Technical Notes on the Alive and Out of Hospital Percentage (AOH)

For the Dialysis Facility Reports

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Contents

1 Introduction

The Alive and Out of Hospital Percentage (AOH) reported in Table 4 of the Dialysis Facility Reports (DFR) is the proportion of patient time at risk that patients were both alive and not in the hospital during a given time period, adjusted for patient characteristics. A higher AOH Percentage indicates the positive outcome of patients in that dialysis facility having had more time alive and out of hospital during the reporting period and conversely a lower AOH Percentage indicates patients in that dialysis facility having had less time alive and out of hospital during the reporting period. The motivation behind the development of the AOH Percentage stems from the complex inter-relationship between survival and hospital utilization.

In the DFR, both an unadjusted and adjusted version of the percentage of patient time at risk spent alive and out of the hospital are reported, but the adjusted version is referred to as the AOH Percentage. To compute the adjusted version of the measure, we utilize a regression model that contains outcome-related factors or covariates, such as age, diabetes, nursing home status, comorbidities and body mass index (BMI).

In the DFR, we also report the AOH Percentages for a given region, which are provided for comparison purposes, so that each facility's AOH Percentage can be compared to the AOH Percentage for the region in which it is located.

The document is organized as follows. Section 2 gives required administrative details. In Section 3 and 4, we detail a two-stage modeling approach for computing the AOH Percentage, adjusted for patients' characteristics. Section 5 gives a detailed description for computing p-values and confidence intervals, which accounts for possible uncertainty or random variations that may be beyond the control of the facilities. We give some final remarks in Section 6.

2 Assignment of Patients to Facilities for the AOH Percentage Calculation

As patients can receive dialysis treatment at more than one facility in a given year, we assign each patient day to a facility (or no facility, in some cases) based on a set of conventions below, which largely align with those for the Standardized Mortality Ratio (SMR) and the Standardized Hospitalization Ratio (SHR). We detail patient inclusion criteria, facility assignment and how to count days at risk, all of which are required for the risk adjustment model.

2.1 General Inclusion Criteria for Dialysis Patients

Because a patient's follow-up in the database can be incomplete during the first 90 days of ESRD therapy, we only include a patient's follow-up into the tabulations after that patient has received chronic renal replacement therapy for at least 90 days. Thus, hospitalizations, mortality and survival during the first 90 days of ESRD do not enter into the calculations. This minimum 90-day period also assures that most patients are eligible for Medicare insurance, either as their primary or secondary insurer. It also excludes from analysis patients who die or recover during the first 90 days of ESRD.

2.2 Identifying Facility Treatment Histories for Each Patient

For each patient, we identify the dialysis provider at each point in time. Starting with day 91 after onset of ESRD, we attribute patients to facilities. Unlike the Standardized Mortality Ratio (SMR) and Standardized Hospitalization Ratio (SHR), patients do not have to be treated at a facility for at least 60 days in order to be attributed to it. Patients were removed from facilities three days prior to transplant in order to exclude the transplant hospitalization. Patients who withdrew from dialysis or recovered renal function were excluded from analysis.

If a period of one year passed with neither dialysis claims nor SIMS information to indicate that a patient was receiving dialysis treatment, we considered the patient lost to follow-up and did not continue that patient in the analysis. When dialysis claims or other evidence of dialysis reappeared, the patient was then re-assigned to a particular facility.

2.3 Days at Risk for Medicare Dialysis Patients

After patient treatment histories are defined, as described above, periods of follow-up time (or patient-records) are created for each patient. A new time period begins each time the patient is determined to be at a different facility, or at the start of each month. Due to the time sensitive nature of how AOH Percentage is calculated, time of year must be adjusted for, so records are created at the monthly level. For example, a patient's death in March should not be deemed worse than a patient's death in September just due to the fact that the patient who died in March will have less time alive that year. This is why data is evaluated at the monthly level and adjusted for in the modeling process. Additionally, all time at risk for patients that die during the reporting period is extended through the end of the year in order for the time spent alive and out of hospital to be calculated appropriately. Time at risk is not extended for patients that die from causes unrelated to dialysis, which aligns with the exclusion for the Standardized Mortality Ratio (SMR).

Because we can only identify hospitalizations if they appear in Medicare inpatient claims, we only include patients during time periods in which we are reasonably sure that all of the patient's hospitalizations would be included in Medicare billing records. Therefore, we require that patients reach a certain level of Medicare-paid dialysis bills, have Medicare inpatient claims during the period, or are enrolled in Medicare Advantage during the period. Specifically, a patient-month within a given dialysis patient-period is included in the AOH Percentage calculations when at least one of the following is true:

(1) The patient had $1,200+ of Medicare-paid dialysis claims or at least one Medicare inpatient claim (hospital or SNF) during that month or one of the two prior months.

