Effect of Boarding on Mortality in ICUs

Robert Stretch, MD[1]; Nicolás Della Penna, BA[2]; Leo Anthony Celi, MD, MS, MPH[3]; Bruce E. Landon, MD, MBA, MSc[4,5]

Objectives: Hospitals use a variety of strategies to maximize the availability of limited ICU beds. Boarding, which involves assigning patients to an open bed in a different subspecialty ICU, is one such practice employed when ICU occupancy levels are high, and beds in a particular unit are unavailable. Boarding disrupts the normal geographic colocation of patients and care teams, exposing patients to nursing staff with different training and expertise to those caring for nonboarders. We analyzed whether medical ICU patients boarding in alternative specialty ICUs are at increased risk of mortality.

Design: Retrospective cohort study using an instrumental variable analysis to control for unmeasured confounding. A semiparametric bivariate probit estimation strategy was employed for the instrumental model. Propensity score matching and standard logistic regression (generalized linear modeling) were used as robustness checks.

Setting: The medical ICU of a tertiary care nonprofit hospital in the United States between 2002 and 2012.

Patients: All medical ICU admissions during the specified time period.

Interventions: None.

Measurements and Main Results: The study population consisted of 8,429 patients of whom 1,871 were boarders. The instrumental variable model demonstrated a relative risk of 1.18 (95% CI, 1.01–1.38) for ICU stay mortality for boarders. The relative risk of in-hospital mortality among boarders was 1.22 (95% CI, 1.00–1.49). GLM and propensity score matching without use of the instrument yielded similar estimates. Instrumental variable estimates are for marginal patients, whereas generalized linear modeling and propensity score matching yield population average effects.

Conclusions: Mortality increased with boarding of critically ill patients. Further research is needed to identify safer practices for managing patients during periods of high ICU occupancy. (*Crit Care Med* 2018; 46:525–531)

Key Words: bed occupancy; evidence-based facility design; intensive care units; surge capacity

[1]Department of Medicine, Beth Israel Deaconess Medical Center, Boston, MA.

[2]Research School of Computer Science, Australian National University, Canberra, ACT, Australia.

[3]Laboratory for Computational Physiology, Massachusetts Institute of Technology, Cambridge, MA.

[4]Department of Health Care Policy, Harvard Medical School, Boston, MA.

[5]Division of General Medicine and Primary Care, Department of Medicine, Beth Israel Deaconess Medical Center, Boston, MA.

Drs. Stretch, Della Penna, Celi, and Landon participated equally in the design of the study. Drs. Stretch and Della Penna gathered and analyzed the data. Dr. Della Penna performed the statistical analysis. Drs. Stretch, Della Penna, Celi, and Landon drafted the article. All authors read and approved the final article.

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For information regarding this article, E-mail: landon@hcp.med.harvard.edu

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The number of ICU beds in the United States increased by 15.1% between 2000 and 2009. Despite this growth in capacity, shrinkage in the total number of hospital beds (1) and changing patterns of inpatient care have resulted in higher ICU occupancy levels and increased rates of refused ICU admissions and night discharges to floor beds (2, 3). Hospitals have developed a number of strategies to deal with the allocation decisions that result from high ICU occupancy. Among the most common strategies are various forms of "boarding" which involve caring for patients in an alternative location when a bed is not available in the "appropriate specialty ICU." For instance, critically ill patients may remain in the emergency department until an ICU bed becomes available. In other cases, patients may be admitted to an "alternative specialty ICU" (e.g., a medical patient assigned a surgical ICU bed) for management by either the "local ICU team," who may possess less relevant expertise, or by the "diagnosis-appropriate ICU team" albeit at a distance (**Fig. 1**).

