

# **Discharge to Community Claims-Based Measure for Home Health: Risk Adjustment Methodology**

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## <span id="page-4-0"></span>**1 INTRODUCTION**

The Improving Medicare Post-Acute Care Transformation Act of 2014 (IMPACT Act), enacted on October 6, 2014, requires standardization of the *Discharge to Community* measure across four post-acute care (PAC) settings: home health agencies (HHAs), skilled nursing facilities (SNFs), long-term care hospitals (LTCHs), and inpatient rehabilitation facilities (IRFs). The *Discharge to Community* measure for HHAs estimates the risk-standardized rate of patients (Medicare Fee-for-Service [FFS] beneficiaries) who are discharged to the community following a home health (HH) episode, do not have an unplanned readmission to an acute care hospital or LTCH in the 31 days following discharge to community, and remain alive during the 31 days following discharge to community.

This report summarizes the statistical risk model, variable specifications, the variable selection process, and the performance of the risk adjustment model for the claims-based *Discharge to Community* measure calculated for the home health Medicare FFS population. Section 2 describes the statistical risk model. Then Section 3 details the set of potential risk factors and each variable's specifications. Next, Section 4 describes how a subset of these risk factors was selected for the final predictive model. Section 5 evaluates the risk adjustment model's performance and appropriateness for this measure. Finally, Appendix A provides the risk adjustment model results.

# **2 STATISTICAL RISK MODEL**

In alignment with the IRF, LTCH, and SNF discharge to community measures, we used a hierarchical logistic regression method to predict the probability of a discharge to the community. Patient characteristics related to discharge and a marker for the specific discharging facility are included in the equation. We utilized a hierarchical model in order to account for both individual patient characteristics as well as the clustering of patient characteristics within HHAs. The statistical model estimates both the average predictive effect of the patient characteristics across all HHAs, and the degree to which each HHA has an effect on discharges to the community that differs from that of the average HHA. The HHA effects are assumed to be randomly distributed around the average (according to a normal distribution). When computing the HHA effect, hierarchical modeling accounts for the known predictors of discharge to the community, on average, such as patient characteristics, the observed HHA rate, and the number of HHA stays eligible for inclusion in the measure. The estimated HHA effect is determined mostly by the HHA's own data if the number of eligible stays is relatively large (as the estimate would be relatively precise), but is adjusted toward the average if the number of eligible stays is small (as that would yield a less precise estimate).

We used the following model:

Let  $Y_{ii}$ , denote the outcome (equal to 1 if patient *i* has a discharge to the community, 0 otherwise) for a patient *i* at facility  $j$ ;  $Z_{ij}$  denotes a set of risk adjustment variables. We assume the outcome is related to the risk adjusters via a logit function with dispersion:

$$
logit\left(Prob(Y_{ij})\right) = \alpha_j + \beta \times Z_{ij} + \varepsilon_{ij}
$$

$$
\alpha_i = \mu + \omega_i; \omega_i \sim N(0, \tau^2)
$$

where  $\overline{Z}$ ij = (Z1, Z2, ... Zk) is a set of k patient-level risk adjustment variables; alpha sub j represents the HHA-specific intercept; mu is the adjusted average outcome across all facilities; tau squared is the between-HHA variance component; and epsilon approximately equal to the N of sigma squared at zero is the error term. The hierarchical logistic regression model is estimated using SAS software (PROC GLIMMIX: SAS/STAT User's Guide, SAS Institute Inc.).

The estimated equation is used twice in the measure. The sum of the probabilities of discharge to the community of all patients in the HHA measure, including both the effects of patient characteristics and the HHA, is the "predicted number" of discharges to the community after adjusting for the HHA's case mix. The same equation is used without the HHA effect to compute the "expected number" of discharges to the community for the same patients at the average HHA. The ratio of the predicted-to-expected number of discharges to the community is a measure of the degree to which discharged to the community are higher or lower than what

<span id="page-6-0"></span>would otherwise be expected. This standardized risk ratio is then multiplied by the mean discharge to the community rate for all HHA stays for the measure, yielding the riskstandardized discharge to the community rate for each HHA.

# **3 VARIABLE SPECIFICATION**

To account for beneficiary characteristics that may affect the risk of discharge to community, the risk adjustment model uses potential risk factors that fall into three categories:

- (1) Demographics;
- (2) Care received during a prior proximal hospitalization (if one occurred); and
- (3) Other care received within one year of the HH stay.

The following sub-sections detail risk factors in each of these categories in turn.

# **3.1 Factor 1: Demographics**

Demographic risk factors included in the risk adjustment model are age and sex, enrollment status, and activities of daily living (ADL) scores.

