# Using ICU Congestion as a Natural Experiment*

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Over 20 years ago, Bone et al (1) completed a comprehensive review of evidence on two questions: which patients benefit from ICU admission and what impact does being cared for in the ICU have on the outcomes of those who benefit?

Of the hundreds of studies that Bone et al (1) reviewed to answer these questions, only two were case-control studies. Although they recommended prospective, randomized clinical trials, what followed were additional observational studies (2, 3), since trials in time-sensitive and dangerous circumstances are regarded as infeasible.

Both questions now loom large in an era of "Choosing Wisely" because subsequent general (4) and disease-specific (5, 6) observational studies find that some patients with similar characteristics prior to hospital admission have similar outcomes regardless of ICU admission.

In this issue of *Critical Care Medicine*, Kim et al (7) examine outcomes of ICU-eligible patients admitted from the emergency department (ED) to a medical service in 15 Kaiser hospitals. The authors used a scoring system that measures physiologic derangement and risk of mortality based on 14 laboratory values collected in the 24 hours before admission to the hospital. They deemed patients ICU eligible if predicted mortality fell in the highest 20% among patients admitted during a 1-year window of observation. This cohort's inpatient mortality exceeded 6%.

Kim et al (7) used an instrumental variable approach to assess the impact of ICU admission on patients who are admitted to the ICU only during times of low congestion (<90% occupancy). The type of model they used is sometimes referred to as a two-stage model. The first stage determined how much ICU congestion predicts whether a patient will be admitted to the ICU. Then the second stage quantified the effect of ICU admission on clinical outcomes for those patients whose acceptance into the ICU was impacted by congestion. Kim et al (7) estimate that in a scenario of unlimited ICU capacity, patients excluded from the ICU due to congestion would instead have been admitted and thereby prevented 7.5 hospital readmissions and 253.8 hospital days.

Although no observational study carries the evidential heft of a randomized controlled trial, the authors selected one of the strongest study designs available. This method is considered stronger than a case-control study because, in some situations, it can minimize bias due to unobserved and observed variables. In this case, the authors use the natural experiment of fluctuating ICU congestion to simulate randomization of similar ICU eligible patients either admitted to or excluded from initial ICU admission. This study design pivots on the assumption that ICU eligible patients admitted when ICUs are congested do not systematically differ from those when the ICUs are not congested.

New study methods developed in the past 5–10 years are as easy to apply as the two-stage model they used and are proven to produce less biased results (8).Without rerunning these data using the newer models, it is hard to judge how the results might be impacted. Published evidence suggests that it is bounded and not huge (9).

The selection of a cohort carries a tremendous amount of weight in an observational study (10). Although the cutpoint used by Kim et al (7) to determine ICU eligibility may be contested, it seems reasonable because it corresponds with a rise in predicted mortality. Patients excluded from the study, including all those admitted for surgery, confines the study's conclusions to roughly half of ICU admissions.

As the authors acknowledge, a study that relies upon an instrumental variable can only estimate a treatment effect for a subset of the overall study population. In this case, the population is best conceptualized as patients who 1) were admitted through the ED to a medical service and 2) would not have been admitted to the ICU if it was congested. This means that the study findings do not apply to patients who would always or never be admitted to the ICU regardless of the level of ICU congestion.

The study occurred in a health system that is not representative of mainstream American care. Kaiser combines health insurance with healthcare delivery, and its physicians are salaried employees of a medical group wholly dedicated to serving health insurance plan enrollees. Conscious of the need to operate

*See also p. 1814.

**Key Words:** admission decision; appropriateness; critical care

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within a global budget that enables Kaiser to offer more affordable health insurance, it is plausible that ICU eligible patients excluded from ICUs during periods of congestion at Kaiser hospitals differ from patients excluded from ICUs at other hospitals.

Bone et al (1) called for methods and models capable of "identifying which patients are either not sick enough for admission or are too sick to benefit from intensive care." The study of Kim et al (7) contributes strong evidence regarding who will benefit from admission to the ICU. Future studies utilizing different instrumental variables could assess the impact of ICU admission on other subpopulations. To further clarify the thresholds at which a patient might be too sick or too well to benefit from ICU care, point-of-care randomization could be used. Point-of-care randomization can examine the effect of ICU treatment when the care team and the patient (or their designated representative) are at equipoise for how to proceed with treatment (11). Such an approach to randomization of ICU admission decisions in a more representative group of American hospitals would enable an even stronger and more generalizable study design.

