts, risk adjustment operates as expected.

The reason for this effect may also lie in the level of care that can be provided in different settings. Home health agencies have lower capacity to monitor and treat conditions, so they are more likely to send patients to a hospital. Meanwhile, LTCH patients, already in a hospital setting, may not require transfer to an acute-care hospital, because the necessary monitoring and treatment can be provided there. These points imply that for two identical patients treated in home health and LTCHs experiencing the same adverse event during their PAC stay, the one treated in home health would be more likely to be hospitalized. This is consistent with the higher hospitalization rate for home health after regression adjustment that holds observed patient characteristics constant.

Given these points, we see the risk-adjustment approach as working as expected given the use of a single equation for risk adjustment across different PAC settings. Risk adjustment reveals that for a given type of patient (i.e., holding patient factors equal), within-stay hospitalization rates are substantially higher if the patients are treated in home health than in LTCHs (and this difference is greater than would be expected based on the unadjusted hospitalization rates in the two settings).

Importantly, we see the more expected narrowing of differences across settings after adjustment in the post-stay measures (table 5, second panel), where patients are on more of an equal footing with

many more patients discharged home (and the length of exposure is a fixed window of 30 days). The post-stay period can include patients discharged to a different PAC setting, but a large share are discharged home, which, without any PAC, makes the cases more comparable.

The findings of substantial changes in rates by setting before and after risk adjustment make clear that the risk adjustment has an impact on the hospitalization rates. If it were merely the case that the risk adjustment model had very little ability to predict, it would show up in these findings as risk adjustment being ineffectual – quite different from what we find.[10]

Returning to the question of why the risk-adjusted within-stay hospitalization rates in figure 1 do not have a narrower distribution than the unadjusted rates, note that the total variation in each measure can be decomposed into parts due to how rates vary within each of the settings and a part due to how mean rates vary across settings. In three of the four settings (SNFs, IRFs, and LTCHs), variation within setting is lower in the adjusted rates (which would tend to make adjusted rates vary *less* overall than the unadjusted rates). Within the home health setting, variation is higher in the adjusted rates. Across settings, we see more variability in mean rates after adjustment. Both of the latter two factors would tend to make adjusted rates vary *more* than the unadjusted rates. The net result of these differences, working in opposite directions, is that the total variability of the unadjusted and adjusted rates is about the same.

Variation in Hospitalization Rates across Settings for Specific Patient Groups

As an alternative approach to examining whether risk adjustment is operating properly, we focus on some narrowly defined groups of patients based on their primary reason for treatment. The multivariate regression models hold patient characteristics fixed, but in a way that is not easily visualized. Here we look at narrowly defined groups of patients as an approach to "manually" holding patient characteristics fixed. Consistency in patterns of rates by setting using full risk adjustment and for narrow groups of patients with similar characteristics would suggest that risk adjustment is working as expected.

We focus first on findings for all-cause within-stay hospitalizations, as shown in table 6. For context and completeness, the first panel reports mean provider-weighted unadjusted and risk-adjusted hospitalization rates by setting, such as we report for two of the outcomes in table 5. The table also reports stay-weighted risk-adjusted hospitalization rates. We find that the stay-weighted measures are similar to the provider-weighted measures and show very similar differences by setting. We report the stay-weighted numbers because they provide a better point of comparison with the stay-level results for the specific patient groups that follow.

TABLE 6

Within-Stay All-Cause Hospitalization Rates and Range across PAC Settings, Overall and for Selected Groups

