

# Diabetes EDAC Risk Adjustment and Model Performance Testing

## Risk Adjustment

The goal of risk adjustment is to adjust for case-mix differences across the hospitals. Risk adjustment supports fair and accurate comparison of outcomes across measured entities by including an adjustment for factors such as patient age, comorbid diseases, and indicators of patient frailty, which are clinically relevant and have relationships with the outcome. In pursuing a risk adjustment approach that best leverages the data, we used a framework based largely on individual ICD-10 codes for risk adjustment. The main advantage of leveraging ICD-10 codes in place of alternative methods that employ an ICD-10 grouper (such as CMS's Condition Categories, or CCs) is the ability to address the clinical heterogeneity found in the broadly defined CCs. Our previous research indicates that the model performance of the mortality measures is significantly improved by using individual codes instead of CCs (Krumholz et al., 2019).

The Diabetes EDAC measure adjusts for case-mix differences among hospitals based on the clinical status of the patient at the time of the index admission. Accordingly, only comorbidities that convey information about the patient at that time or in the 12 months prior, and not complications that arise during the index hospitalization, are included in the risk adjustment.

The process for determining patient comorbidities present at the time of the index admission from the index admission claim/encounter data uses a present-on-admission (POA) algorithm. The POA algorithm applies only in the case of secondary diagnosis codes on the index admission used in the risk adjustment of a measure. In brief, an ICD-10-CM code on the index admission is used in risk adjustment if one of the following is true:

1. The POA indicator for the secondary diagnosis code = 'Y' on the index admission.
2. The secondary diagnosis code is classified as a POA-exempt code that is considered "always POA" (as designated by our clinical experts).
3. If the index claim/encounter data is void of POA coding (that is, no reported POA indicator values for any of the secondary diagnoses), then the secondary diagnosis is used in risk adjustment if it is NOT mapped to a CC that is included in the potential complications list.

This measure does not include an adjustment for social drivers of health because the association between social drivers of health and health outcomes can be due, in part, to differences in the quality of health care that these groups of patients receive. The intent is for this measure to adjust for patient demographic and clinical characteristics while illuminating important quality differences.

The measure does not adjust for patients' admission source or their discharge disposition (for example, skilled nursing facility) because these factors are associated with the structure of the healthcare system, not solely with patients' clinical comorbidities.

## Selection of Clinical Risk Variables

Risk variables were selected using a data-driven, empiric approach, followed by minor adjustments for face validity. For candidate risk variables, we used a 70% randomly selected sample of data from the CY2022 dataset and included all secondary ICD-10 codes documented as POA during the index admission (except for the palliative care code of Z51.5, which, effective October 1, 2021, was considered POA-exempt), and both principal and secondary ICD-10 codes in the 12 months prior to admission from any inpatient, outpatient, and professional provider claims. We also considered age, frailty, and an indicator for whether the admission was Medicare Advantage (MA) vs. Fee-for-Service (FFS).

The variable selection of individual ICD-10 codes mainly relied on data-driven methodologies involving three key steps: 1) identifying candidate risk variables for testing in the risk model, 2) evaluating the bivariate association with outcome, and 3) consideration of associations between other non-individual-ICD-10 code variables, including frailty, with the outcome. In the first step, we screened and included ICD-10 codes identified at the index admission (index codes) and those captured in the 12 months prior to admission (pre-index codes) if their prevalence exceeded 0.5% and 2.5%, respectively. Further, co-occurring index and pre-index codes (at the admission level) with Pearson correlation coefficients greater than 0.8 were combined into one risk variable. Finally, pairs of identical index and pre-index ICD-10 codes with similar odds ratios that acted in the same direction (where the difference in association with the outcome, measured by odds ratio (OR), was less than 0.2) were merged. We note that frequencies were based on a 100% sample, but that all subsequent steps were based on a 70% sample.

In the second step, we included the remaining candidate variables (including age) in a multivariable logistic regression model that underwent variable selection through 1,000 iterations of bootstrapping. We selected variables that were statistically significantly associated with the outcome ( $p < 0.05$ ) in at least 80% of the bootstrapped samples. We determined if additional variables should be added to the multivariate model by examining if there was a resulting increase in the model c-statistic (using a threshold of at least 0.0005 increase in c-statistic for each additional variable, or an increase of at least 0.005 for including additional variables within the next 5% of bootstrapped samples [variables that were statistically significantly associated with the outcomes in at least 75% of the bootstrapped samples]); however, increases in the c-statistic did not meet these thresholds when additional variables were evaluated.

In addition, based on evidence from the literature, expert input, guidance from the consensus-based entity for measure endorsement, the [Assistant Secretary for Planning and Evaluation](#), input from other stakeholders, and prior testing results, we included a claims-based indicator of frailty in the final model. This indicator was developed for [CMS's Multiple Chronic Conditions \(MCC\) measure](#). We did not include sex as a variable since sex can be considered a socio-demographic variable.

For the combined MA and FFS cohort, the risk-adjustment model was updated to include an MA indicator (versus FFS) as a main effect. This was to adjust for the generally higher prevalence of comorbidities in the MA cohort, especially among the pre-index variables that were derived from services in the outpatient setting (e.g., physician visits).

The process described above for identifying risk variables resulted in the selection of 46 variables. We then reviewed this list and made the following minor adjustments for face validity, resulting in a final list with 42 variables (see Table 1 below):

- *Laterality*: When an ICD-10 code identified a variable that indicated a laterality (e.g. a left or right side of the body), we ensured that the same code for the other side of the body, and codes identified as bilateral and unspecified for laterality, were included. For example, the pre-index (in the prior 12 months) ICD-10 code for “Pain in left foot” (M79.672) was selected during the bootstrapping step, and we added “Pain in right foot” (M79.671) and “Pain in unspecified foot” (M79.673).
- *Deduplication*: During bootstrapping, three ICD-10 codes were selected that overlapped with the MCC frailty variable (history code Z89.421 and index codes E44.0 and E43); we removed the overlapping codes from the list of selected variables.