Based on the author's findings, it is conceivable that adding ICU beds would enable more patients to benefit from ICU admission. However, rather than build more ICU beds, smoothing hospital patient flow and ICU census by scheduling elective surgical cases to take advantage of naturally recurring valleys in ICU demand (12) has been shown to decrease the occurrence and adverse impact of ICU congestion (13). There are additional alternatives such as critical care outreach teams that provide a wider range of care for patients outside the ICU (14) and reducing ICU complications via expanded intensivist coverage via telemedicine (15).

The closing advice of Bone et al (1) still resonates today, "The data that are available suggest that there is a group of patients with moderately severe illness…who will benefit from being in the ICU…What is required now is that we delineate the… upper and lower boundaries for these moderately ill patients…to ensure that those patients who can potentially benefit from ICU care will receive it. Those patients who are either too ill or not ill enough can be treated more effectively in other hospital locations."

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# Association Among ICU Congestion, ICU Admission Decision, and Patient Outcomes*

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**Objectives:** To employ automated bed data to examine whether ICU occupancy influences ICU admission decisions and patient outcomes.

**Design:** Retrospective study using an instrumental variable to remove biases from unobserved differences in illness severity for patients admitted to ICU.

**Setting:** Fifteen hospitals in an integrated healthcare delivery system in California.

**Patients:** Seventy thousand one hundred thirty-three episodes involving patients admitted via emergency departments to a medical service over a 1-year period between 2008 and 2009.

**Interventions:** None.

**Measurements and Main Results:** A third of patients admitted via emergency department to a medical service were admitted under high ICU congestion (more than 90% of beds occupied). High ICU congestion was associated with a 9% lower likelihood of ICU admission for patients defined as eligible for ICU admission. We further found strong associations between ICU admission and patient outcomes, with a 32% lower likelihood of hospital readmission if the first inpatient unit was an ICU. Similarly, hospital length of stay decreased by 33% and likelihood of transfer to ICU from other units–including ICU readmission if the first unit was an ICU–decreased by 73%.

**Conclusions:** High ICU congestion is associated with a lower likelihood of ICU admission, which has important operational implications and can affect patient outcomes. By taking advantage of our ability to identify a subset of patients whose ICU admission decisions are affected by congestion, we found that, if congestion were not a barrier and more eligible patients were admitted to ICU, this hospital system could save approximately 7.5 hospital readmissions and 253.8 hospital days per year. These findings could help inform future capacity planning and staffing decisions. (*Crit Care Med* 2016; 44:1814–1821)

**Key Words:** admission decision; hospital bed capacity; length of stay; quality of health care; readmission

***See also p. 1936.**

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Ideally, ICU patient admission decisions would be determined solely by medical necessity. However, defining "medical necessity" is a complex task; a critical care task force established criteria for ICU admission, discharge, and triage, and the lack of data linking criteria to patient outcomes resulted in consensus-based and (self-described) arbitrary criteria (1). Furthermore, ICUs often operate close to capacity (2), and high ICU congestion makes ICU care decisions far more challenging. Although the association between high ICU congestion and fewer ICU admission requests and actual admissions is well documented (3–9), previous studies considered only patients referred to ICU or patients identified as "critically ill" using subjective screening criteria.

To understand what factors affect ICU admission, it is necessary to also consider the impact on patients who are not admitted to ICU. Evaluating these factors requires a method for measuring a patient's illness severity. Most ICU-related studies employ ICU scores created and validated using only ICU patients (e.g., Acute Physiology and Chronic Health Evaluation scores (7, 8)). Clearly, existing ICU scores may be inappropriate for measuring illness severity for patients outside of ICU (10).

The purpose of this study was to quantify the effect of ICU congestion on ICU admission decisions and, in turn, the effect of ICU admission on patient outcomes for all inpatients. We employed the Laboratory Acute Physiology Score (LAPS) (11) and an estimated probability of mortality based on multiple factors (11). The two scores, developed and validated using inpatient data including medical/surgical patients and critical care patients, can be assigned to any inpatient and allowed us to do risk adjustment in estimation models. Additionally, LAPS was used to define an eligible cohort for ICU admission. Because LAPS is an objective metric of patient severity, computed from laboratory test results obtained in the 24 hours preceding hospitalization, our selection criterion differs from previously used criteria that depend heavily on doctors' discretion and may be subject to biases.

We quantified the effect of ICU admission in terms of several patient outcomes: hospital readmissions, transfers from other units to ICUs, and hospital length of stay (LOS). One important challenge was the endogeneity of ICU admission decisions, due to unobservable factors affecting both admission decisions and patient outcomes. That is, patients who are more likely to be admitted to ICU are also more likely to have worse outcomes, which could lead us to underestimate the value of ICU admission. We used the instrumental variable (IV) approach to remove potential biases. We also considered the hospital resources associated with changes in ICU admission decisions. Our analyses can be used to establish better ICU admission standards and to inform future cost-effectiveness analyses for ICU capacity and staffing. A similar study, using the same dataset and a comparable estimation approach, focuses on evaluating various ICU admission strategies in an effort to develop a standardized ICU admission strategy (12).