	HH	IRF	LTCH	SNF	Range	*N*
All stays						
Provider-weighted, unadjusted	0.167	0.080	0.128	0.170	0.090	26,118
Provider-weighted, risk-adjusted	0.207	0.078	0.056	0.144	0.151	26,118
Stay-weighted, risk-adjusted	0.206	0.079	0.052	0.143	0.154	20,054,872
Primary diagnosis: Stroke						
All	0.164	0.075	0.109	0.163	0.089	506,119
SOI 1	0.121	0.047	0.080	0.101	0.074	32,237
SOI 2	0.144	0.055	0.063	0.120	0.089	242,301
SOI 3	0.199	0.095	0.117	0.184	0.103	192,910
SOI 4	0.247	0.138	0.118	0.283	0.165	38,342
Primary diagnosis: COPD						
All	0.244	0.095	0.064	0.182	0.180	571,358
SOI 1	0.167	0.049	0.090	0.108	0.118	70,559
SOI 2	0.236	0.070	0.046	0.146	0.190	264,070
SOI 3	0.289	0.093	0.060	0.193	0.229	199,723
SOI 4	0.307	0.153	0.085	0.249	0.222	36,404
Primary diagnosis: Infection–surgical						
All	0.256	0.133	0.142	0.258	0.125	206,333
SOI 1	0.151	0.067	0.047	0.119	0.104	2,682
SOI 2	0.181	0.077	0.084	0.151	0.104	24,026
SOI 3	0.264	0.116	0.117	0.238	0.148	81,153
SOI 4	0.290	0.153	0.159	0.296	0.143	98,470

Sources: Urban Institute analysis of Medicare claims data from the Standard Analytical Files and the Common Medicare Environment enrollment database.

Notes: PAC = post-acute care. HH = home health. IRF = inpatient rehabilitation facility. LTCH = long-term care hospital. SNF = skilled nursing facility. SOI = severity of illness. COPD = chronic obstructive pulmonary disease. Rates in shaded cells are based on fewer than 100 stays.

The second panel of table 6 reports hospitalization rates for stroke patients overall and by severity of illness. Shaded cells indicate rates based on fewer than 100 cases, which are therefore measured with less precision. For stroke overall, and within each severity of illness (SOI) group, we see substantial variability in hospitalization rate across settings. There is a large degree of variability in hospitalization rates across settings even within these narrowly defined patient groups, just as we see in the adjusted rates from the multivariate models that control for all included case-mix factors. The substantial variation we see across settings even when focusing on a narrowly-defined set of patients with the same primary reason for treatment and same level of severity suggests that there are likely to be systematic setting differences, separate from patient risk, that give rise to differences in hospitalization rates by setting. Also, for each severity level for stroke patients, and overall, we see home health and SNF having the higher hospitalization rates as compared with IRF and LTCHs. This fits with the pattern that we see in the both the provider- and stay-weighted adjusted estimates.

For patients with chronic obstructive pulmonary disease (panel 3 of table 6), we find even larger ranges in hospitalization rates across settings, and the rank orders in SOI groups 2, 3, and 4 align with

our risk-adjusted findings overall. For surgical infection patients in the fourth panel of table 6, we again see substantial variability across settings and patterns similar to our overall risk-adjusted results. Taken together, these findings for patients with specific health conditions, showing hospitalization patterns by setting consistent with those of our overall results, suggest that the risk-adjustment approach is operating in a reasonable manner.

Shifting to the findings for all-cause 30-day post-stay hospitalizations (table 7), we find that risk adjustment narrows the range of hospitalization rates across settings. Risk adjustment still has the effect, though, of raising rates for home health and IRF, and lowering them for LTCH and SNF. But the starting point for the unadjusted rates is different. With the within-stay measure, patients vary in length of stay exposure and the settings differ in their ability to respond to sudden changes in patient condition. By comparison, the post-stay measure is for a fixed window of time, in which patients are more frequently at home or in a less intensive PAC setting. Once patients have largely been discharged home, we see risk adjustment narrowing the post-stay hospitalization rates relative to the unadjusted rates.

TABLE 7

Post-Stay 30-Day All-Cause Hospitalization Rates and Range across PAC Settings, Overall and for Selected Groups

