Title
The Boarding Patient: Effects of ICU and Hospital Occupancy Surges on Patient Flow

Journal
Production and Operations Management, 27(12)

ISSN
1059-1478

Authors
Long, Elisa F
Mathews, Kusum S

Publication Date
2018-12-01

DOI
10.1111/poms.12808

Peer reviewed

Published in final edited form as:
Prod Oper Manag. 2018 December ; 27(12): 2122–2143. doi:10.1111/poms.12808.

The Boarding Patient: Effects of ICU and Hospital Occupancy Surges on Patient Flow

Elisa F. Long,
UCLA Anderson School of Management, 110 Westwood Plaza, Suite B508, Los Angeles, California 90095, USA, elisa.long@anderson.ucla.edu

Kusum S. Mathews
Icahn School of Medicine at Mount Sinai, Division of Pulmonary, Critical Care, and Sleep Medicine, Department of Medicine, Annenberg Building Floor 5, 1468 Madison Avenue, New York City, New York 10029, USA, kusum.mathews@mssm.edu

Abstract

Patients admitted to a hospital's intensive care unit (ICU) often endure prolonged boarding within the ICU following receipt of care, unnecessarily occupying a critical care bed, and thereby delaying admission for other incoming patients due to bed shortage. Using patient-level data over two years at two major academic medical centers, we estimate the impact of ICU and ward occupancy levels on ICU length of stay (LOS), and test whether simultaneous "surge occupancy" in both areas impacts overall ICU length of stay. In contrast to prior studies that only measure total LOS, we split LOS into two individual periods based on physician requests for bed transfers. We find that "service time" (when critically ill patients are stabilized and treated) is unaffected by occupancy levels. However, the less essential "boarding time" (when patients wait to exit the ICU) is accelerated during periods of high ICU occupancy and, conversely, prolonged when hospital ward occupancy levels are high. When the ICU and wards simultaneously encounter bed occupancies in the top quartile of historical levels—which occurs 5% of the time—ICU boarding increases by 22% compared to when both areas experience their lowest utilization, suggesting that ward bed availability dominates efforts to accelerate ICU discharges to free up ICU beds. We find no adverse effects of high occupancy levels on ICU bouncebacks, in-hospital deaths, or 30-day hospital readmissions, which supports our finding that the largely discretionary boarding period fluctuates with changing bed occupancy levels.

Keywords

intensive care unit; hospital operations; health care management; empirical analysis

1. Introduction

Of the 36 million hospital admissions occurring each year in the United States, more than one-quarter involve a stay in an intensive care unit (ICU) (Barrett et al. 2014, Weiss and Elixhauser 2014). As the population aged 65 and older increases by more than 50% between 2015 and 2030 (U.S. Department of Health and Human Services 2015), demand for ICU care by the elderly and those with complex medical conditions will continue to rise. A significant component of hospital expenditures, ICU-related costs exceed $130 billion per year—or 4% of all US health care costs—with a disproportionate amount spent on patients staying longer than 2 weeks (Halpern 2009, U.S. Centers for Medicare and Medicaid Services, 2015). Despite a 15% increase in ICU bed capacity from 2000 to 2009, substantial variability exists in the number of ICU beds across hospitals, leading to recurrent admission delays from lack of bed availability in areas with high ICU utilization and insufficient beds (Lucas et al. 2009, Wallace et al. 2015). Although average ICU occupancy was only 68% in 2005, some hospitals, especially academic medical centers, regularly face occupancy levels exceeding 90% (Wunsch et al. 2013), often requiring the rationing of scarce critical care beds. Such capacity-constrained systems could benefit from even modest improvements in patient throughput, particularly by reducing unnecessary time spent in the ICU.

High occupancy rates engender chronic bed shortages, which are further exacerbated by unpredictable patient arrivals from the emergency department (ED), variable ICU length of stay (LOS), critical care-level staffing shortages, and insufficient coordination with other inpatient units. Although LOS mostly consists of "service time," when critically ill patients are stabilized and treated, many patients experience a subsequent delay in transfer to the Medicine wards, which we newly define as ICU "boarding time." Boarding is a well-described phenomenon within the emergency department (Chalfin et al. 2007), when patients often stay for several additional hours while awaiting hospital admission due to a lack of available inpatient beds. However, drivers of excessive boarding within the ICU have not been carefully examined.

Boarding patients no longer require critical care-level services but continue to occupy scarce ICU beds. Because ICU boarding time is not clinically necessary, its duration is largely discretionary: an attending critical care physician requests a patient's transfer to a bed outside the ICU, but the patient continues to board for an unspecified period of time. Consequently, many hospitals do not even record ICU boarding times, hindering efforts to identify possible causes of such inefficiencies. We postulate that a shorter ICU LOS during periods of peak ICU utilization, as previously observed (Chan et al. 2012, KC and Terwiesch 2009, 2012), may be partially explained by a shorter boarding time as hospital staff accelerate patient transfers from the ICU to the wards. Conversely, delayed transfers out of the ICU may also stem from understaffed or bed-constrained wards, or prioritization of ward beds to non-ICU patients (Johnson et al. 2013, Levin et al. 2003). How the opposing effects of such bed shortages materialize when the ICU and wards face simultaneously high occupancy levels has not been previously investigated.

Intensive care unit congestion creates bottlenecks for other hospital units, especially the ED and post-surgery care area, leading to overcrowding, delays in care, and negative financial consequences due to revenue loss from ambulance diversion and patients leaving without being seen (McConnell et al. 2005, Pines et al. 2011). In most hospitals, resources within the ED and wards are not as advanced as in the ICU, leading to suboptimal care of critically ill patients awaiting ICU admission (Renaud et al. 2009). ICU patients already face the highest mortality rate in the hospital (10–38% nationwide) and admission delays have been linked to higher in-hospital mortality of critically ill patients (Chalfin et al. 2007). Identifying opportunities to increase system efficiency can help decrease congestion, reduce admission delays, and improve the quality and quantity of care delivered.

Our study is motivated by our clinical observations at two independent hospitals that following receipt of care, ICU patients often face excessively long wait times for transfer to the wards. Regularly caring for high numbers of ward-ready patients is clinically frustrating, uses limited ICU resources inefficiently, and exacerbates admission delays for incoming patients. We aim to provide insights into drivers of such inefficiencies and identify opportunities for improvement. We highlight key operational targets for improved efficiency (e.g., targeted boarding times, bed prioritization during occupancy surges) to help alleviate admission delays, decrease wasted ICU resources, and improve a hospital's ability to accommodate more ICU admissions, improving patient care while simultaneously increasing revenue (Kim et al. 2016). Our study offers three contributions:

- We extend prior studies that examine ICU length of stay and occupancy levels. We separate LOS into a service time and non-essential boarding time, when patients await transfer to the wards. Our study is the first empirical analysis of ICU boarding times, and our results suggest that the shorter LOS observed during high occupancy is explained by an abbreviated boarding period. Hospital managers should measure this time interval and other discretionary periods during a patient's hospital stay, and use them as performance metrics to help identify opportunities to streamline ICU-ward transitions and increase patient throughput.
- In addition to estimating a "speed up" effect when ICU occupancy is high, we find a simultaneous "slow down" effect during high ward occupancy, with patients enduring up to 67% longer boarding times when wards are full. Ward bed availability appears to dominate, with a net 22% longer boarding time observed when the ICU and wards are concurrently in the highest quartile of occupancy vs. lowest quartile, based on past patient census data. Even when wards are partially full (75–85% beds occupied), ICU boarding is significantly longer, suggesting that hospital staff may be too conservative with delaying ICU-ward transfers, creating upstream bottlenecks in the ICU and eventually the emergency department.
- Additional strengths of our findings are rooted in the granularity of the datasets, which include detailed administrative timestamps and hourly census reports at two large academic medical centers. Unlike prior studies (KC and Terwiesch 2009, 2012), our research focuses on the Medicine ICU, using data from two institutions with similar staffing models and admission policies. Compared to other ICUs (e.g., Surgery, Cardiothoracic), the Medicine ICU typically cares for emergent, nonelective admissions with a wider range of diagnoses and comorbidities, allowing our results to generalize to a wider range of patient populations.

2. Related Literature

Identifying how patient care is impacted by concomitant workload, including bed utilization levels, is needed as hospitals increasingly face bed and staffing shortages, adding to existing pressure to rapidly turnover beds (Halpern 2011). The effects of bed capacity strain on decisions pertaining to ICU *admission*, critical care *treatment*, and *discharge* have been examined in related studies.

2.1. Admission Practices

Many ICU patients first seek medical care in the ED, a hospital area that similarly faces resource constraints, variable patient severity, and downstream bottlenecks affecting bed availability. As ICU patients often require immediate care, a priority triage policy is a widespread practice in most hospitals. In one empirical study, Kim et al. (2014) find that the likelihood of ICU admission drops significantly when the ICU is crowded, even among high-severity patients. The study cohort is ED patients, and may therefore overestimate congestion costs as patients can receive some critical care services within the ED itself. In particular, non-ED ward patients who clinically deteriorate and require ICU care have worse prognoses, on average, than patients admitted from the ED to the ICU (Liu et al. 2012, Town et al. 2014). Our study's patient cohort includes both locations of origin (ED and wards) prior to ICU admission, an important distinction as hospital resources and staffing differ by location.

Although current state legislation requires fixed nurse-to-patient ratios, a dynamic nurse staffing policy could improve patient care and minimize the probability of excessive delays for patients (De Vericourt and Jennings 2011). Dobson et al. (2010) develop a preemptive priority queuing model to examine scheduled and unscheduled admissions of surgery patients who subsequently require ICU care. Reducing wait times before ICU admission not only improves operational performance and throughput, it also benefits patients directly. One observational study finds that timely ICU admission reduces 28-day mortality by 30% (Edbrooke et al. 2011). Other studies demonstrate that delaying ICU admission can prolong ICU length of stay (Chalfin et al. 2007) and increase the risk of death (Cardoso et al. 2011). Thus a vicious cycle is born: chronic bed shortages contribute to admission delays and longer wait times, which can increase LOS, further exacerbating bed shortages.

2.2. Treatment Decisions

Recent empirical studies suggest that patients receive differential care during busy periods. Kuntz et al. (2015) estimate an occupancy "tipping point" of 92.5% in German hospitals, whereby in-hospital patient mortality significantly increases above this value, perhaps due to increased cognitive load or exhaustion among providers. KC and Terwiesch (2009) examine the impact of hospital "load" (bed utilization) and "overwork" (a measure of high average load prior to admission) on LOS for Cardiothoracic Surgery patients, and find that high contemporaneous load results in a shorter stay. In a related study, KC and Terwiesch (2012) find that when bed occupancy is high, Cardiothoracic ICU patients are discharged early to a lower acuity unit, improving bed availability but increasing the risk of ICU "bounceback." Chan et al. (2014) show that decreasing ICU LOS in times of congestion improves bed availability but at the cost of higher readmissions, ultimately increasing physician and nurse workload. In these studies, only total ICU length of stay is measured (in an integer number of days), which presumes that active care occurs throughout this period. In our setting, like in many hospitals (Peltonen et al. 2015), patients board in the ICU before transferring to the wards. We therefore separate LOS into service and boarding periods to examine which, if any, segment of patient care is accelerated in times of congestion.

While ICU service time should, theoretically, reflect each patient's clinical needs, boarding time is largely discretionary. In systems with discretionary tasks, changes in capacity can paradoxically increase congestion (Hopp et al. 2007). These authors note that queue pooling with discretionary service times can negatively impact system performance, an observation corroborated with real-world data from the ED. Dedicated staffing of ED physicians to separate patient queues can reduce LOS, as physicians directly observe their current workload (Song et al. 2015). In the ICU, however, LOS typically spans several days or weeks—as compared to hours in the ED—precluding a single physician from caring for an ICU patient for the entire duration of a multi-day stay.

The relationship between hospital workload (i.e., number of patients seeking medical care) and providers' decisions to perform discretionary tasks is examined by Freeman et al. (2017) in a UK maternity unit. The authors find that during periods of high workload, patients not requiring complex care are less likely to receive an epidural and subsequently experience a shorter LOS. In a related study, Ibanez et al. (2017) find that experienced radiologists use more discretion when deciding what sequence to complete a set of tasks. The authors note that batching tasks based on similar criteria may improve throughput, perhaps due to reduced cognitive load of the physicians. In our ICU setting, we examine how a shorter LOS attributed to high workload (i.e., bed occupancy level), as observed in other studies, could be explained by a speed-up of the discretionary boarding time. Although we do not examine physician- or nurse-specific effects of accelerating ICU boarding due to data limitations, our consistent finding of accelerated boarding during periods of congestion warrant further investigation into human drivers of such behavior.

2.3. Discharge Policies

Similar to admission or staffing practices, studies have examined varying discharge policies in times of capacity strain. Shi et al. (2015) develop a stochastic queuing model of hospital inpatients with dynamic discharge policies, which reduce admission delays and ED wait times in times of peak utilization. A priority ICU discharge policy based on readmission and mortality probabilities is also considered by Chan et al. (2012), although the model does not include boarding ICU patients.