#### *3.1.1 Age and Sex*

The risk adjustment model includes age and sex as covariates. Age-sex interactions allow the model to account for the differing effects of age on the outcomes for each sex. Age is subdivided into 12 bins for each sex: ages 18-34, 35-44, 45-54, five-year age bins from 55 to 95, and one bin for ages over 95. 65-69, Male is the reference group.

#### *3.1.2 Enrollment Status*

The model employs aged (reference), end stage renal disease (ESRD), and disability as covariates for the original reason for Medicare entitlement.

#### *3.1.3 Activities of Daily Living Scores*

The Home Health Prospective Payment System (HH-PPS) calculates an Activity of Daily Living (ADL) Severity Score by combining responses from several Outcome and Assessment Information Set (OASIS) fields. The ADL Severity Score is calculated using four methods that differ by how much weight is assigned to the OASIS variables that comprise the score. These four scores are then combined with information related to episode timing (early/late status) and the number of therapy visits to determine which Severity Score is placed on the five-character Health Insurance Prospective Payment System (HIPPS) code as the ADL Severity Score. The risk adjustment model includes all four Severity Scores (i.e., ADL 1-4).

#### <span id="page-7-0"></span>**3.2 Factor 2: Care Received during the Prior Proximal Hospitalization**

Because beneficiaries who enter home health care from prior proximal hospitalizations<sup>[1](#page-7-1)</sup> may have different health statuses, this model takes into account beneficiaries' immediate prior care setting, principal diagnoses, and procedures.

#### *3.2.1 Length of Prior Proximal Hospitalization*

The length of the prior proximal hospitalization is included in the model as a binary variable: 0-30 days (reference) and greater than or equal to 31 days.

#### *3.2.2 Clinical Classification Software (CCS) during Prior Proximal Hospitalization*

The risk model relies on CCS diagnosis and procedure groups to adjust for beneficiary health status during a prior proximal hospitalization, if a prior proximal hospitalization occurred. CCS diagnosis groups are defined using principal diagnosis codes from the prior proximal hospitalization. CCS procedure groups are defined using procedure codes recorded during the prior proximal hospitalization.

# **3.3 Factor 3: Other Care Received within One Year of Stay**

To further account for beneficiaries who may have different health statuses entering into home health, this model adjusts for the beneficiaries' number of prior acute discharges, number of emergency department visits, number of skilled nursing facility visits, number of long-term care hospital visits, and Hierarchical Condition Categories (HCC) comorbidities.

#### *3.3.1 Number of Prior Acute Discharges*

The model adjusts for the number of prior acute hospital discharges in the past year, excluding those that took place within 30 days prior to the start of home health or resumption of care. The number of prior acute discharges is classified in the model as 0 (i.e., no prior acute discharge; reference group), 1, 2, 3, 4, 5, 6, 7, 8, 9, and 10 or more discharges.

#### *3.3.2 Number of Outpatient Emergency Department Visits*

The model also takes into account whether or not an outpatient emergency department (ED) visit took place within one year of the HH stay (i.e., 0 ED visits [reference] or 1 or more ED visits).

#### *3.3.3 Number of Skilled Nursing Facility Visits*

The model adjusts for whether or not a skilled nursing facility took place within one year of the HH stay (i.e., 0 SNF visits [reference] or 1 or more SNF visits).

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<span id="page-7-1"></span><sup>1</sup> Prior proximal hospitalizations for the *Discharge to Community* measure are defined as a short-term acute-care or psychiatric stay within 30 days prior to home health admission. Prior proximal hospitalizations are indicated by the discharge date from an inpatient claim for an acute care hospital (CMS Certification Numbers [CCN] ending in 0001-0879, 0880-0899, and 1300-1399) or psychiatric facility (CCNs ending in 4000-4499).

#### <span id="page-8-0"></span>*3.3.4 Number of Long-Term Care Hospital Visits*

The model adjusts for whether or not a long-term care hospital visit took place within one year of the HH stay (i.e., 0 LTCH visits [reference] or 1 or more LTCH visits).

#### *3.3.5 Hierarchical Condition Categories (HCC) Comorbidities*

To account for beneficiary health status within one year of the HH stay, the risk adjustment model also relies on the HCC framework<sup>[2](#page-8-1)</sup>. The risk adjustment model includes 54 hierarchically ranked HCCs based on the 2009 CMS-HCC risk adjustment model. HCC comorbidities are defined using secondary diagnoses from the prior proximal hospitalization (if a prior proximal hospitalization occurred) and all other diagnoses recorded in the inpatient, outpatient, and carrier settings during the year prior to the home health stay.

