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## The relative contribution of provider and ED-level factors to variation among the top 15 reasons for ED admission

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### ABSTRACT

**Study objective:** We examine adult emergency department (ED) admission rates for the top 15 most frequently admitted conditions, and assess the relative contribution in admission rate variation attributable to the provider and hospital.

**Methods:** This was a retrospective, cross-sectional study of ED encounters ( $\geq 18$  years) from 19 EDs and 603 providers (January 2012–December 2013), linked to the Area Health Resources File for county-level information on healthcare resources. “Hospital admission” was the outcome, a composite of inpatient, observation, or intra-hospital transfer. We studied the 15 most commonly admitted conditions, and calculated condition-specific risk-standardized hospital admission rates (RSARs) using multi-level hierarchical generalized linear models. We then decomposed the relative contribution of provider-level and hospital-level variation for each condition. **Results:** The top 15 conditions made up 34% of encounters and 49% of admissions. After adjustment, the eight conditions with the highest hospital-level variation were: 1) injuries, 2) extremity fracture (except hip fracture), 3) skin infection, 4) lower respiratory disease, 5) asthma/chronic obstructive pulmonary disease (A&C), 6) abdominal pain, 7) fluid/electrolyte disorders, and 8) chest pain. Hospital-level intra-class correlation coefficients (ICC) ranged from 0.042 for A&C to 0.167 for extremity fractures. Provider-level ICCs ranged from 0.026 for abdominal pain to 0.104 for chest pain. Several patient, hospital, and community factors were associated with admission rates, but these varied across conditions.

**Conclusion:** For different conditions, there were different contributions to variation at the hospital- and provider-level. These findings deserve consideration when designing interventions to optimize admission decisions and in value-based payment programs.

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### 1. Introduction

There were 136 million visits to hospital-based emergency departments (ED) in 2011; of those, 14% were admitted to the hospitals [1]. Approximately 50% of overall hospital admissions originate in the ED, a proportion that has been increasing since the early 1990s [2]. Aggregate annual costs of admissions from the ED are estimated at \$218 billion in the United States, approximately 8.3% of national healthcare expenditures [3].

Understanding and reducing admission rate variation is important given the greater focus on value in healthcare from Medicare Access and CHIP Reauthorization Act of 2015 (MACRA) and other legislation, and the promulgation of new payment models, which has bi-partisan support [4,5]. While variation is not intrinsically bad, its presence may suggest both high cost for low-severity admits and unnecessary risk from high-severity discharges. Reducing admission rate variation for conditions with high variation may produce billions in savings in national healthcare expenditures [6].

Several studies have examined ED admission decisions. For example, two-fold provider-level admission rate variation has been reported for specific conditions such as chest pain, trauma, and pneumonia, and for overall admissions [7–10]. Hospital-level and county-level admission

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rate variation has also been shown using a large samples of U.S. hospitals and counties [11–13]. Hospital-level, condition-specific variation has also been demonstrated, with considerable variation occurring for mood disorders, chest pain, skin infections, urinary tract infections, and chronic obstructive pulmonary disease [14]. While prior studies have examined many facets of admission variation including provider and hospital-level contributors, no study to our knowledge has simultaneously examined these factors, nor decomposed their relative contribution for conditions that commonly result in hospital admission from the ED.

We study common conditions that result in hospital admission from the ED using a broad sample of patient-level data from 19 EDs to assess which conditions have the greatest admission rate variation, and explore the relative contribution on provider-level, hospital-level, and community-level factors to explain the observed variation.

## 2. Methods

### 2.1. Study design and setting

This was a retrospective, cross-sectional study using de-identified demographic and diagnosis data from LogixHealth, a private company that provides coding, billing, and operational (performance) analytics services for EDs nationwide. Although different ED characteristics were provided, no hospitals were individually identifiable. We included 1,492,674 ED visits for patients  $\geq 18$  years of age from January 1, 2012 through December 31, 2013 from 19 different EDs in the LogixHealth database. These were a geographically diverse group of EDs from across the U.S. Data from the LogixHealth database were linked with data from the Area Health Resources Files (AHRF) to include county characteristics in the database [15]. The AHRF is a county-unit database managed by the Health Resources and Services Administration which contains data collected from >50 sources, including the U.S. Census Bureau, Centers for Medicare & Medicaid Services, Bureau of Labor Statistics, and American Medical Association. The AHRF covers an extensive range of data that includes county descriptors, economic data, health professions data, and health facility data. Each hospital in the LogixHealth database was assigned a corresponding county code, based on the zip code in which the hospital resides, which was linked with AHRF data. The county characteristics used in the analyses included per capita income (\$30,000–\$49,999, \$50,000 or more), the number of primary care providers in the community (100–499, 500–1499, 1500 or more), the percentage of persons less than age 65 in the county without health insurance (7–13.9%, 14% or more), and hospital residence in a metropolitan statistical area (yes, no).

