4.4.4a *[If risk factors are addressed by any method (4.4.1)]* **Attach Risk Adjustment Modeling and/or Stratification Specifications** *

Provide detailed risk adjustment model and/or stratification specifications, including the method(s), risk factor data sources, and equations, as applicable Please list all risk factors in your conceptual model, clearly indicating which factors were available/tested and which (if any) were retained in final model and/or stratification plan. Also include the data source, code with descriptor, and coefficient for each risk factor in the final risk adjustment model or stratification plan, as appropriate.
One file only; 256 MB limit; Allowed types: .xls; .xlsx; .csv

Approach to Variable Selection

Our approach to risk adjustment was tailored to and appropriate for a publicly reported outcome measure, as articulated in the American Heart Association (AHA) Scientific Statement, "Standards for Statistical Models Used for Public Reporting of Health Outcomes."[1] The measure estimates hospital-level 30-day all-cause RSRRs using hierarchical logistic regression models. In brief, the approach simultaneously models data at the patient and hospital levels to account for variance in patient outcomes within and between hospitals.[2]

The approach to risk adjustment is the only component of the Hybrid HWR measure that differs from the original HWR measure methodology. The original HWR measure uses claims data to adjust for two aspects of risk: 1) case mix or how sick individual admitted patients are; and, 2) service mix or the proportion of admitted patients with various different principal discharge diagnoses. Different claims data are used to assess each of these.

To select candidate variables for the Hybrid risk model, we began with the list of all administrative claims-based risk-adjustment variables included in the claims-only HWR measure, described below. We then added EHR-based risk variables, also described below.

Claims-based Risk Variables

In order to select the comorbid risk variables during the original development of this measure, we developed a "starter" set of 30 variables drawn from previous readmission measures (AMI, heart failure, pneumonia, hip and knee arthroplasty, and stroke). Next, we reviewed all the remaining CMS-CCs and determined on a clinical basis whether they were likely to be relevant to an all-condition measure. We selected 11 additional risk variables to consider.

Using data from the index admission and any admission in the prior 12 months, we ran a standard logistic regression model for every discharge condition category with the full set of candidate risk adjustment variables. We compared odds ratios for different variables across different condition categories (excluding condition categories with fewer than 700 readmissions due to the number of events per variable constraints). We selected the final set of comorbid risk variables based on the following principles:

- We excluded risk variables that were statistically significant for very few condition categories, given that they would not contribute much to the overall models.
- We excluded risk variables that behaved in clinically incoherent ways. For example, we dropped risk variables that sometimes increased risk and sometimes decreased risk, when we could not identify a clinical rationale for the differences.
- We excluded risk variables that were predominantly protective when we felt this protective effect was not clinically reasonable but more likely reflected coding factors. For example, drug/alcohol abuse without dependence (CC 53) and delirium and encephalopathy (CC 48) were

both protective for readmission risk although clinically they should increase patients' severity of illness.

- Where possible, we grouped together risk variables that were clinically coherent and carried similar risks across condition categories. For example, we combined coronary artery disease (CCs 83-84) with cerebrovascular disease (CCs 98, 99, and 103).
- We examined risk variables that had been combined in previous CMS publicly reported measures, and in one instance separated them: for cancers, the previous measures generally pool 5 categories of cancers (CCs 8 to 12), together. In our analysis, lung cancer (CC 8) and other severe cancers (CC 9) carried higher risks, so we separated them into a distinct risk variable and grouped other major cancers (CC 10), benign cancers (CC 11), and cancers of the urinary and GI tracts (CC 12) together. Consistent with other publicly reported measures, we also left metastatic cancer/leukemia (CC 7) as a separate risk variable.

Complications occurring during hospitalization are not comorbid illnesses, may reflect hospital quality of care, and therefore should not be used for risk adjustment. Hence, conditions that may represent adverse outcomes due to care received during the index hospital stay are not included in the risk-adjusted model (see the current list in Hybrid Risk-Variable Complications of Care in the Data Dictionary). CCs on this list were not counted as a risk variable in our analyses if they appeared only on the index admission.