(2) The Medicare Enrollment Database (EDB) indicates the patient was enrolled in Medicare Advantage during the month.

The intention of the criteria is to assure completeness of the relevant hospitalization information for all patients included in the analysis.

3 Models for Calculating Adjusted AOH Percentage

The AOH Percentage for each facility is derived from a logistic binomial regression model with facility-specific fixed effects. The model is estimated within a generalized estimating equations (GEE) framework (Liang and Zeger, 1986): point estimates of the regression coefficients and facility effects are obtained under a working independence assumption, while robust (sandwich) standard errors are used to account for the within-patient correlation that arises from repeated monthly observations. The model is run separately for each calendar year reported in the DFR.

We denote by Y_{ijk} the number of days alive and out of hospital (AOH days) for patient i at facility j during calendar month k, and by N_{ijk} the number of days at risk for that patient during that month. The outcome is modeled as

$$Y_{ijk} \mid N_{ijk} \sim \text{Binomial}\big(N_{ijk},\ \pi_{ijk}\big),$$

where the probability π_{ijk} of being alive and out of hospital on any given at-risk day satisfies the logistic model

$$\text{logit}\big(\pi_{ijk}\big) = \log\left(\frac{\pi_{ijk}}{1-\pi_{ijk}}\right) = \alpha_j + \mathbf{X}_{ijk}^{\top}\boldsymbol{\beta}.$$

Here, α_j is the facility-specific intercept for facility j, $\mathbf{X}_{ijk}$ is the vector of covariates for patient i at facility j during calendar month k, and $\boldsymbol{\beta}$ is the corresponding p-dimensional vector of regression coefficients. The facility-specific intercepts $\{\alpha_j : j = 1, \ldots, m\}$ are treated as fixed effects, so that each of the m facilities has its own intercept estimated from the data.

The patient characteristics $\mathbf{X}_{ijk}$ included in the model are: age at the start of the at-risk period, duration of

ESRD (vintage), calendar month (with January as the reference category), diabetes as cause of ESRD, nursing home status (categorized as a short-term stay of 1–89 days and a long-term stay of 90 or more days in the prior 365 days), body mass index (BMI) at incidence (categorized as underweight, normal, overweight, or obese per World Health Organization criteria (WHO, 2020), with obese serving as the reference group), Medicare Advantage coverage (as a continuous proportion of time at risk), race, ethnicity, comorbidities at incidence, and 91 prevalent comorbidities identified through Medicare inpatient claims. The comorbidities at incidence include: atherosclerotic heart disease, other cardiac disease, congestive heart failure, inability to ambulate, chronic obstructive pulmonary disease, inability to transfer, malignant neoplasm, cancer, peripheral vascular disease, cerebrovascular disease, tobacco use (current smoker), alcohol dependence, and drug dependence. Categorical indicator variables are included as covariates to flag records with missing values for cause of ESRD and comorbidities at incidence.
All facility-specific intercepts α_j and regression coefficients $\boldsymbol{\beta}$ are estimated simultaneously by maximizing the binomial log-likelihood

$$\ell(\boldsymbol{\alpha}, \boldsymbol{\beta}) = \sum_j \sum_i \sum_k \left[Y_{ijk} \left(\alpha_j + \mathbf{X}_{ijk}^\top \boldsymbol{\beta} \right) - N_{ijk} \log \left(1 + \exp\left(\alpha_j + \mathbf{X}_{ijk}^\top \boldsymbol{\beta} \right) \right) \right],$$

where the inner sums range over all patient-month observations at facility j. The estimation is carried out using a Newton–Raphson algorithm that exploits the block structure of the joint information matrix through the Schur complement, enabling efficient computation despite the large number of facility-specific parameters (Wu, 2022).