	HH	IRF	LTCH	SNF	Range	*N*
All stays						
Provider-weighted, unadjusted	0.109	0.164	0.304	0.241	0.195	26,118
Provider-weighted, risk-adjusted	0.139	0.183	0.203	0.223	0.084	26,118
Stay-weighted, risk-adjusted	0.142	0.192	0.202	0.222	0.080	15,484,869
Primary diagnosis: Stroke						
All	0.085	0.126	0.177	0.168	0.093	374,984
SOI 1	0.063	0.095	0.156	0.118	0.092	25,240
SOI 2	0.075	0.106	0.127	0.144	0.069	189,065
SOI 3	0.105	0.151	0.164	0.188	0.083	135,742
SOI 4	0.120	0.177	0.205	0.222	0.103	24,828
Primary diagnosis: COPD						
All	0.121	0.242	0.242	0.248	0.127	332,985
SOI 1	0.085	0.161	0.175	0.192	0.107	42,825
SOI 2	0.117	0.199	0.223	0.227	0.110	148,174
SOI 3	0.145	0.256	0.244	0.260	0.115	120,183
SOI 4	0.155	0.279	0.253	0.272	0.124	21,624
Primary diagnosis: Infection–surgical						
All	0.116	0.219	0.228	0.244	0.128	136,071
SOI 1	0.058	0.108	0.088	0.131	0.073	2,112
SOI 2	0.089	0.191	0.174	0.177	0.102	17,590
SOI 3	0.127	0.212	0.221	0.244	0.117	52,690
SOI 4	0.124	0.229	0.237	0.262	0.138	63,678

Sources: Urban Institute analysis of Medicare claims data from the Standard Analytical Files and the Common Medicare Environment enrollment database.

Notes: PAC = post-acute care. HH = home health. IRF = inpatient rehabilitation facility. LTCH = long-term care hospital. SNF = skilled nursing facility. SOI = severity of illness. COPD = chronic obstructive pulmonary disease. Rates in shaded cells are based on fewer than 100 stays.

Similar tables for the other hospitalization outcome measures are provided in appendix tables A.1–A.6. For the 14-day all hospitalization within-stay measure (table A.1), we find that the overall hospitalization rate for home health is higher than that for SNF before adjustment (0.059 versus 0.087), but these rates are the same (0.076) after risk adjustment. The hospitalization rate for LTCH is reduced from 0.063 before adjustment to 0.030 after adjustment. We find again that risk adjustment raises hospitalization rates for home health and lowers them for SNF and LTCH, but here we see this occurs even for a fixed window of 14 days within stay.

Determination of Minimum Provider Sample Size

One concern when producing performance measures for individual providers is that the estimates for providers with few stays (low volume) will not be reliable enough to distinguish one provider from another. Working with MedPAC staff, we set a minimum threshold for the number of stays required to report a given hospitalization measure for a provider. The minimum was set to ensure that all reported estimates meet a specified standard of reliability. We use separate minimums for each outcome.

The share of providers not meeting the minimum size threshold differs across outcomes and settings. Using three years of data, 25 percent of providers have an insufficient number of stays to meet the size threshold for the within-PAC 14-day rate. In contrast, 11 percent of providers have insufficient numbers of stays to meet the size threshold for the within-PAC 100-/120-day rate. The latter measure varies considerably across settings: the threshold number of stays leads to exclusion of 16 percent of home health agencies, 2 percent of IRFs and LTCHs, and 8 percent of SNFs.

We followed common practice in defining reliability for a given provider as

$$Reliability_j = \frac{SD^2}{SD^2 + {SE_j}^2}$$

where *SD* is the standard deviation of the fixed effects across all facilities and SE_j is the standard error of the estimated fixed effect for provider *j*. We chose to set a minimum sample size (provider volume of stays) to achieve a reliability of at least 0.7.[11] With a reliability of 0.7, 70 percent of the total variation in hospitalization owes to differences in estimated true rates across providers, and 30 percent owes to random variation within providers.[12]

To choose the minimum sample size for a given measure of hospitalization, we calculate the median reliability among facilities within relatively narrow ranges of provider volume. We set a minimum provider size according to the smallest range with a median reliability of 0.7. As shown in table 8, the minimum size thresholds vary considerably across outcome measures. Higher minimums are consistently observed for measures with potentially avoidable hospitalizations; with their lower incidence rates, the potentially avoidable measures have a lower reliability for a given level of provider volume.

TABLE 8

Minimum Provider Size for Each Measure

	All hospitalizations	Avoidable hospitalizations
Within PAC, 14 days	140	250
Within PAC, 100/120 days	60	100
Post PAC, 14 days	60	140
Post PAC, 30 days	60	120

Sources: Urban Institute analysis of Medicare claims data from the Standard Analytical Files and the Common Medicare Environment enrollment database.
Note: PAC = post-acute care.