There is evidence to suggest that delaying transition from the emergency department to the ICU is harmful (4, 5). A large multicenter retrospective cohort study also demonstrated that admitting patients to an alternative specialty ICU for management by the local ICU team, who have different expertise, is

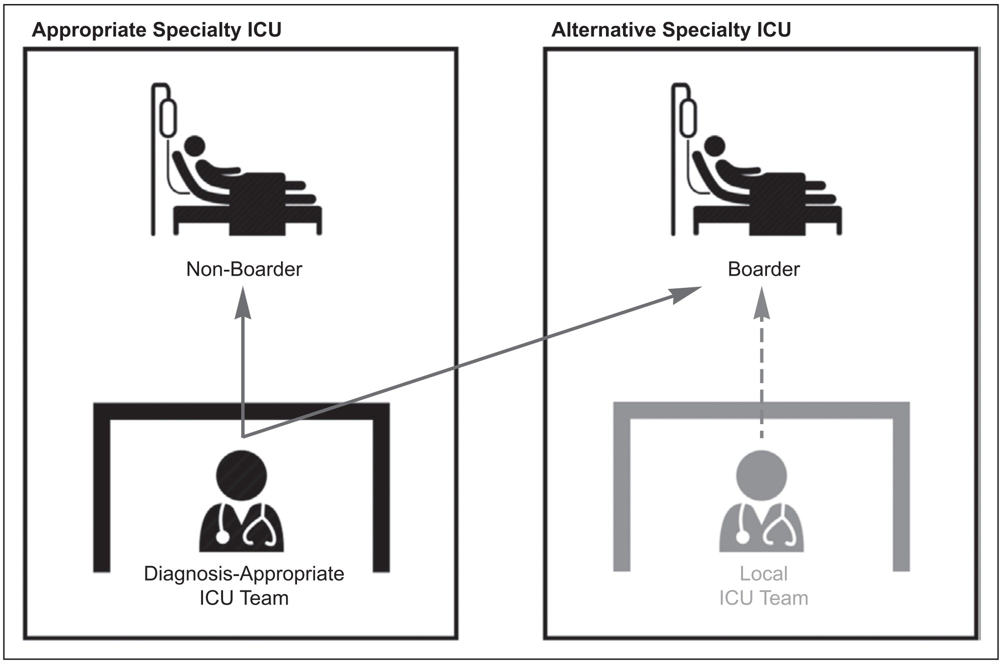

Figure 1. Schematic of different types of boarding. Red arrows illustrate the type analyzed in this study, in which "diagnosis-appropriate ICU teams" care for patients in both the appropriate and alternative specialty ICUs. Gray arrows illustrate a variation in which boarders are cared for by the "local ICU team" instead of the diagnosis-appropriate team.

associated with increased mortality (6). To our knowledge, however, no study has examined the practice of admitting critically ill patients to alternative specialty ICUs for management by the diagnosis-appropriate ICU team. The proposed benefits of specialized ICUs include pooling of patients with similar diagnoses, thereby improving outcomes through reduction of diagnostic variability and concentration of nursing expertise (6). However, the adaptations that specialty ICUs undergo to provide optimal care for their target patient population may affect their capacity to care for "non-target" critically ill patients in the event of bed shortages in other ICUs. In particular, nurses typically specialize in a specific type of ICU care and are trained to identify and respond to a discrete set of clinical problems commonly encountered within their unit (e.g., arrhythmia after cardiac surgery).

Even when cared for by the diagnosis-appropriate ICU team, patients admitted to an alternative specialty ICU are exposed to staff who may have less familiarity managing the clinical conditions for which they require intensive care. This type of boarding also introduces geographic barriers between patients and physicians that may cause delays in the recognition and treatment of changes in their condition. We hypothesized that critically ill patients boarding in alternative specialty ICUs are at higher risk of mortality than nonboarders, even when cared for by diagnosis-appropriate ICU teams.

MATERIALS AND METHODS

Setting

We performed a retrospective, single-center cohort study using the Multi Parameter Intelligent Monitoring in Intensive Care (MIMIC-III) database (7). MIMIC-III is a publicly available dataset comprising of more than 61,000 ICU stays between 2002 and 2012 at Beth Israel Deaconess Medical Center, a tertiary care nonprofit hospital in the United States.

Cohort Selection

We included all subjects aged 18 years old or older cared for by the medical ICU (MICU) team at any point during their hospital stay. To ensure independence of observations, only the most recent ICU admission for each subject was analyzed.

We excluded subjects whose primary team at any point during their admission was nonmedical, as this might imply a reason for boarding in a non-MICU aside from capacity constraints.

