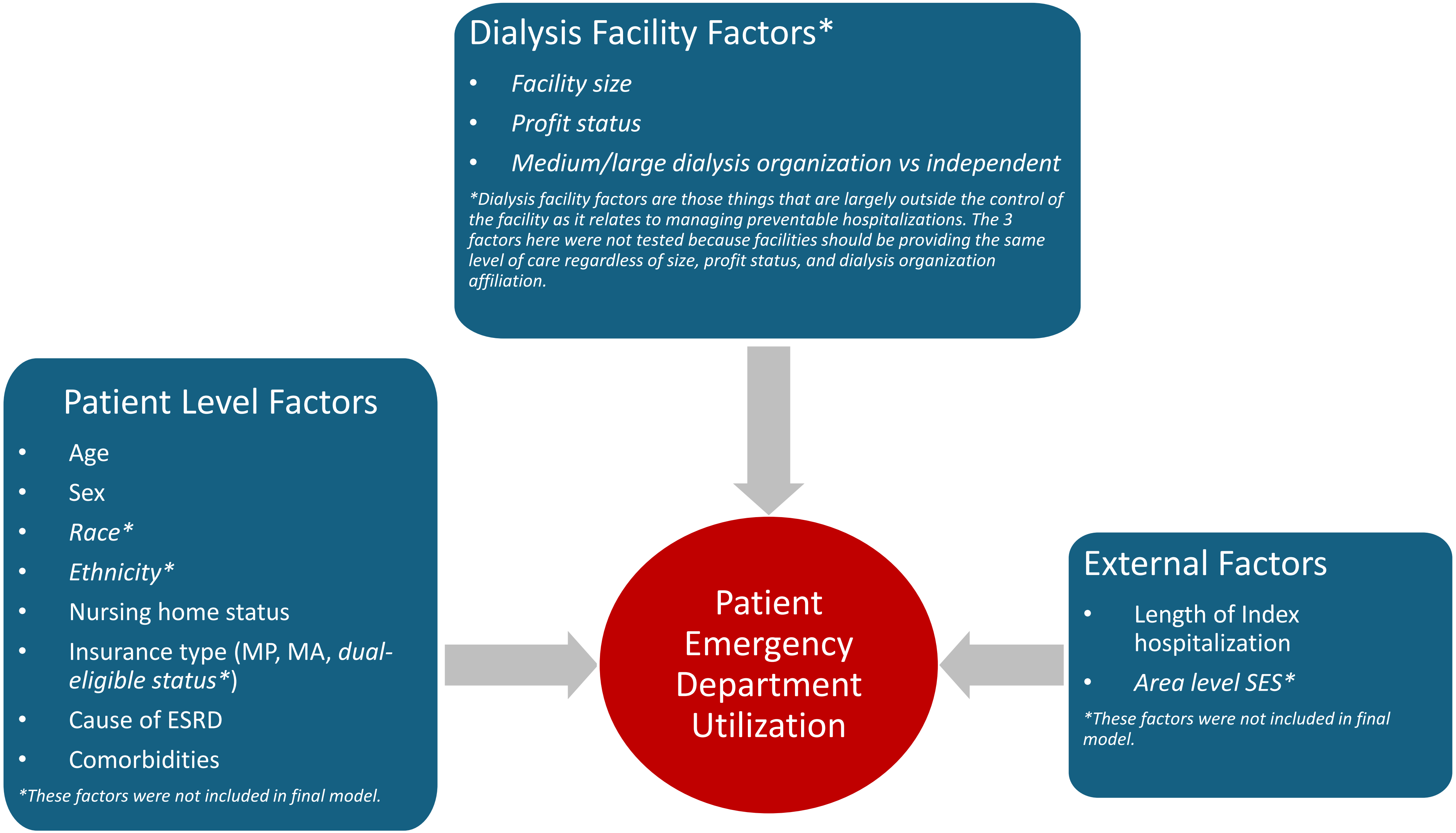
5.4.2a Attach Conceptual Model

3566 Standardized Ratio of Emergency Department Encounters Occurring Within 30 Days of Hospital Discharge (ED30) for Dialysis Facilities