## MATERIALS AND METHODS

This project was approved by the Kaiser Permanente Northern California (KPNC) and Columbia University Institutional Review Board for the Protection of Human Subjects.

### Setting

KPNC serves approximately 3.9 million members. We studied 15 hospitals in KPNC. The study sample consisted of all patient episodes directly admitted to an inpatient unit from emergency departments (EDs) and meeting these criteria: 1) overnight hospitalization began during the 1-year study period; 2) episode did not include any inter-hospital transfers; 3) 15 years old or older at the time of admission; 4) admitted to a medical service; and 5) the hospital had no reorganization of the intermediate care unit (if one existed) during the episode.

### The IV Approach

This study had two objectives: first was to examine whether ICU occupancy influences ICU admission decisions, as explained below in "The Admission Decision Model." Second was to estimate the causal effect of ICU admission, influenced by ICU occupancy, on various patient outcomes as described in "The Patient Outcome Model."

The ideal experiment to address our second objective would be to randomly assign patients to ICUs versus other units, regardless of illness severity, and then compare patient outcomes. Since such an experiment is impossible, an observational study is a reasonable alternative. Such study, however, may be biased due to unobserved treatment selection biases.

In our case, unobserved severity factors (e.g., poor perfusion, agitation) affect both ICU admission and patient outcomes, making ICU admission decisions endogenous. We used an IV approach to reduce this bias. An IV is used to "mimic" a randomized study by randomly assigning patients to receive treatment, which for our study is ICU admission. Wooldridge (13) and Baiocchi et al (14) provide details of the IV approach. Using ICU occupancy as the instrument, we quantify the effect of ICU admission by comparing differences in outcomes between patients who have similar observable characteristics but received different treatments due to our instrument. In what follows, we explain our models and the validity of our instrument in detail.

### The Admission Decision Model

The dependent variable was ICU admission. In KPNC, ICUs have a nurse-to-patient ratio of 1:1 to 1:2. The two other inpatient units, general wards and intermediate care units, have ratios of 1:3.5 to 1:4 and 1:2.5 to 1:3, respectively.

The principal independent variable (or "instrument" in our IV approach) was "ICU occupancy level," defined as ICU occupancy divided by ICU bed capacity. Our data included every unit each patient was transferred to, along with unit admission and discharge date and time, which allowed calculating unit bed census at any point. We defined "ICU bed capacity" in each hospital as the 95th percentile value of the ICU bed census measured every hour of the entire study period. For ICU occupancy, we used the occupancy measured 1 hour before a patient was discharged from the ED to an inpatient unit, to capture the occupancy closest to when the ICU admission decision was made.

Additional predictors were age, gender, hospital admission diagnosis group (11), and two illness severity scores—the LAPS (11) and estimated probability of mortality, which included diagnoses and comorbidities as well as the LAPS (11). These scores allow us to risk adjust for the impact patient severity factors may have on ICU admission decisions and patient outcomes. They are assigned once, at the time of hospital admission.

We controlled for seasonality by including ED admission month, time, and day-of-week indicators. We also included hospital fixed effects because the effect of ICU occupancy level on ICU admission might vary from one hospital to another.

We used a probit model to estimate the ICU Admission Decision model. Probit models estimate the probability that an observation with particular characteristics will have one of two possible responses (15). Logit models are also commonly employed for dichotomous-dependent variables. Probit and logit models yield similar inferences.

### The Patient Outcome Models

We focused on four dependent variables: in-hospital mortality (Mortality), hospital readmission (Readmit), remaining hospital LOS (ReHospLOS), and transfer to ICU (TransferUp).

Mortality and Readmit are standard patient outcomes (16). We defined hospital readmission (Readmit) as a new hospital admission within 2 weeks following the index hospital discharge. We excluded patients who died in the index hospitalization in the Readmit model because such patients could not be readmitted.

Remaining hospital stay is used to access the impact of ICU admission on hospital LOS. ReHospLOS is measured as the number of calendar days between first inpatient unit discharge day and hospital discharge day; because afternoon hospital discharges are predominant (regardless of the first inpatient unit discharge time), using intervals defined by calendar days rather than hours produced more valid results. The ReHospLOS model included patients with in-hospital mortality because excluding them had minimal effects on our results.

We considered TransferUp because transfer to the ICU from other inpatient units can be a result of physiologic deterioration (17, 18). Patients who stayed only in the ICU could not experience such transfers; hence, we used TransferUp as an outcome measure only for the patients who stayed in a general ward or an intermediate care unit at least once.