Table 1 shows the risk variable frequencies and odds ratios for the final risk variables selected by the process described above.

**Table 1. Diabetes EDAC: Prevalence of ICD-10-Based Risk Variables and Adjusted OR with 95% Confidence Intervals (January 1, 2022-December 31, 2023)**

Variable Name	Description	Percentage (%) (N=370,594)	OR (95% CI)
AGE	Age, mean (SD)	75.1 (7.17)	1.00 (1.00-1.00)
ICD-10 codes during the index admission			
IND_B9561	Methicillin susceptible Staphylococcus aureus infection as the cause of diseases classified elsewhere	2.87	0.81 (0.80-0.82)
IND_C7951	Secondary malignant neoplasm of bone	0.57	1.29 (1.25-1.33)
IND_D631	Anemia in chronic kidney disease	13.44	1.32 (1.31-1.33)
IND_D638	Anemia in other chronic diseases classified elsewhere	4.27	1.22 (1.21-1.24)
IND_D649	Anemia, unspecified	10.21	1.13 (1.12-1.14)
IND_E860	Dehydration	12.40	0.97 (0.96-0.98)
IND_E871	Hypo-osmolality and hyponatremia	13.44	1.12 (1.11-1.13)
IND_I10	Essential (primary) hypertension	35.81	0.82 (0.81-0.82)
IND_I447	Left bundle-branch block, unspecified	0.92	1.07 (1.04-1.09)
IND_I96	Gangrene, not elsewhere classified	5.20	1.18 (1.17-1.20)
IND_N400	Benign prostatic hyperplasia without lower urinary tract symptoms	8.76	0.94 (0.93-0.95)
IND_R188	Other ascites	0.60	1.64 (1.59-1.68)
IND_T380X5A	Adverse effect of glucocorticoids and synthetic analogues, initial encounter	0.95	1.26 (1.23-1.29)
IND_T383X6A	Underdosing of insulin and oral hypoglycemic [antidiabetic] drugs, initial encounter	1.70	0.91 (0.89-0.93)
IND_Z515	Encounter for palliative care	2.75	0.97 (0.95-0.98)

Variable Name	Description	Percentage (%) (N=370,594)	OR (95% CI)
IND_Z66	Do not resuscitate (DNR)	8.61	0.93 (0.92-0.94)
IND_Z7984	Long term (current) use of oral hypoglycemic drugs	29.55	0.85 (0.85-0.86)
IND_Z79899	Other long term (current) drug therapy	27.99	0.91 (0.90-0.91)
ICD-10 codes in the 12 months prior to admission			
PRE_E1010	Type 1 diabetes mellitus with ketoacidosis without coma	3.93	1.26 (1.24-1.27)
PRE_E1151	Type 2 diabetes mellitus with diabetic peripheral angiopathy without gangrene	38.03	1.02 (1.02-1.03)
PRE_E860	Dehydration	17.75	1.12 (1.12-1.13)
PRE_E875	Hyperkalemia	19.36	1.17 (1.17-1.18)
PRE_E876	Hypokalemia	16.72	1.17 (1.17-1.18)
PRE_F17210	Nicotine dependence, cigarettes, uncomplicated	11.57	1.09 (1.08-1.10)
PRE_I739	Peripheral vascular disease, unspecified	38.42	1.07 (1.06-1.08)
PRE_I96	Gangrene, not elsewhere classified	14.02	1.05 (1.04-1.06)
PRE_J90	Pleural effusion, not elsewhere classified	14.18	1.29 (1.28-1.30)
PRE_R000	Tachycardia, unspecified	10.99	1.13 (1.12-1.14)
PRE_R1110	Vomiting, unspecified	4.59	1.15 (1.14-1.17)
PRE_R296	Repeated falls	8.89	1.14 (1.13-1.15)
PRE_Z1231	Encounter for screening mammogram for malignant neoplasm of breast	9.39	0.91 (0.90-0.92)
PRE_Z7952	Long term (current) use of systemic steroids	3.45	1.21 (1.19-1.22)
PRE_Z9114	Patient's other noncompliance with medication regimen	5.17	1.19 (1.18-1.20)
PRE_Z9119	Patient's noncompliance with other medical treatment and regimen	3.42	1.15 (1.14-1.17)
ICD-10 codes either during the index admission or 12 months prior to admission			
E11649	Type 2 diabetes mellitus with hypoglycemia without coma	21.90	1.14 (1.13-1.15)
J449	Chronic obstructive pulmonary disease, unspecified	24.67	1.11 (1.11-1.12)
COMB1: IND_I70261 IND_I70262	Atherosclerosis of native arteries of extremities with gangrene, right leg Atherosclerosis of native arteries of extremities with gangrene, left leg	12.99	1.28 (1.27-1.29)