After obtaining estimates $\hat{\alpha}_j$ and $\widehat{\boldsymbol{\beta}}$ from the model, we compute the adjusted AOH Percentage for each facility using the following direct standardization procedure (He, 2018). For a given facility j, the predicted probability that patient i is alive and out of hospital in month k, under the effect of facility j, is

$$\hat{\pi}_{ijk} = \frac{\exp\left(\hat{\alpha}_j + \mathbf{X}_{ijk}^\top \widehat{\boldsymbol{\beta}} \right)}{1 + \exp\left(\hat{\alpha}_j + \mathbf{X}_{ijk}^\top \widehat{\boldsymbol{\beta}} \right)}.$$

The adjusted AOH Percentage for facility j is then defined as the weighted average of these predicted probabilities over all patients in the national data:

$$\hat{\pi}_j = \frac{\sum_l \sum_i \sum_k N_{ilk} \, \hat{\pi}_{ijk}}{\sum_l \sum_i \sum_k N_{ilk}},$$

where the sums range over all calendar months k, all facilities l, and all patients i treated at facility l in month k, and N_{ilk} denotes the number of at-risk days for patient i at facility l during month k. Note that $\hat{\pi}_{ijk}$ in the numerator uses facility j's estimated intercept $\hat{\alpha}_j$ combined with each patient's own covariates $\mathbf{X}_{ijk}$, regardless of which facility l actually treated the patient. In this way, $\hat{\pi}_j$ represents the AOH Percentage that would be expected if all patients in the nation were treated at facility j, providing a standardized basis for comparison across facilities.

The national average AOH Percentage, $\hat{\pi}$, is computed similarly but uses each patient's own facility effect:

$$\hat{\pi} = \frac{\sum_l \sum_i \sum_k N_{ilk} \, \hat{\pi}_{ilk}}{\sum_l \sum_i \sum_k N_{ilk}},$$

where

$$\hat{\pi}_{ilk} = \frac{\exp\left(\hat{\alpha}_l + \mathbf{X}_{ilk}^\top \widehat{\boldsymbol{\beta}} \right)}{1 + \exp\left(\hat{\alpha}_l + \mathbf{X}_{ilk}^\top \widehat{\boldsymbol{\beta}} \right)}$$

uses the patient's own facility intercept $\hat{\alpha}_l$. The adjusted AOH Percentage reported in the DFR for facility j is $\hat{\pi}_j \times 100\%$.

3.1 Missing Data

Patients with missing data are not excluded from the model. Patients with missing diagnosis are included in the "other" diagnosis group. For the purposes of calculation, BMI missing values are included in the obese group. Patients with missing race are included in the "other" race group strata and classified as non-White in the model. Patients with missing ethnicity are classified as "unknown" ethnicity. No patients were missing age or date of first ESRD treatment. The model also includes indicator variables identifying patients with missing values for cause of ESRD and incident comorbidities.

4 Calculation of AOH Percentage P-Values and Confidence Intervals

To assess whether a facility's AOH Percentage differs significantly from the national average, we compute facility-level standardized AOH Percentages score using robust sandwich variance estimators (White, 1980; Liang and Zeger, 1986). Standard errors are clustered at the patient level to account for within-patient correlation, yielding valid inference even when the working model assumes independence across observations within each patient.

We begin by describing the robust variance estimation procedures for the regression coefficients **β** and the facility-specific intercepts α_j, and then detail the computation of the AOH Percentage score, p-values, and confidence intervals.

4.1 Robust Inference for Regression Coefficients (β)

Let $r_{ijk} = Y_{ijk} - N_{ijk}\,\hat{\pi}_{ijk}$ denote the residual for patient i at facility j in month k. Because each patient may contribute observations across multiple months, standard model-based variance estimates that assume independence across observations can understate the true variability. To account for within-patient correlation, we employ a robust clustered sandwich variance estimator of the general form $\widehat{\mathrm{Var}}(\hat{\boldsymbol{\beta}}) = \mathbf{A}^{-1}\,\mathbf{B}\,\mathbf{A}^{-1}$, where **A** is the model-based information matrix and **B** is the empirical "meat" that captures the observed variability.

The information matrix for the joint parameter $(\boldsymbol{\alpha}, \boldsymbol{\beta})$ has a block structure with facility-specific and covariate components. The Schur complement is used to eliminate the facility-specific parameters and obtain the effective information for **β** alone. The meat matrix is constructed by first aggregating residuals and score contributions at the patient level within each facility — so that within-patient correlation is properly captured — and then forming outer products of these aggregated quantities. Because **β** and **α** are estimated simultaneously, the sandwich variance also includes cross-terms that account for the covariance between the two sets of estimators.
The robust standard error of the qth regression coefficient, $\widehat{\mathrm{SE}}(\hat{\beta}_q)$, is extracted from the diagonal of the resulting sandwich variance matrix. The Wald test statistic for testing $H_0: \beta_q = 0$ is

$$Z_q = \frac{\hat{\beta}_q}{\widehat{\mathrm{SE}}(\hat{\beta}_q)},$$

with a two-sided p-value $p_q = 2\,\Phi\left(-\left|Z_q\right|\right)$, where $\Phi(\cdot)$ denotes the standard normal cumulative distribution function.