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<span id="page-8-1"></span> $2^2$  CMS-HCC Mappings of ICD-9 Codes: Mappings are included in the software at the following website: <http://www.cms.gov/Medicare/Health-Plans/MedicareAdvtgSpecRateStats/Risk-Adjustors.html>

# <span id="page-9-0"></span>**4 VARIABLE SELECTION**

Several steps were implemented to develop a model that accounts for important risk factors while also ensuring that the model is not over fit to the data. The Least Absolute Shrinkage and Selection Operator (LASSO) was one of the analyses used to guide the variable selection process. The LASSO technique is designed to develop models that minimize prediction error in a manner that does not overfit the data. The nature of the LASSO function encourages parameter estimates of unimportant predictors to shrink to zero (which effectively eliminates these variables from the model). Additionally, the LASSO technique utilizes cross-validation to establish the set of model predictors that consistently result in a relatively low prediction error. The remainder of this section describes why the LASSO method for variable selection is particularly useful in this context and outlines the measure selection process.

## **4.1 Use of LASSO for Model Selection**

LASSO is particularly appropriate for the home health discharge to community measure because of the need to select a parsimonious set of predictors from a large number of available variables as well as the need for a risk model that performs consistently across data updates. A large number of independent variables were under consideration for this measure, including diagnosis and procedure code groupings, age-sex interactions and prior healthcare utilization, among others. While it is important to consider all of the available variables, it is also important to avoid overfitting the data. Because of sample-specific relationships, a model that minimizes prediction error in one sample may be too closely tailored and generate large prediction errors in another sample. Given that the discharge to community risk adjustment model will be applied to new data as the measure is updated annually, it is important that model performance remain consistent across data updates. Because LASSO utilizes cross-validation to evaluate prediction error, it lends itself well to generating models that perform consistently across datasets; thus, it is expected that the risk-adjustment model will perform consistently as data are updated annually.

#### **4.2 Covariate Selection Methodology**

Considering the volume of independent covariates available for this model, multiple steps were taken to eliminate variables that do not improve the model's predictive ability or that do not predict discharges to the community risk in a consistent manner. All variable selection activities were performed using a training dataset comprised of an eighty percent random sample of the population of eligible home health stays. Covariate selection occurred in three stages:

(1) Before initiating the LASSO, we eliminated all independent variables that have fewer than 500 occurrences in our population across all three years of data. The population consisted of roughly 6.3 million home health stays, so this eliminated covariates appearing in approximately 0.01% of stays and which were unlikely to meaningfully

improve model performance. Furthermore, we eliminated all variables with zero dischargers to the community in any individual year. As described below in #3, this exclusion was necessary to run annual logistic regression models assessing each covariate's stability over time. When zero discharges to the community were observed in a given year for a particular variable, it was observed that there were also zero or very low numbers of discharges to the community for the same variable in adjacent years.

- (2) LASSO was implemented using the "glmnet" package in R to select which of the remaining variables were important to include in the risk model.
- (3) Lastly, after the LASSO provided a list of suitable model covariates, we checked to ensure that each covariate's predictive ability is consistent across calendar years (because the final model will be applied to annually updated data). To test this, we constructed logistic regression models controlling for the list of variables provided by LASSO, stratified by calendar year. If the point estimates for a particular variable were not consistently above or below the null across calendar years, then that variable was eliminated from the final model.

# <span id="page-11-0"></span>**5 MODEL PERFORMANCE**

This section evaluates the risk adjustment model and illustrates its appropriateness for the discharge to community measure. First, Section 5.1 describes the analysis performed to confirm that the variables selected by LASSO were appropriate for the final hierarchical model. Section 5.2 examines how risk adjustment affects the distribution of discharge to the community rates overall. Finally, Section 5.3 evaluates the model fit in both the training and validation datasets. The final population comprised of 6,325,578 home health stays attributed to 12,316 HHAs. The detailed model results are included in Appendix A.

## **5.1 Comparison of Parameter Estimates between the LASSO and Random Effects Models**

The LASSO model used for variable selection does not account for the clustering of eligible stays within HHAs. The final hierarchical risk adjustment model, on the other hand, does account for this clustering. Therefore, it was important to confirm that the variables selected using LASSO were also appropriate for the final risk model. To this end, we compared the parameter estimates of the covariates remaining in the risk model after implementing LASSO between two hierarchical logistic regression models: one that accounts for the clustering of stays and another that does not. We found the model coefficients were very close across these two models; therefore, we concluded that the variables selected using LASSO were also appropriate for the final hierarchical risk model.