To the best of our knowledge, no prior studies have empirically examined simultaneous occupancies in a focal ICU and downstream wards, and the interaction between them. Measuring concurrent workload is fundamental to understanding the network of servers constituting patient flow through a hospital. When allocating scarce inpatient beds, bed management teams must weigh competing interests: elective admissions from clinics and outside hospitals vs. unpredictable demand from the ED, ICUs, and internal wards (Bekker and Koeleman 2011, Jweinat et al. 2013). Despite partial automation of this process, many institutions' bed management decisions remain decentralized, with wards often self-regulating patient inflow (admissions/transfers) based on expected outflow (discharges) (Schmidt et al. 2013).

3. Setting and Hypotheses

3.1. Patient Flow Process

In a typical US hospital setting, patients admitted to the ICU arrive from the ED or inpatient bed, including the Medicine wards (Figure 1). In our dataset, about half of all Medicine ICU patients are admitted directly from the ED. Once an available ICU bed is assigned, "service time" commences during which patients are resuscitated, stabilized, and receive active management of their critical illness. Service terminates if a patient dies, or survives and is deemed clinically ready for a lower level of care and staff request transfer from the ICU to the wards, known as a "booking." Per hospital policy, physicians do not preemptively request ward transfer before the patient is clinically ready. While waiting for transfer, patients experience ICU "boarding" when they physically remain in the ICU bed but no longer receive high-intensity services. In our setting, patients experience an average service time and boarding time of 3.3 days and 15.1 hours, respectively, both with high variability. If a patient clinically deteriorates and requires reinitiation of critical care-level interventions, service time commences again until the physician requests a new booking time in the future; we only consider these final booking times in our analysis.

Patients exit the ICU upon physical transfer to the wards, where they complete their stay until hospital discharge, death, or ICU "bounceback," if they require critical care services again prior to discharge. In our data, 7% of patients bounceback to the ICU and are considered new ICU arrivals. Due to their advanced health, ICU patients are more susceptible to dying in the hospital. In our setting, 22% of patients die during the current hospital stay, of which more than half die within the ICU; these latter patients are excluded from our analysis as their ICU length of stay is truncated at time of death. Of those who survive and are discharged, 26% are readmitted to the hospital within 30 days, some of whom may require an ICU stay, which we also consider a new arrival.

3.2. Data Summary

Our dataset includes patient-level timestamps for all Medicine ICU (MICU) patients admitted to two hospitals over approximately a 2-year period ($n = 2557$). Our study settings are informed by firsthand clinical experience within the ICUs at both hospitals. Data elements were electronically queried from the hospitals' bed management systems and electronic health records and manually validated using internal ICU and departmental logs. Key variables and patient characteristics are summarized in Table 1.

Hospital A is a tertiary and regional academic medical center in the Northeastern United States, which provides critical care services for patients within a 51-bed Medicine ICU, along with five other ICUs (Surgery, Neurosurgery, Cardiothoracic Surgery, Pediatrics, and Neonatal Medicine), which we exclude in our analysis. Hospital B is a large tertiary academic medical center in an urban Northeastern US city with a 14-bed Medicine ICU and five other adult ICUs (Surgery, Neurosurgery, Cardiac, Cardiac Surgery, Cardiothoracic Surgery), which we also exclude. The Medicine wards consist of 436 beds at Hospital A and 624 beds at Hospital B. For simplicity, we refer to the Medicine ICU simply as the ICU in our setting.

In contrast to KC and Terwiesch (2009, 2012) who examine the Cardiothoracic ICU setting, we focus on Medicine ICU patients, including all unplanned and emergent admissions, who exhibit a broader range of diagnoses, disease acuity, and complex comorbidities, leading to a highly variable LOS for this cohort. ICUs in other disciplines often include a large percentage of elective admissions, with routine ICU utilization for post-operative or post-procedural monitoring. Admission, discharge, and bounceback decisions within these other ICUs, such as a Cardiothoracic ICU, are typically made by the attending surgeon or outside cardiologist. In contrast, throughout a Medicine ICU stay, the attending ICU physician is the primary decision-maker. In both hospitals included in our dataset, the Medicine ICU is staffed by attending physicians with additional care provided by trainees or mid-level providers (e.g., clinical fellows, senior resident physicians), with a fixed patient-to-nurse ratio of 2:1, in line with hospital policy.

Our patient-level dataset includes patients admitted at Hospital A from 2010 to 2011 and at Hospital B from 2012 to 2014. We observe dates and exact times for ICU bed assignment, booking, and transfer to the wards (Figure 1). Patients who died within the ICU itself are excluded from the regression models, as they did not have a booking or transfer time to the wards. Average ICU service time is shorter at Hospital A than Hospital B (2.6 days vs. 4.1 days, $p < 0.0001$), in part because lower acuity patients, who typically have shorter service times, are instead admitted directly to the wards at Hospital B. In-hospital mortality is also lower at Hospital A than Hospital B (14% vs. 33%, $p < 0.0001$), reflecting the higher acuity patient composition at Hospital B.

We include additional patient covariates, including origin prior to ICU admission (ED or other unit), patient age, health insurance status (Medicare, Medicaid, or other), and primary diagnosis-related group (DRG) code, using major diagnostic categories (Appendix Table A1). Also available for Hospital B is a severity-of-illness score for each patient, based on a validated, widely used metric called the University HealthSystem Consortium (now Vizient) risk-adjusted mortality model. The severity score ranges from 0 to 1, corresponding to a patient’s probability of dying during the hospitalization, calculated using the primary diagnosis and comorbidities (e.g., respiratory failure, sepsis diagnosis, hypotension) present at admission.

For both hospitals, we observe hourly census counts of patients in Medicine ICU and ward beds, which we convert to bed utilization percentages, normalized based on historic levels at each hospital (Figure 2). Average bed utilization is 91% in the ICU and 82–89% in the Medicine wards. For each patient, ICU and ward “occupancy” refers to the proportion of beds within the Medicine ICU and wards, respectively, occupied at the time that a patient completes service before transfer out of the ICU. Table 2 presents correlations between key variables, which help motivate our hypotheses.

3.3. Hypotheses Formulation

Intensive care unit length of stay depends on clinical factors such as patient age, illness severity, diagnostic category, and the presence of multiple chronic conditions. Additional system-level factors, such as ICU crowding, may also impact LOS as prior studies have demonstrated (Chan et al. 2012, KC and Terwiesch 2009, 2012). Similar to these studies and other large cross-sectional studies (Wagner et al. 2013), we hypothesize that as occupancy in the Medicine ICU increases, overall LOS decreases. When the ICU is crowded, physician and nursing staff may try to free up beds for incoming patients by accelerating patient transfers, resulting in a reduced LOS for existing ICU patients.

As the Medicine wards directly receive patients transferred out of the ICU, we conjecture that increased ward occupancy creates downstream bottlenecks, thereby increasing ICU length of stay (Johnson et al. 2013). Our clinical observations at both hospitals suggest that as the Medicine wards become full, hospital staff tend to delay patient transfers from the ICU and instead prioritize beds for incoming patients from the ED, clinic, or other hospitals, often leading to a longer LOS for ICU patients. Despite ICU stays being more costly and higher sources of revenue for the hospital, there are external pressures affecting patient throughput management. For instance, expediting ward admission for waiting ED patients has been associated with improved patient satisfaction (Bartlett and Fatovich 2009, Ng et al. 2010).

We empirically test these two relationships—and the simultaneous effect of high occupancy in both areas—using more robust specifications and hourly census measures, an improvement over prior models, using only midnight census counts, considering the frequent changes in patient occupancy throughout the day (e.g., in a typical day, eight patients are newly admitted to the Medicine ICU at Hospital A).

We define $TotalLOS_i$ as the total ICU length of stay for patient i, and $OccupancyICU_i$ and $OccupancyWard_i$ as the fraction of occupied beds within the ICU or Medicine wards, respectively, at the time patient i completes ICU service. Our first hypothesis to test is:

Hypothesis 1. *Higher ICU occupancy is correlated with shorter ICU lengths of stay; higher ward occupancy is correlated with longer ICU lengths of stay.*

$$\frac{\partial TotalLOS_i}{\partial OccupancyICU_i} < 0, \quad \frac{\partial TotalLOS_i}{\partial OccupancyWard_i} > 0$$

Some recent studies posit that total LOS, especially when measured in an integer number of days, is an overly crude metric to use when examining the subtle effects of capacity strain on patient outcomes (Howell 2011, Mathews and Long 2015). We seek to build upon previous clinical observations by separating ICU length of stay ($TotalLOS_i$) into the elements commonly considered by hospital management: a clinical portion, denoted in our study as service time ($Service_i$), and a discretionary portion defined as boarding time ($Boarding_i$). At both hospitals under consideration, service time commences upon physical ICU bed assignment and continues until a bed transfer request is made by the attending ICU physician. At this point, boarding time immediately begins and then ends once the patient is physically transferred out of the unit. For each patient *i*:

$$TotalLOS_i = Service_i + Boarding_i \tag{1}$$

Our empirical framework specifically tests for early termination of service time during periods of capacity strain. It is possible that clinicians may prioritize patients for early discharge during periods of bed capacity strain, may ration existing beds in anticipation of new patient arrivals, and/or may down-triage existing ICU occupants as a means to combat cognitive overload caused by an excessive number of high-acuity patients. Any of these behaviors could lead to reduced ICU service time when ICU occupancy levels peak. We therefore examine whether ICU service time varies with crowdedness in both the ICU and wards (Hypothesis 2a), which would support the notion that patients receive different quality of care when bed capacity is strained.

HYPOTHESIS 2A. *Higher ICU occupancy results in a shorter service time, and higher ward occupancy results in a longer service time.*

$$\frac{\partial Service_i}{\partial OccupancyICU_i} < 0, \quad \frac{\partial Service_i}{\partial OccupancyWard_i} > 0 \tag{2}$$

One alternative explanation—consistent with our clinical experience—is that the boarding portion of LOS is accelerated as the ICU becomes congested. When available ICU beds are scarce, staff may transfer patients out of the ICU more quickly and, conversely, higher ward occupancy may delay transfers, leading to longer ICU boarding times. While ICU service completion is determined by the attending ICU physician, boarding time is more discretionary, potentially affected by a host of external factors including operational or staffing constraints, ward bed availability, and competing priorities for ward bed assignment (e.g., to offload the ICU, ED, or post-anesthesia care unit; to receive more elective admissions or direct admissions from the clinic). This conjecture is supported by the hospital management literature that examines how bed assignment and rationing in times of congestion are employed as a means to maintain patient throughput (Jweinat et al. 2013, Reddy et al. 2015). Our study is the first to empirically measure ICU boarding in a large ICU patient cohort. Unlike prior studies (Chan et al. 2012, KC and Terwiesch 2009, 2012), we test whether patients experience reduced ICU boarding times (Hypothesis 2b) during peak ICU occupancy and, conversely, increased ICU boarding times during peak ward occupancy.

HYPOTHESIS 2B. *Higher ICU occupancy results in a shorter boarding time, and higher ward occupancy results in a longer boarding time.*

$$\frac{\partial Boarding_i}{\partial OccupancyICU_i} < 0, \quad \frac{\partial Boarding_i}{\partial OccupancyWard_i} > 0 \tag{3}$$

In contrast to the Surgical and Cardiothoracic ICUs examined in other studies, the Medicine ICU cares for critically ill patients with a wider range of diagnoses and acuity levels. Medicine ICU physicians and nurses, therefore, face not just changing occupancy levels, but also fluctuating distributions of *overall* patient acuity. One mitigating concern is that higher (or lower) acuity patients may not be initially admitted to an ICU that is already caring for sicker patients. If this were true, we would expect a negative (or positive) correlation between a patient's severity score at time of admission—computed as the predicted probability of in-hospital death—and that of other patients. However, we see no evidence to support this, as illustrated in Figure 3a for 1123 patients treated at Hospital B. Our clinical experience supports the observation that if a bed is available, then a patient will be admitted, regardless of the existing composition of patients in the unit. In testing Hypotheses 2a,b, we include a variable to control for the individual patient's severity, as well as average severity of other patients concurrently treated in the ICU. Figure 3b illustrates how average severity in the unit varies with occupancy.

Previous studies show conflicting results regarding the impact of ICU congestion on patient health outcomes. KC and Terwiesch (2009) find that after Cardiothoracic Surgery, an abbreviated LOS and early discharge, due to ICU congestion and increased demand for beds from other possible admissions, can increase patient mortality. Baker et al. (2009) and Town et al. (2014) both find a higher risk of readmission during periods of high patient volume, potentially related to early discharge from the ICU. However, in a large database analysis, Iwashyna et al. (2009) find that mortality risk does not differ based on daily census at time of ICU admission. All of these studies treat ICU LOS as one homogeneous measure. In contrast, our clinical observations suggest that patients often board in the ICU while awaiting transfer due to lack of bed availability on the wards. To examine whether a speed-up of care for some patients, resulting from high concurrent occupancy within the ICU, adversely affects patient outcomes, we test the following three hypotheses:

HYPOTHESIS 3A. *Higher ICU occupancy increases ICU bouncebacks.*

$$\frac{\partial Bounceback_i}{\partial OccupancyICU_i} > 0 \tag{4}$$

HYPOTHESIS 3B. *Higher ICU occupancy increases in-hospital mortality.*

$$\frac{\partial Death_i}{\partial OccupancyICU_i} > 0 \tag{5}$$

HYPOTHESIS 3C. *Higher ICU occupancy increases hospital readmissions.*

$$\frac{\partial Readmission_i}{\partial OccupancyICU_i} > 0 \tag{6}$$

If higher ICU occupancy leads to abbreviated ICU service times, then we would expect these patients to be more likely to revisit the ICU during their current hospital stay (Hypothesis 3a), have a higher risk of in-hospital death after ICU transfer (Hypothesis 3b), and/or be readmitted to the hospital within 30 days of discharge (Hypothesis 3c).

