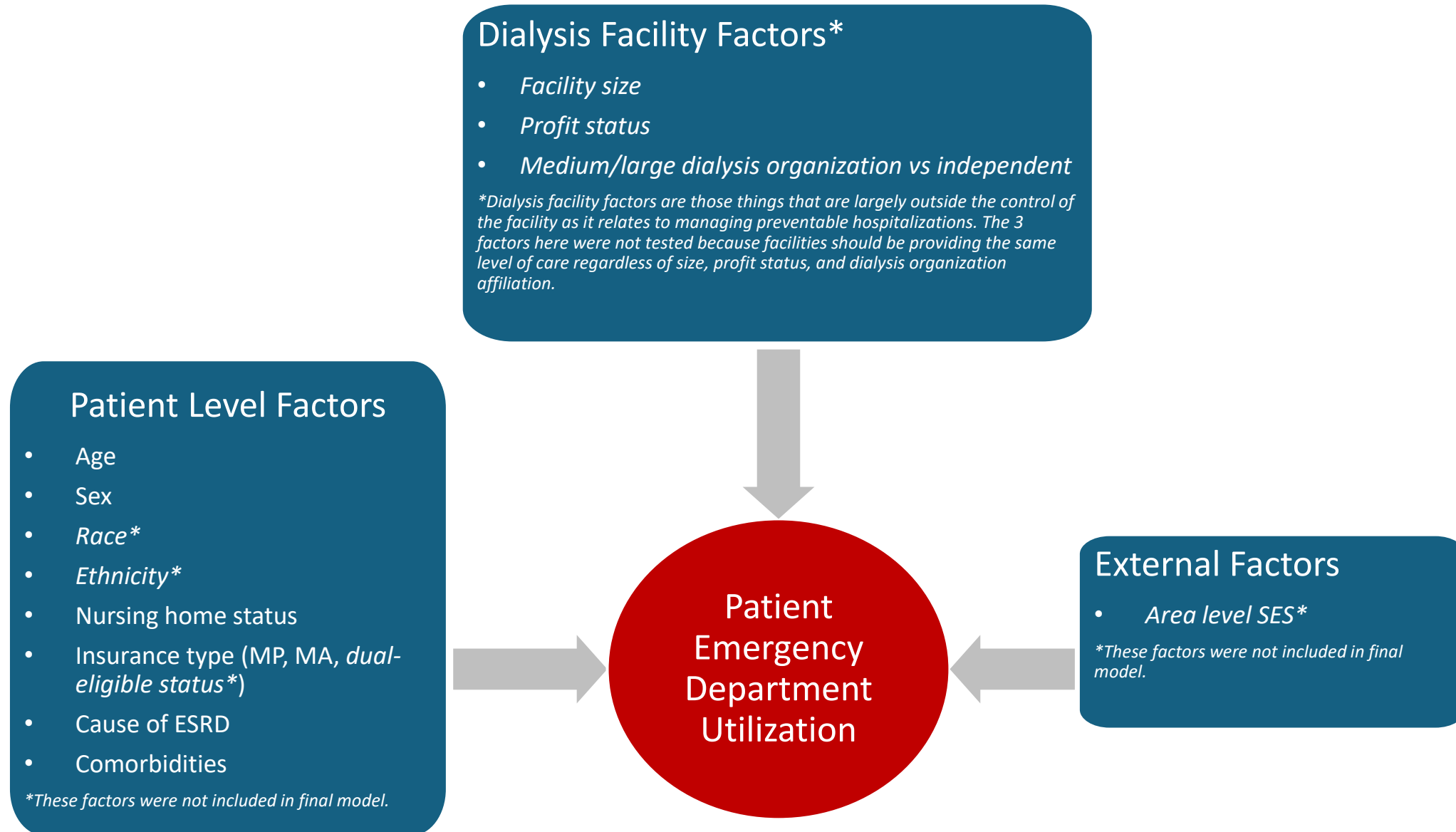


#3565 Standardized Emergency Department Encounter Ratio (SEDR) for Dialysis Facilities