4.2 Robust Inference for Facility-Specific Effects (α_j)

The robust standard error of the facility-specific intercept $\hat{\alpha}_j$ is of central importance, as it directly determines the standard error of the adjusted AOH Percentage for facility j and hence the AOH Percentage score used for identifying outlier facilities.

Under working independence, the model-based variance of $\hat{\alpha}_j$ is $I^{-1}_{\alpha_j\alpha_j}$, where

$$I_{\alpha_j\alpha_j} = \sum_i \sum_k N_{ijk}\ \hat{\pi}_{ijk}(1-\hat{\pi}_{ijk})$$

is the diagonal entry of the information matrix corresponding to facility j. However, this estimate ignores within-patient correlation. To obtain a robust variance, we employ the same sandwich approach as for **β**, but with a simpler structure since α_j is a scalar parameter specific to facility j.

The meat is constructed by first aggregating residuals within each patient: for patient i at facility j, the aggregated residual is $\tilde{r}_i = \sum_k r_{ijk}$, summing over all months in which the patient is at risk. The clustered meat for facility j is then

$$M_j = \sum_{\substack{\text{patients} \\ i \in j}} \tilde{r}_i^{\,2}.$$

By aggregating at the patient level before squaring, M_j captures the covariance among a patient's monthly observations. The robust sandwich variance and standard error of $\hat{\alpha}_j$ are

$$\widehat{\mathrm{Var}}(\hat{\alpha}_j) = \frac{M_j}{I_{\alpha_j\alpha_j}^2}, \qquad \widehat{\mathrm{SE}}(\hat{\alpha}_j) = \frac{\sqrt{M_j}}{I_{\alpha_j\alpha_j}}.$$

The robust Wald test statistic for testing $H_0: \alpha_j = \tilde{\alpha}$, where $\tilde{\alpha}$ is a suitable national null value, is

$$W_j = \frac{\hat{\alpha}_j - \tilde{\alpha}}{\widehat{\mathrm{SE}}(\hat{\alpha}_j)},$$

with a two-sided p-value $p_j = 2\,\Phi(-|W_j|)$.

4.3 The AOH Percentage Score, P-Values, and Confidence Intervals

Having obtained robust standard errors for the facility-specific intercepts, we derive the standard error of the adjusted AOH Percentage $\hat{\pi}_j$ using the delta method. Since $\hat{\pi}_j$ is a smooth function of $\hat{\alpha}_j$ (with $\widehat{\boldsymbol{\beta}}$ and all patient covariates treated as fixed), the delta method yields

$$\widehat{\mathrm{SE}}(\hat{\pi}_j) = \left|\frac{\partial \hat{\pi}_j}{\partial \alpha_j}\right| \cdot \widehat{\mathrm{SE}}(\hat{\alpha}_j).$$

From the definitions of $\hat{\pi}_j$ and $\hat{\pi}_{ijk}$, and using the fact that the derivative of the logistic function satisfies $\partial \hat{\pi}_{ijk} / \partial \alpha_j = \hat{\pi}_{ijk}(1-\hat{\pi}_{ijk})$, we obtain

$$\frac{\partial \hat{\pi}_j}{\partial \alpha_j} = \sum_l \sum_i \sum_k w_{ilk}\ \ \hat{\pi}_{ijk}\,(1-\hat{\pi}_{ijk}),$$

where

$$w_{ilk} = \frac{N_{ilk}}{\sum_{k'} \sum_{l'} \sum_{i'} N_{i'l'k'}}$$

is the normalized weight for patient i at facility l in month k, and the sum ranges over all patient-month observations in the national data.

The AOH Percentage score for facility j is defined as

$$\hat{Z}_j = \frac{\hat{\pi}_j - \hat{\pi}}{\widehat{\mathrm{SE}}(\hat{\pi}_j)},$$

where $\hat{\pi}$ is the national average AOH Percentage. The AOH Percentage score measures how many standard errors the facility's adjusted AOH Percentage deviates from the national average. A positive AOH Percentage score indicates that the facility's patients spend more time alive and out of hospital than the

national average, while a negative score indicates less time alive and out of hospital than the national average.