Patient severity-of-illness may, of course, affect the likelihood of an ICU bounceback, hospital readmission, or death, possibly confounding our coefficient estimates if certain patients are selected for early ICU discharge when occupancy is high. Unsurprisingly, severity-of-illness at ICU admission was significantly higher among patients who died within the current hospital stay than for those who survived (mean 0.22 vs. 0.11, $p <$ 0.0001). Severity-of-illness was modestly higher among those patients who later experienced an ICU bounceback (mean 0.15 vs. 0.12, $p = 0.08$); and there was no significant difference in severity among those patients who survived the initial hospital stay and were readmitted to the hospital within 30 days (mean 0.11 vs. 0.11, $p = 0.95$). In the full regression models, we control for severity-of-illness at time of admission when testing Hypotheses 3a–c.

4. Empirical Specifications

4.1. ICU Length of Stay

Our first model considers total ICU length of stay ($TotalLOS_i$) as the dependent variable to examine its relationship with ICU and ward occupancy levels ($OccupancyICU_i$ and $OccupancyWard_i$), controlling for individual patient characteristics ($\mathbf{X}_i$): age (Age_i); severity level at ICU admission defined as the predicted mortality probability ($Severity_i$) for Hospital B only; indicator if the patient arrives to the ICU from the emergency department (ED_i); health insurance type ($Medicaid_i$, $Medicare_i$, or $Other_i$); and categorical variables for primary diagnosis-related group code (DRG_i).

We additionally control for non-medical, operational factors: hospital where patient is admitted ($HospitalA_i$ or $HospitalB_i$); average severity level of other patients concurrently treated in the ICU ($OtherSeverity_i$); and month ($Month_i$), day of week ($Weekday_i$), and time of day ($Dayshift_i$) at completion of ICU service. For each set of regressions, we present nested models with base results that include only the control variables. Because $TotalLOS_i$ is positive and highly skewed, we use the natural logarithm and obtain the following model specification to test Hypothesis 1:

$$\begin{aligned}\ln\left(TotalLOS_i\right) = \lambda_0 + \lambda_1 OccupancyICU_i \\ + \lambda_2 OccupancyWard_i + \boldsymbol{\beta}\mathbf{X}_i + \varepsilon_i\end{aligned} \quad (7)$$

We specify two similar models to separate total ICU length of stay into service time (Hypothesis 2a) and boarding time (Hypothesis 2b):

$$\begin{aligned}\ln\left(Service_i\right) = \sigma_0 + \sigma_1 OccupancyICU_i \\ + \sigma_2 OccupancyWard_i + \boldsymbol{\beta}\mathbf{X}_i + \varepsilon_i\end{aligned} \quad (8)$$

$$\ln(Boarding_i) = \tau_0 + \tau_1 OccupancyICU_i + \tau_2 OccupancyWard_i + \boldsymbol{\beta}\mathbf{X}_i + \varepsilon_i \tag{9}$$

Patients who die within the ICU have censored service times, typically experience no boarding times, and do not transfer to the wards. We therefore exclude this cohort in the preceding models.

In each regression model, we break ICU and ward occupancy into four quartiles based on historical bed utilization at each hospital, to capture non-linear effects on service or boarding time. We include an interaction term, defined as "surge occupancy," for simultaneously high occupancy in the ICU and wards (both in the highest quartile of historical levels, normalized by hospital).

4.2. Patient Outcomes

Patients who are transferred out of the ICU before they are clinically ready due to bed shortages may experience subsequent clinical deterioration, requiring additional care with a return to the ICU, or bounceback, as observed in other patient populations (KC and Terwiesch 2012). We specify a logistic regression model for the probability of ICU bounceback during the current hospital stay to test our Hypothesis 3a:

$$\ln\left(\frac{P(Bounceback_i)}{1 - P(Bounceback_i)}\right) = \alpha_0 + \alpha_1 OccupancyICU_i + \alpha_2 OccupancyWard_i + \boldsymbol{\beta}\mathbf{X}_i + \varepsilon_i \tag{10}$$

In serious cases, patients who receive abbreviated or suboptimal care during periods of high ICU occupancy may be at increased risk of dying within the hospital (Hypothesis 3b) which we test, using a similar logit model:

$$\ln\left(\frac{P(Death_i)}{1 - P(Death_i)}\right) = \delta_0 + \delta_1 OccupancyICU_i + \delta_2 OccupancyWard_i + \boldsymbol{\beta}\mathbf{X}_i + \varepsilon_i \tag{11}$$

Finally, we test whether high ICU occupancy increases the probability of being readmitted to the hospital within 30 days, (Hypothesis 3c), assuming the patient survives the initial hospitalization:

$$\ln\left(\frac{P\left(Readmission_i\right)}{1-P\left(Readmission_i\right)}\right)=\rho_0+\rho_1 OccupancyICU_i + \rho_2 OccupancyWard_i+\boldsymbol{\beta}\mathbf{X}_i + \varepsilon_i \tag{12}$$

Odds ratios $e^{\alpha 1}$, $e^{\delta 1}$, or $e^{\rho 1}$ exceeding 1 would lend support to a hypothesis that patients completing ICU service during a period of high ICU occupancy are more likely to experience an ICU bounceback, inhospital death, or hospital readmission within 30 days, respectively. We examine these particular metrics, as ICU bouncebacks measure the level of rework if initial service times are abbreviated; 30-day readmissions are common hospital performance measures due to recent changes in Medicare reimbursement rates; and all three outcomes clearly capture patient well-being.

5. Results

5.1. ICU Length of Stay

Consistent with prior studies (Chan et al. 2012, KC and Terwiesch 2009, 2012), we find that higher ICU occupancy is associated with shorter total LOS. In particular, during the highest quartile of ICU occupancy, total LOS is 14% to 19% shorter than when occupancy is in the lowest quartile (Table 3, models 2–4). Conversely, higher Medicine ward occupancy is correlated with a longer total ICU LOS: ward occupancy in the third highest quartile corresponds to a 10% longer ICU LOS than during the lowest quartile; during the highest quartile, LOS is 18% longer. Total ICU LOS averages 3.1 days (Hospital A) or 4.9 days (Hospital B), suggesting that a 10% increase in LOS amounts to nearly one-half day. Both of these findings offer support to Hypothesis 1.

Patients admitted to the ICU who originate in the ED have a 21% shorter LOS than those from other hospital areas, with an average LOS of 79 hours vs. 110 hours ($p < 0.0001$). ICU patients arriving from non-ED locations have higher mortality than those from the ED (Delgado et al. 2013), possibly due to under-triage of the original admission condition, progression or complications of the original condition, or delayed recognition of impending clinical deterioration. One DRG classification related to organ transplant surgery (representing 3% of ICU patients at Hospital A and 14% at Hospital B) is associated with substantially longer LOS (258 hours vs. 86 hours, $p < 0.0001$). This is clinically sound, as patients undergoing organ transplantation who decompensate enough to warrant an ICU stay will likely require an extensive stay in the ICU because of comorbidities, immunosuppression, and other factors.

5.1.1. Service Time—When LOS is split into service and boarding periods, we find no support for Hypothesis 2a. ICU and ward occupancy have no statistically significant effect on ICU service time, whether occupancy is grouped by quartile (Table 4, models 2–4) or measured as a continuous variable. We do find that patients treated at Hospital A have a substantially shorter service time, consistent with our summary statistics and clinical observations that Hospital B typically admits critically ill patients with higher severity-of-illness, in part due to a smaller unit size (14 beds). As expected, ICU patients arriving from the ED have significantly shorter service time as they tend to be lower acuity than those arriving from other locations within the hospital.

5.1.2. Boarding Time—Upon examining the relationship between bed occupancy and ICU boarding time, we find strong support for Hypothesis 2b. Across both hospitals, we observe an increasing marginal effect of occupancy on boarding time as either the ICU and wards become full (Table 4, model 3). During the highest quartile of ICU occupancy (>95% beds occupied at Hospital A; 100% beds occupied at Hospital B), boarding time is 67% shorter compared to the lowest quartile (<88% occupied beds at Hospital A; <86% beds occupied at Hospital B). In other words, when available ICU beds are scarce, patients experience minimal boarding and very efficient transfers out of the ICU.

Conversely, we observe longer ICU boarding times as ward occupancy rises, across all quartiles. Ward occupancy in the second, third, and fourth quartiles correspond to 27%, 48%, and 67% longer boarding times, respectively, relative to the lowest quartile, controlling for concurrent ICU occupancy levels (Table 4, model 3). The increasing magnitude demonstrates that patients board in the ICU for longer periods of time as ward beds become increasingly scarce. Average ICU boarding times by ward occupancy are as follows: 10.4 hours (first quartile), 13.9 hours (second quartile), 16.6 hours (third quartile), and 19.2 hours (fourth quartile).

Based on hourly census reports, ICU and ward occupancy levels are mildly positively correlated ($\rho = +0.25$ at Hospital A; $\rho = +0.11$ at Hospital B). Prior studies that ignore concurrent ward occupancy may therefore mis-estimate the impact of ICU census alone on LOS (Appendix Figure A1). The coefficient for ICU occupancy becomes more statistically significant once ward occupancy is controlled for, highlighting that ICU and ward occupancy levels are positively correlated, but have opposing effects on ICU boarding time. Including all control variables, bed occupancy levels, and an occupancy interaction term, we obtain an adjusted $R^2 = 0.20$, in line with other empirical models of ICU length of stay (KC and Terwiesch 2009, Kim et al. 2014).

5.1.3. Surge Occupancy—Including an interaction for simultaneously high ICU and ward occupancy (both in the fourth quartile), results in a net 22.1% longer boarding time ($p = 0.03$) compared to when both areas are in the lowest quartile of occupancy (Table 4, model 4). Although high ICU occupancy may induce shorter boarding times, a lack of available ward beds appears to dominate, resulting in a net longer ICU stay. In our hospital settings, approximately 5% of patients complete service during periods of surge occupancy, with the surge lasting an average duration of 6.2 hours.

Figure 4 shows the predicted mean ICU service time and ICU boarding time by ICU and ward occupancy quartiles, across both hospitals. As demonstrated in the empirical results, occupancy appears to have no statistically significant effect on ICU service time, but does strongly relate to ICU boarding time, with ICU and ward occupancy levels exhibiting opposing effects. Predicted boarding ranges from approximately 6 hours (when ICU occupancy is at its highest and the wards are not full) up to 21 hours (when ward occupancy is at its highest and the ICU is partly full).

5.1.4. Dayshift and Weekday—Time-of-day or day-of-week may affect a patient's service time or boarding, due to differences in nursing shift changes, transport services, or competition for beds from other hospital areas. Although 51% of patients arrive to the ICU during the dayshift (7am to 7pm), approximately 92% of patients complete service during this window, and these latter patients experience 30% longer service times and 35% longer boarding times, compared to those booked during the nightshift, controlling for bed occupancy and patient characteristics (Table 4). Our results also show that patients completing ICU service on a weekday (between Monday and Friday) experience no difference in ICU service time, but do endure 10% longer boarding times than those ending on weekends.

One potential explanation for these findings is that more scheduled and elective hospital admissions occur during the dayshift and on weekdays. Hospital staff may reserve ward beds in anticipation of these admitted patients, resulting in longer boarding times for ICU patients awaiting transfer to the wards. We see some evidence of this in our estimate for weekday dropping in magnitude and significance when ward occupancy levels are controlled for (Table 4, models 2–3). We note that *OccupancyWard* and *Weekday* have a positive correlation coefficient of +0.18, and this effect is robust across other (log-linear) specifications.

5.1.5. Hospital-Specific Effects—We include a *HospitalA* dummy variable in the previous regressions (Tables 3–4) and we also split the data into separate regressions for each hospital (Table 5). At Hospital A, the magnitude of the association between ICU or ward occupancy and boarding time is greater than at Hospital B (Table 5, model 4). Hospital A has a substantially larger Medicine ICU (51 beds) than at Hospital B (14 beds) with more daily ICU admissions. Additionally, patients at Hospital A have a lower overall mortality rate and spend nearly two fewer days in the ICU, leading to more daily patient discharges at Hospital A. Hence, more opportunities to speed up boarding times may exist at Hospital A if more patients complete service and are ready for transfer each day.

5.1.6. Severity-of-Illness—We add the patient *Severity* control variable (Table 5, models 4–6) for Hospital B only. Unsurprisingly, we find that severity is strongly related to ICU service time: an increase in patient severity score of 0.10 (equivalent to a 10 percentage point increase in predicted inhospital mortality) corresponds to a 16.3% longer ICU service time (Table 5, model 4). We find no statistically significant relationship between severity and boarding time, consistent with our clinical observations that accelerated boarding times are largely driven by bed availability in the ICU and on the wards.