5.4.2. Conceptual Model Rationale

#3565 Standardized Emergency Department Encounter Ratio (SEDR) for Dialysis Facilities

- Patient age: Age (continuous); Age squared
- Sex
- Diabetes as cause of ESRD
- ESRD duration: categorized as 91 days-6 months, 6 months-1 year, 1-2 years, 2-3 years, 3-5 years, or 5+ years as of the period start date.
- Medicare Advantage coverage
- Nursing home status in previous 365 days:
 - No Nursing Home care (0 days)
 - Short-term NH care (1 - 89 days)
 - Long-term NH care (90 - 365 days)
- BMI at incidence of ESRD
 - <18.5
 - 18.5-24.9
 - 25-29.9
 - ≥30
- Calendar year
- The following incident comorbidities are included. They are taken from the CMS-2728 form. Each comorbidity is included as a separate covariate in the model.
 - Alcohol dependence
 - Atherosclerotic heart disease
 - Cerebrovascular disease
 - Chronic obstructive pulmonary disease
 - Congestive heart failure
 - Diabetes that is not the primary cause of ESRD
 - Drug dependence
 - Inability to ambulate
 - Inability to transfer
 - Malignant neoplasm or cancer
 - Other cardiac disease
 - Peripheral vascular disease
 - Tobacco use (current smoker)
 - No Medical Evidence (CMS-2728) Form
 - At least one of the comorbidities listed
- A set of prevalent comorbidities based on Medicare claims (individual comorbidities categorized into 66 groups).
 - Includes an adjustment for less than 6 months of Medicare covered months in prior calendar year
- Beside main effects, two-way interaction terms between age, sex, and cause of ESRD are also included:
 - Diabetes as cause of ESRD*Sex

- Diabetes as cause of ESRD*Age
- Age*Sex

Prevalent comorbidities (see appendix) are determined using the previous calendar year of CMS claims. We grouped individual comorbidities into clinically related categories. Each comorbidity group is included as a separate covariate in the model. If a patient has less than 6 Medicare covered months in the prior calendar year, we consider prevalent comorbidities to be “missing” for that patient even if there are comorbidities identified in claims.

The modeling process has two stages. At stage I, a stratified model is fitted to the national data with piecewise-constant baseline rates and stratification by facility. Specifically, the model is of the following form

$$Pr(\text{Emergency department encounter on day } t \text{ given covariates } X) = r_{ok}(t) \exp(\beta' X_{ik})$$

where X_{ik} is the vector of covariates for the i^{th} patient in the k^{th} facility and β is the vector of regression coefficients. Time t is measured from the start of ESRD. The baseline rate function $r_{ok}(t)$ is specific to the k^{th} facility, and is assumed to be a step function with break points at 6 months, 1 year, 2 years, 3 years and 5 years since the onset of dialysis. This model allows the baseline emergency department rates to vary between strata (facilities), but assumes that the regression coefficients are the same across all strata; this approach is robust to possible differences between facilities in the patient mix being treated. The stratification on facilities is important in this phase to avoid bias due to possible confounding between covariates and facility effects.

At stage II, the relative risk estimates from the first stage are used to create offsets and an unstratified model is fitted to obtain estimates of an overall baseline rate function. That is, we estimate a common baseline rate of encounters, $r_o(t)$, across all facilities by considering the model

$$Pr(\text{Emergency department encounter on day } t \text{ given covariates } X) = r_o(t) R_{ik},$$

where $R_{ik} = \exp(\beta' X_{ik})$ is the estimated relative risk for patient i in facility k obtained from stage I. In our computation, we assume the baseline to be a step function with 6 unknown parameters, $\alpha_1, \dots, \alpha_6$, to estimate. These estimates are used to compute the expected number of encounters given a patient's characteristics.

Specifically, let t_{iks} represent the number of days that patient i from facility k is under observation in the s^{th} time interval with estimated rate α_s . The corresponding expected number of emergency department encounters in the s^{th} interval for this patient is calculated as

$$E_{iks} = \alpha_s t_{iks} R_{ik}.$$

It should be noted that t_{iks} and hence E_{iks} can be 0 if patient i from facility k is never at risk during the s^{th} time interval. Summing the E_{iks} over all 6 intervals and all N_k patients in facility k gives

$$\text{Exp} = \sum_i \sum_s E_{iks} = \sum_i \sum_s \alpha_s t_{iks} R_{ik},$$

which is the expected number of emergency department encounters during follow-up at that facility.