Case Definitions

Subjects were defined as "boarders" if cared for by a MICU team but assigned a bed in a non-MICU including surgical, trauma, cardiac, and neurology ICUs. Conversely, "nonboarders" were defined as subjects cared for by a MICU team and assigned beds located within the geographic confines of the MICU.

Measurements and Outcomes

The publicly available MIMIC-III database applies random time-shifts to protect confidentiality. After approval by the institutional review board of Beth Israel Deaconess Medical Center, we obtained real date and bed assignment information for each ICU stay and used this to reconstruct the hospital ICU census.

ICU stay mortality was determined a priori as the primary outcome and in-hospital mortality as a secondary outcome. Longer term outcomes such as 30-day mortality were not available in our dataset. During preliminary data preparation, we identified numerous occasions where death occurred within minutes or hours "after" ICU discharge (**Fig. E1**, Supplemental Digital Content 1, http://links.lww.com/CCM/D100; and **Table E1**, Supplemental Digital Content 1, http://links.lww.com/CCM/D100). This was likely due to a combination of expected deaths (subjects transitioned to comfort-focused care transferred out of the ICU shortly prior to expiring), unexpected deaths, and minor time discrepancies inherent to mixed administrative and clinical data. We therefore not only broadened our definition to include deaths within 24 hours of ICU discharge as occurrences of the primary outcome in our preferred model, but also conducted multiple sensitivity analyses for robustness (**eAppendix**, Supplemental Digital Content 1, http://links.lww.com/CCM/D100).

Approach for Addressing Unmeasured Confounding

The decision to board a patient is nonrandom. If two patients are vying for the last available MICU bed, the decision about which to assign boarder status is likely influenced by unmeasured patient factors such as perceived severity of illness. Naive analyses that are unable to account for these important confounders may yield biased results. Controlling for confounders using standard regression is reasonable when they are both known and measurable; however, many factors that influence boarding decisions are not easily quantifiable.

One approach that can be used to account for nonrandom assignment is an instrumental variable analysis. This involves a two-stage regression in which an instrumental variable—related to the exposure but not the outcome of the study—is used to reduce bias secondary to unobserved baseline characteristics (8). Instrumental variable methods can be an effective means of overcoming unmeasured treatment selection biases present in observational data (9). They can produce effect estimates similar to those of randomized controlled trials and are superior to simple multivariable risk adjustment or propensity score matching when unmeasured selection effects are present (10). Importantly, instruments should be related to the treatment assignment but not to the outcome of interest other than through the assignment variables. We used the "number of open MICU beds" as our instrument to examine the effect of boarding on mortality. MICU occupancy levels provide a source of variation in the likelihood of boarding unrelated to the characteristics of patients themselves or their potential outcomes. As remaining beds decrease, the probability that a newly admitted MICU patient will become a boarder increases (**Fig. E2**, Supplemental Digital Content 1, http://links.lww.com/CCM/D100). Except through this proposed causal pathway, however, the number of remaining beds should not be predictive of mortality and therefore meets the criteria for an instrument. Fitting a binomial generalized additive model, this instrument accounts for 37.9% of variance in boarder status when used as the only regressor.

Since fewer remaining MICU beds also is correlated with a greater number of patients being cared for by the MICU team, we controlled for "census size" to avoid confounding due to patient volume. We also controlled for age, gender, year, and Elixhauser comorbidities (11). Acuity of illness at time of ICU admission was adjusted for using the Oxford Acute Severity of Illness Score (OASIS) (12).

Statistical Analyses

R version 3.2.2 (R Foundation for Statistical Computing, Vienna, Austria) was used for statistical analyses. We employed a semiparametric bivariate probit estimation strategy, consisting of a bivariate generalized additive probit model for boarder status and mortality, linked by a copula. Splines were used to account for nonlinearity of the effect on observed values on the latent probabilities. The Akaike information criterion was used to compare copula fit (**Table E2**, Supplemental Digital Content 1, http://links.lww.com/CCM/D100).

In addition to the preferred semiparametric model, we performed two other statistical analyses as robustness checks: standard logistic regression and propensity score matching. Aside from exclusion of the instrument, these models used the same outcomes and covariates as the semiparametric model. For the propensity score analysis, boarders were one-to-one matched to controls using a nearest neighbor algorithm with replacement. Match balance is reported in **Table E7** (Supplemental Digital Content 1, http://links.lww.com/CCM/D100).