Variable Name	Description	Percentage (%) (N=370,594)	OR (95% CI)
IND_I70263 PRE_I70261 PRE_I70262 PRE_I70263	Atherosclerosis of native arteries of extremities with gangrene, bilateral legs		
COMB2: IND_M86171 IND_M86172 IND_M86179	Other acute osteomyelitis, right ankle and foot Other acute osteomyelitis, left ankle and foot Other acute osteomyelitis, unspecified ankle and foot	9.41	0.82 (0.81-0.83)
COMB3: IND_I70221 IND_I70222 IND_I70223 PRE_I70221 PRE_I70222 PRE_I70223	Atherosclerosis of native arteries of extremities with rest pain, right leg Atherosclerosis of native arteries of extremities with rest pain, left leg Atherosclerosis of native arteries of extremities with rest pain, bilateral legs	10.61	1.12 (1.11-1.13)
COMB4: PRE_M79672 PRE_M79671 PRE_M79673	Pain in left foot Pain in right foot Pain in unspecified foot	23.25	1.03 (1.03-1.04)
COMB5: PRE_I70201 PRE_I70202 PRE_I70203	Unspecified atherosclerosis of native arteries of extremities, right leg Unspecified atherosclerosis of native arteries of extremities, left leg Unspecified atherosclerosis of native arteries of extremities, bilateral legs	14.70	1.02 (1.02-1.03)
<b>Other risk variables</b>			
MA	MA (versus FFS)	54.76	1.09 (1.08-1.10)
MCCFI	Multiple Chronic Conditions Frailty Index	68.12	1.29 (1.28-1.30)

## The Role of Economic Disadvantage

Because our risk variable selection process was based on an empirical approach using individual ICD-10 codes related to a patients' clinical status at admission and in the 12 months prior to admission, we separately considered Dual-eligible status and its impact given clinical risk factors in the risk model, and between patient- and hospital-level factors. Although some recent literature evaluates the relationship between poverty and the EDAC outcome, few studies directly address specific causal pathways or examine the role of the hospital in these pathways (see, for example; Jacobs et al., 2018; Trivedi et al., 2014).

## Conceptual Model

Our conceptual model described below builds on published literature as well as our empirical analyses and identifies several overlapping pathways whereby patients may experience worse outcomes.

- **Comorbidities and economic risk:** Patients who are poor may have worse health at the time of hospital admission and patient comorbidities are known risk factors for post-discharge acute care use in patients hospitalized for diabetes (Rubin et al., 2023; Karunakaran, Zhao, & Rubin, 2018). Patients who have lower income may have a worse general health status and may present for their hospitalization with a greater severity of underlying illness (Owens et al., 2022). Economic disadvantage, which can be characterized by patient-level or neighborhood/community-level (as proxy for patient-level) variables, may contribute to worse health status at admission due to competing priorities, financial constraints, or lack of health insurance. Given that these risk factors all lead to worse general health status, this causal pathway should be largely accounted for by current clinical risk-adjustment. We note that patient comorbidities and economic disadvantage overlap in their contribution to worse health outcomes; and our empirical evidence shows that clinical and markers of poverty overlap in their contribution to the outcome.
- **Differential care:** We know from empirical evidence that across almost all hospitals (more than 90% with sufficient data for assessment) for some conditions, patients with dual eligibility have higher rates of readmission when compared with non-dual eligible patients in the same hospital (within-hospital disparities), after accounting for comorbidities (Silvestri et al., 2022). Lack of tailoring of interventions to reduce the risk of readmission, such as post-discharge follow up may affect those patients with less financial resources; poor patients are known to have lower rates of follow up after discharge and higher rates of post-discharge acute care utilization (Khodneva et al., 2023).
- **Low-quality hospitals:** Poor patients from under-resourced areas may receive care at lower quality hospitals. Patients of lower income and lower education may have lower access to high quality facilities, in part, because such facilities may be less likely to be found in geographic areas where large populations of patients living in poverty reside (Fahrenbach et al., 2020). Specifically for diabetes, research has shown that poor outcomes for poor patients are exacerbated when treatment occurred within low quality health systems (Wong et al., 2024). Thus, patients with low income may be more likely to be treated in lower quality hospitals, which can contribute to an increased risk of readmission.
- **Residual risk:** Ultimately, poor patients may experience worse outcomes related to factors only partially under control of the healthcare system. Income or wealth may affect the likelihood of readmission without directly affecting health status at admission or the quality of care received during the hospital stay. For instance, while a hospital may make appropriate care decisions and provide tailored care and education, a lower-income patient may still have a worse outcome post-discharge due to competing economic priorities or a lack of access to care outside of the hospital (Downing et al., 2018).

These proposed pathways are complex to distinguish analytically. They also have different implications on the decision to risk adjust or not depending on the degree that hospitals can mitigate the increased risk.

## Variables Reflecting Economic Disadvantage used in Testing

Based on the available literature, and given the limited availability of valid and reliable variables for poverty that can be tested in claims data, we selected Dual-eligible status for testing.

Dual eligibility for Medicare and Medicaid is available at the patient level in the Medicare Master Beneficiary Summary File. The eligibility threshold for aged 65 or older Medicare patients considers both income and assets. For the dual-eligible (DE) indicator, there is a body of literature demonstrating differential health care and health outcomes among beneficiaries (ASPE, 2020).

## Economic Disadvantage Testing

Because our risk variable selection process was constructed via an empirical approach based on individual ICD-10 codes related to a patients' clinical status at admission and in the 12 months prior to admission, we separately considered indicators of economic disadvantage and the relationships between clinical factors and dual eligibility (DE) status.

To understand the incremental impact of economic disadvantage on the Diabetes EDAC measure results, we assessed the following: prevalence of DE among hospitals, association with the unadjusted outcome, odds ratios in bivariate and multivariable models, model calibration for patients with DE status, and impact on measure scores. Each analysis is described in more detail below. All analyses used the CY2022/2023 dataset (two years of Medicare Advantage (MA)+Fee-for-Service (FFS) data, January 1, 2022-December 31, 2023).

### ***Patient-Level Analyses***

The proportion of patients with DE status among the Diabetes EDAC cohort was 26%. (see Table 2).

**Table 2. Diabetes EDAC: Patient-Level Prevalence of Dual Eligibility status, January 1, 2022 - December 31, 2023, N=370,594**

Variable	Patient Prevalence (%)
Dual Eligibility (DE)	26.0

As shown in Table 3, unadjusted days in acute care for patients with DE were higher than for patients without DE (mean unadjusted days for DE vs non-DE, 202 vs 162).

