Mortality Risk Adjustment Methodology

for University Health System's Clinical Data Base

The University Health System Consortium (UHC) risk adjusts length of stay (LOS), costs, and mortality in the Clinical Data Base (CDB). Additionally, complications are risk adjusted in the CDB using a complication profiler. The risk adjustment process for LOS, costs and mortality involves four steps: (1) assignment of a Severity of Illness (SOI) and Risk of Mortality (ROM) level to each case; (2) selection of a patient population to serve as the basis of the model to provide norms; (3) use of regression techniques to predict probability of mortality and LOS and costs based on the normative patient population; and (4) assignment of an expected probability of mortality, LOS and costs to **every patient** in the CDB.

(1) Assignment of Severity of Illness and Risk of Mortality Levels

Patient characteristics impact resource utilization and clinical outcome greatly. To ensure equitable inter-hospital comparison of outcomes, it is necessary to adjust for differences in patient characteristics. A number of patient classification schemes have been developed to address the issue of patient severity. While each of these schemes defines severity differently, most are similar in one respect: they use specific combinations patient demographics and principal and secondary diagnoses and procedures to define different levels of severity and complexity of treatment.

The APR-DRG Grouper, developed by 3M Health Information Systems, is used by UHC to assign a level of illness severity and a risk of mortality level for each patient in the CDB. The APR-DRGs were developed as an expansion of the DRG system to address patient severity of illness and risk of mortality as well as resource intensity. The development process for the APR-DRGs involved an iterative process of formulating clinical hypotheses and then testing the hypotheses with historical data. Separate clinical models for severity of illness and risk of

mortality were developed for each of the base APR-DRGs and then tested with historical data to review the clinical hypotheses.

In the APR-DRG system a patient is assigned three distinct descriptors:

- The base APR-DRG (e.g., APR-DRG 044 Intracranial Hemorrhage or APR-DRG 194 Heart Failure)
- The severity of illness (SOI) subclass
- The risk of mortality (ROM) subclass

The underlying clinical principle of the APR-DRGs is that the SOI or ROM subclass of a patient is largely dependent on the patient's underlying problem and that patients with high SOI or ROM are usually characterized by multiple serious illnesses. The determination of the SOI and ROM is disease specific, i.e., the significance attributed to comorbid conditions is dependent on the underlying problem. High SOI and ROM are primarily determined by the interaction of multiple illnesses involving multiple organ systems which result in patients who are difficult to treat and tend to have poor outcomes.

The four SOI and ROM subclasses are:

1 Minor
2 Moderate
3 Major
4 Extreme

Although the subclasses are numbered sequentially, the numeric values represent categories and not scores. It is not meaningful to average the numeric values of the SOI or ROM subclasses across a group of patients to compute an average severity score. The SOI or ROM subclasses can be used as categories within which category-specific rates for an outcome are calculated to represent an expected value for that SOI or ROM subclass.

(2) Identification of Patient Population for Model Generation

The identification of a patient population for model generation is a very important step of building risk adjustment models and should be linked with its purpose. "Broadly construed, risk adjustment attempts to account for all factors other than the health care intervention itself or the process of care that may explain variation in patient outcomes. Four factors may account for observed differences in outcomes: differences in how well available data sources represent reality; differences in significant risk factors among patients; random variation; or differences in the effectives of the health services provided or the process of care". (Iezzoni, 1997 page 200) A poorly identified patient population will not allow a clinician accurately determine where differences in outcomes occur.

The three components of UHC's identification of a patient population for model generation include using the MSDRG classification system, using only patients that entered one of our academic medical center members, and cleaning the data. UHC believes that choosing a model population must take into account the homogeneity or a group as well as appropriate sample size. For example, a model could be built with patient's that are similar in demographics and comorbid conditions, but the sample would be so low that a robust model could not result. At the other end of the spectrum, all patients in a very large dataset could be considered the model population, but overfitting would result as few similarities would result. Therefore, UHC has chosen to use our academic medical center patient's from the last two years in a base MSDRG as our model population. We only use patients from our academic medical centers in order to be the most relevant to our owners. In total, these 85 hospitals add approximately 2.7 million inpatient discharges to the database each year. UHC does not collect hospice patients. Finally, cases

flagged as "bad data" and transfers out to another acute care hospital are excluded from the model population.