Propensity score approaches minimize selection bias arising from "observable" variables but do not control for "unmeasured" confounders. For the standard logistic regression model, an alternative approach to minimizing selection bias was employed: the sample was restricted to subjects who either boarded when there were no remaining MICU beds or did not board when three or more beds remained available. Under these conditions, there is no opportunity for discretion in whether a patient will become a boarder; however, this decreases the sample size.

RESULTS

The study population included 8,429 subjects of whom 1,871 were boarders. **Table 1** shows patient and ICU operating characteristics at time of admission, stratified by boarding status and instrument value (i.e., high vs low numbers of remaining MICU beds). Patient characteristics were relatively balanced between boarders and nonboarders, as well as among different values of the instrument. The largest difference was the proportion of patients with primary diagnoses of circulatory (17.5% vs 11.0%) or gastrointestinal (13.9% vs 16.7%) disease. These differences largely dissipated after stratification by the instrument.

Average census size was predictably higher for boarders and patients admitted when few beds remained. Unadjusted ICU stay mortality was 2.0% higher among boarders (17.4% vs 15.5%) (**Table 2**) and 2.1% higher among patients admitted when few beds remained (17.3% vs 15.2%) (**Fig. E3**, Supplemental Digital Content 1, http://links.lww.com/CCM/D100). Similarly, unadjusted in-hospital mortality was 1.9% higher among boarders (20.5% vs 18.6%) and 2.2% higher among patients admitted when few beds remained (20.5% vs 18.3%). Mean ICU length of stay was similar between groups. Post-ICU hospital length of stay was 5.2 days for boarders versus 4.5 days for nonboarders, a difference that persisted when stratifying by number of remaining MICU beds.

Using the instrumental variable semiparametric model, the risk ratio (RR) for ICU stay mortality among boarders was 1.18 with 95% CI of 1.01–1.38 (**Table 3**). This corresponded to a local average treatment effect—mean change in absolute mortality for those patients induced to board due to instrument value—of 1.76% (95% CI, 0.02–3.53%). The estimate was robust to the definition of ICU stay mortality (**Table E4**, Supplemental Digital Content 1, http://links.lww.com/CCM/D100). Boarding also increased the risk of in-hospital mortality (RR, 1.22; 95% CI, 1.00–1.49). Plots of the regularized splines of the fitted semiparametric model are shown in **Figure E4** (Supplemental Digital Content 1, http://links.lww.com/CCM/D100). OASIS and Elixhauser scores

TABLE 1. Baseline Patient and ICU Operating Characteristics Stratified by Boarding Status and Number of Remaining Medical ICU Beds