**Table 3. Diabetes EDAC: Patient-Level Unadjusted Days in Acute Care for Admissions with and without Dual Eligibility (DE), January 1, 2022 - December 31, 2023**

Variable	Number of Patients	Mean Unadjusted Days in Acute Care (SD)
Dual Eligible	96,190	202 (430)
Non-Dual Eligible	274,404	162 (385)

Similarly, the odds ratio (OR) for outcome among DE vs non-DE patients was 1.46 (95% CI: 1.43–1.50) in unadjusted models. However, this association was attenuated towards the null after adjustment for

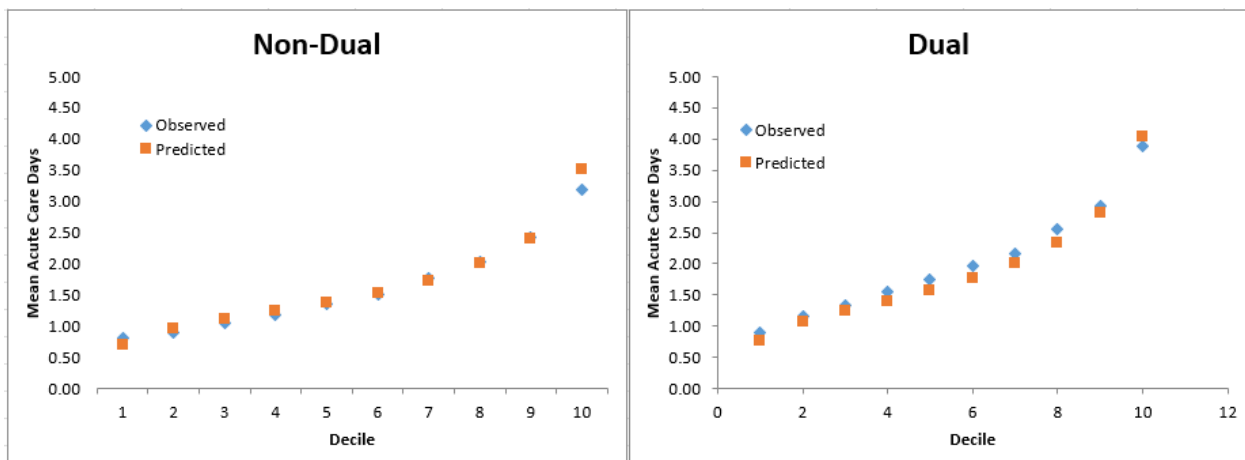
clinical risk variables in the final model (ORs: 1.10 [95% CI: 1.09–1.11]) (Table 4), suggesting that part of the association between DE and the outcome is explained by overlap with clinical risk factors.

**Table 4. Odds Ratios for DE status versus not in Diabetes EDAC Models Before and After Adjustment for Clinical Risk Variables (January 1, 2022–December 31, 2023)**

Variable	OR for DE: Unadjusted for Clinical Risk Variables (95% CI)	OR for DE: Adjusted for Clinical Risk Variables (95% CI)
Dual Eligible	1.46 (1.43-1.50)	1.10 (1.09-1.11)

To determine if the patient-level model was well calibrated in the absence of adjustment for DE status, we also examined model calibration (see Figure 1). The results show that the model is well calibrated for both DE and non-DE status patients.

**Figure 1. Diabetes EDAC: Calibration Plots for Non-Dual Eligible and Dual Eligible Patients at the Index Admission in Diabetes EDAC Cohort (January 1, 2022 – December 31, 2023)**



### Hospital-Level Analyses

While patient-level unadjusted days in acute care for patients with DE status are higher than for patients without DE status, we also know that the patient-level risk conferred by economic and clinical risk variables overlap. Therefore, we wanted to understand the impact of each variable at the hospital level on the risk-adjusted Diabetes EDAC measure score. For these analyses, we calculated measure scores with and without DE status and then calculated the differences in measure scores and the correlation between measure scores. We also analyzed measure scores stratified by the proportion of patients with DE status within hospitals.

Our hospital-level measure score testing results show minimal impacts of DE status on measure scores. Measure scores calculated with and without DE status are highly correlated (Pearson correlation coefficients at or near 1) and differences between measure scores are very small (Table 5; Figure 2). Furthermore, the distribution of measures scores for hospitals in the highest proportion of patients with

DE status (fifth quintile) overlaps with the distribution of measure scores within the other quintiles (Figure 3).

**Table 5. Diabetes EDAC Measure Scores and Correlation Between Measure Scores, for Measure Scores Calculated with and without Dual Eligibility Status (DE) (January 1, 2022-December 31, 2023)**

Variable	Difference in Measure Scores: Median	Difference in Measure Scores: IQR (25 <sup>th</sup> percentile to 75 <sup>th</sup> percentile)	Pearson Correlation Coefficient (p-value)
DE status	0.25	-0.91 to 1.01	0.998 (p<0.0001)