The two-sided p-value for testing whether facility j's adjusted AOH Percentage differs significantly from the national average is

$$p_j = 2\left[1 - \Phi\left(|\hat{Z}_j|\right)\right],$$

and the 95% confidence interval for the facility's true adjusted AOH Percentage is

$$\hat{\pi}_j \pm 1.96 \times \widehat{\mathrm{SE}}\left(\hat{\pi}_j\right).$$

4.4 Flagging Rules

For reporting purposes, we identify outlier facilities from amongst those with at least 11 patients during the time period. A facility is classified as follows based on its AOH Percentage score:

- If $\hat{Z}_j > 1.96$, the facility is said to have outcomes that are "better than expected." This indicates that the facility's adjusted AOH Percentage is significantly above the national average at the 5% significance level, meaning that patients at this facility spend significantly more time alive and out of the hospital.
- If $\hat{Z}_j < -1.96$, the facility is said to have outcomes that are "worse than expected." This indicates that the facility's adjusted AOH Percentage is significantly below the national average at the 5% significance level.
- If $-1.96 \leq \hat{Z}_j \leq 1.96$, the facility is said to have outcomes that are "as expected."

The threshold of ± 1.96 corresponds to a two-sided significance level of $\alpha = 0.05$ based on the standard normal distribution. Equivalently, a facility is flagged as an outlier if and only if its 95% confidence interval for $\hat{\pi}_j$ does not contain the national average $\hat{\pi}$.

4.5 Example

We illustrate the computation of the AOH Percentage score, p-value, and confidence interval using a hypothetical facility j with at least 11 patients. Suppose that this facility serves a patient population that is older and has a higher comorbidity burden than the national average. The table below compares the unadjusted (crude) and risk-adjusted quantities for this facility:

	Unadjusted	**Adjusted**
Facility AOH Percentage	$\tilde{\pi}_j = 34.8\%$	$\hat{\pi}_j = 35.9\%$
National average AOH Percentage	$\tilde{\pi} = 35.0\%$	$\hat{\pi} = 35.2\%$
Standard error	$\widehat{\mathrm{SE}}\left(\tilde{\pi}_j\right) = 0.004$	$\widehat{\mathrm{SE}}\left(\hat{\pi}_j\right) = 0.003$
Standardized score	$\tilde{Z}_j = -0.500$	$\hat{Z}_j = 2.333$
P-value	0.617	0.020
95% CI	(0.340, 0.356)	(0.353, 0.365)
Flag	as expected	better than expected

The crude AOH Percentage for facility j is simply the observed proportion of AOH days among the facility's own patients. Without risk adjustment, the crude rate of 34.8% falls slightly below the crude national

average of 35.0%, yielding a standardized score of $\tilde{Z}_j = (0.348 - 0.350)/0.004 = -0.500$ and a non-significant p-value of 0.617.

After fitting the model described in Section 3 and applying the direct standardization procedure, both the facility-level and national quantities change. The risk-adjusted AOH Percentage for facility j increases to 35.9%, reflecting the fact that, after accounting for the facility's sicker patient mix, the facility actually achieves a higher-than-expected proportion of days alive and out of hospital. The adjusted national average also shifts to 35.2%. The AOH Percentage score is computed as

$$\hat{Z}_j = \frac{\hat{\pi}_j - \hat{\pi}}{\widehat{\mathrm{SE}}(\hat{\pi}_j)} = \frac{0.359 - 0.352}{0.003} = \frac{0.007}{0.003} \approx 2.333.$$

The two-sided p-value is $p_j = 2[1 - \Phi(2.333)] = 2(1 - 0.9902) = 0.020$, and the 95% confidence interval is $0.359 \pm 1.96 \times 0.003 = (0.353,\ 0.365)$, or equivalently, 35.3% to 36.5%. Since $\hat{Z}_j > 1.96$, it is classified as "better than expected."

This example illustrates how risk adjustment can change the conclusion: without adjustment, the facility appears to perform as expected ($p = 0.617$), whereas the adjusted analysis correctly identifies it as performing significantly better than expected ($p = 0.020$).

5 Final Remarks

This document details the computation of the AOH Percentage, which was designed to be a quality of life measure through the reporting of patient time spent alive and out of the hospital. Our proposed methods are based on several statistical publications developed by the investigators of UM-KECC and have been tested in various settings. In general, the validity of any standardized measures largely depend on the validity of risk-adjustment models. As proper choices of risk adjusters are vital in the process, our practical principles lie in scientific relevance and caution of sequel. That is, we choose risk adjusters that are scientifically relevant to the outcome, while avoiding choosing those that may be affected by the quality of care.

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