Conclusion

This analysis demonstrates the feasibility of calculating a uniform, risk-adjusted measure of hospitalization rates across all PAC providers. Given the design of a single-equation risk model estimated with pooled data from multiple distinctive settings, our risk models perform as expected. The risk factors we use are similar to those used in the various setting-specific models. The overall predictive ability of the models as measured by their C-statistics is comparable to the predictive ability of the models CMS uses to adjust readmission rates for acute care hospitals.

As is typical in risk-adjustment models, the distribution of post-stay hospitalization rates is narrower after risk adjustment. Though we do not see the same narrowing for the all within-stay hospitalization measure, we view the pattern of results we obtain by setting to be reasonable and consistent with what we would expect given the differences for some of the patients across settings (particularly between home health and LTCH) and the nature of treatment in each setting. The reasonableness of the results is further confirmed by focusing on select narrow groups of patients (a form of manual risk-adjustment). The pattern of results across settings we observe within each patient group largely mimics what we observe in the risk adjusted rates overall.

The risk-adjusted hospitalization rates differ substantially across settings. These differences may partially reflect differences in practice patterns that are unlikely to narrow without a unified PAC prospective payment system. Until there is a unified PAC prospective payment system, the measures described here should be used mainly to compare providers within setting rather than across settings.

Appendix

TABLE A.1

Within-Stay 14-Day All-Cause Hospitalization Rates and Range across PAC Settings, Overall and for Selected Groups

	HH	IRF	LTCH	SNF	Range	*N*
All stays						
Provider-weighted unadjusted	0.059	0.069	0.063	0.087	0.028	26,118
Provider-weighted risk-adjusted	0.076	0.068	0.032	0.076	0.044	26,118
Stay-weighted provider-risk adjusted	0.084	0.07	0.030	0.076	0.054	19,660,113
Primary diagnosis: Stroke						
All	0.071	0.062	0.062	0.080	0.018	506,119
SOI 1	0.054	0.040	0.060	0.051	0.020	32,237
SOI 2	0.062	0.045	0.050	0.056	0.016	242,301
SOI 3	0.086	0.077	0.063	0.091	0.028	192,910
SOI 4	0.111	0.111	0.065	0.146	0.081	38,342
Primary diagnosis: COPD						
All	0.088	0.085	0.034	0.093	0.058	571,358
SOI 1	0.055	0.045	0.054	0.049	0.010	70,559
SOI 2	0.080	0.065	0.032	0.068	0.048	264,070
SOI 3	0.115	0.083	0.029	0.100	0.086	199,723
SOI 4	0.137	0.134	0.047	0.140	0.093	36,404
Primary diagnosis: Infection – surgical						
All	0.112	0.110	0.066	0.132	0.065	206,333
SOI 1	0.073	0.067	0.019	0.060	0.054	2,682
SOI 2	0.075	0.066	0.038	0.067	0.038	24,026
SOI 3	0.109	0.096	0.051	0.114	0.063	81,153
SOI 4	0.135	0.126	0.076	0.159	0.083	98,470

Sources: Urban Institute analysis of Medicare claims data from the Standard Analytical Files and the Common Medicare Environment enrollment database.

Notes: PAC = post-acute care. HH = home health. IRF = inpatient rehabilitation facility. LTCH = long-term care hospital. SNF = skilled nursing facility. SOI = severity of illness. COPD = chronic obstructive pulmonary disease. Rates in shaded cells are based on fewer than 100 stays.