**Figure 2. Diabetes EDAC: Measure Scores Calculated with and Without Dual Eligibility (N=4,193 hospitals)**

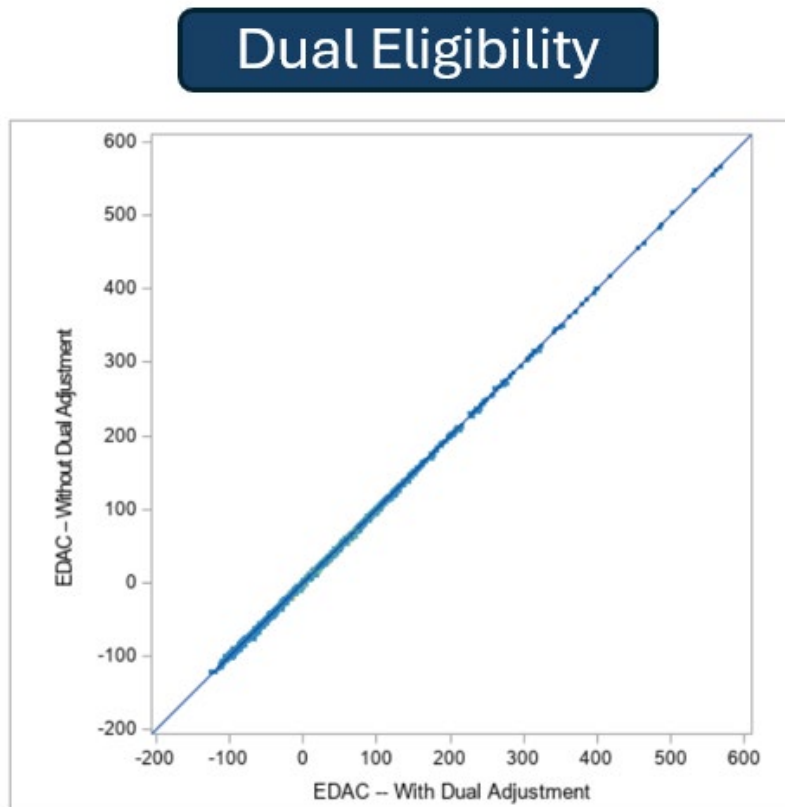
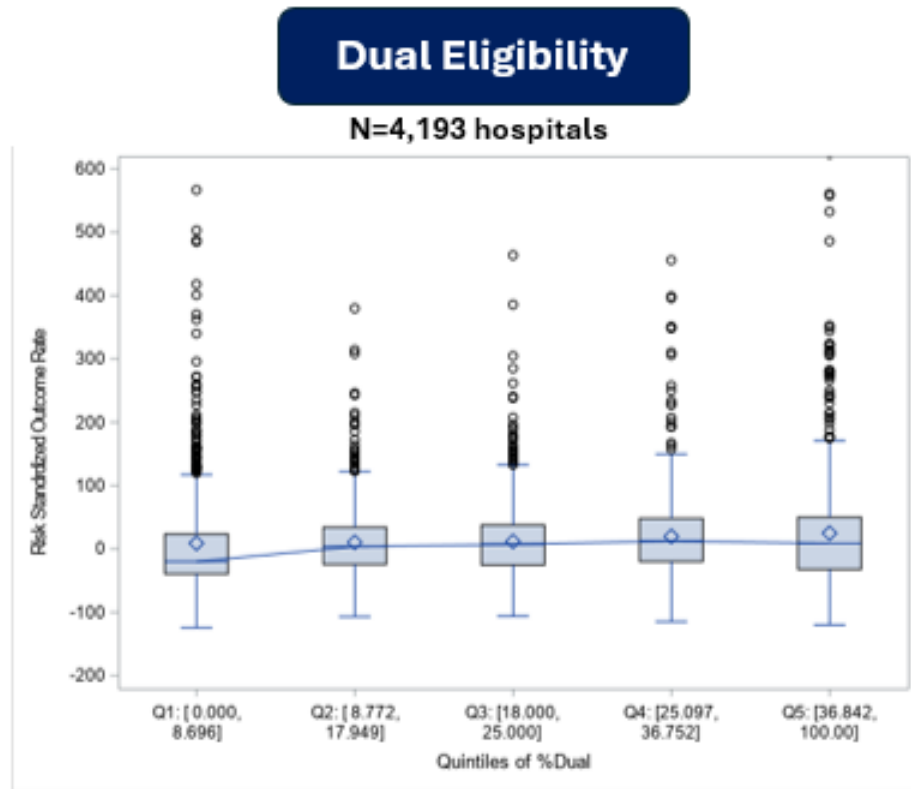


Figure 3. Diabetes EDAC: Measure Scores by Hospital-Proportion of Patients with Dual Eligibility



### Economic Disadvantage Testing: Conclusion

Overall, our results show that patients with DE status have a higher risk of the EDAC outcome, but that there is little impact at the hospital level on measure scores. Patients with DE status have higher unadjusted rates of the outcome, and even after adjusting for the clinical risk variables in the model, odds ratios remain greater than 1, and significant. However, we find that that the impact of DE on measure scores is minimal: measure scores calculated with and without DE status are highly correlated (Pearson coefficient near 1), and differences between measure scores calculated with and without DE status are small. In addition, the distribution of measure scores across quintiles of the hospital proportion of patients with DE status overlap. We also found that the model performs well for patients with DE status. These empiric results support the decision to not adjust the measure for DE status.

## Model Performance Testing

### Methods

To assess model performance, we assessed model discrimination and calibration, as well as overfitting.

To assess discrimination, we computed two discrimination statistics, the **c-statistic** and **predictive ability**. The c-statistic is the probability that predicting the outcome is better than chance, which is a measure of how accurately a statistical model is able to distinguish between a patient with and without the outcome. Predictive ability measures the ability to distinguish high-risk subjects from low-risk subjects; therefore, for a model with good predictive ability, we would expect to see a wide range in observed outcomes between the lowest and highest deciles of predicted outcomes.

For **model calibration**, we assessed calibration plots, with mean predicted and mean observed days in acute care plotted against deciles of predicted days in acute care. The closer the predicted days are to the observed days, the better calibrated the model is. We assess calibration for all patients, and for important subsets of patients (those undergoing amputation vs. no amputation, those undergoing dialysis vs. no dialysis at the index admission, those with Type 1 vs. Type 2 diabetes, Medicare Advantage vs. Medicare FFS, and patients with and without the DE status).