The key predictor variable was the ICU admission decision. As described previously, ICU admission decisions are endogenous. We use ICU occupancy as the instrument variable to remove potential biases. ICU occupancy level is a valid instrument (14, 19) because of the following: 1) ICU occupancy level directly preceding ICU admission is unrelated to the patient severity factors of the new patient; 2) occupancy affects ICU admission decisions (we validated this with the results from the Admission Decision model); 3) ICU occupancy level directly preceding ICU admission affects patient outcomes only through its effect on the likelihood of ICU admission; and 4) moving from low-to-high ICU occupancy is unlikely to increase the admission probability of any patient.

Studies have shown that congestion could affect patient outcomes (20–22). To address point number 3 mentioned above, we controlled for the average hospital occupancy level during each patient's hospital stay. The correlation between the average hospital occupancy and the ICU occupancy directly preceding hospital admission (our IV) was only 0.24. We also controlled for all the other predictors included in the Admission Decision model. **Appendix Figure 1** illustrates our econometric framework.

We estimated patient outcome models via maximum likelihood estimation method. Mortality, TransferUp, and Readmit have binary responses, so we used the bivariate probit model. Because we found that ReHospLOS was overdispersed for a Poisson distribution, we used a negative binomial regression for ReHospLOS, which is capable of modeling overdispersion.

## RESULTS

### Patient Cohort

We employed a dataset of 192,409 hospitalizations collected over 1.5 years. **Figure 1** illustrates our patient cohort selection. We utilized patient flow data from all 192,409 hospitalizations (* in Fig. 1) to derive the maximum capacity and hour-by-hour occupancy level of each inpatient unit. We restricted our study to 12 months in the center of the 1.5-year time period to ensure correct measurement of ICU capacity and occupancy. For simplicity, we excluded patients who experienced interhospital transport. Because surgical schedules, which we did not have access to, could affect the care of surgical patients, we focused on patients admitted via EDs to medical services. We excluded hospitalizations during rare occurrences of intermediate care unit reorganization (such as reducing the number of beds). The final dataset consisted of 70,133 hospitalizations (** in Fig. 1).

Summary characteristics (i.e., age, illness severity, and in-hospital mortality) of patients admitted to different inpatient units are in **Supplementary Table 1** (Supplemental Digital Content 1, http://links.lww.com/CCM/B875). **Table 1** provides

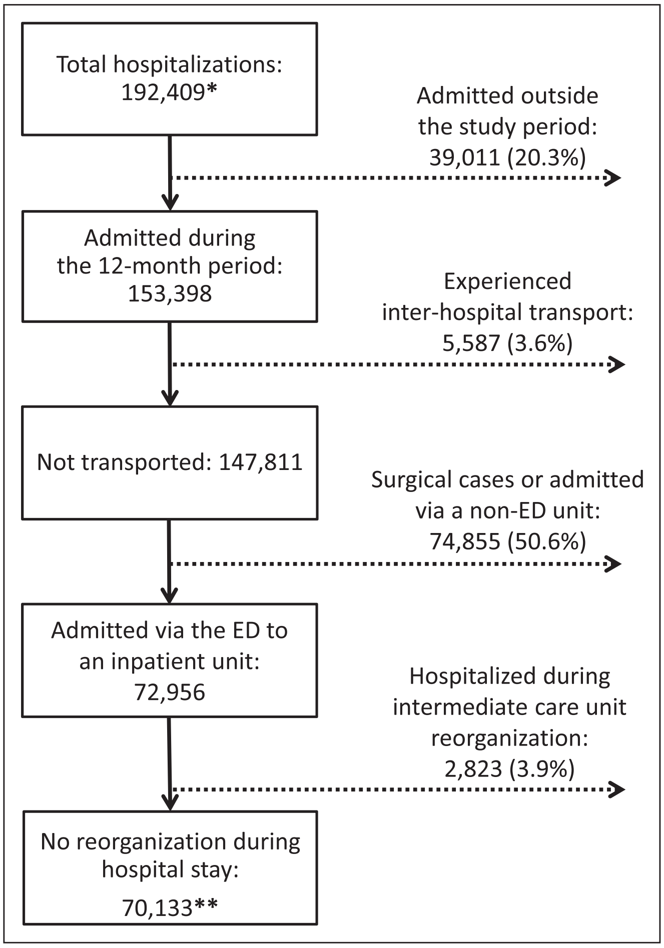


**Figure 1.** Patient cohort. The top box shows that we used 192,409 episodes as the patient cohort to derive the maximum capacity and hour-by-hour occupancy of each inpatient unit. After exclusions, the remaining 70,133 episodes in the bottom box were used to estimate the ICU admission model and patient outcome models. ED = emergency department.