Conversely, average severity-of-illness of *other* patients in the ICU has no impact on the index patient's service time, supporting the notion that ICU care is not adversely affected by either the number or severity of neighboring patients. Boarding time, however, is substantially longer when average severity of other ICU patients is high (Table 5, models 5–

6). Given that boarding appears to be largely discretionary, it is not surprising that this segment of care is prolonged when neighboring patients may require more intensive nursing support. Nevertheless, our estimates for ICU and ward occupancy levels continue to hold, with even higher magnitudes once *OtherSeverity* is included. Finally, we test an interaction between *OtherSeverity* and high ICU occupancy (we use the third quartile because Hospital B's ICU is at 100% occupancy in both the third and fourth quartiles), but find no significant effect on service or boarding times (Table 5, model 6).

5.2. Patient Outcomes

Our empirical study provides no evidence to support Hypotheses 3a, 3b, or 3c. In particular, ICU and ward occupancy are not associated with a higher ICU bounceback probability (Table 6). Other model specifications, including a probit regression or linear probability model, show no relationship between ICU occupancy and bounceback probability. Consistent with our prior findings, patients admitted to the ICU from the ED are less likely to bounceback to the ICU after transfer to the wards ($OR = 0.51$, $p < 0.001$) reflecting our clinical observation that ICU patients admitted from the ED tend to be less critically ill and undergo shorter ICU stays than non-ED patients (Table 6, models 7–10). Patients with higher severity-of-illness at the time of initial ICU admission are also more likely to bounceback to the ICU, controlling for other covariates (Table 6, models 11–12).

Among patients who survive their initial ICU stay and subsequently transfer to the wards, about 11% die during the current hospitalization, either on the wards or another hospital area. Several patient characteristics (ED origin, insurance status) are associated with a risk of in-hospital death (Table 7). As expected, patient severity-of-illness is highly correlated with in-hospital death ($OR = 25.12$, $p < 0.0001$), providing validation for this metric (Table 7, models 11–12). We find no adverse effect of ICU occupancy on mortality. We do, however, find that higher ward occupancy corresponds to a *lower* risk of in-hospital death, with a more pronounced effect at Hospital B. To test whether this relates to prolonged boarding times, we include a control for *Boarding*, but find that ward occupancy is still negatively associated with in-hospital mortality. One conjecture based on our clinical experience at Hospital B is that during periods of high ward occupancy, ICU patients who are not expected to survive may be transferred to a hospice facility instead of being directly admitted to the wards (or, equivalently, when ward occupancy is low, terminally ill patients are cared for on the wards instead of going to hospice). Although patients transferred to hospice typically die shortly thereafter, they are recorded as a "discharge" in our dataset.

Upon examining 30-day hospital readmissions (among those patients who survive the initial hospitalization), we again find no relationship between ICU or ward occupancy and readmission probability (Table 8). We do find that older patients and those on Medicaid or Medicare insurance are more likely to be readmitted to the hospital within 30 days (Table 8), a well-documented finding in the medical literature (Hines et al. 2014). Once we control for patient severity (Table 8, models 11–12), these results are no longer significant, although the sample size is reduced to only those patients at Hospital B who survive the index hospitalization.

As a robustness check, we consider models that control for ICU *Service* and *Boarding* times. For each outcome (ICU bounceback, death, and 30-day readmission), the addition of these variables has no effect on our initial estimates (Tables 6–8). Altogether, these results support our finding that occupancy levels only impact ICU boarding time—which has minimal clinical impact on patients' functional status—and do not accelerate critical care service time, as previously claimed.

5.2.1. DRG Code—While running the preceding logistic regressions for patient outcomes, some observations are dropped because the categorical variable DRG perfectly predicts the outcome; an additional three observations are dropped because of missing DRG codes. In particular, all 79 patients in DRG classes MDC13 (Female Reproductive System), MDC14 (Pregnancy and Childbirth), MDC15 (Newborn and Neonates), MDC20 (Alcohol/ Drug Use or Induced Mental Disorders), and MDC24 (Multiple Significant Trauma) do not experience an ICU bounceback. These variables perfectly predict the "failure" outcome and are therefore omitted, resulting in $n = 2475$ observations for both hospitals.

For in-hospital deaths, all 89 patients in the following DRG classes do not die: MDC02 (Eye), MDC09 (Skin, Subcutaneous Tissue and Breast), MDC13 (Female Reproductive System), MDC14 (Pregnancy and Childbirth), MDC20 (Alcohol/Drug Use or Induced Mental Disorders), and MDC24 (Multiple Significant Trauma). Following this, we obtain $n = 2465$ observations.

Finally, all 18 patients in DRG classes MDC13 (Female Reproductive System), MDC14 (Pregnancy and Childbirth), MDC15 (Newborn and Neonates), MDC19 (Mental Diseases and Disorders), and MDC24 (Multiple Significant Trauma) are not readmitted to the hospital within 30 days, resulting in $n = 2536$ observations. As a robustness check, if the *DRG* categorical variable is entirely omitted, ICU occupancy still has no effect on bouncebacks, deaths, or hospital readmission.

6. Discussion

Our study examines how segments of patient care in the clinically diverse Medicine ICU are altered at providers' discretion due to concomitant workload levels, as observed in other health care settings (Freeman et al. 2017). By re-examining prior studies that empirically investigate the impact of ICU occupancy on LOS, our study demonstrates that occupancy-driven acceleration of care occurs within a period we newly define as "ICU boarding," when patients await transfer to the wards. Moreover, concurrent ward bed shortages dominate ICU occupancy effects, increasing net ICU boarding times. We see no adverse effects of ICU occupancy on bouncebacks, in-hospital mortality, or 30-day hospital readmission, consistent with our finding that only the discretionary boarding period changes during peak occupancy while critical care service time remains unaltered. From a patient's perspective, this is reassuring because hospital staff are not cutting short critical care service but rather reducing the largely unnecessary boarding period prior to ward transfer.

The absence of a statistically significant relationship between ICU occupancy and bounceback probability differ from prior studies, which may be explained in part by different patient populations. In our setting, 7% of patients bounceback to the ICU, consistent with a large meta-analysis (Hosein et al. 2014) estimating a bounceback rate of 5–6% in the Medicine ICU. In contrast, KC and Terwiesch (2012) observe that 14% of Cardiothoracic ICU patients bounceback—more than twice the rate in Medicine ICUs—highlighting not just different clinical outcomes between the studies but also potentially different decision-making processes.

In the Cardiothoracic ICU, 70% of patients are scheduled admissions, whereas virtually no Medicine ICU patients are scheduled in our setting. Although surgeons cannot schedule surgeries with advance knowledge of occupancy, procedures are often rescheduled due to a lack of available inpatient beds. Tagarakis et al. (2011) find that 16% of cardiac surgeries are ultimately rescheduled, with more than half due to bed or staffing shortages. Rescheduled patients face a higher predicted mortality rate (15% vs. 10%, $p < 0.01$), resulting in lower average acuity for patients who undergo surgery. The shorter LOS observed by KC and Terwiesch (2012) in peak occupancy periods may be partly explained by a different patient composition. The higher proportion of patients revisiting the Cardiothoracic ICU in KC and Terwiesch (2012) could also be partly supply-induced. With a lower average occupancy of 85%, staff may be more willing to fill available beds with bounceback patients, especially because future bed demand for scheduled admissions is known in advance. In contrast, the Medicine ICU typically faces internal pressure from the hospital to maintain available beds to accommodate spontaneous arrivals of patients requiring ICU care.

One key difference among ICU specialties is whether the attending physician assigned to the patient is primarily based within the unit itself. The Medicine ICU, known as a “closed unit,” requires decisions pertaining to patient admission and discharge to be made by the attending critical care physician. In contrast, Surgery and Cardiothoracic ICUs are typically “open units” where the (external) surgeon decides the course of treatment including discharge timing. Such a distinction is important when measuring the acceleration or delay of patient discharge from the ICU, as open units are subject to additional exogenous sources of variation due to surgeon availability and/or competition for beds from other inpatient areas. The Medicine ICU, therefore, is an ideal setting for our analysis because of the distinct set of physician decision-makers.

Although our study population is limited to the Medicine ICU, our findings may be of general interest given the heterogeneity in conditions present and important connection between the Medicine ICU and other hospital areas. About half of all Medicine ICU patients are admitted directly from the emergency department, and patient transfer delays out of the ICU undoubtedly trigger delays for incoming ICU patients, further exacerbating ED boarding and eventually ED wait times. Additionally, when bed utilization surges hospital-wide for clinical reasons, such as the onset of influenza season, the Medicine ICU is typically the targetward for these critically ill patients, more so than any other inpatient unit. Our observations using this cohort can be applied by hospital leadership and planners to improve health care delivery and patient throughput.

6.1. Implications for Practice

Our empirical results offer support for broader initiatives that hospital managers should consider to improve the entire ICU patient flow process, from bed assignment, through service and boarding times, to physical transfer to a ward bed. Virtually every large US hospital has implemented electronic medical records, making timestamps for bed assignment and discharge readily available. However, few hospitals also record timestamps for bed *requests*, precluding hospital managers from examining drivers of long ICU boarding times. Given the operational importance of expediting patient transfers from the ICU to the wards, hospitals should, at a minimum, measure periods of inefficiency such as ICU boarding time, so as to better identify targets for improvement.

Within our two-hospital setting, our study suggests that boarding times can differ by a factor of four, and close attention should be paid to simultaneously high occupancy surges within both the ICU and wards. Although this condition occurs less than 5% of the time, the combination of increased demand for the Medicine ICU and downstream ward beds creates the perfect storm—when ICU beds are most needed, boarding time is at its longest. This prolonged LOS further exacerbates ICU bed strain, creating delays for incoming ICU patients who then contribute to prolonged wait times in the ED. During these periods of strained capacity, the hospital could temporarily boost staffing and mobilize nursing teams and respiratory therapists to attend to patients who require an ICU bed but are unable to immediately receive one. Moving to a flexible-bed model (Best et al. 2015) where ICU capacity temporarily increases during high demand would increase throughput and reduce rejections of critical care patients from other hospitals due to limited bed availability. However, consideration should be given to potential negative effects of extra capacity in a connected system of ED, ICU, and ward beds (Berry Jaeker et al. 2013).

Implementing a threshold-based policy to prioritize patients exiting the ICU for a ward bed could reduce ICU congestion (e.g., once wards reach 80% occupancy, ICU patients receive a ward bed before admitted ED patients). At present, ICU patients board for 4 to 8 hours when wards are only partially full and such a priority rule, if feasible, could improve turnover. This slow-down of ICU transfers may occur because ward beds are spread across many independent units (e.g., Oncology, Cardiology, etc.) that are each behaving myopically without considering the aggregate effect on ICU bed strain. Better coordination across the ICU and all Medicine wards could streamline transfers out of the ICU, reducing ICU admission delays for incoming patients. Delaying ICU admission for some patients while simultaneously allowing others to spend needless hours boarding in the ICU is costly, both financially and clinically (Shmueli et al. 2003, Sprung et al. 2013).

In a related paper (Mathews and Long 2015), we use our empirical results to simulate different bed allocation policies. Achieving a 2-hour ICU boarding time for all patients could reduce ICU admission delays by 25% and decrease ICU occupancy by 10%, helping alleviate bottlenecks in other congested areas such as the ED or post-surgical care units. With the average daily cost of an ICU bed ranging from $3,000 to $11,000 (Dasta et al. 2005, Huynh et al. 2013), even a small reduction in ICU boarding times, during which hospitals typically do not receive full reimbursement, could generate enormous savings. The highest costs and revenue-generating opportunities of an ICU patient's hospitalization are typically within the first two days (Dasta et al. 2005); utilizing valuable ICU beds by patients awaiting transfer to the wards leads to a loss in potential revenue. Alternative revenue sources include patient admissions from outside hospitals and elective surgeries (Bekes et al. 2004, Kim et al. 1999), but such opportunities require streamlined patient flow.

Intensive care units require the highest degree of clinician training and nursing care in the hospital, and these beds should be turned over as quickly as possible. We find that patients who complete ICU service between 7am and 7pm experience significantly longer boarding times. A discharge policy that triggers a rapid transfer to the wards for patients who have finished receiving care will help free up beds for newly arriving patients. Reallocating housekeeping and transfer staff to the busier dayshift may also alleviate some congestion arising from long boarding times.

Our study has several limitations. First, we control for each patient's severity-of-illness using a validated risk-adjusted mortality model only at Hospital B, limiting our predictive power. Moreover, this severity score is static, based on the predicted probability of in-hospital death at time of ICU admission. Future studies that incorporate a dynamic severity score, such as the Rothman Index (Kim et al. 2017), could better measure a patient's evolving health status. Second, we use average severity-of-illness of other patients concurrently treated in the ICU, but a combined severity/occupancy metric may better capture workload. Third, we do not observe other key variables, including physician experience, shift length, or physician/nurse team dynamics, all of which may affect providers' cognitive load and subsequent clinical decision-making (Kuntz et al. 2015). Our dataset includes detailed timestamps only for Medicine ICU patients, which represents only a portion of most hospital stays. A more comprehensive examination of LOS in the ED and wards—as well as time spent *waiting* to transfer to and from the ICU—is warranted. Fourth, our analysis is for only two academic hospitals, and institution-specific bed capacity constraints and ICU admission/discharge policies likely exist. Finally, we cannot determine whether terminally ill patients are more likely to be transferred to hospice care when few ward beds are available, leading to a supposed reduction in the inhospital death rate. Closer examination of hospital disposition—and its relationship to ICU and ward occupancy levels —could be a fruitful area to explore.