Characteristics	Treatment (Full Sample)		Treatment (Restricted Sample)		Instrument (Full Sample)	
	Nonboarder ($n = 6,558$)	Boarder ($n = 1,871$)	Nonboarder ($n = 3,319$)	Boarder ($n = 902$)	Beds ≥ 2 ($n = 5,510$)	Beds ≤ 1 ($n = 2,919$)
Patient characteristics						
Age, mean (SD)	62.2 (17.4)	62.6 (17.2)	61.8 (17.2)	62.7 (17.5)	62.3 (17.3)	62.4 (17.4)
Male, *n* (%)	3,525 (53.8)	1,016 (54.3)	1,787 (53.8)	484 (53.7)	2,966 (53.8)	1,575 (54.0)
Race, *n* (%)						
White	4,536 (69.2)	1,324 (70.8)	2,250 (67.8)	637 (70.6)	3786 (68.7)	2,074 (71.1)
Black	894 (13.6)	236 (12.6)	478 (14.4)	120 (13.3)	736 (13.4)	394 (13.5)
Other	1,128 (17.2)	311 (16.6)	591 (17.8)	145 (16.1)	988 (17.9)	451 (15.5)
OASIS score, mean (SD)	32.8 (9.6)	32.6 (9.7)	32.6 (9.6)	32.8 (9.6)	32.8 (9.6)	32.8 (9.5)
Simplified Acute Physiology Score, mean (SD)	18.1 (5.7)	18.3 (5.8)	18.0 (5.7)	18.2 (5.8)	18.2 (5.7)	18.3 (5.7)
Sequential Organ Failure Assessment score, mean (SD)	4.7 (3.6)	4.5 (3.4)	4.6 (3.6)	4.5 (3.4)	4.7 (3.6)	4.6 (3.5)
Elixhauser score, mean (SD)	6.8 (7.2)	6.7 (7.2)	6.5 (7.2)	6.5 (7.3)	6.7 (7.2)	7.0 (7.2)
Healthcare Cost and Utilization Project Clinical Classification Software (17) level 1 diagnosis, *n* (%)						
Diseases of the respiratory system	1,246 (19.0)	334 (17.9)	605 (18.2)	176 (19.5)	1000 (18.1)	580 (19.9)
Infectious and parasitic diseases	1,151 (17.6)	300 (16.0)	601 (18.1)	156 (17.3)	945 (17.2)	506 (17.3)
Diseases of the digestive system	1,098 (16.7)	260 (13.9)	552 (16.6)	132 (14.6)	911 (16.5)	447 (15.3)
Injury and poisoning	819 (12.5)	231 (12.3)	434 (13.1)	110 (12.2)	700 (12.7)	350 (12.0)
Diseases of the circulatory system	721 (11.0)	328 (17.5)	330 (9.9)	124 (13.7)	657 (11.9)	392 (13.4)
Endocrine, nutritional, and metabolic diseases and immunity disorders	350 (5.3)	106 (5.7)	188 (5.7)	51 (5.7)	311 (5.6)	145 (5.0)
Mental illness	336 (5.1)	82 (4.4)	172 (5.2)	49 (5.4)	265 (4.8)	153 (5.2)
Diseases of the genitourinary system	266 (4.1)	79 (4.2)	127 (3.8)	38 (4.2)	223 (4.0)	122 (4.2)
Other[a]	220 (3.4)	58 (3.1)	121 (3.6)	24 (2.7)	192 (3.5)	87 (3.0)
Neoplasms	218 (3.3)	65 (3.5)	112 (3.4)	27 (3.0)	191 (3.5)	91 (3.1)
Diseases of the nervous system and sense organs	133 (2.0)	28 (1.5)	77 (2.3)	15 (1.7)	115 (2.1)	46 (1.6)
Mechanical ventilation in first 24 hr, *n* (%)	2,387 (36.4)	671 (35.9)	1,217 (36.7)	338 (37.5)	2,006 (36.4)	1,052 (36.0)
ICU operating characteristics						
Census, mean (SD)	11.6 (3.3)	13.9 (3.6)	10.4 (2.9)	15.1 (3.4)	11.2 (3.2)	13.9 (3.4)
Census OASIS score, mean (SD)	32.6 (4.3)	32.5 (3.7)	32.3 (4.8)	32.6 (3.3)	32.4 (4.5)	32.8 (3.5)
Census Elixhauser score, mean (SD)	8.4 (3.2)	8.4 (2.6)	8.5 (3.4)	8.5 (2.4)	8.5 (3.2)	8.3 (2.7)
Weekday admission, *n* (%)	4,752 (72.5)	1,335 (71.4)	2,362 (71.2)	633 (70.2)	3,968 (72.0)	2,119 (72.6)

OASIS = Oxford Acute Severity of Illness Score.

[a]Diagnostic categories constituting < 1% of the sample were combined (**Table E3,** Supplemental Digital Content 1, http://links.lww.com/CCM/D100).