(3) Regression Models

Logistic regression models are constructed for the binary outcome variable in-hospital mortality, and multiple regression models are developed for the continuous outcome variables of LOS and cost. Separate models are built for base MS-DRG. In 2007, UHC developed 337 models each for LOS, costs and mortality. Strict exclusion rules are applied before building the regression models. For example, only base MS-DRGs with more than 100 cases and an incidence rate greater than 1% are modeled for mortality. Due to the potential for serious estimation problems related to a sparse contingency table, another layer of exclusion criteria is also imposed, i.e., observed incidence counts (rate multiplied by number of cases) must be greater than 50. Independent variables included in all the regression models are:

- ROM subclass for mortality, and SOI subclass for LOS and costs
- Patient Age
- Patient Sex
- Admit source = transfer from another acute care hospital
- Admit source = transfer from skilled nursing facility
- Admit source = long term care facility
- Low SES (based on Medicaid, Self-Pay, Charity as primary payer)
- Admit status = emergency
- Patient Race
- Comorbid conditions defined by the Agency for Healthcare Research and Quality (AHRQ) based on research by Elixhauser, et al including:
    - Congestive heart failure
    - Valvular disease
    - Pulmonary circulation disorders
    - Perpheral vascular disorders
    - Hypertension (complicated and uncomplicated)
    - Paralysis
    - Other neurological disorders
    - Chronic pulmonary disease
    - Diabetes (complicated and uncomplicated)
    - Hypothyroidism

- Renal failure
- Liver disease
- Peptic ulcer disease excluding bleeding
- AIDS
- Lymphoma
- Metastatic cancer
- Solid tumor without metastasis
- Rheumatoid arthritis/collagen vascular diseases
- Coagulopathy
- Obesity
- Weight loss
- Fluid and electrolyte disorders
- Blood loss anemia
- Deficiency anemias
- Alcohol abuse
- Drug abuse
- Psychoses
- Depression

Each year, clinician input and literature review is used to add additional variables for specific patient populations. For example, palliative care identified by ICD-9-CM diagnosis code V66.7 is included in models for conditions such as heart failure, stroke, AIDS, and malignancies. Additional diagnoses and/or procedures specific to certain patient populations such as neonatology, oncology, transplants, pediatrics, obstetrics, spinal surgery, ventilator support, cardiac surgery, cardiology, neurosciences, and other high impact DRGs and Base MS-DRGs are included in the models for those patients. UHC updates the models each year to include the latest 2 years worth of academic medical centers. It is at this time that recommendations from a member committee on risk adjustment are included in the risk adjustment process.

A standard cross validation statistical method is used to ensure the stability of the parameter estimates. Data are randomly split into training and validation samples. Key model diagnostics include the c-index and the Hosmer-Lemeshow test. A c-index >= 0.70 is generally

accepted as indicating good discrimination by a model. No mortality models with c-index values < 0.70 are accepted for the CDB. The final regression models are then constructed using the full data set. When a mortality model for base MS-DRG fails the validation tests, each case in the DRG or Base MS-DRG is assigned the observed mortality value stratified first by the ROM subclass from the APR-DRG grouper and then by whether or not the patient was transferred from another acute care hospital. This occurs mainly for one of two reasons: the incidence of the outcome variable is too low, or the patient population is small. Base MS-DRGs with very low observed mortality (<= 1% or < 50 deaths) are not modeled for mortality. For those base MS-DRGs, expected mortality is based on observed mortality stratified first by ROM subclass within the DRG or Base MS-DRG and then by transfer status. For mortality models, goodness of fit tests (e.g., Hosmer-Lemeshow tests) are run to determine how well the model predicts the outcome. Only models that "pass" the goodness of fit tests are used to estimate expected probability of mortality.

Potential causes of biased differences between observed and expected values derived from regression models include the following:

- Omitted Risk Factor(s) - If factors that are significantly related to outcome are not included in the risk adjustment model, the model can underestimate the expected values for hospitals having a disproportionate share of patients with the missing risk factor(s).
- Biased Reporting of Risk Factor(s) - If a hospital consistently under or over reports risk factor(s) with influential effects on the model estimates, then its expected values will be systematically biased. Since severity of illness estimation,

risk of mortality estimation, and comorbidity counts depend on the accuracy of ICD-9-CM coding, review of medical records for accuracy is very important.

- Biased Statistical Model - If the statistical model is not well calibrated and tested for systematic over or under estimation, then the model may systematically over or under estimate expected values. The literature has shown that this type of bias is not important for analyses at the individual patient level. However, when aggregating to the hospital level, model-related bias may become influential, since institutional differences were not fully accounted for by the model.

To minimize the effects of these factors, hospitals should carefully evaluate coding consistency, completeness and accuracy, including the coding of UB-04 fields like admission source and admission status, as well as ICD-9-CM diagnosis and procedure coding.

(4) Application of Models to Entire Database

The output from a stable model includes a coefficient for each of the variables found to be statistically significant predictors of the outcome, i.e., mortality in the population that was modeled. Using the coefficients for each of the statistically significant predictor variables and a flag indicating whether the variable was present in the patient, UHC then calculates a predicted value for each patient in the CDB. All patients in the database are assigned predicted values for mortality, LOS and costs.