6.2. Conclusions

Our study finds that the largely discretionary ICU boarding time following receipt of care is accelerated during periods of ICU congestion, but increasingly prolonged as ward beds become scarce. Boarding accounts for 15% of total ICU length of stay, reducing throughput and contributing to ICU admission delays for other patients. An additional component of ICU care is the decision-making by physicians, nurses, and other staff; in future research we intend to examine how hospitals can better align incentives to reduce unnecessary time spent in the ICU while improving patient care.

Acknowledgments

KSM has received study support from the NIH National Heart, Lung, and Blood Institute (Awards: 1K12HL109005-PI: Richardson; and 1K23HL130648-PI: Mathews) and the 2016 Unrestricted Grant in Critical Care from the American Thoracic Society Foundation. The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Heart, Lung, and Blood Institute, the National Institutes of Health, or the ATS Foundation.

Appendix

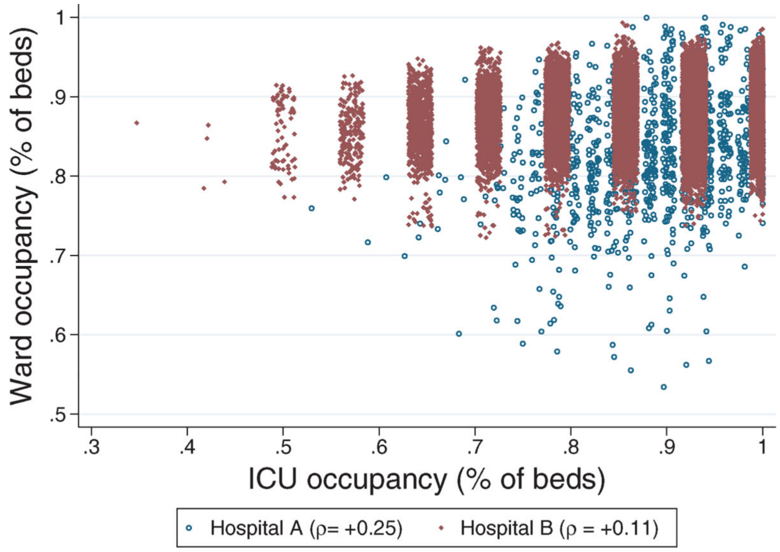

Figure A1.

Correlation Between Hourly Intensive Care Unit (ICU) and Medicine Ward Occupancy Levels [Color figure can be viewed at wileyonlinelibrary.com]

Note: Hospital A has 51 ICU beds + 436 ward beds; Hospital B has 14 ICU beds + 624 ward beds.

Table A1

Distribution of Primary Diagnosis Related Group (DRG) Codes, by Hospital

DRG code	Description	Hospital A (%)	Hospital B (%)
001–015	Pre-MDC (Surgical Transplant)	3.1	13.8
020–103	MDC 01: Nervous System	3.5	2.2
113–125	MDC 02: Eye	0.1	1.0
129–159	MDC 03: Ear, Nose, Mouth & Throat	0.8	13.6
163–208	MDC 04: Respiratory System	20.9	4.4
215–316	MDC 05: Circulatory System	7.8	17.4
326–395	MDC 06: Digestive System	11.4	1.3
405–446	MDC 07: Hepatobiliary System & Pancreas	4.6	2.7
453–566	MDC 08: Musculoskeletal System & Connective Tissue	2.4	3.3
570–607	MDC 09: Skin, Subcutaneous Tissue & Breast	0.4	0.0
614–645	MDC 10: Endocrine, Nutritional & Metabolic System	6.7	0.0
652–700	MDC 11: Kidney & Urinary Tract	6.3	6.3
707–730	MDC 12: Male Reproductive System	0.0	22.5
734–761	MDC 13: Female Reproductive System	0.3	0.0
764–782	MDC 14: Pregnancy, Childbirth & Puerperium	0.3	0.0
789–795	MDC 15: Newborn & Other Neonates (Perinatal Period)	0.0	0.2
799–816	MDC 16: Blood, Blood-forming Organs & Immunological Disorders	1.5	4.6
820–849	MDC 17: Myeloproliferative Diseases	1.5	0.0

DRG code	Description	Hospital A (%)	Hospital B (%)
853–872	MDC 18: Infectious & Parasitic Diseases and Disorders	14.9	0.1
876–887	MDC 19: Mental Diseases and Disorders	0.2	0.0
894–897	MDC 20: Alcohol/Drug Use or Induced Mental Disorders	3.9	0.2
901–923	MDC 21: Injuries, Poisonings & Toxic Effects of Drugs	5.8	0.0
927–935	MDC 22: Burns	0.0	0.0
939–951	MDC 23: Factors Influencing Health Status	0.3	1.8
955–965	MDC 24: Multiple Significant Trauma	0.1	0.0
969–979	MDC 25: Human Immunodeficiency Virus Infection	1.3	3.7
981–989	Unrelated Operating Room Procedures	1.7	0.2
998–999	Invalid and Ungroupable DRGs	0.0	0.6

Note: MDC, major diagnostic category.

References

Baker DR, Pronovost PJ, Morlock LL, Geocadin RG, Holzmueller CG. 2009 Patient flow variability and unplanned readmissions to an intensive care unit. Crit. Care Med 37(11): 2882–2887. [PubMed: 19866504]

Barrett ML, Smith MW, Elixhauser A, Honigman LS, Pines JM. 2014 Utilization of intensive care services, 2011: Statistical brief #185 Healthcare Cost and Utilization Project (HCUP). Agency for Healthcare Research and Quality, Rockville, MD.

Bartlett S, Fatovich DM. 2009 Emergency department patient preferences for waiting for a bed. Emergency Med. Austral 21(1): 25–30.

Bekes CE, Dellinger RP, Brooks D, Edmondson R, Olivia CT, Parrillo JE. 2004 Critical care medicine as a distinct product line with substantial financial profitability: The role of business planning. Crit. Care Med 32(5): 1207–1214. [PubMed: 15190974]

Bekker R, Koeleman PM. 2011 Scheduling admissions and reducing variability in bed demand. Health Care Manage. Sci 14(3): 237–249.

Berry Jaeker JB, Tucker AL, Lee MH. 2013 Increased speed equals increased wait: The impact of a reduction in emergency department ultrasound order processing time Working paper, Harvard Business School, Boston, MA.

Best TJ, Sandikci B, Eisenstein DD, Meltzer DO. 2015 Managing hospital inpatient bed capacity through partitioning care into focused wings. Manuf. Serv. Oper. Manag 17(2): 57–76.

Cardoso LTQ, Grion CMC, Matsuo T, Anami EHT, Kauss IAM, Seko L, Bonametti A. 2011 Impact of delayed admission to intensive care units on mortality of critically ill patients: A cohort study. Crit. Care 15(1): R28. [PubMed: 21244671]

Chalfin DB, Trzeciak S, Likourezos A, Baumann BM, Dellinger RP. 2007 Impact of delayed transfer of critically ill patients from the emergency department to the intensive care unit. Crit. Care Med 35(6): 1477–1483. [PubMed: 17440421]

Chan CW, Farias VF, Bambos N, Escobar GJ. 2012 Optimizing ICU discharge decisions with patient readmissions. Oper. Res 60(6): 1323–1341.

Chan CW, Yom-Tov G, Escobar GJ. 2014 When to use speedup: An examination of service systems with returns. Oper. Res 62(2): 462–482.

Dasta JF, McLaughlin TP, Mody SH, Piech CT. 2005 Daily cost of an intensive care unit day: The contribution of mechanical ventilation. Crit. Care Med 33(6): 1266–1271. [PubMed: 15942342]

De Vericourt F, Jennings OB. 2011 Nurse staffing in medical units: A queuing perspective. Oper. Res 59(6): 1320–1331.

Delgado MK, Liu V, Pines JM, Kipnis P, Gardner MN, Escobar GJ. 2013 Risk factors for unplanned transfer to intensive care within 24 hours of admission from the emergency department in an integrated healthcare system. J. Hosp. Med 8(1): 13–19. [PubMed: 23024040]

Dobson GH, Lee H, Pinker E. 2010 A model of ICU bumping. Oper. Res 58(6): 1564–1576.

Edbrooke DL, Minelli C, Mills GH, Iapichino G, Pezzi A, Corbella D, Jacobs P, Lippert A, Wiis J, Pesenti A, Patroniti N, Pirracchio R, Payen D, Gurman G, Bakker J, Kesecioglu J, Hargreaves C, Cohen SL, Baras M, Artigas A, Sprung CL. 2011 Implications of ICU triage decisions on patient mortality: A cost-effectiveness analysis. Crit. Care 15(1): R56. [PubMed: 21306645]

Freeman M, Savva N, Scholtes S. 2017 Gatekeepers at work: An empirical analysis of a maternity unit. Management Sci. 63(10): 3147–3167.

Halpern NA 2009 Can the costs of critical care be controlled? Curr. Opin. Crit. Care 15(6): 591–596. [PubMed: 19823083]

Halpern SD 2011 ICU capacity strain and the quality and allocation of critical care. Curr. Opin. Crit. Care 17(6): 648–657. [PubMed: 21986461]

Hines AL, Barrett ML, Jiang HJ, Steiner CA. 2014 Conditions with the largest number of adult hospital readmissions by payer, 2011: Statistical brief #172 Healthcare Cost and Utilization Project (HCUP). Agency for Healthcare Research and Quality, Rockville, MD.

Hopp WL, Iravani SMR, Yuen GY. 2007 Operations systems with discretionary task completion. Management Sci. 53(1): 61–77.

Hosein FS, Roberts DJ, Turin TC, Zygun D, Ghali WA, Stelfox HT. 2014 A meta-analysis to derive literature-based benchmarks for readmission and hospital mortality after patient discharge from intensive care. Crit. Care 18(6): 715. [PubMed: 25551448]

Howell MD 2011 Managing ICU throughput and understanding ICU census. Curr. Opin. Crit. Care 17(6): 626–633. [PubMed: 21934614]

Huynh TN, Kleerup EC, Wiley JF, Savitsky TD, Guse D, Garber BJ, Wenger NS. 2013 The frequency and cost of treatment perceived to be futile in critical care. JAMA Intern. Med 173(20): 1887–1894. [PubMed: 24018712]

Ibanez MR, Clark JR, Huckman RS, Staats BR. 2017 Discretionary task ordering: Queue management in radiological services. Management Sci Articles in Advance, pp. 1–19.

Iwashyna TJ, Kramer AA, Kahn JM. 2009 Intensive care unit occupancy and patient outcomes. Crit. Care Med 37(5): 1545–1557. [PubMed: 19325466]

Johnson DW, Schmidt UH, Bittner EA, Christensen B, Levi R, Pino RM. 2013 Delay of transfer from the intensive care unit: A prospective observational study of incidence, causes, and financial impact. Crit. Care 17(4): R128. [PubMed: 23826830]

Jweinat J, Damore P, Morris V, D'Aquila R, Bacon S, Balcezak TJ. 2013 The safe patient flow initiative: A collaborative quality improvement journey at Yale-New Haven Hospital. Jt. Comm. J. Qual. Patient Saf 39(10): 447–459. [PubMed: 24195198]

KC DS, Terwiesch C. 2009 Impact of workload on service time and patient safety: An econometric analysis of hospital operations. Management Sci. 55(9): 1486–1498.

KC DS, Terwiesch C. 2012 An econometric analysis of patient flows in the cardiac intensive care unit. Manuf. Serv. Oper. Manag 14(1): 50–65.

Kim SC, Horowitz I, Young KK, Buckley TA. 1999 Analysis of capacity management of the intensive care unit in a hospital. Eur. J. Oper. Res 115(1): 36–46.

Kim S-H, Chan CW, Olivares M, Escobar GJ. 2014 ICU admission control: An empirical study of capacity allocation and its implication for patient outcomes. Management Sci. 61(1): 19–38.

Kim S-H, Chan CW, Olivares M, Escobar GJ. 2016 Association among ICU congestion, ICU admission decision, and patient outcomes. Crit. Care Med 44(10): 1814–1821. [PubMed: 27332046]

Kim S-H, Pinker EJ, Rimar J, Bradley EH. 2017 Refining workload measure in hospital units: From census to acuity-adjusted census in Intensive Care Units Working paper, USC, Marshall School of Business, Los Angeles, CA.

Kuntz L, Mennicken R, Scholtes S. 2015 Stress on the ward: Evidence of safety tipping points in hospitals. Management Sci. 61(4): 754–771.