TABLE 2. Outcomes Stratified by Boarding Status and Number of Remaining Medical ICU Beds

Characteristics	Treatment (Full Sample)		Treatment (Restricted Sample)		Instrument (Full Sample)	
	Nonboarder (*n* = 6,558)	Boarder (*n* = 1,871)	Nonboarder (*n* = 3,319)	Boarder (*n* = 902)	Beds ≥ 2 (*n* = 5,510)	Beds ≤ 1 (*n* = 2,919)
ICU mortality, *n* (%)						
Strictly during ICU stay	937 (14.3)	296 (15.8)	438 (13.2)	142 (15.7)	771 (14.0)	462 (15.8)
Including ≤ 24 hr after ICU stay	1,014 (15.5)	326 (17.4)	470 (14.2)	160 (17.7)	836 (15.2)	504 (17.3)
Including ≤ 48 hr after ICU stay	1,050 (16.0)	335 (17.9)	483 (14.6)	165 (18.3)	863 (15.7)	522 (17.9)
ICU length of stay, d, mean (SD)	3.7 (5.0)	3.9 (6.3)	3.8 (5.1)	3.9 (5.9)	3.7 (5.3)	3.8 (5.4)
Post-ICU hospital length of stay, d, mean (SD)	4.5 (6.6)	5.2 (7.6)	4.3 (5.9)	5.5 (8.0)	4.5 (6.3)	5.1 (7.8)
Total hospital length of stay, d, mean (SD)	8.3 (8.4)	9.2 (9.9)	8.0 (7.9)	9.4 (10.0)	8.2 (8.2)	8.9 (9.6)
ICU-free days, mean (SD)[a]	19.3 (10.9)	18.7 (11.2)	19.5 (10.8)	18.8 (11.2)	19.3 (10.9)	18.8 (11.2)
Hospital mortality, *n* (%)	1,223 (18.6)	384 (20.5)	578 (17.4)	192 (21.3)	1,008 (18.3)	599 (20.5)

[a]Defined as days alive and free from the need for intensive care, from time of ICU admission to day 28.

TABLE 3. Results of the Instrumental, Logistic Regression and Propensity Score Models

Modeling approach	ICU Stay Mortality		In-Hospital Mortality	
	Estimate[a]	95% CI	Estimate[a]	95% CI
Instrumental variable analysis[b]	1.18	1.01–1.38	1.22	1.00–1.49
Logistic regression (using restricted sample)[c]	1.40	1.05–1.86	1.33	1.02–1.72
Propensity score matching[d]	1.14	0.99–1.29	1.13	0.98–1.28

[a]Instrumental variable analysis produces risk ratios; all other methods produce odds ratios.

[b]Estimated coefficients for age, Oxford Acute Severity of Illness Score, Elixhauser score, and team census are shown in Figure E4 (Supplemental Digital Content 1, http://links.lww.com/CCM/D100); those for parametric coefficients are shown in **Table E5** (Supplemental Digital Content 1, http://links.lww.com/CCM/D100).

[c]Estimated coefficients shown in **Table E6** (Supplemental Digital Content 1, http://links.lww.com/CCM/D100).

[d]This approach does not control for unmeasured confounders. Results of covariate balancing shown in Table E7.

were highly correlated with ICU stay mortality. We found no evidence, however, that census size within the observed range affected this outcome ($p = 0.16$) (Fig. E4, Supplemental Digital Content 1, http://links.lww.com/CCM/D100).

The noninstrumental logistic regression model, using a restricted sample to minimize selection bias due to measured and unmeasured confounders, produced concordant results: boarding increased ICU (odds ratio [OR], 1.40; 95% CI, 1.05–1.86) and in-hospital (OR, 1.33; 95% CI, 1.02–1.72) mortality. Propensity score models—which only adjusted for selection bias due to “measured” confounders—approached, but did not reach, statistical significance and yielded lower point estimates for the effect of boarding on ICU (OR, 1.14; 95% CI, 0.99–1.29) and in-hospital (OR, 1.13; 95% CI, 0.98–1.28) mortality.

DISCUSSION

In this large study of ICU boarding, we find that admission to alternative specialty ICUs for management by diagnosis-appropriate teams increases ICU and in-hospital mortality. These findings underscore the importance of bed allocation strategies in ensuring optimal care of critically ill patients.

There are two likely contributors to these findings. First, specialty ICUs are staffed by nurses and other personnel with training specific to their unit’s target population. Thus, staff in alternative specialty ICUs in this study may have been less experienced in the recognition and treatment of problems commonly encountered in the care of MICU patients. Second, time delays and other differences in care stemming from the geographic distance between boarders and their treating physicians likely play a role. The frequency with which physicians are able to assess boarders tends to be lower, decreasing the likelihood that changes in clinical status will be detected early with subsequent initiation of appropriate interventions.