**TABLE 1. Patient Characteristic and Outcome Variables Summary Statistics**

| Patient Characteristics and Outcomes | Not in Eligible Cohort[a] | Eligible Cohort | Entire Cohort |
|---|---|---|---|
| No. of hospitalizations | 55,583 | 14,550 | 70,133 |
| Age (median, mean ± SD) | 68.0, 65.0 ± 18.0 | 78.0, 74.8 ± 14.5 | 70.0, 67.0 ± 17.8 |
| Laboratory-Based Acute Physiology Score[b] (median, mean ± SD) | 17.0, 16.9 ± 11.3 | 51.0, 54.6 ± 13.4 | 20.0, 24.7 ± 19.3 |
| Predicted Pr (mortality)[c] (median, mean ± SD) | 0.01, 0.03 ± 0.04 | 0.09, 0.13 ± 0.12 | 0.02, 0.05 ± 0.08 |
| Top five primary conditions (11) | GI bleeding (13.1%) | GI bleeding (11.2%) | GI bleeding (12.7%) |
| | Chest pain (11.3%) | Pneumonia (8.5%) | Chest pain (9.5%) |
| | Seizures (6.2%) | Acute respiratory failure (6.5%) | Seizures (5.6%) |
| | Infections (5.7%) | Congested heart failure (5.5%) | Pneumonia (5.5%) |
| | Acute respiratory failure (5.2%) | Diabetic ketoacidosis and related metabolic (5.2%) | Infections (5.5%) |
| ICU admission rate (%) | 7.5 | 19.2 | 9.9 |
| Mortality (%) | 2.3 | 12.3 | 4.3 |
| TransferUp[d] (%) | 2.3 ($n$ = 54,329) | 5.2 ($n$ = 13,873) | 2.9 ($n$ = 68,200) |
| Readmit[e] (%) | 9.1 ($n$ = 54,329) | 13.8 ($n$ = 12,758) | 10.0 ($n$ = 67,087) |
| ReHospLOS (d) | 2.0, 3.4 ± 4.4 | 4.0, 5.5 ± 6.2 | 3.0, 3.9 ± 4.9 |

GI = gastrointestinal.

[a]See text and Figure 2 for explanation of how eligible cohort was defined. We focused on four dependent variables: in-hospital mortality (mortality), transfer-up to a higher level of care (TransferUp), hospital readmission (Readmit), and hospital length-of-stay (ReHospLOS).

[b]Laboratory-Based Acute Physiology Score (LAPS) (11) measures physiologic derangement at admission and is mapped from 14 laboratory test results, such as arterial pH and WBC, obtained in the 24 hr preceding hospitalization to an integer value that can range from 0 to a theoretical maximum of 256. The maximum LAPS value in our dataset was 166, with minimum value 0. Increasing degrees of physiology derangement are reflected in a higher LAPS.

[c]Predicted probability of mortality; its predictors include LAPS and Comorbidity Point Score (11).

[d]Because patients who stayed only in the ICU never experience transfer-up, we used TransferUp as outcome measures only for patients who stayed in inpatient units other than the ICU at least once. The number of such patients in parenthesis.

[e]We considered patients who did not have in-hospital death in the Readmit model since patients who died cannot be readmitted. The number of such patients in parenthesis.

summary statistics of the patient outcome variables (i.e., Mortality, TransferUp, Readmit, and ReHospLOS).

## Eligible Cohort for ICU Admission

Although all of the 70,133 patients were used in our estimations, many of them would not even be considered for ICU admission; quantifying the benefit of ICU admission for such patients would be misleading. The IV estimation approach is indeed only valid for patients who “comply” with the instrument (19). That is, the IV analysis provides unbiased estimates for the “marginal” patients whose ICU admission is affected by ICU congestion.

Many factors contribute to the likelihood of ICU admission, so isolating the marginal patients who comply with the IV can be challenging. As an approximate approach, we defined an eligible cohort for ICU admission. We considered an ED patient to be eligible for ICU admission if the patient’s LAPS was greater than or equal to the 80th percentile value of all of the 70,133 patients’ LAPS values, which was 40. In other words, 20% of the 70,133 ED patients, with the largest LAPS values, met our definition as eligible for ICU admission. We picked