Levin PD, Worner TM, Sviri S, Goodman SV, Weiss YG, Einav S, Weissman C, Sprung CL. 2003 Intensive care out flow limitation–frequency, etiology, and impact. J. Crit. Care 18(4): 206–211. [PubMed: 14691893]

Liu V, Kipnis P, Rizk NW, Escobar GJ. 2012 Adverse outcomes associated with delayed intensive care unit transfers in an integrated healthcare system. J. Hosp. Med 7(3): 224–230. [PubMed: 22038879]

Lucas R, Farley H, Twanmoh J, Urumov A, Olsen N, Evans B, Kabiri H. 2009 Emergency department patient flow: The influence of hospital census variables on emergency department length of stay. Acad. Emerg. Med 16(7): 597–602. [PubMed: 19438415]

Mathews KS, Long EF. 2015 A conceptual framework for improving critical care patient flow and bed utilization. Ann. Am. Thorac. Soc 12(6): 886–894. [PubMed: 25822477]

McConnell KJ, Richards CF, Daya M, Bernell SL, Weathers CC, Lowe RA. 2005 Effect of increased ICU capacity on emergency department length of stay and ambulance diversion. Ann. Emerg. Med 45(5): 471–478. [PubMed: 15855939]

Ng D, Vail G, Thomas S, Schmidt N. 2010 Applying the Lean principles of the Toyota Production System to reduce wait times in the emergency department. Can. J. Emerg. Med 12(1): 50–57.

Peltonen LM, McCallum L, Siirala E, Haataja M, Lundgrén-Laine H, Salanterä S, Lin F. 2015 An integrative literature review of organisational factors associated with admission and discharge delays in critical care. Biomed. Res. Int 2015: 1–12.

Pines JM, Batt RJ, Hilton JA, Terwiesch C 2011 The financial consequences of lost demand and reducing boarding in hospital emergency departments. Ann. Emerg. Med 58(4): 331–340. [PubMed: 21514004]

Reddy AJ, Pappas R, Suri S, Whinney C, Yerian L, Guzman JA. 2015 Impact of throughput optimization on intensive care unit occupancy. Am. J. Med. Qual 30(4): 317–322. [PubMed: 24755479]

Renaud B, Santin A, Coma E, Camus N, Van Pelt D, Hayon J, Gurgui M, Roupie E, Hervé J, Fine MJ, Brun-Buisson C, Labarere J. 2009 Association between timing of intensive care unit admission and outcomes for emergency department patients with community-acquired pneumonia. Crit. Care Med 37(11): 2867–2874. [PubMed: 19770748]

Schmidt R, Geisler S, Spreckelsen C. 2013 Decision support for hospital bed management using adaptable individual length of stay estimations and shared resources. BMC Med. Inform. Decis. Mak 13(3): 1–19. [PubMed: 23289362]

Shi P, Chou MC, Dai JG, Ding D, Sim J. 2015 Models and insights for hospital inpatient operations: Time-dependent ED boarding time. Management Sci. 62(1): 1–28.

Shmueli A, Sprung CL, Kaplan EH. 2003 Optimizing admissions to an intensive care unit. Health Care Manage. Sci 6(3): 131–136.

Song H, Tucker AL, Murrell KL. 2015 The diseconomies of queue pooling: An empirical investigation of emergency department length of stay. Management Sci. 61(12): 3032–3053.

Sprung CL, Danis M, Iapichino G, Artigas A, Kesecioglu J, Moreno R, Lippert A, Curtis JR, Meale P, Cohen SL, Levy MM, Truog RD. 2013 Triage of intensive care patients: Identifying agreement and controversy. Intensive Care Med. 39(11): 1916–1924. [PubMed: 23925544]

Tagarakis GI, Karangelis D, Voucharas C, Daskalopoulos ME, Koufakis T, Mouzaki M, Lampoura S, Papadopoulos D, Sataitidis I, Tsilimingas NB. 2011 Why are heart operations postponed? J. Cardiothoracic Surg 6(1): 106.

Town JA, Churpek MM, Yuen TC, Huber MT, Kress JP, Edelson DP. 2014 Relationship between ICU bed availability, ICU readmission, and cardiac arrest in the general wards. Crit. Care Med 42(9): 2037–2041. [PubMed: 24776607]

U.S. Centers for Medicare and Medicaid Services. 2015 National health expenditure data. Available at https://www.cms.gov/research-statistics-data-and-systems/statistics-trends-and-reports/nationalhealthexpenddata/ (accessed date October 1, 2017).

U.S. Department of Health and Human Services. 2015 Projected future growth of the older population. Available at https://www.acl.gov/aging-and-disability-in-america/data-and-research/projectedfuture-growth-older-population (accessed date October 1, 2017).

Wagner J, Gabler NB, Ratcliffe SJ, Brown SE, Strom BL, Halpern SD. 2013 Outcomes among patients discharged from busy intensive care units. Ann. Intern. Med 159(7): 447–455. [PubMed: 24081285]

Wallace DJ, Angus DC, Seymour CW, Barnato AE, Kahn JM. 2015 Critical care bed growth in the United States. A comparison of regional and national trends. Am. J. Respir. Crit. Care Med 191(4): 410–416. [PubMed: 25522054]

Weiss AJ, Elixhauser A. 2014 Overview of Hospital Stays in the United States, 2012: Statistical brief #180 Healthcare Cost and Utilization Project (HCUP). Agency for Healthcare Research and Quality, Rockville, MD.

Wunsch H, Wagner J, Herlim M, Chong DH, Kramer AA, Halpern SD. 2013 ICU occupancy and mechanical ventilator use in the United States. Crit. Care Med 41(12): 2712–2719. [PubMed: 23963122]

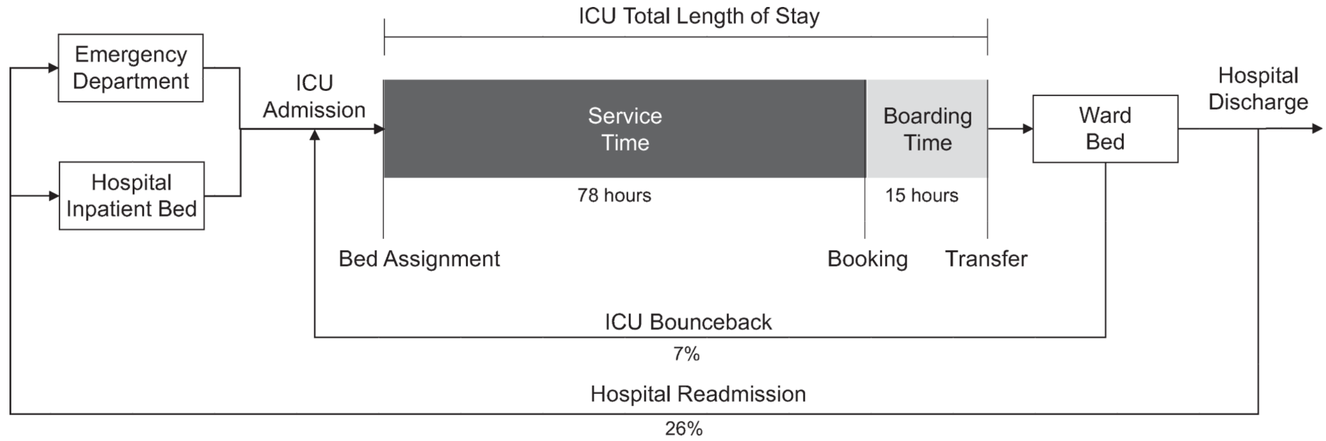

Figure 1.
Intensive Care Unit (ICU) Patient Flow with Average Service and Boarding Times, as well as the Fraction of Patients with ICU Bounceback or 30-Day Hospital Readmission

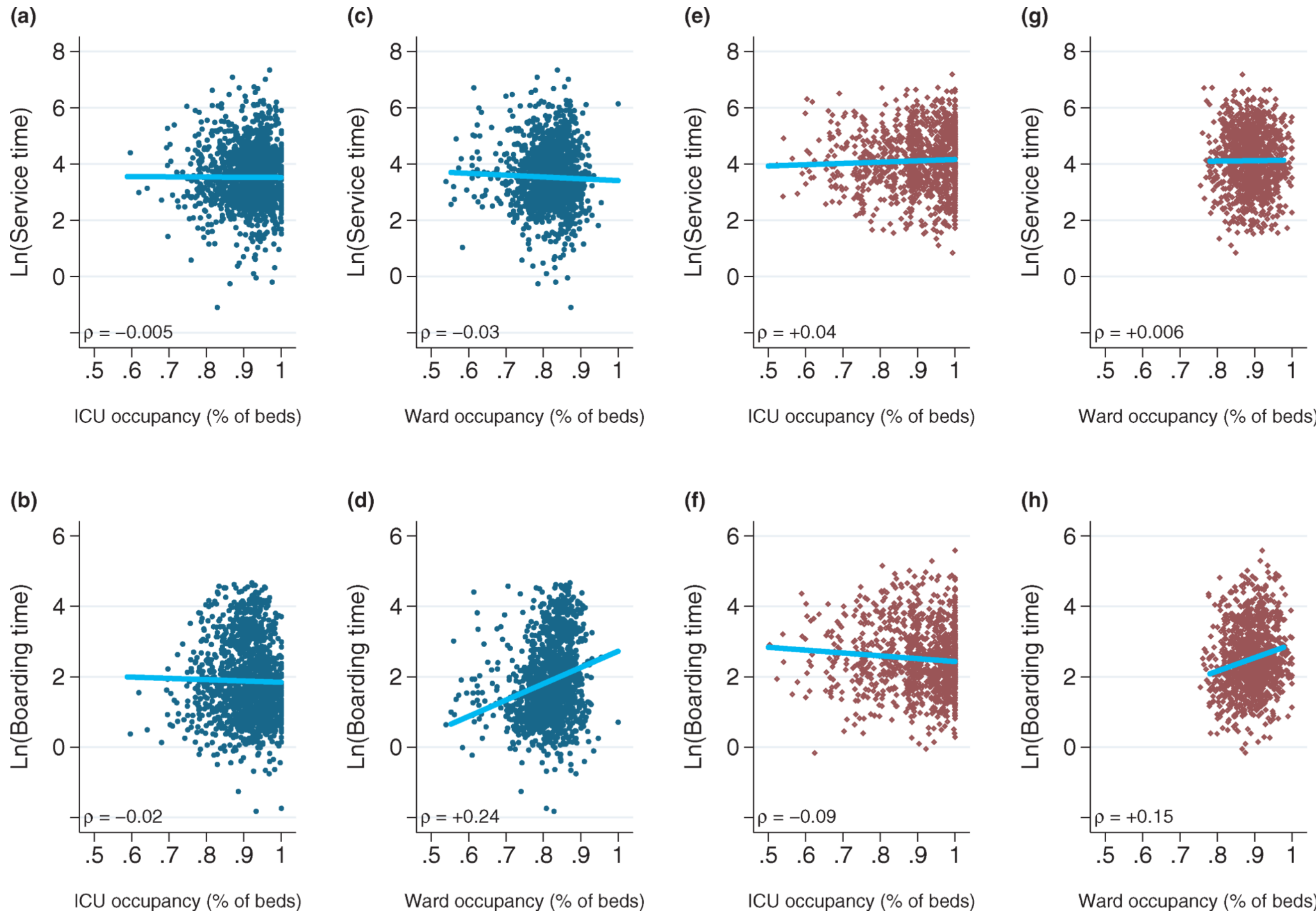

Figure 2.

Scatterplot of Each Patient's Intensive Care Unit (ICU) Service Time (top row) or Boarding Time (bottom row) vs. ICU and Medicine Ward Occupancy Levels at Hospital A (a)–(d) or Hospital B (e)–(h) [Color figure can be viewed at wileyonlinelibrary.com]

Author Manuscript
Author Manuscript
Author Manuscript

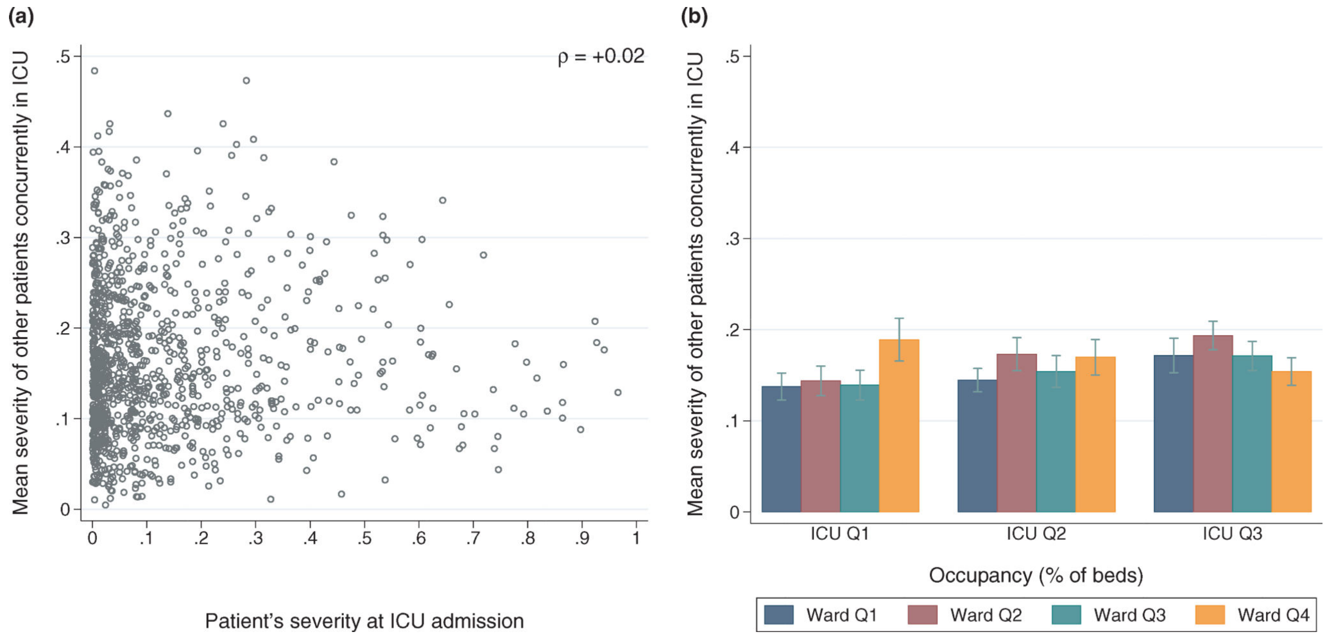

Figure 3.