5.4.2. Conceptual Model Rationale

CBE ID 3566, Standardized Ratio of Emergency Department Encounters Occurring Within 30 Days of Hospital Discharge (ED30) for Dialysis Facilities

The model accounts for a set of patient-level characteristics:

- Sex
- Age
- Medicare Advantage coverage
- Years on dialysis
- Diabetes as cause of ESRD
- Nursing Home status in previous 365 days
    - No Nursing Home care (0 days)
    - Short-term Nursing Home care (1 - 89 days)
    - Long-term Nursing Home care (90 - 365 days)
- BMI at incidence of ESRD
    - <18.5
    - 18.5-25
    - 25-30
    - >=30
- Length (days) of index hospitalization
- A set of prevalent comorbidities based on Medicare inpatient claims (individual comorbidities categorized into 66 groups).

Prevalent comorbidities are determined using the previous 12 months of CMS claims after the index discharge. We grouped individual comorbidities into clinically related categories. Each comorbidity group is included as a separate covariate in the model.

To estimate the probability of a 30-day emergency department encounter, we use a three-stage model, the first of which is a fixed-effects logistic regression model. In this first stage, facility-hospital combinations are included as fixed effects, adjusting for a set of patient-level characteristics. The results of this step are estimates of the regression coefficients of patient-level characteristics in the logistic regression model. These regression coefficients are then used as an offset variable in the second stage model. The results from this model are unbiased regardless of correlation between hospital effects and patient-case mix.

The second stage of the model is a double random-effects logistic regression model. In this stage of the model, both dialysis facilities and hospitals are represented as random effects, and the sum of regression adjustments multiplied by estimated parameters obtained from the first stage are included as the offset variable. From this model, we obtain the estimated standard deviation of the random effects of hospitals [1].

The third stage of the model is a mixed-effects logistic regression model, in which dialysis facilities are modeled as fixed effects and hospitals are modeled as random effects, with the standard deviation specified as equal to its estimates from the second stage and the estimated parameters obtained in the first stage are included as the offset variable. The expected number of emergency department encounters for each facility is estimated as the summation of the probabilities of emergency department encounters of all patients in this facility and assuming the national norm (i.e., the median) for facility effect. This model accounts for a given facility's case mix using the same set of patient-level characteristics as those in the first stage model.

The equations used in the measure calculation are as follows:

- To estimate the probability of 30-day emergency department encounter, we use a three-stage approach. The main model, which produces the estimates used to calculate ED30, takes the form:

$$\log \{p_{ijk}/(1-p_{ijk})\} = r_i + \alpha_j + \beta^T Z_{ijk}, \qquad (1)$$

  Where p_{ijk} represents the probability of an emergency department encounter for the k^{th} discharge among patients from the i^{th} facility who are discharged from j^{th} hospital, and Z_{ijk} represents the set of patient-level characteristics. Here, r_i is the fixed effect for facility and α_j is the random effect for hospital j. It is assumed that the $\alpha_j s$ arise as independent normal variables variables (i.e., $\alpha_j \sim N(0, \sigma^2)$).

- We then use the estimates from this model to calculate each facility's ED30:

$$ED30_i = O_i / E_i = O_i / \Sigma_{j \epsilon H(i)} \Sigma_k \acute{P}_{ijk}, \qquad (2)$$

  where, for the i^{th} facility, O_i is the number of observed emergency department encounter, E_i is the expected number of emergency department encounter for discharges, H(i) is the collection of indices of hospitals from which patients are discharged, and $\acute{P}_{ijk}$ is the predicted probability of emergency department encounter under the national norm for each discharge. Specifically, $\acute{P}_{ijk}$ takes the form