Several different statistical methods were used to safeguard the validity of our analysis against the possibility that boarders were systematically sicker than nonboarders due to selection bias. We used a dataset with detailed prospectively collected data that allowed us to control for disease severity. We then designated an instrumental variable approach—a technique commonly used to control for unmeasured confounding—as our a priori methodology to ensure that there were no unobserved patient characteristics simultaneously influencing boarding decisions and mortality risk. Logistic regression was applied to a restricted sample wherein selective pressures were unlikely to be present. Finally, we used propensity score matching wherein study cohorts were balanced on "measured" confounders alone. Results were consistent for all approaches, although propensity score matching did not quite reach statistical significance. Of note, instrumental variable analyses models estimate the effect on "marginal" patients (i.e., meaning a patient who is a boarder due to a lack of remaining MICU beds who would not have been a boarder if the supply of beds had not been limited), whereas logistic regression and propensity score matching produce "population average" estimates (i.e., all boarders, irrespective of the reason for boarding). In this study, we would expect the "marginal" and "average" treatment estimates to be very similar because there is no logical reason for a patient to board aside from capacity constraints.

Lott et al (6) demonstrated higher mortality among patients admitted to alternative specialty ICUs, with RRs of 1.22–1.41 for acute coronary syndromes, ischemic stroke, and intracranial hemorrhage, although they did not identify the physician teams caring for these patients. Similarly, Kuntz et al (13) identified increased hospital mortality and length of stay among ward patients not geographically colocalized with their care team. Our study adds to existing knowledge by demonstrating that the deleterious effects of boarding extend to even those patients cared for specifically by diagnosis-appropriate ICU teams.

We found no association between ICU stay mortality and census size within the observed range. This is in contrast to a prior study that demonstrated increasing ICU mortality rates with excess ICU workload, with up to a two-fold increase in mortality during periods of high workload as defined by average nursing requirement per occupied bed and peak ICU occupancy (14). The authors of that study acknowledge two important limitations that may explain this discrepancy. First, during periods of higher ICU occupancy, nurses without appropriate specialist training cared for the additional patients. Second, some patients were assigned beds not geographically colocalized with their ICU team. It is therefore possible that the increased mortality observed with higher censuses in that study was misattributed to ICU workload when in fact due to boarding.

Our study has several limitations. It is not possible to entirely exclude the possibility of an alternative causal pathway through which the number of open ICU beds could influence mortality. One review of instrumental variable analyses in the medical literature revealed that many published studies lacked adjustment for instrument-outcome confounders (15). In our study, the balanced baseline patient characteristics after stratification by instrument provide some evidence against instrument-outcome confounding; however, it is impossible to conclusively prove the validity of the exclusion restriction. This study was also not designed to address a related form of boarding in which the treating ICU team's specialty does not match the patient's primary medical problem. Additionally, generalizability is limited by the study's single-center design. Finally, although census size at time of admission has been proposed as a reasonable measure of "ICU strain" (16)—owing to the importance of rapid initial treatment in many critical illnesses—it is possible that alternative specifications of strain could yield different results. However, constructs of workload that rely on data generated after pseudorandomization are endogenous to the outcome and should be avoided.

There are several important implications of our study. First, our findings support existing literature suggesting that the organization and delivery of critical care have a significant impact on patient outcomes. Second, hospitals that employ boarding as an institutional practice should consider investigating alternative strategies to manage and minimize their ICU overflow (e.g., reducing rates of improper ICU admissions). Finally, clinicians should be mindful that boarding independently increases a patient's risk of mortality and consider clinical practice modifications to improve their situational awareness of changes in the care of these patients.

Despite growing emphasis on the use of "big data" to usher forth the era of precision medicine, we should not overlook the potential for this same information to improve outcomes through the lens of operations management. Datasets that combine clinical and operational data can help inform and improve healthcare delivery.

CONCLUSIONS

Boarding of critically ill patients may lead to increased ICU and in-hospital mortality. We hypothesize that the excess risk relates to both geographic barriers between physicians and patients, as well as differences in training and specialization of nurses between specialty ICUs.

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