Average Severity-of-Illness of All Other Patients Concurrently Treated in the Intensive Care Unit (ICU) vs. (a) Patient Severity-of-Illness at Time of ICU Admission Based on Predicted Probability of Death and (b) ICU and Ward Occupancy Quartiles (Hospital B only) [Color figure can be viewed at wileyonlinelibrary.com]

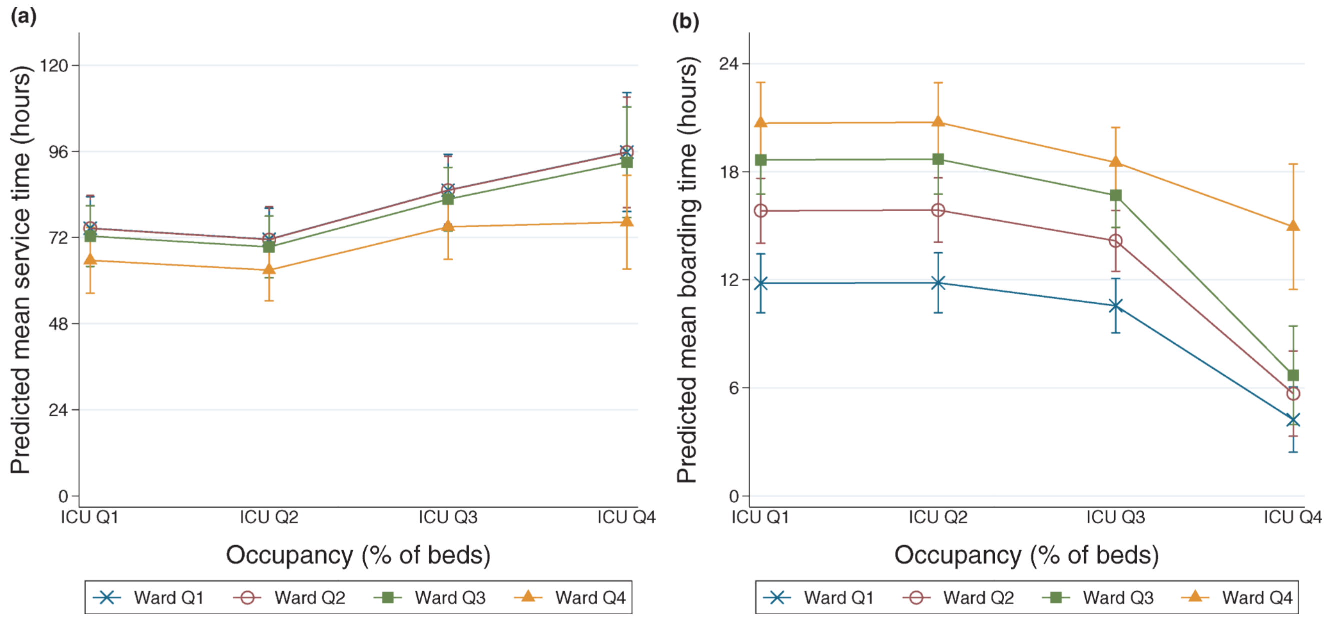

Figure 4.

Predicted Mean and 95% Confidence Intervals for (a) Intensive Care Unit (ICU) Service Time and (b) ICU Boarding Time by ICU and Ward Occupancy Quartiles, Where ICU Q4 & Ward Q4 Denotes a Period of “Surge Occupancy” [Color figure can be viewed at wileyonlinelibrary.com]

Note: Predictions based on marginal effects from Table 4, model 4.

Table 1

Variable Definitions and Summary Statistics for Both Hospitals

		Hospital A		Hospital B	
Variable	**Description**	**Mean**	**SD**	**Mean**	**SD**
Operational metrics					
TotalLOS	Total ICU length of stay, including service and boarding (hours)	73.3	107.1	116.9	110.3
Service	ICU service time, involving receipt of critical care services, starting at bed assignment until ICU physician request for ward transfer (hours)	61.2	103.9	98.5	106.7
Boarding	ICU boarding time, during which the patient is clinically ready for ward transfer and awaits bed availability (hours)	12.1	15.9	18.7	21.2
OccupancyICU	Fraction of ICU beds occupied at the time a patient completes ICU service	0.91	0.06	0.91	0.10
OccupancyWard	Fraction of ward beds occupied at the time a patient completes ICU service	0.82	0.06	0.89	0.03
Post-ICU outcomes					
Death	Patient died during current hospital stay (indicator)	0.14	-	0.33	-
Bounceback	Patient returned to ICU during current hospital stay (indicator)	0.05	-	0.08	-
Readmission	Patient readmitted to hospital within 30 days after discharge (indicator)	0.29	-	0.21	-
Patient characteristics					
DeathICU	Patient died in ICU (excluded from analysis)	0.08	-	0.21	-
ED	Patient admitted to ICU from emergency department (indicator)	0.64	-	0.45	-
Severity	Patient's severity-of-illness at ICU admission, calculated as predicted probability of in-hospital death	-	-	0.12	0.17
OtherSeverity	Average severity-of-illness of other patients concurrently treated in the ICU, excludes index patient	-	-	0.16	0.08
Age	Patient's age at ICU admission (years)	61.2	17.9	58.3	16.9
Medicaid	Patient's primary insurance is Medicaid (indicator)	0.21	-	0.28	-
Medicare	Patient's primary insurance is Medicare (indicator)	0.57	-	0.49	-
Dayshift	Patient completes ICU service on dayshift, 7am-7pm (indicator)	0.90	-	0.96	-
Weekday	Patient completes ICU service on weekday, Mon-Fri (indicator)	0.74	-	0.76	-
Month	Patient completes ICU service during month (categorical)	-	-	-	-
DRG	Primary diagnosis-related group code (categorical)	-	-	-	-
Hospital	Hospital of ICU admission (categorical)	0.56	-	0.44	-

Table 2

Correlations Between Key Variables

	Service	Boarding	OccupICU	OccupWard	Severity	OtherSeverity	Death	Bounceback	Readmission
Service	1.00								
Boarding	0.12	1.00							
OccupancyICU	0.04	−0.05	1.00						
OccupancyWard	−0.02	0.15	0.22	1.00					
Severity	0.29	0.02	0.09	0.02	1.00				
OtherSeverity	−0.03	0.07	0.16	0.07	0.02	1.00			
Death	0.19	0.06	0.01	−0.04	0.25	−0.03	1.00		
Bounceback	0.09	0.04	0.00	−0.04	0.05	0.05	0.20	1.00	
Readmission	−0.09	−0.01	−0.01	0.01	−0.05	0.04	−0.19	−0.08	1.00

Note. Correlations between *Severity* and *OtherSeverity* are based on $n = 1123$ observations at Hospital B. All other correlations are based on $n = 2557$ observations at both hospitals.

Table 3

Predictors of Intensive Care Unit (ICU) Total Length of Stay at Both Hospitals

	ln *(TotalLOS)*			
	(1)	**(2)**	**(3)**	**(4)**
OccupancyICUQ2		−0.064 (0.045)	−0.077 (0.045)	−0.076 (0.045)
OccupancyICUQ3		0.027 (0.044)	0.005 (0.044)	0.006 (0.044)
OccupancyICUQ4		−0.138 (0.060)*	−0.174 (0.061)**	−0.194 (0.069)**
OccupancyWardQ2			0.058 (0.048)	0.059 (0.048)
OccupancyWardQ3			0.097 (0.048)*	0.099 (0.048)*
OccupancyWardQ4			0.185 (0.051)***	0.176 (0.053)***
ICUQ4 × WardQ4				0.060 (0.103)
HospitalA	−0.475 (0.050)***	−0.437 (0.052)***	−0.431 (0.052)***	−0.432 (0.052)***
ED	−0.216 (0.035)***	−0.214 (0.035)***	−0.212 (0.035)***	−0.212 (0.035)***
Medicaid	−0.043 (0.049)	−0.051 (0.049)	−0.050 (0.049)	−0.050 (0.049)
Medicare	−0.021 (0.048)	−0.028 (0.048)	−0.032 (0.048)	−0.033 (0.048)
Age	0.013 (0.005)*	0.012 (0.005)*	0.012 (0.005)*	0.012 (0.005)*
Age^2	0.000 (0.000)*	0.000 (0.000)*	0.000 (0.000)*	0.000 (0.000)*
Dayshift	0.187 (0.063)**	0.189 (0.063)**	0.198 (0.063)**	0.198 (0.063)**
Weekday	0.067 (0.038)	0.068 (0.038)	0.035 (0.039)	0.034 (0.039)
Month	Included	Included	Included	Included
DRG	Included	Included	Included	Included
Observations	2557	2557	2557	2557
Adjusted R^2	0.18	0.19	0.20	0.20

Notes: Standard errors in parentheses.

Significance levels:

(*) $p < 0.05$

(**) $p < 0.01$

(***) $p < 0.001$.

Table 4

Predictors of Intensive Care Unit (ICU) Service Time and Boarding Time at Both Hospitals

	In (*Service*)				In (*Boarding*)			
	(1)	**(2)**	**(3)**	**(4)**	**(1)**	**(2)**	**(3)**	**(4)**
OccupancyICUQ2		−0.073 (0.052)	−0.074 (0.053)	−0.075 (0.053)		−0.020 (0.053)	−0.063 (0.052)	−0.056 (0.052)
OccupancyICUQ3		0.069 (0.051)	0.066 (0.052)	0.064 (0.052)		−0.054 (0.052)	−0.129 (0.051)*	−0.117 (0.051)*
OccupancyICUQ4		−0.002 (0.070)	−0.004 (0.071)	0.015 (0.082)		−0.536 (0.072)***	−0.668 (0.071)***	−0.807 (0.081)***
OccupancyWardQ2			0.008 (0.056)	0.006 (0.056)			0.267 (0.055)***	0.278 (0.055)***
OccupancyWardQ3			−0.016 (0.056)	−0.018 (0.056)			0.481 (0.056)***	0.497 (0.056)***
OccupancyWardQ4			0.017 (0.060)	0.026 (0.063)			0.669 (0.059)***	0.603 (0.062)***
ICUQ4 × WardQ4				−0.057 (0.121)				0.425 (0.120)***
HospitalA	−0.474 (0.059)***	−0.470 (0.061)***	−0.471 (0.061)***	−0.471 (0.061)***	−0.543 (0.060)***	−0.401 (0.062)***	−0.378 (0.061)***	−0.378 (0.061)***
ED	−0.270 (0.041)***	−0.268 (0.041)***	−0.268 (0.041)***	−0.267 (0.041)***	−0.004 (0.042)	−0.001 (0.042)	0.006 (0.041)	0.005 (0.041)
Medicaid	−0.004 (0.058)	−0.014 (0.058)	−0.014 (0.058)	−0.013 (0.058)	−0.076 (0.059)	−0.082 (0.059)	−0.079 (0.057)	−0.079 (0.057)
Medicare	0.007 (0.056)	0.001 (0.056)	0.001 (0.056)	0.002 (0.057)	−0.062 (0.058)	−0.075 (0.057)	−0.085 (0.056)	−0.091 (0.056)
Age	0.010 (0.006)	0.010 (0.006)	0.010 (0.006)	0.010 (0.006)	0.017 (0.006)**	0.016 (0.006)*	0.015 (0.006)*	0.015 (0.006)*
Age^2	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)**	0.000 (0.000)*	0.000 (0.000)*	0.000 (0.000)*
Dayshift	0.259 (0.074)***	0.257 (0.074)***	0.256 (0.074)***	0.257 (0.074)***	0.250 (0.076)**	0.265 (0.075)***	0.304 (0.074)***	0.303 (0.073)***
Weekday	0.025 (0.044)	0.024 (0.045)	0.023 (0.046)	0.023 (0.046)	0.214 (0.046)***	0.222 (0.045)***	0.099 (0.045)*	0.094 (0.045)*
Month	Included	Included	Included	Included	Included	Included	Included	Included
DRG	Included	Included	Included	Included	Included	Included	Included	Included
Observations	2557	2557	2557	2557	2557	2557	2557	2557
Adjusted R^2	0.16	0.16	0.16	0.16	0.12	0.14	0.19	0.20

Notes: Standard errors in parentheses.

Significance levels:

(*) $p < 0.05$

(**) $p < 0.01$

(***) $p < 0.001$.