Let Obs be the observed total number of emergency department encounters at this facility. The SEDR for emergency department encounters is the ratio of the observed total encounters to this expected value, or

$$\text{SEDR} = \text{Obs}/\text{Exp}$$

Rationale:

In this model for SEDR, covariates are taken to act multiplicatively on the ED rate and the adjustment model is fitted with facility defining strata so as to provide valid estimates even if the distribution of adjustment variables differs across facilities [8, 9, 7, 11, 17, 20, 21]. All analyses are done using SAS.

In general, adjustment factors for the SEDR were selected based on several considerations. Our starting point was the Standardized Hospitalization Ratio (SHR) (CBE 1463) which is the model on which we developed SEDR. We began with a large set of patient characteristics (listed above), which were first evaluated for face validity by the 2016 TEP. Factors considered appropriate were then investigated with statistical models to determine if they were related to ED encounters.

We identify all unique ICD-9/10 diagnosis codes from each patient's prior year of Medicare claims. We group these diagnosis codes by diagnosis area using the Agency for Healthcare Research and Quality (AHRQ) Clinical Classifications Software (CCS) diagnosis categories. A list of ICD-9/10 codes used for the calculation is provided in the attached data dictionary/code list.

Methodology for prevalent comorbidity selection: We began the selection process with the 283 AHRQ CCS groupers for calendar year 2015. We eliminated the following 32 groupers either due to a possible association with facility care, a reflection of underlying kidney disease, or because they were not appropriate adjusters for our analysis.

AHRQ CCS Groupers Excluded	Description
2	Septicemia
123	Influenza
156	Nephritis / Nephrosis
157	Acute Kidney Failure
158	Chronic Kidney Disease
254	Rehabilitation care; fitting of prostheses; and adjustment of devices
255	Administrative/social admission
256	Medical examination/evaluation
257	Other aftercare
258	Other screening for suspected conditions
259	Residual codes; unclassified
E-Codes	21 Groupers total

Next, five categories of specific ICD-9 codes were removed from the remaining 251 AHRQ CCS groupers. These codes, listed in the Appendix, may be associated with dialysis facility care and include diagnoses such as secondary hyperparathyroidism, fluid overload, hyperkalemia, and vascular access infections. Once these specific ICD-9 codes were excluded, the 251 CCS groupers were consolidated down to a set of 130 nascent groups that we developed by combining similar CCS categories that had specificity beyond what was needed for our risk adjustment.

The selection of prevalent comorbidities was derived using a boosting variable selection method that was applied to the 130 nascent groups to identify a subset of prevalent comorbidities based on their ability to predict outpatient ED encounters. This process is more selective than traditional forward step-wise model building in selecting covariates. The boosting method [12] included the following steps:

1. Use forward stage-wise regression to iteratively detect comorbidities. That is, given the inclusion of some comorbidities, this method identifies additional comorbidity predictors to add to the analysis model.
2. Randomly draw bootstrapped samples and repeatedly apply the boosting procedure on each bootstrapped sample. The variables are ranked based on their selection frequencies.
3. Apply an empirical Bayes false discovery rate (FDR) controlling procedure [3,10] to effectively control the fraction of false discoveries. This procedure is able to control the FDR at a preselected level $0 < q < 1$ (FDR-controlling parameter). For instance, if $q = 0.1$ and 10 variables are selected with an estimated FDR less than q , at most 1 of these 10 variables would be expected to be a false positive. This is an equivalent process to assessing the statistical significance of the association between the predictor variable and an emergency department encounter.