$$\acute{P}_{ijk} = \exp(\check{r}_M + \breve{\alpha}_j + \dot{B}^T Z_{ijk}) / \{1 + \exp(\check{r}_M + \breve{\alpha}_j + \dot{B}^T Z_{ijk})\}, \qquad (3)$$

  which estimates the probability that a discharge from hospital j of an individual in facility i with characteristics Z_{ijk} would result in an emergency department encounter if the facility effect corresponded to the median of national facility effects, denoted by $\check{r}_M$. Here, $\breve{\alpha}_j$ and $\dot{B}$ are estimates from model (1). The sum of these probabilities is the expected number of emergency department encounters E_i at facility i; e.g., the number of emergency department encounters that would have been expected in facility i had they progressed to the emergency department encounter at the same rate as the national population of dialysis patients. If a facility has less than 11 discharges, they are excluded from the measure for the purposes of modeling.

Selection of clinical factors

The specific list of prevalent comorbidities included was determined based on an empirical evaluation of prevalent comorbidities associated with risk of an ED encounter.

We identify all unique ICD-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-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 can 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 included the following steps [25-29]:

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 [2,3] 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.

Selection of SDS/SES factors

SDS/SES factors were evaluated based on appropriateness (whether related to differences in outcomes), empirical association with the outcome (ED visits within 30 days of a hospital discharge), 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 the general population and has received considerable attention over the years [2]. There is also overlap between patient-level SDS factors such as race, and area level SES. For example, race may interact with lower income, neighborhood poverty, residential segregation, levels of educational attainment, and unemployment levels that jointly influence key health outcomes related to morbidity and acute care use [3, 4].

Race, insurance status (dual-eligibility), younger age, and SES have been shown to be predictors of emergency department utilization in the general population [5-9]. For example, a study by Zuckerman and Shen (2004) reported that black adults had higher odds than whites of being occasional users compared to non-ED users. This difference between blacks and whites was larger when comparing frequent-users to non-users [8]. However, they also found few differences in the likelihood of frequent ED use when comparing patients that are privately insured versus uninsured while frequent ED use was more likely among those with public insurance (i.e., Medicaid) [8]. 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 by Cunningham et al 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. However, there was no significant difference in primary access between infrequent and frequent users, suggesting that access to care did not explain variation in ED utilization [10]. In addition to younger age, another study reported that those who were single/divorced, single-parents, had high school education or less, and had lower income were more likely to be frequent users of the ED [11]. 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 [12]. Finally, trends in ED use show differences by sex (female), age 45-64), and geography (the Midwest) and in large central metropolitan areas [13].

Emergency department utilization after an acute visit is associated with age and insurance type. For example, Hastings et al., report that Medicare beneficiaries that had a return ED visit or other acute care encounter were associated with older age, and Medicaid status, along with higher chronic health burden

[8]. Chu and Pei found that in addition to clinical risk factors, socioeconomic characteristics of patient were predictive of early emergency readmission among elderly patient population [14].

In the ESRD population, low health literacy (a proxy of SES) was found to be predictive of ED use in one study [15] 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 [16]. 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, along with higher comorbidity [17]. 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) [18]. Treatment adherence was also found to be a risk factor for emergency department visits [19]. This suggests that there may be related SDS/SES or community level factors that adversely impact patient adherence to dialysis treatment.

Area-level factors, typically operating as proxies of patient level factors, have also been found to influence acute care use, such as readmission [20, 21]as well as ED use [13]. Additionally, area-level SES have been observed to be associated with poor outcomes in ESRD patients [22]). Given these observed linkages we tested available patient- and area-level SDS/SES variables based on the conceptual relationships as 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 (University of Wisconsin, 2013 v1.5) [23]. The ADI reflects a full set of SES characteristics, including measures of income, education, and employment status, measured at the ZIP code level. Singh [24] has applied the index in a variety of contexts, including analysis of county-level mortality rates. 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 [21].

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