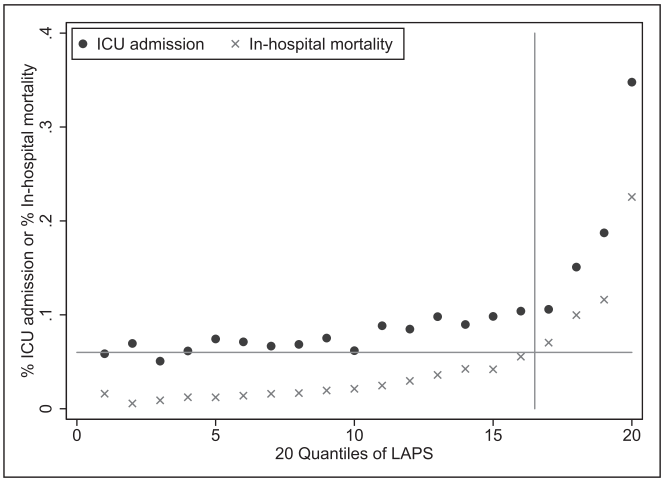


**Figure 2.** Percentage ICU admission and in-hospital mortality by Laboratory Acute Physiology Score (LAPS) value. The $x$-axis shows 20 quantiles of LAPS and the $y$-axis shows the observed percentage of ICU admissions and in-hospital mortality at each quantile group. We use this figure to define an eligible cohort for ICU admission (patients in the sickest four of the 20 quantiles) in the *Results* section.

LAPS greater than or equal to 40 because these patients had high in-hospital mortality rate (> 6%) and high ICU admission rate (> 10%). See **Figure 2** for details.

Our eligible cohort selection criterion is objective, unlike previously used selection criteria (3–9) that depend heavily on doctors' discretion and may be subject to biases. Compared to the ineligible cohort, the eligible cohort is sicker, as measured by the illness severity scores. Its top three primary conditions were gastrointestinal bleeding, pneumonia, and acute respiratory failure. See Table 1 for comparisons with patients who are not in the eligible cohort.

### Effect of ICU Occupancy on ICU Admission

On average, 80% of ICU beds were occupied. We considered three possible ICU occupancy levels: normal (< 90% of beds occupied), high (> 90% of beds occupied), and very high (all beds occupied). In our data, ICU occupancy level was normal 67% of the time, high 24%, and very high 9%.

The effect of ICU occupancy level was negative and statistically significant (**Table 2**). Increasing ICU occupancy from normal to high decreased the average ICU admission probability for eligible patients from 20.4% to 18.6% (a 9% decrease). Increasing ICU occupancy level from normal to very high decreased the probability to 10.9% (a 47% decrease).

### Effect of ICU Admission on Patient Outcomes

**Table 3** summarizes the results of patient outcome models. Except for the Mortality model, the coefficients of ICU admission were negative and statistically significant in all models, suggesting a strong association between ICU admission and better patient outcomes. (Because in-hospital mortality was rare in our sample [4.2%], there was not enough power to estimate the

**TABLE 2. Likelihood of ICU Admission Model Estimation Results**

| | | Marginal Effects | |
|---|---|---|---|
| Covariate[a] | Coefficient[b] | Average Absolute Change[c] | Average Relative Change[d] (%) |
| 90% ≤ ICU occupancy < 100% | −0.08 (0.02)[e] | −0.02 | −9 |
| 100% ≤ ICU occupancy[f] | −0.51 (0.03)[e] | −0.10 | −47 |
| Age[g] (40–64) | −0.18 (0.03)[e] | −0.05 | −16 |
| Age (65–74) | −0.33 (0.03)[e] | −0.09 | −30 |
| Age (75–84) | −0.48 (0.03)[e] | −0.12 | −40 |
| Age (85–) | −0.70 (0.04)[e] | −0.16 | −55 |
| LAPS[h] (0–39) | 0.01 (0.00)[e] | | |
| LAPS (39–69) | 0.02 (0.00)[e] | | |
| LAPS (69–89) | 0.03 (0.00)[e] | | |
| LAPS (89–) | 0.01 (0.01)[i] | | |
| Pr (mortality)[h] (0–0.004) | 28.04 (10.60)[j] | | |
| Pr (mortality) (0.004–0.075) | −1.24 (0.53)[i] | | |
| Pr (mortality) (0.75–0.2) | −0.94 (0.34)[j] | | |
| Pr (mortality) (0.2–) | −0.58 (0.22)[j] | | |
| No. of hospitalizations | 70133 | | |
| Pseudo $R^2$ | 0.18 | | |

LAPS = Laboratory-Based Acute Physiology Score.

[a]Admitting diagnosis; hospital entry month, day, and time dummies; and hospital dummies were also included as covariates but are not reported due to space limitations.

[b]Coefficient estimates from probit regression (SEs in parenthesis) are shown.

[c]Average absolute change—computed for categorical variables only—in ICU admission rate if we condition that all eligible patients were under each category instead of the base category. The base category for ICU occupancy is "ICU occupancy < 90%" and the base category for age groups is "age (15–39)."

[d]Average relative change—computed for categorical variables only—in ICU admission rate if we condition that all eligible patients were under each category instead of the base category.

[e]$p < 0.001$.