The boosting method resulted in a set of 67 groups that were predictive of an ED encounter. This list of prevalent comorbidities was presented to the ED TEP in June 2017 and received unanimous support for inclusion in the SEDR and ED30 measures. Since then, due to changes in the CCS groupers, we removed CCS 55 grouper “Fluid and electrolyte disorders”, as this condition is likely to be associated with facility care and therefore should not be included as a risk factor since fluid management is under the purview of the facility. The final set of comorbidity groups is 66.

SDS/SES factors were evaluated based on appropriateness (whether related to differences in outcomes), empirical association with the outcome, and as supported in published literature.

The relationship among patient-level SDS, socioeconomic disadvantage, access to care, and acute care utilization such as hospitalization and emergency department use is well-established in studies in the general population and has received considerable attention over the years [1]. There is also overlap between patient-level SDS factors such as race, and area-level SES. For example, blacks and other minority races, compared to whites, disproportionately tend to have lower income, experience more neighborhood poverty, residential segregation, levels of educational attainment, and unemployment levels. Together these jointly influence key health outcomes related to morbidity and acute care use [28-29].

Race, insurance status (dual-eligibility), younger age, and SES have been shown to be predictors of emergency department utilization in the general population [4, 6, 15, 19, 30]. For example, a study reported that black adults had higher odds than whites of being occasional users compared to non-ED users [30]. This difference between blacks and whites was larger when comparing frequent-users to non-users [30]. However, they also found few differences in the likelihood of frequent ED use when comparing patients that have private insurance versus those who are uninsured, while frequent ED use was more likely among those with public insurance (i.e., Medicaid) [30]. Those with lower income also had higher odds of being occasional and frequent ED users, while individuals with some college had lower odds of being an occasional or frequent user of the ED, compared to those with no high school

diploma. An analysis of frequent ED use at two urban hospitals found that frequent ED use was associated with younger age, and that frequent users were more likely to be black [9]. However, there was no significant difference in primary care access between infrequent and frequent users, suggesting that access to care did not explain variation in ED utilization. In addition to younger age, another study reported that those who were single/divorced, single-parents, had high school education or less, or had lower income were more likely to be frequent users of the ED [26]. Among dual-eligible patients that receive care from a Federally Qualified Health Center (FQHC), relative rates of ED use were lower compared to dual-eligibles that did not receive care from an FQHC, suggesting the importance of access to primary care. Finally, trends in ED use show differences by sex (female), age (45-64), and geography (the Midwest) and in large central metropolitan areas [25, 29].

In the ESRD population, low health literacy (a proxy of SES) was found to be predictive of ED use in one study, as well as SDS/SES factors of younger age, female sex, black race, and public insurance (Medicaid) while lower ED use was associated with private insurance [13, 22]. ESRD patients discharged from a skilled nursing facility that had a subsequent emergency department encounter within 30 days were more likely to be of black race, have dual Medicare-Medicaid status, and higher comorbidity [14]. In ESRD patients that received a transplant, higher risk of ED use was associated with younger age, female sex, black race, Hispanic ethnicity, and public insurance (Medicaid) [23]. Treatment adherence was also found to be a risk factor for emergency department visits [5]. This suggests that there may be related SDS/SES or community level factors that adversely impact patient treatment adherence.

Area-level factors, typically operating as proxies of patient level factors, have also been found to influence acute care use, such as readmission as well as ED use [16, 18, 25]. Additionally, area-level SES has been observed to be associated with poor outcomes in ESRD patients [2].

Given these observed linkages we tested available patient- and area-level SDS/SES variables based on the conceptual relationships described above and demonstrated in the literature, as well as the availability of data for analysis.

In our analyses assessing the impact on facility level emergency department use by ESRD patients, we use the publicly available Area Deprivation Index (ADI) originally developed by Singh and colleagues at the University of Wisconsin. We applied the updated ADI based on 2009-2013 census data [27]. The ADI reflects a full set of SES characteristics, including measures of income, education, and employment status, measured at the ZIP code level. Singh has applied the index in a variety of contexts, including analysis of county-level mortality rates [24]. Singh found area differences in mortality associated with low SDS. Over the period studied, mortality differences widened because of slower mortality reductions in more deprived areas. The ADI has also been applied to the calculation of risk-adjusted rates of hospital readmission [18].

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