TABLE A.2

Within-Stay 14-Day Avoidable Hospitalization Rates and Range across PAC Settings, Overall and for Selected Groups

	HH	IRF	LTCH	SNF	Range	*N*
All stays						
Provider-weighted unadjusted	0.024	0.02	0.02	0.037	0.017	26,118
Provider-weighted risk-adjusted	0.031	0.022	0.009	0.031	0.022	26,118
Stay-weighted provider-risk adjusted	0.033	0.023	0.009	0.031	0.024	18,762,576
Primary diagnosis: Stroke						
All	0.019	0.013	0.015	0.027	0.015	506,119
SOI 1	0.054	0.040	0.060	0.051	0.020	32,237
SOI 2	0.015	0.008	0.006	0.016	0.010	242,301
SOI 3	0.026	0.017	0.017	0.032	0.015	192,910
SOI 4	0.038	0.030	0.016	0.059	0.044	38,342
Primary diagnosis: COPD						
All	0.049	0.039	0.014	0.050	0.035	571,358
SOI 1	0.030	0.013	0.027	0.026	0.017	70,559
SOI 2	0.045	0.027	0.014	0.037	0.031	264,070
SOI 3	0.064	0.038	0.012	0.053	0.053	199,723
SOI 4	0.076	0.065	0.019	0.074	0.056	36,404
Primary diagnosis: Infection – surgical						
All	0.041	0.038	0.023	0.056	0.034	206,333
SOI 1	0.016	0.011	0.000	0.011	0.016	2,682
SOI 2	0.022	0.013	0.008	0.018	0.014	24,026
SOI 3	0.040	0.032	0.014	0.045	0.031	81,153
SOI 4	0.053	0.045	0.028	0.073	0.045	98,470

Sources: Urban Institute analysis of Medicare claims data from the Standard Analytical Files and the Common Medicare Environment enrollment database.

Notes: PAC = post-acute care. HH = home health. IRF = inpatient rehabilitation facility. LTCH = long-term care hospital. SNF = skilled nursing facility. SOI = severity of illness. COPD = chronic obstructive pulmonary disease. Rates in shaded cells are based on fewer than 100 stays.

TABLE A.3

Within-Stay Avoidable Hospitalization Rates and Range across PAC Settings, Overall and for Selected Groups

	HH	IRF	LTCH	SNF	Range	*N*
All stays						
Provider-weighted unadjusted	0.068	0.022	0.04	0.076	0.054	24,099
Provider-weighted risk-adjusted	0.086	0.025	0.017	0.064	0.069	24,099
Stay-weighted provider-risk adjusted	0.085	0.026	0.016	0.061	0.069	19,894,578
Primary diagnosis: Stroke						
All	0.046	0.016	0.027	0.060	0.043	506,119
SOI 1	0.030	0.008	0.000	0.035	0.035	32,237
SOI 2	0.037	0.010	0.008	0.039	0.031	242,301
SOI 3	0.062	0.022	0.033	0.069	0.047	192,910
SOI 4	0.083	0.039	0.029	0.119	0.090	38,342
Primary diagnosis: COPD						
All	0.136	0.044	0.025	0.100	0.112	571,358
SOI 1	0.087	0.016	0.045	0.061	0.071	70,559
SOI 2	0.132	0.029	0.016	0.081	0.116	264,070
SOI 3	0.165	0.044	0.023	0.106	0.142	199,723
SOI 4	0.171	0.075	0.033	0.135	0.138	36,404
Primary diagnosis: Infection – surgical						
All	0.096	0.044	0.045	0.112	0.068	206,333
SOI 1	0.031	0.011	0.000	0.029	0.031	2,682
SOI 2	0.055	0.017	0.015	0.044	0.039	24,026
SOI 3	0.100	0.037	0.034	0.098	0.066	81,153
SOI 4	0.115	0.053	0.053	0.137	0.085	98,470

Sources: Urban Institute analysis of Medicare claims data from the Standard Analytical Files and the Common Medicare Environment enrollment database.

Notes: PAC = post-acute care. HH = home health. IRF = inpatient rehabilitation facility. LTCH = long-term care hospital. SNF = skilled nursing facility. SOI = severity of illness. COPD = chronic obstructive pulmonary disease. Rates in shaded cells are based on fewer than 100 stays.