Table 5

Predictors of Intensive Care Unit (ICU) Service Time and Boarding Time, by Individual Hospital

	In (*Service*)				In (*Boarding*)			
	(4)	**(4)**	**(5)**	**(6)**	**(4)**	**(4)**	**(5)**	**(6)**
	Hospital A	**Hospital B**	**Hospital B**	**Hospital B**	**Hospital A**	**Hospital B**	**Hospital B**	**Hospital B**
OccupancyICUQ2	−0.107 (0.075)	−0.033 (0.074)	−0.013 (0.075)	−0.014 (0.075)	0.019 (0.079)	−0.218 (0.068) **	−0.237 (0.069) ***	−0.236 (0.069) ***
OccupancyICUQ3	0.030 (0.082)	0.063 (0.071)	0.091 (0.073)	0.130 (0.139)	−0.143 (0.087)	−0.269 (0.066) ***	−0.299 (0.067) ***	−0.347 (0.128) **
OccupancyICUQ4	−0.056 (0.093)				−0.842 (0.098) ***			
OccupancyWardQ2	0.049 (0.076)	−0.054 (0.082)	−0.054 (0.084)	−0.054 (0.084)	0.363 (0.080) ***	0.174 (0.076) *	0.179 (0.078) *	0.179 (0.078) *
OccupancyWardQ3	0.044 (0.079)	−0.063 (0.080)	−0.061 (0.082)	−0.062 (0.082)	0.703 (0.083) ***	0.248 (0.074) ***	0.271 (0.075) ***	0.272 (0.076) ***
OccupancyWardQ4	0.014 (0.095)	0.001 (0.088)	0.007 (0.090)	0.003 (0.091)	0.941 (0.099) ***	0.260 (0.081) **	0.276 (0.083) ***	0.281 (0.084) ***
ICUQ4 × WardQ4	0.016 (0.134)				0.254 (0.140)			
Severity		1.512 (0.178) ***	1.541 (0.180) ***	1.540 (0.180) ***		−0.204 (0.165)	−0.188 (0.165)	−0.186 (0.166)
OtherSeverity			−0.351 (0.383)	−0.255 (0.479)			1.298 (0.352) ***	1.183 (0.441) ***
OtherSeverity × ICUQ3				−0.246 (0.737)				0.293 (0.678)
ED	−0.400 (0.057) ***	−0.077 (0.059)	−0.075 (0.060)	−0.074 (0.060)	−0.063 (0.060)	0.087 (0.055)	0.078 (0.055)	0.077 (0.055)
Medicaid	−0.150 (0.080)	0.104 (0.082)	0.078 (0.083)	0.078 (0.083)	−0.063 (0.084)	−0.063 (0.075)	−0.062 (0.077)	−0.062 (0.077)
Medicare	−0.100 (0.075)	0.062 (0.084)	0.067 (0.085)	0.068 (0.085)	−0.083 (0.078)	−0.065 (0.077)	−0.078 (0.079)	−0.079 (0.079)
Age	0.022 (0.008) **	−0.006 (0.010)	−0.006 (0.010)	−0.006 (0.010)	0.016 (0.009)	0.013 (0.009)	0.014 (0.009)	0.014 (0.009)
Age^2	0.000 (0.000) *	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Dayshift	0.301 (0.085) ***	0.085 (0.149)	0.104 (0.151)	0.105 (0.151)	0.389 (0.089) ***	0.182 (0.137)	0.164 (0.139)	0.163 (0.139)
Weekday	−0.054 (0.062)	0.095 (0.067)	0.097 (0.069)	0.097 (0.069)	−0.025 (0.065)	0.216 (0.062) ***	0.220 (0.063) ***	0.219 (0.063) ***
Month	Included	Included	Included	Included	Included	Included	Included	Included
DRG	Included	Included	Included	Included	Included	Included	Included	Included
Observations	1434	1123	1123	1123	1434	1123	1123	1123
Adjusted R^2	0.13	0.13	0.13	0.13	0.18	0.06	0.08	0.08

Notes: Standard errors in parentheses.

Significance levels:

(*) $p < 0.05$

(**)$p < 0.01$

(***)$p < 0.001$.

Table 6

Predictors of Intensive Care Unit (ICU) Bounceback (return to ICU during index hospitalization) at Both Hospitals

	P(Bounceback)					
	(7)	(8)	(9)	(10)	(11)	(12)
	Both	**Both**	**Both**	**Both**	**Hospital B**	**Hospital B**
Service		1.001 (0.001)		1.001 (0.001)	0.998 (0.001)	0.998 (0.001)
Boarding		0.999 (0.004)		1.001 (0.004)	0.998 (0.006)	0.999 (0.006)
OccupancyICUQ2			1.066 (0.242)	1.065 (0.242)	1.085 (0.341)	1.194 (0.382)
OccupancyICUQ3			1.276 (0.277)	1.256 (0.273)	1.475 (0.435)	1.559 (0.477)
OccupancyICUQ4			1.138 (0.430)	1.102 (0.423)		
OccupancyWardQ2			0.734 (0.170)	0.738 (0.172)	0.614 (0.211)	0.617 (0.220)
OccupancyWardQ3			0.586 (0.140)*	0.591 (0.143)*	0.748 (0.243)	0.814 (0.271)
OccupancyWardQ4			0.689 (0.180)	0.694 (0.184)	0.791 (0.281)	0.865 (0.317)
ICUQ4 × WardQ4			0.767 (0.464)	0.785 (0.477)		
HospitalA	0.781 (0.180)	0.784 (0.181)	0.801 (0.197)	0.811 (0.200)		
Severity					4.025 (2.648)*	5.086 (3.395)*
OtherSeverity						8.302 (12.87)
ED	0.503 (0.091)***	0.509 (0.093)***	0.505(0.092)***	0.510 (0.093)***	0.448 (0.120)**	0.418 (0.116)**
Medicaid	0.644 (0.164)	0.637 (0.162)	0.631 (0.161)	0.626 (0.160)	0.517 (0.181)	0.482 (0.172)
Medicare	1.061 (0.240)	1.052 (0.238)	1.054 (0.239)	1.048 (0.238)	1.130 (0.360)	1.023 (0.332)
Age	1.059 (0.033)	1.057 (0.033)	1.061 (0.033)	1.058 (0.033)	1.201 (0.065)***	1.192 (0.065)**
Age^2	0.999 (0.000)*	0.999 (0.000)*	0.999 (0.000)*	0.999 (0.000)*	0.998 (0.000)***	0.998 (0.000)***
Dayshift	2.307 (1.105)	2.302 (1.105)	2.353 (1.135)	2.351 (1.138)	0.786 (0.540)	0.775 (0.540)
Weekday	0.620 (0.111)**	0.608 (0.109)**	0.661 (0.122)*	0.647 (0.120)*	1.095 (0.309)	1.099 (0.318)
Month	Included	Included	Included	Included	Included	Included
DRG	Included	Included	Included	Included	Included	Included
Observations	2475	2475	2475	2475	1033	1033
Pseudo R^2	0.10	0.10	0.11	0.11	0.16	0.16

Notes: Odds ratios based on logistic regressions. Standard errors in parentheses.

Significance levels:

(*) $p < 0.05$

(**) $p < 0.01$

(***) $p < 0.001$.

Table 7

Predictors of In-Hospital Death after Transfer from Intensive Care Unit (ICU) to Wards at Both Hospitals

	P(Death)					
	(7)	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
	Both	**Both**	**Both**	**Both**	**Hospital B**	**Hospital B**
Service		1.003 (0.001)***		1.003 (0.001)***	1.004 (0.001)***	1.004 (0.001)***
Boarding		0.999 (0.003)		1.001 (0.003)	0.997 (0.005)	0.997 (0.005)
OccupancyICUQ2			0.857 (0.161)	0.866 (0.164)	1.084 (0.290)	1.116 (0.302)
OccupancyICUQ3			1.293 (0.229)	1.240 (0.222)	1.298 (0.331)	1.340 (0.350)
OccupancyICUQ4			1.084 (0.342)	1.016 (0.330)		
OccupancyWardQ2			0.756 (0.146)	0.754 (0.148)	0.408 (0.116)**	0.411 (0.119)**
OccupancyWardQ3			0.537 (0.107)**	0.548 (0.111)**	0.353 (0.099)***	0.359 (0.101)***
OccupancyWardQ4			0.672 (0.141)	0.682 (0.145)	0.283 (0.086)***	0.291 (0.089)***
ICUQ4 × WardQ4			0.689 (0.341)	0.684 (0.348)		
HospitalA	0.497 (0.096)***	0.518 (0.101)***	0.511 (0.104)**	0.540 (0.112)**		
Severity					25.12 (13.44)***	28.25 (15.31)***
OtherSeverity						0.282 (0.401)
ED	0.283 (0.043)***	0.285 (0.044)***	0.281 (0.043)***	0.283 (0.044)***	0.259 (0.062)***	0.264 (0.065)***
Medicaid	0.557 (0.117)**	0.535 (0.114)**	0.549 (0.116)**	0.530 (0.114)**	0.444 (0.133)**	0.429 (0.130)**
Medicare	0.545 (0.104)**	0.533 (0.103)**	0.543 (0.104)**	0.535 (0.104)**	0.465 (0.134)**	0.464 (0.136)**
Age	1.047 (0.027)	1.047 (0.028)	1.048 (0.027)	1.047 (0.028)	0.991 (0.036)	0.992 (0.037)
Age^2	1.000 (0.000)	1.000 (0.000)	1.000 (0.000)	1.000 (0.000)	1.000 (0.000)	1.000 (0.000)
Dayshift	0.942 (0.272)	0.926 (0.269)	0.920 (0.268)	0.905 (0.266)	2.978 (2.310)	2.874 (2.237)
Weekday	1.380 (0.230)	1.304 (0.219)	1.509 (0.260)*	1.421 (0.246)*	2.050 (0.540)**	2.029 (0.544)**
Month	Included	Included	Included	Included	Included	Included
DRG	Included	Included	Included	Included	Included	Included
Observations	2465	2465	2465	2465	1056	1056
Pseudo R^2	0.14	0.16	0.15	0.17	0.25	0.25

Notes: Odds ratios based on logistic regressions. Standard errors in parentheses.

Significance levels:

(*) $p < 0.05$

(**) $p < 0.01$

(***) $p < 0.001$.

Table 8

Predictors of 30-day Hospital Readmission at Both Hospitals

	P(Readmission)					
	(7)	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
	Both	**Both**	**Both**	**Both**	**Hospital B**	**Hospital B**
Service		0.998 (0.001)**		0.998 (0.001)**	0.998 (0.001)	0.998 (0.001)
Boarding		1.002 (0.003)		1.001 (0.003)	1.007 (0.004)	1.006 (0.004)
OccupancyICUQ2			0.901 (0.121)	0.889 (0.120)	0.774 (0.166)	0.746 (0.163)
OccupancyICUQ3			1.000 (0.132)	1.014 (0.135)	1.001 (0.201)	0.940 (0.194)
OccupancyICUQ4			0.873 (0.173)	0.890 (0.179)		
OccupancyWardQ2			1.286 (0.183)	1.283 (0.184)	1.143 (0.273)	1.190 (0.294)
OccupancyWardQ3			1.202 (0.173)	1.182 (0.173)	1.071 (0.250)	1.158 (0.279)
OccupancyWardQ4			1.087 (0.177)	1.072 (0.178)	0.958 (0.245)	1.031 (0.273)
ICUQ4 × WardQ4			0.799 (0.243)	0.807 (0.246)		
HospitalA	1.554 (0.234)**	1.488 (0.227)**	1.631 (0.256)**	1.549 (0.245)**		
Severity					0.393 (0.230)	0.421 (0.250)
OtherSeverity						2.820 (3.093)
ED	1.090 (0.113)	1.054 (0.110)	1.090 (0.114)	1.055 (0.111)	1.176 (0.199)	1.167 (0.202)
Medicaid	1.570 (0.241)**	1.573 (0.242)**	1.557 (0.240)**	1.556 (0.240)**	1.284 (0.316)	1.190 (0.298)
Medicare	1.670 (0.245)***	1.670 (0.245)***	1.673 (0.246)***	1.669 (0.246)***	1.693 (0.417)*	1.614 (0.403)
Age	1.054 (0.018)**	1.055 (0.018)**	1.054 (0.018)**	1.055 (0.018)**	1.050 (0.032)	1.054 (0.033)
Age^2	1.000 (0.000)***	1.000 (0.000)***	1.000 (0.000)***	1.000 (0.000)***	1.000 (0.000)	0.999 (0.000)
Dayshift	1.008 (0.181)	1.010 (0.181)	1.006 (0.182)	1.006 (0.182)	0.983 (0.417)	1.106 (0.494)
Weekday	1.010 (0.113)	1.012 (0.114)	1.025 (0.120)	1.030 (0.120)	1.097 (0.214)	1.076 (0.214)
Month	Included	Included	Included	Included	Included	Included
DRG	Included	Included	Included	Included	Included	Included
Observations	2536	2536	2536	2536	1089	1089
Pseudo R^2	0.04	0.05	0.05	0.05	0.05	0.06

Notes: Odds ratios based on logistic regressions. Standard errors in parentheses.

Significance levels:

(*) $p < 0.05$

(**) $p < 0.01$

(***) $p < 0.001$.

Author Manuscript
Author Manuscript
Author Manuscript