This resulted in a final risk-adjustment model that included 32 CC-based variables. Additional variables related to service line adjustment are described below.

Service mix adjustment:

The measure includes many different discharge condition categories that differ in their baseline readmission risks. In addition, hospitals differ in their relative distribution of these condition categories (service mix). To adjust for service mix, the measure uses an indicator variable for the discharge condition category in addition to risk variables for comorbid conditions. The models include a condition-specific indicator for all condition categories with sufficient volume (defined as those with more than 1,000 admissions nationally in a given year for Medicare FFS data) as well as a single indicator for conditions with insufficient volume in each model.

EHR-based risk variables

The CCDE specific to the risk adjustment for the HWR measure consists of patients' age, weight, the first set of vital signs captured within 2 hours of the start of the episode of care, and the results of the first complete blood count and basic chemistry panel drawn within 24 hours of the start of the episode of care. If the patient has values captured prior to admission, for example from the emergency department, pre-operative, or other outpatient area within the hospital, the logic also supports extraction of the first resulted vital signs and laboratory tests within 24 hours prior to the start of the inpatient admission. Preliminary work had established that the CCDE could be used to risk adjust measures of 30-day readmission across a variety of common and costly medical conditions. Application of these same data elements to the original HWR measure allows us to examine the use of the CCDE in a broader cohort of hospitalized medical and surgical patients as well as to examine its utility in predicting hospital readmission. Therefore, CORE specifically sought to determine whether the use of clinical data for risk adjustment in place of, or in combination with, comorbidity data from Medicare claims would improve the discrimination of the HWR models or the reliability of the measure.

As described in the original methodology report, to determine if adding the CCDE improved risk adjustment, we compared four risk-adjustment strategies: the original HWR approach that used claims-

only data; and three new approaches that used the CCDE in various combinations with claims data. One model applied the CCDE to the full HWR risk-adjustment model, which include the Principal Diagnosis CCSs. We assumed that this model would out-perform models that used only clinical or only claims data because it is the most comprehensive model. A second model used only the CCDE for risk adjustment. A third model used the CCDE in addition to the principal discharge diagnoses CCS from the original HWR risk-adjustment model. We selected the best-performing alternative model based on discrimination in terms of the C-statistic. Based on superior model discrimination (see Table 18 below), the CCDE with Original HWR model was identified as the best-performing model of those evaluated and this model was carried forward for measure development and testing using hierarchical logistic regression. The other two approaches that included the CCDE were discarded.

Table 1. Risk Adjustment Performance by Specialty cohort (C-statistic)

Specialty Cohort	HWR	HWR + CCDE	CCDE+Principal Diagnosis	CCDE Only
Surgery/Gynecology	0.800	0.802	0.770	0.617
Cardiorespiratory	0.653	0.668	0.645	0.611
Cardiovascular	0.713	0.731	0.692	0.686
Neurology	0.670	0.708	0.674	0.672
Medicine	0.646	0.651	0.611	0.585

Although the 5 risk models use a common set of claims variables, the CCDE variables and principal discharge diagnoses CCSs are not the same across specialty cohort models. Only those data elements that are statistically significant in each individual model are included. We estimate a hierarchical logistic regression model for each specialty cohort separately, and the coefficients associated with each variable may vary across specialty cohorts.

The final set of risk-adjustment variables with their frequencies for each specialty cohort, including service-line adjustments, can be found in the Data Dictionary.

References:

1. Krumholz HM, Brindis RG, Brush JE, et al. 2006. Standards for Statistical Models Used for Public Reporting of Health Outcomes: An American Heart Association Scientific Statement From the Quality of Care and Outcomes Research Interdisciplinary Writing Group: Cosponsored by the Council on Epidemiology and Prevention and the Stroke Council Endorsed by the American College of Cardiology Foundation. Circulation 113: 456-462
2. Normand S-LT, Shahian DM. 2007. Statistical and Clinical Aspects of Hospital Outcomes Profiling. Stat Sci 22 (2): 206-226.