The example below illustrates the calculation of expected probability of mortality for a stroke patient (DRG 14).

Model Group: # 14 - Spec CV dis exc TIA (DRG 14)

Model Diagnostics: Calculation: Chi-sq = 20.411 Validation: Chi-sq = 38.383, F = 1.881, p = 0.1803

Final: Max VIF = 2.789, Hosmer-Lemeshow = 48.622, p = p < 0.001, df = 10, C = 0.822

Mean Observed = 0.1334, Mean Expected = 0.1334

Cases = 21,394

Model Method = Logistic Regression

Model Results (Significant Predictors)

Coeff	Explanatory Variable	Coeff	Explanatory Variable
3.292	ROM = 4 (Extreme)	-0.423	CC Fluid & Electr Disorders
2.856	Palliative Flag	-0.490	CC Congestive Heart Failure
1.830	ROM = 3 (Major)	-0.609	CC Peripheral Vasc Disease
0.500	Female, Age >= 85	-0.649	CC Psychoses
0.489	Male, Age >= 85	-0.663	CC Deficiency Anemias
0.473	Female, 80 <= Age < 85	-0.772	CC Diabetes w/ CCs
0.448	CC Renal Failure	-0.807	CC Pulm Circulation Disease
0.417	Male, 80 <= Age < 85	-0.845	CC Depression
0.414	Admission Source = Emergency	-1.177	CC Pept Ulcer Dis X Bleed
0.402	Admit Src = Transf From Acute	-1.304	CC Acq Immune Def Synd
-0.190	CC Diabetes w/o CCs	-1.600	Male, 1 <= Age < 18
-0.320	CC Hypothyroidism	-1.652	CC Weight Loss
-0.392	CC Valvular Disease		

Patient Y Characteristics

Black Male

Age 54

Transferred from another hospital

Emergency admit status

APR-DRG ROM = Extreme

Principal Dx = 430 (subarachnoid hemorrhage)

Medicaid

CC COPD

CC CHF

CC Drug abuse

CC Coronary artery disease

CC Asymptomatic HIV status

CC History of DVT/embolism with long-term anticoagulant use

For each of the significant explanatory variables from the model determine whether that variable was present for this patient. If a variable is present it receives a value of 1, if not present its value is 0. For each of the significant predictor variables, multiply the variable's coefficient from the model times the patient value for that variable:

Variable	**Value**	**X**	**Coeff.**	**=**	**Result**
ROM = 4 (Extreme)	1		3.292		3.292
Palliative care	0		2.856		0
ROM = 3 (Major)	0		1.830		0
Female, Age >= 85	0		0.500		0
Male, Age >= 85	0		0.489		0
Female, 80<=Age< 85	0		0.473		0
CC Renal failure	0		0.448		0
Male, 80<=Age< 85	0		0.417		0
Adm stat emergency	1		0.414		0.414
Adm src trns frm acute	1		0.402		0.402
CC Diabetes w/o CCs	0		-0.190		0
CC Hypothyroidism	0		-0.320		0
CC Valvular disease	0		-0.392		0

CC Fluid & electro dis	0	-0.423	0
CC CHF	1	-0.490	-0.490
CC Periph vasc dis	0	-0.609	0
CC Psychoses	0	-0.649	0
CC Defic anemias	0	-0.663	0
CC Diabetes w/ CCs	0	-0.772	0
CC Pulm Circ Dis	0	-0.807	0
CC Depression	0	-0.845	0
CC Pept ulc dis exc bld	0	-1.177	0
CC Acq imm def synd	0	-1.304	0
Male, 1 <= Age < 18	0	-1.600	0
Male, 1 <= Age < 18	0	-1.600	0
CC Weight loss	0	-1.652	0

Formula for calculating expected mortality for a case

$$\text{expected mortality} = \frac{\exp(\text{intercept} + \sum_{i=1}^{n}(\text{coeff}i * \text{var}i)}{1+\exp(\text{intercept} + \sum_{i=1}^{n}(\text{coefficient} * \text{var}i)}$$

where n = # of significant variables or risk factors; var$i$ = 1 or 0 for variable i present in this patient or not ; coeff$i$ = coefficient for variable i

exp is the exponential function or $\exp(x) = e^x$ (e.g., exp(0) = 1, exp(1) = 2.718, etc.)

Using this formula Patient Y's expected probability of mortality = 0.4960.

Model Calibration

To ensure that the models are well calibrated for each of the fiscal years to which they are applied, intercept values and coefficients for each of the variables found to be statistically significant during model generation are re-calculated for each fiscal year. The intercept values and coefficients from the model results for the most recently completed fiscal year are applied to the next fiscal year's data until that fiscal year is completed. At that time the models are re-calibrated for the just completed fiscal year. This process is then repeated for each future fiscal year.

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