TABLE A.4

Post-Stay 14-Day All-Cause Hospitalization Rates and Range across PAC Settings, Overall and for Selected Groups

	HH	IRF	LTCH	SNF	Range	*N*
All stays						
Provider-weighted unadjusted	0.073	0.099	0.189	0.175	0.116	24,702
Provider-weighted risk-adjusted	0.096	0.111	0.116	0.161	0.065	24,702
Stay-weighted provider-risk adjusted	0.098	0.118	0.115	0.158	0.06	15,484,869
Primary diagnosis: Stroke						
All	0.050	0.072	0.100	0.115	0.065	374,984
SOI 1	0.038	0.056	0.089	0.078	0.051	25,240
SOI 2	0.043	0.059	0.054	0.094	0.051	189,065
SOI 3	0.063	0.086	0.096	0.131	0.068	135,742
SOI 4	0.070	0.108	0.119	0.167	0.097	24,828
Primary diagnosis: COPD						
All	0.073	0.144	0.136	0.167	0.094	332,985
SOI 1	0.050	0.075	0.093	0.126	0.076	42,825
SOI 2	0.071	0.117	0.126	0.151	0.080	148,174
SOI 3	0.087	0.152	0.136	0.176	0.090	120,183
SOI 4	0.097	0.179	0.146	0.184	0.087	21,624
Primary diagnosis: Infection – surgical						
All	0.071	0.133	0.129	0.177	0.107	136,071
SOI 1	0.037	0.084	0.029	0.092	0.063	2,112
SOI 2	0.052	0.111	0.090	0.116	0.064	17,590
SOI 3	0.077	0.128	0.119	0.173	0.095	52,690
SOI 4	0.077	0.141	0.137	0.198	0.121	63,678

Sources: Urban Institute analysis of Medicare claims data from the Standard Analytical Files and the Common Medicare Environment enrollment database.

Notes: PAC = post-acute care. HH = home health. IRF = inpatient rehabilitation facility. LTCH = long-term care hospital. SNF = skilled nursing facility. SOI = severity of illness. COPD = chronic obstructive pulmonary disease. Rates in shaded cells are based on fewer than 100 stays.

TABLE A.5

Post-Stay 14-Day Avoidable Hospitalization Rates and Range across PAC Settings, Overall and for Selected Groups

	HH	IRF	LTCH	SNF	Range	*N*
All stays						
Provider-weighted unadjusted	0.024	0.034	0.081	0.063	0.057	19,598
Provider-weighted risk-adjusted	0.032	0.041	0.045	0.057	0.025	19,598
Stay-weighted provider-risk adjusted	0.033	0.044	0.046	0.057	0.024	14,984,394
Primary diagnosis: Stroke						
All	0.014	0.019	0.043	0.039	0.029	374,984
SOI 1	0.009	0.012	0.022	0.026	0.017	25,240
SOI 2	0.011	0.015	0.018	0.031	0.020	189,065
SOI 3	0.019	0.025	0.040	0.046	0.026	135,742
SOI 4	0.023	0.034	0.054	0.062	0.040	24,828
Primary diagnosis: COPD						
All	0.040	0.079	0.071	0.095	0.055	332,985
SOI 1	0.025	0.043	0.072	0.071	0.047	42,825
SOI 2	0.038	0.066	0.071	0.088	0.050	148,174
SOI 3	0.049	0.082	0.069	0.100	0.051	120,183
SOI 4	0.056	0.098	0.073	0.104	0.049	21,624
Primary diagnosis: Infection – surgical						
All	0.024	0.047	0.055	0.072	0.048	136,071
SOI 1	0.008	0.036	0.000	0.023	0.036	2,112
SOI 2	0.015	0.034	0.040	0.039	0.026	17,590
SOI 3	0.027	0.045	0.051	0.070	0.042	52,690
SOI 4	0.028	0.050	0.059	0.083	0.055	63,678

Sources: Urban Institute analysis of Medicare claims data from the Standard Analytical Files and the Common Medicare Environment enrollment database.

Notes: PAC = post-acute care. HH = home health. IRF = inpatient rehabilitation facility. LTCH = long-term care hospital. SNF = skilled nursing facility. SOI = severity of illness. COPD = chronic obstructive pulmonary disease. Rates in shaded cells are based on fewer than 100 stays.