[f]We define the capacity of each ICU of the 15 hospitals as the 95th percentile of the hourly bed occupancy distribution of that unit (see *The Admission Decision Model* section). That is, ICU occupancy ≥ 100% essentially means the ICU occupancy is above the 95th percentile of its hourly occupancy distribution.

[g]Age were included as categorical variables representing the following five groups: 15–39 (base), 40–64, 65–74, 75–84, and 85 years and older.

[h]The severity scores, Laboratory-Based Acute Physiology Score, and predicted Pr (mortality), were included with piece-wise linear specifications, with corresponding intervals indicated in brackets.

[i]$p < 0.05$.

[j]$p < 0.01$.

**TABLE 3. Instrumental Variable Analysis Results: Effect of ICU Admission on Patient Outcomes and Average-Estimated Marginal Effects Among Eligible[a] Patients**

| Patient Outcome | Coefficient[b] | Marginal Effects | |
|---|---|---|---|
| | | Average Absolute Change[c] | Average Relative Change[d] (%) |
| Mortality | −0.04 (0.13) | −0.01 | −6 |
| TransferUp | −0.64 (0.17)[e] | −0.05 | −73 |
| Readmit | −0.23 (0.13)[f] | −0.05 | −32 |
| ReHospLOS (d) | −0.40 (0.01)[e] | −1.7 | −33 |

[a]See text and Figure 2 for explanation of how eligible cohort was defined.
[b]Coefficient estimates of ICU admission decision (SEs in parenthesis) for each patient outcome model are shown.
[c]Average absolute change in each outcome if we condition that all eligible patients are admitted to ICU instead of other inpatient units.
[d]Average relative change in each outcome if we condition that all eligible patients are admitted to ICU instead of other inpatient units.
[e]$p < 0.001$.
[f]$p < 0.1$.

effect of ICU admission in the Mortality model.) Table 3 also reports the marginal effects whose magnitudes are significant; for instance, admitting all eligible patients to ICU would decrease the likelihood of hospital readmission by 32% on average.

To confirm that the decision to admit to the ICU is endogenous, we tested whether the correlation between the admission decision and the outcome models' errors is zero (12). The results supported our hypothesis that ICU admission decisions were endogenous—that is, affected by unobserved severity factors that also affected patient outcomes—in all patient outcome models.

## DISCUSSION

Our results support the importance of controlling for the endogeneity of ICU admission decision. Comparing the IV estimates to those without IV (Table 3; **Supplementary Table 2** [Supplemental Digital Content 2, http://links.lww.com/CCM/B876]), we observed a significant difference in the coefficients. Because ICU patients tend to be sicker, a portion of which is unobserved and cannot be controlled for, the naive estimates (without IVs) tend to underestimate the benefit of ICU admission. In the Readmit and ReHospLOS models, the bias was so severe that it led to a positive correlation between being admitted to an ICU and having adverse outcomes.

We note that a few studies have used the IV approach to examine the effects of ICU admission on patient outcomes. For instance, Shmueli et al (7) also used the ICU congestion level as an IV to study the impact of denied ICU admission on mortality for patients who are referred for ICU admission, and Valley et al (23) used the distance to a hospital with high ICU admission as an IV to study the impact of ICU admission on mortality among older patients with pneumonia. In contrast, we consider a broader class of inpatients and patient outcomes in addition to mortality, which makes this study more generalizable compared to the existing literature.

To gauge the implications of our results, we quantified the benefit of ICU admission on hospital resources. By considering a hypothetical situation in which unlimited ICU capacity were available, we found 149.3 more eligible patients would have been admitted to the ICU in 1 year in this hospital system. Using our results in Table 3 to compute the potential savings in patient outcomes (Readmit and ReHospLOS), we estimated that admitting the 149.3 patients could have saved about 7.5 hospital readmissions and 253.8 hospital days (Section A of **Appendix 1** for details). We believe our analysis can help inform future cost-benefit analysis for ICU capacity planning and staffing.

This study has several limitations: 1) the IV approach estimates the average effect of ICU admission over the subset of patients whose ICU admission decisions depend on ICU occupancy. This means that the effect of ICU admission estimated through our approach might not apply to the most severely ill patients and the most healthy patients if their ICU admission decision is not affected and/or does not comply with our IV; 2) all study participants were members of a single integrated healthcare delivery system and single insurer; 3) only hospitalized patients were included, despite the possibility that ICU and hospital congestion could have blocked additional patient hospitalizations; and 4) we did not examine the impact of timely ICU admission on in-hospital mortality due to insufficient data.

Our study also has several strong points. Our study covers 15 hospitals of different sizes, specialties, and locations, which helps to validate the robustness and generalizability of the results. Our data have detailed information on every unit in which patients stayed, which allows us to compute occupancy levels at any point of time in the study period.