### 2.2. Outcomes

The primary outcome for the study was hospital admission, defined as inpatient admission, observation unit admission, or transfer to another acute care facility. Observation admissions were included as they signified an emergency physicians' decision that a patient requires additional care beyond the ED. Transfers were included because they usually occur to admit a patient to a different hospital for a service not available at the initial hospital [16]. We treated multiple ED visits by the same patient at different time points as different episodes of care.

### 2.3. Data processing

We used data from LogixHealth, which included patient age, gender, ICD-9 diagnosis codes, the shift of ED admission, admitting physician's license type (medical doctor v. physician assistant), discharge disposition status, as well as facility characteristics such as trauma center level and annual volume. We focused on the 15 conditions with the highest frequency of hospital admission in the dataset, and our sample consisted of ED patients who were diagnosed with one of these 15

conditions. We defined clinical conditions by classifying patient ICD-9 codes into Clinical Classification Software (CCS) categories. CCS is a tool developed by the Healthcare Cost and Utilization Project (HCUP), which combines over 17,900 ICD-9 diagnosis codes to a smaller number of clinically meaningful categories. Some CCS categories were combined manually for conditions that are managed similarly in the ED. An example of a manually combined category is asthma/COPD (which includes asthma, and bronchiectasis). Common ICD-9 codes associated with each CCS category are reported in Appendix Table 1.

### 2.4. Data analysis

We calculated condition-specific risk-standardized admission rates (RSARs) for each hospital, using multi-level hierarchical generalized linear models (HGLM). This approach is analogous to the methodology that CMS uses to measure hospital 30-day readmission and mortality rates for major conditions [17]. It has also been used by a prior study that also examines variation in ED admission rates [12].

The estimation of condition-specific RSARs occurred in two stages. We first estimated the log-odds of hospital admission as a function of individual risk factors and two random effects that accounted for hospital-level variation as well as provider-level variation nested within the hospital. Patient characteristics included age, gender, time of ED visit (15:01–23:00, 23:01–7:00, and 7:01–15:00 as the reference group), and a continuous Elixhauser Comorbidity index calibrated based on ICD-9 diagnosis codes. Elixhauser uses 30 categories of comorbid illness to assign weights for comorbidity and risk where higher values mean greater comorbidity [18]. This model not only separated within-hospital variation from between-hospital variation, but also assessed the relative contribution of variation at the hospital-level versus provider-level.

Next, we calculated the *risk-standardized admission ratio* for each condition at each hospital, by dividing the number of predicted admissions by the number of expected admissions at a given hospital. We then multiplied the ratio by the unadjusted sample mean admission rate of each condition to obtain the condition-specific hospital-level RSAR. The number of expected admissions of a hospital was estimated from the HGLM assuming the hospital's case-mix and a constant intercept. The number of predicted admissions was estimated using the same case-mix, but with hospital- and provider-specific intercept terms. As such, the RSAR at a given hospital depends on its case mix as well as the underlying hospital admission rate. An RSAR below (or above) the unadjusted mean admission rate indicates that the hospital's admission rate is lower (or higher) than that of an average hospital with similar case-mix.

We assessed model discrimination using C-statistic which reports the area under receiver operating characteristic (ROC) curve, and indicates the probability that the model-predicted admission risk for an admitted patient is higher than a non-admitted patient. Researchers consider C-statistics of 0.7 to 0.8 to indicate reasonable discrimination, and C-statistics of >0.8 indicate excellent discrimination [19].

We reported the mean and interquartile range (IQR) of RSARs for each condition, and use violin plots to illustrate the dispersion of RSARs across hospitals. We selected the top 8 conditions with the greatest variability for further investigation as described below, which were ranked based on the variation in the *risk-standardized admission ratio* for each condition. For each of the 8 conditions, we examined the intra-class correlation coefficients (ICCs) at the hospital- and provider-level from the nested HGLM models. The ICCs represent the variance of random intercepts as a share of the total variance of the error term in the HGLM. Conditional on the fixed-effects covariates, the hospital-level ICC indicates the share of residual variance explained at the hospital-level; and the provider-level ICC indicates the share of residual variance explained within hospital at the provider level. A comparison of hospital- and provider-level ICCs enables us to assess the relative contribution of unobserved hospital and provider factors in the variance of ED admission rates.

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