In addition, we provide an analysis of **overfitting**. Overfitting refers to the phenomenon in which a model accurately describes the relationship between predictive variables and outcomes in the development dataset but fails to provide valid predictions in new patients. Estimated calibration values of  $\gamma_0$  close to 0 and estimated values of  $\gamma_1$  close to 1 provide evidence of good calibration of the model.

### Results

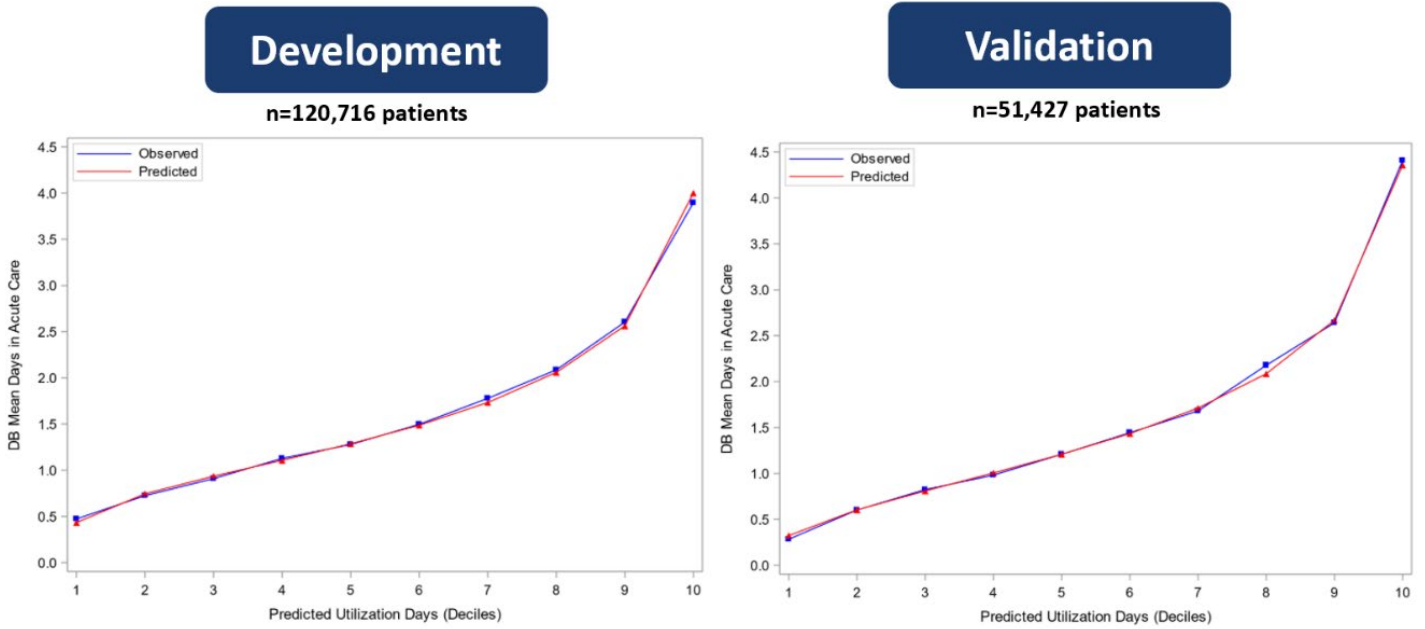
For original measure development using CY2022 data, the c-statistic was 0.68 in the development sample, and 0.70 in the validation sample (Table 6). Predictive ability ranged from 1.66%-13.23% in the derivation sample, and 1.22%-14.43% in the validation sample. Risk decile plots show that higher deciles of the predicted outcomes are associated with higher observed outcomes in both CY2022 (development and validation datasets) and the CY2022/2023 dataset (Figures 4 and 5). Overfitting results are shown in Table 6.

**Table 6. Diabetes EDAC Initial Model Testing Statistics (January 1, 2022 – December 30, 2022)**

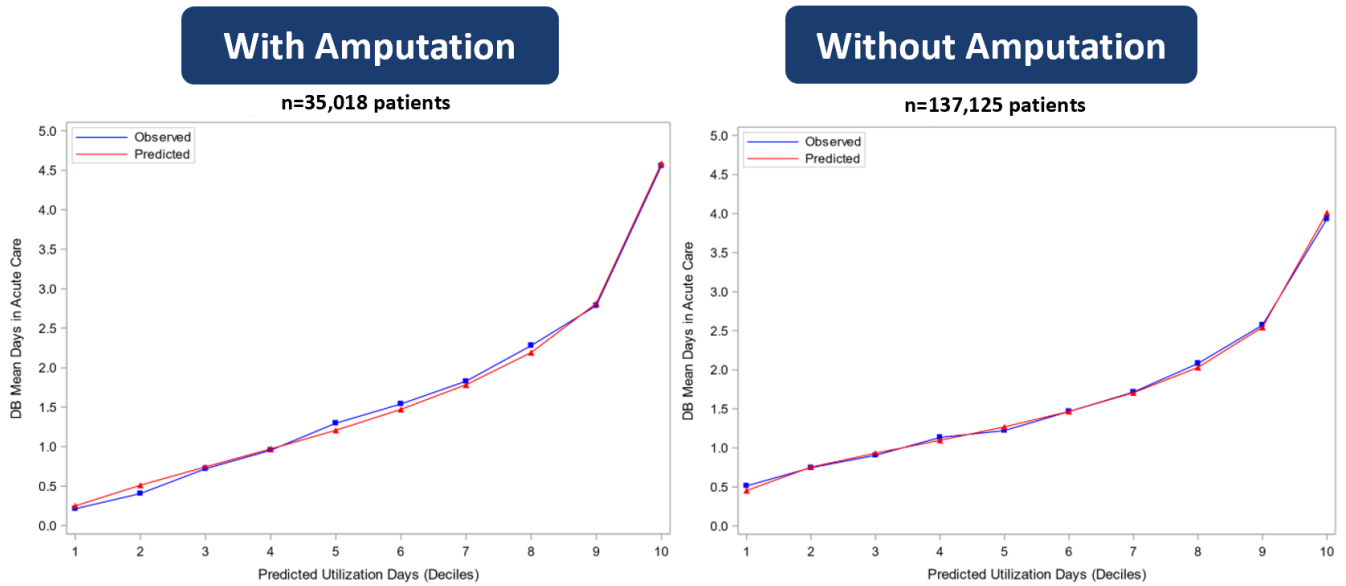
Sample	C-Statistic	Predictive Ability (%)	Overfitting ( $\gamma_0, \gamma_1$ )
Development (n=120,716)	0.68	1.66 – 13.23	0.00, 1.00
Validation (n=51,427)	0.70	1.22 – 14.43	-0.06, 0.96