## CONCLUSIONS

We examined the impact of ICU congestion on patient care and, ultimately, health outcomes. Our findings suggest that ICU occupancy level can have a significant impact on ICU admission decisions and patient outcomes. Although many physicians and nurses acknowledge that denying ICU admission can occur and that it is medically undesirable, the magnitude of the impact is, in general, unknown (24). Our work provides systematic and quantitative measures of the benefit of ICU care on various patient outcomes. Physicians and hospital administrators can leverage such information when determining patient care and ICU capacity and staffing levels.

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## Appendix 1

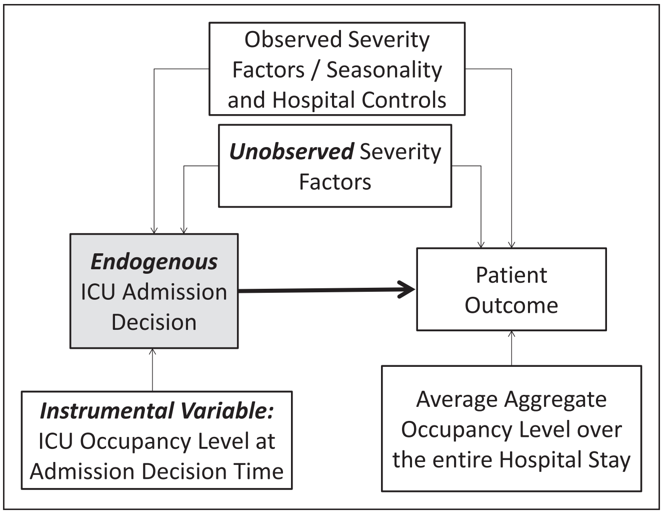
### A. Quantifying the Benefit of ICU Admission on Hospital Resources

Out of the 14,550 eligible patients with LAPS score greater than 40, 4,724 patients were admitted to an inpatient unit when more than 90% of ICU beds were occupied. Among these 4,724 patients, 3,966 patients were admitted to an inpatient unit other than an ICU (and the remaining 758 patients were admitted to an ICU).

We used our ICU Admission Decision model to estimate the increase in ICU admission probability assuming the hypothetical situation where the 3,966 patients arrived when fewer than 90% of ICU beds were occupied (in other words, we considered the hypothetical situation of unlimited ICU capacity, so that the ICU admission decisions are not affected by ICU congestion). For example, consider a patient in our data who had LAPS 92 and who was admitted to a general ward unit when the ICU was very busy (i.e., this patient is among the 3,966 patients). Using our ICU Admission Decision model, the predicted ICU admission probability for this patient is 0.79 when the ICU is not busy and 0.61 when the ICU is very busy; for this patient, the expected increase in ICU admission probability if the patient arrived when the ICU was not busy is 0.18. By adding up the expected increase in ICU admission probability of all of the 3,966 patients, we found that, in expectation, 149.3 more patients would be admitted to ICU.

We used the average absolute change in Table 3 to estimate potential savings in patient outcomes (Readmit and ReHospLOS). Admitting the 149.3 patients would save about 7.5 hospital readmissions and 253.8 hospital days. We believe that our benefit estimates are conservative as they only account for the benefits for the individual patient and not the potential positive externalities on other patients. For instance, if a patient's LOS is reduced, this may decrease congestion and allow more timely access to care for other patients, which is associated with better outcomes (20). In summary, high ICU occupancy level may result in fewer ICU admissions, worse patient outcomes, and more hospital resources.

Our above estimates considered the hypothetical situation where patients were admitted to the hospital when the ICU was not congested. In practice, providing the access to ICU care for 149.3 patients comes with a cost. Thus, when carrying out a cost-benefit analysis for ICU capacity planning and staffing, we advocate not only considering the benefit we computed above, but also carefully estimating the cost of providing ICU care to more patients.




**Appendix Figure 1.** Relationship between the endogenous ICU admission decision and patient outcomes. This figure illustrates the endogeneity of ICU admission decision; observed severity factors and seasonality/hospital controls affect both of the ICU admission decision and patient outcomes. Additionally, patient severity conditions that are unobservable in the data, such as a patient's appearance and cognitive state, are likely to affect both. This endogeneity in ICU admission decision could introduce a positive bias in the estimate of the effect of ICU admission on patient outcomes and lead us to underestimate the value of ICU care. We used the instrumental variable (IV) estimation method to remove this bias and used the ICU occupancy level at admission decision time as the instrument. With this IV approach, the identification was driven by comparing differences in outcomes among patients who have similar observable characteristics but received different treatments only because of different ICU occupancy levels.