## **5.2 Distributions of Observed Rates and Risk Standardized Readmission Rates (RSRRs)**

The unadjusted readmission rates range from 0.0 to 100 percent, with a median of 77.8 percent and a  $10^{th}$  to  $90^{th}$  percentile range of 45.6 to 88.9 percent. The RSRR had a similar distribution, but slightly compressed compared to the unadjusted rates, with a range from 1.1 to 100 percent, a higher median of 82.4 percent and a tighter  $10^{th}$  to  $90^{th}$  percentile range of 50.9 to 92.5 percent. The mean RSRR (76.7%) was slightly higher than the unadjusted rate (72.2%) and the scores had a smaller standard deviation (17.5 % vs. 18.2%). The compression of the RSRR distribution compared to the distribution of observed rates is expected because the hierarchical model adjusts each HHA toward the average performance rate. The extent to which an HHA is adjusted toward the average depends on the number of eligible stays included in the measure for the HHA. Table 5.1 presents the distributions of the observed rates and RSRRs of discharges to the community for agencies with at least 20 home health stays using the full data set. Agencies with fewer than 20 eligible stays were excluded from this summary because they tend to have more extreme rates due to imprecision. There was no evidence of a ceiling effect for this measure and there is a large amount of variation in performance rates across HHAs.



#### <span id="page-12-0"></span>**Table 5.1: Distribution of Observed Rates and RSRRs of Discharges to the Community among Agencies with at least 20 Eligible Stays**

#### **5.3 Predictive Power**

We evaluated the predictive power of the model for both the development sample and the validation sample. Evaluating model fit for the development sample shows how well the model predicts outcomes in the data on which it was developed, while evaluating model fit for the validation sample shows how well the model predicts outcomes outside the data on which it was developed. The area under the receiver operating curve (AUC) statistic, also known as the cstatistic, measures the ability of the model to differentiate between outcomes without resorting to an arbitrary cutoff point. A model that perfectly discriminates between outcomes would have a cstatistic of 1.0, while a model that has no predictive power would have a c-statistic of 0.5. The cstatistic for the development sample was 0.74, which suggests the risk model is well fit to the data in which it was developed. To assess the fit of model in the validation sample, the parameter estimates from the development sample were used to calculate the probability of an event for each home health stay in the validation sample. The c-statistic resulting from the validation dataset was 0.68, which is slightly smaller but comparable to the c-statistic of 0.77 observed in the testing dataset. We also calculated the range of differences between the 10th and 90th percentile of RSRRs in both the training and validation datasets to further ensure the model will perform similarly as new data is added. In the development sample, the range of RSRRs was 51.8 percent to 92.3 percent and the range in the validation sample was 63.2 percent to 90.5. The distribution of RSRRs fall within similar ranges, with the range in the validation being narrower than that of the validation dataset due to the relatively smaller number of eligible stays for each HHA in the validation sample. Overall, these results indicate that the model strongly fit the data and that the model continues to perform well when applied to new data.

# <span id="page-13-0"></span>**6 CONCLUSION**

The report describes the risk adjustment methodology and performance of the *Discharge to Community* measure i the home health population. A hierarchical, multivariate risk-adjustment model was used to derive the HHA-level risk standardized readmission rates (RSRRs). The risk model employs the following sets of covariates:

- (1) Demographics
	- (a) Age and sex
	- (b) Enrollment status
	- (c) Activities of daily living scores
- (2) Care received during the prior proximal hospitalization (if relevant)
	- (a) Length of prior proximal hospitalization
	- (b) Clinical classification software (CCS) diagnosis and procedure categories during prior proximal hospitalization
- (3) Other care received within one year of the HH stay
	- (a) Number of prior acute discharges
	- (b) Number of outpatient emergency department visits
	- (c) Number of skilled nursing facility visits
	- (d) Number of long-term care hospital visits
	- (e) Hierarchical condition categories (HCC) comorbidities

The specific set of 285 covariates used in the model consisted of demographic and healthcare utilization variables as well as clinical characteristics selected through a series of steps including the implementation of LASSO as well as analyses to ensure covariates consistently predict discharge to the community risk over time. Implementing a hierarchical model adjusts for individual demographic and clinical characteristics, accounts for the clustering of stays within HHAs, and compresses the distribution of discharge to community rates (although a large degree of variability remains). Overall, the model strongly fits the data with a c-statistic of 0.74 and performs well when applied to new data.

# <span id="page-15-0"></span>**APPENDIX A: MOEL COEFFICIENTS, P-VALUES, AND MARGINAL EFFECTS**



# **Table A.1: Discharge to Community Post Home Health Measure Logistic Regression Model Results in 2012 - 2013**





