We also found good calibration for important subsets of patients, including for those undergoing amputation vs. no amputation (Figure 5), those with Type 1 vs. Type 2 diabetes (Figure 6), those undergoing dialysis vs. no dialysis at the index admission (Figure 7), Medicare Advantage vs. Medicare FFS (Figure 8), and patients with and without the dual eligibility status (shown previously; see Figure 1 ).

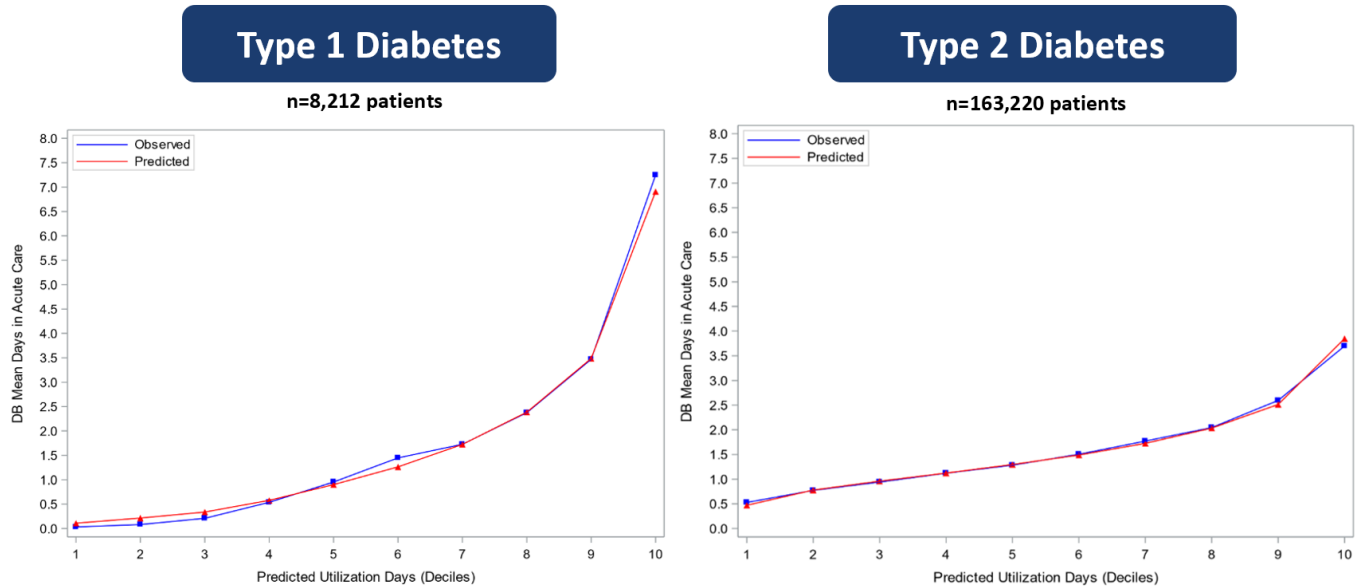
**Figure 4. Diabetes EDAC Initial Development and Validation Cohort Calibration Plot (January 1, 2022 – December 30, 2022)**



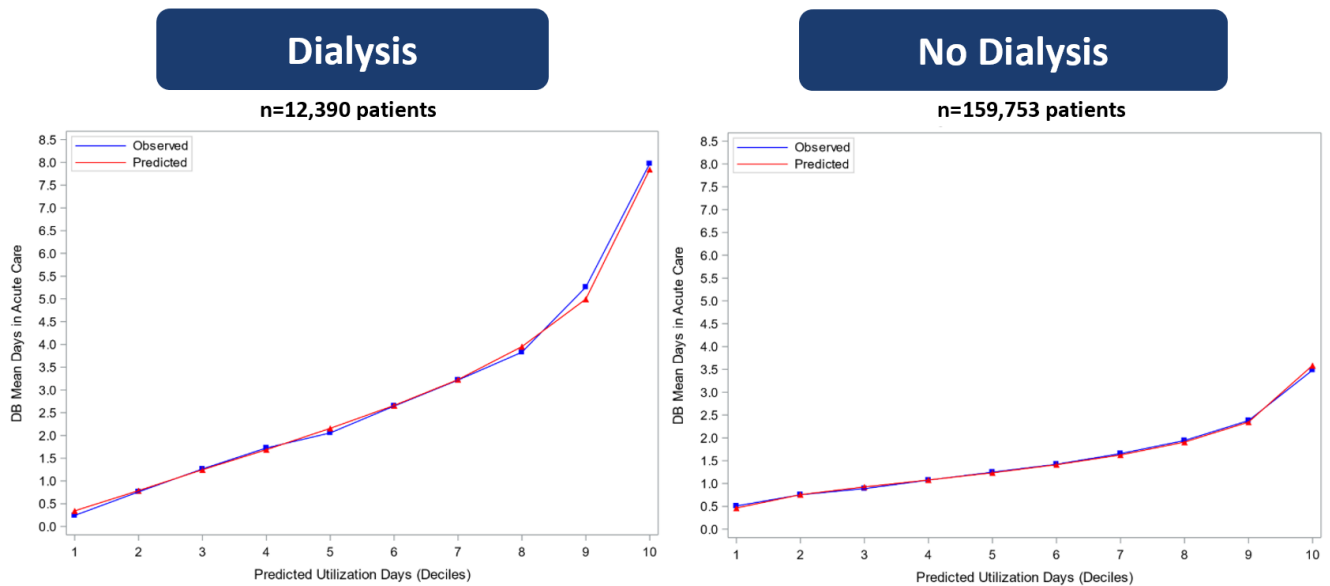
**Figure 5. Diabetes EDAC: Calibration Plot for Patients with and without Amputations in Diabetes EDAC Cohort (January 1, 2022 – December 30, 2022)**