TABLE A.6

Post-Stay 30-Day Avoidable Hospitalization Rates and Range across PAC Settings, Overall and for Selected Groups

	HH	IRF	LTCH	SNF	Range	*N*
All stays						
Provider-weighted unadjusted	0.037	0.056	0.13	0.089	0.093	20,774
Provider-weighted risk-adjusted	0.048	0.068	0.079	0.082	0.034	20,774
Stay-weighted provider-risk adjusted	0.05	0.072	0.08	0.082	0.032	15,136,394
Primary diagnosis: Stroke						
All	0.023	0.035	0.075	0.057	0.051	374,984
SOI 1	0.016	0.021	0.067	0.039	0.051	25,240
SOI 2	0.019	0.027	0.040	0.046	0.027	189,065
SOI 3	0.032	0.045	0.069	0.065	0.037	135,742
SOI 4	0.037	0.056	0.091	0.083	0.054	24,828
Primary diagnosis: COPD						
All	0.066	0.135	0.138	0.143	0.077	332,985
SOI 1	0.043	0.108	0.124	0.110	0.081	42,825
SOI 2	0.063	0.115	0.127	0.132	0.069	148,174
SOI 3	0.082	0.143	0.142	0.150	0.067	120,183
SOI 4	0.087	0.151	0.139	0.155	0.068	21,624
Primary diagnosis: Infection – surgical						
All	0.040	0.079	0.102	0.100	0.062	136,071
SOI 1	0.010	0.048	0.000	0.031	0.048	2,112
SOI 2	0.026	0.059	0.073	0.060	0.048	17,590
SOI 3	0.045	0.076	0.098	0.099	0.054	52,690
SOI 4	0.044	0.085	0.107	0.112	0.067	63,678

Sources: Urban Institute analysis of Medicare claims data from the Standard Analytical Files and the Common Medicare Environment enrollment database.

Notes: PAC = post-acute care. HH = home health. IRF = inpatient rehabilitation facility. LTCH = long-term care hospital. SNF = skilled nursing facility. SOI = severity of illness. COPD = chronic obstructive pulmonary disease. Rates in shaded cells are based on fewer than 100 stays.

Notes

1 As standards of care evolve, or under some idealized standard of care, the admissions considered avoidable could change. For present purposes, we focus on avoidable admissions that reflect the current standard of care.

2 "Draft Measure Specifications: Potentially Preventable Hospital Readmission Measures for Post-Acute Care," Centers for Medicare & Medicaid Services, October 2015, https://www.cms.gov/Medicare/Quality-Initiatives-Patient-Assessment-Instruments/MMS/Downloads/Draft-Measure-Specifications-for-Potentially-Preventable-Hospital-Readmission-Measures-for-PAC-.pdf.

3 "Draft Measure Specifications: Potentially Preventable Hospital Readmission Measures for Post-Acute Care," CMS, 2015.

4 "Hospitalization for Potentially Preventable Complications," NCQA (blog), accessed July 20, 2020, https://www.ncqa.org/hedis/measures/hospitalization-for-potentially-preventable-complications/.

[5] "ICD-9 to ICD-10 Code Search | ICD-10 Code Lookup and Crosswalk," NextGen Healthcare, accessed July 20, 2020, http://www.icd10codesearch.com/.

[6] Fixed-effects logit models were estimated using only the stays from providers with at least one hospitalization of the type being modeled.

[7] Amrei Stammann, Daniel Czarnowske, and Florian Heiss wrote the bife package in R, which is available at https://github.com/amrei-stammann/bife. Bife implements the procedure developed in Stammann, Heiss, and McFadden (2016).

[8] See table 5 of Horwitz and colleagues (2012).

[9] See tables 14–18 of Horwitz and colleagues (2012).

[10] A fixed-effects logit model with no covariates (or no ability to predict) would merely reproduce the distribution of unadjusted provider hospitalization rates.

[11] Many sources suggest a minimum threshold for acceptable reliability of 0.7, which is considerably more stringent than the reliability threshold of 0.4 typically used by CMS. See, for example, Adams and colleagues (2010).

[12] Put differently, the minimum reliability threshold of 0.7 ensures the standard error of the estimates based on the fewest cases is no more than two-thirds of the standard deviation of estimates across all providers.

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