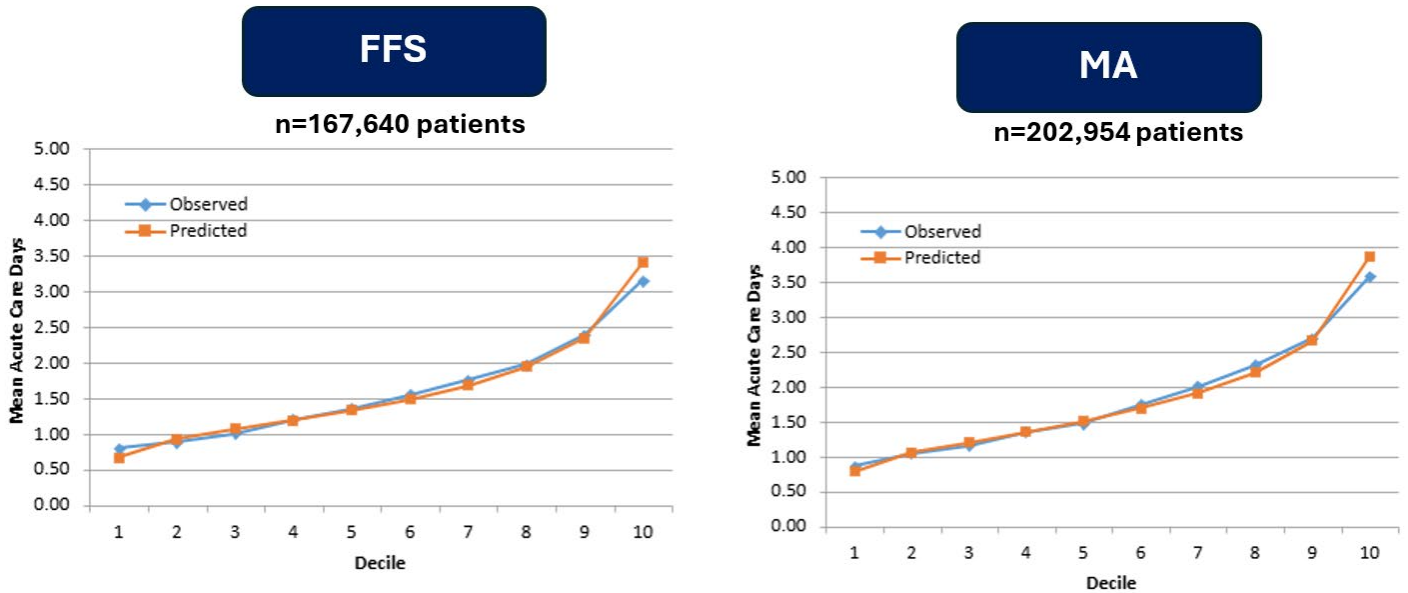
**Figure 6. Diabetes EDAC: Calibration Plot for Patients with Type 1 Diabetes and Type 2 Diabetes in Diabetes EDAC Cohort (January 1, 2022 – December 30, 2022)**



**Figure 7. Calibration Plot for Patients with our without Dialysis at the Index Admission in Diabetes EDAC Cohort (January 1, 2022 – December 30, 2022)**



**Figure 8. Calibration Plot for Fee-for-Service (FFS) and Medicare Advantage (MA) and Patients at the Index Admission in Diabetes EDAC Cohort (January 1, 2022 – December 31, 2023)**



### *Interpretation*

#### **Discrimination**

C-statistics show good model discrimination. Predictive ability results show a wide range between the lowest decile and highest decile, indicating the ability to distinguish high-risk subjects from low-risk subjects.

#### **Calibration**

Higher deciles of the predicted outcomes are associated with higher observed outcomes, which show a good calibration of the model for all patients (Figures 4 and 5), and for important subsets of patients, including those that differ clinically (e.g. Type 1 and Type 2 diabetes), and for those with and without DE status.

#### **Over-fitting ( $\gamma_0$ , $\gamma_1$ )**

If  $\gamma_0$  is substantially far from zero and  $\gamma_1$  is far from one in validation data, there is potential evidence of over-fitting. Our testing results show that in the validation sample,  $\gamma_1$  is close to one and  $\gamma_0$  is close to zero, indicating that we do not see evidence of overfitting and that the model performs well with “new” data.

#### **Overall Interpretation**

Interpreted together, our diagnostic results demonstrate the risk-adjustment model adequately controls for differences in patient characteristics (case mix).

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