Impact of Severity-Adjusted Workload on Health Status of Patients Discharged from an ICU

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Abstract

We examine whether workload has an impact on a direct measure of the health status of patients discharged from Intensive Care Units (ICUs). We use data collected from the medical ICU and the surgical ICU of a major teaching hospital and a relatively new measure of patient acuity called the Rothman Index (RI). The RI is frequently updated during a patient's hospital stay, which enables us to track patients health status very close to the time of their ICU discharge. Leveraging the RI, we measure ICU workload in a novel way that takes into account not only the census but also patient acuity. To our knowledge, this is the first study to show that more acutely ill patients are discharged from an ICU when the severity-adjusted workload is high rather than low. Further, we find that higher severity-adjusted workload is associated with ICU discharge times that start earlier and end later, a shorter ICU length-of-stay (LOS), and an increased likelihood of discharge to a step-down unit. We also find that downstream unit census influences the effect of workload on health status at ICU discharge.

Keywords: empirical operations management; healthcare delivery; intensive care units; severity-adjusted workload; congestion

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1 Introduction

Intensive Care Units (ICUs) are inpatient units that provide the highest level of care in hospitals for critically ill patients. ICUs usually have high utilization, stochastic arrivals, and stochastic patient healing processes, which make it inevitable at times for the demand for ICU care to exceed the capacity of the ICU

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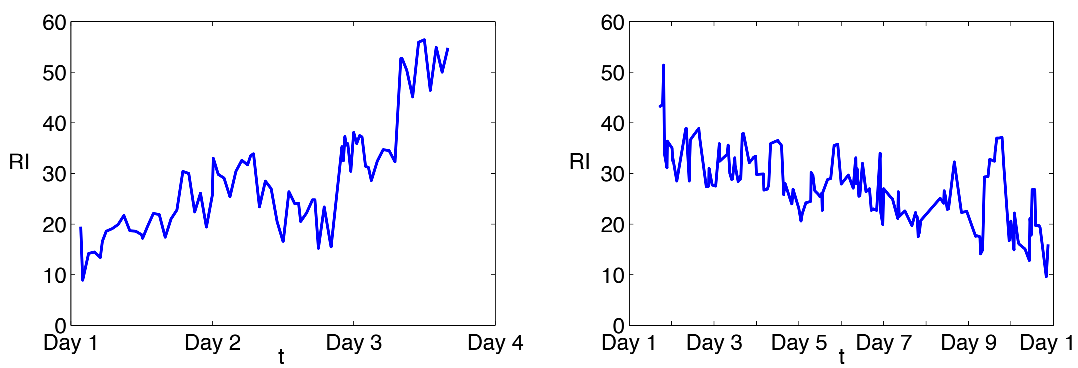
(Iwashyna et al. 2009). Such high workload has been shown to influence care providers to behave adaptively to alleviate the pressure—e.g., discharging patients from the ICU prematurely (Kc and Terwiesch 2012)—and to be associated with greater risk of adverse events—e.g., human error or hospital-acquired infection (Tarnow-Mordi et al. 2000).

It is, however, not yet known whether there is a *direct* association between high workload in an ICU and the health status of patients being discharged from such an ICU. That is, are patients more acutely ill if they leave from an ICU with high workload? In this paper we report on our study of this question, using patient data collected from two ICUs—a Medical ICU and a Surgical ICU—of a large urban U.S. teaching hospital. We take advantage of a relatively new measure of patient acuity called the *Rothman Index* (RI) (Rothman et al. 2013). The novelty of the RI is that in hospitals that implemented the RI system, patients' RIs are automatically calculated from the electronic medical record data and are updated frequently throughout the patients' hospital stays.[1] In our data, patients' RIs were updated every hour while in ICUs, allowing us to track the health status of patients very close to the time of their discharge from an ICU and to examine its direct association with workload.

As an example, Figure 1 shows the changes in RI of two medical ICU patients in our data. More information about the patients appears in Table 1. The patient on the left came into the ICU with a low RI (lower RI indicates poorer condition—see Section 2.1 for a detailed description of RI), stayed for 4 days, and left with a high RI, whereas the patient on the right came into the ICU with a higher RI, stayed for 11 days, and left with a low RI. In other words, the sicker patient (the patient on the left) stayed a shorter time in the ICU but left healthier than the other patient (the patient on the right) who came in healthier. This example illustrates that a longer stay does not necessarily result in improved health status, and thus highlights the need to look beyond the impact of workload on LOS and to examine the direct association between workload and health status.

Figure 1: Rothman Index Scores of Two Medical ICU Patients



[1] A recent Wall Street Journal article discusses the use of the RI: Landro, L. (2015, May 25). Hospitals Find New Ways to Monitor Patients 24/7. Wall Street Journal. Retrieved from http://www.wsj.com.

Table 1: Patient Characteristics of the Two Medical ICU Patients

	Patient on the left	Patient on the right
Age	> 80	> 80
Gender	A	B
Primary Diagnosis	410.71 (Subendocardial infarction)	569.3 (Hemorrhage of rectum and anus)
Primary Procedure	37.22 (Left heart cardiac catheterization)	57.94 (Insertion of indwelling urinary catheter)
DRG	280 (Acute Myocardial Infarction with MCC)	377 (GI hemorrhage with MCC)
# Comorbidities	7	1
ED Admit	Yes	Yes
Payer Medicare	Medicare	
In-hospital death	No	No
Hospital LOS	7 days	14 days

Note. MCC stands for Major Complications or Comorbidities.

Furthermore, we leverage the RI to measure the ICU workload in a new way that takes into account not only the *census* (in other words, the ICU occupancy) but also *how acutely ill* the patients are. The traditional way of defining workload is looking at the patient census only (e.g., see Kc and Terwiesch (2012) and Kim et al. (2015)). However, the acuity of patients in an ICU often varies widely, and the higher-acuity patients require more time and attention of the physicians and nurses, generating more workload (Welton 2007, Miranda and Jegers 2012). For instance, the care an ICU patient receives when he is surrounded by ten very ill patients might differ from the care he receives when he is instead surrounded by ten moderately sick patients, assuming staffing is the same. This impact of patient acuity, alone or in combination with other factors (e.g., census), may drive many of the behaviors of hospital staff, but is understudied. It is even possible that patient acuity is affecting behavior in ways in which hospital staff not aware. We shed light on this, which we think will allow for better management of patients.

1.1 Literature Review

In the operations management literature, there has been an increasing interest in empirically studying the impact of workload on system performance. Many of the studies were conducted in hospital settings. For example, studies examined the impact of emergency room workload on nurse absenteeism rates (Green et al. 2013), on ambulance diversion (Allon et al. 2013), and on service times (Kuntz and Sülz 2013, Batt and Terwiesch 2014). By examining a patient transport service system and a cardiothoracic surgery system, Kc and Terwiesch (2009) studied the impact of workload on service times and quality of care. Freeman and colleagues (2015) examined the impact of workload on resource use and cost of care in a maternity unit. Studies also examined the impact of workload at the hospital level or the hospital department level on the accuracy of hospital discharge coding (Powell et al. 2012), on in-hospital mortality (Kuntz et al. 2015), and on service times (Jaeker and Tucker 2015). Outside of the healthcare operations management literature, Hasija and colleagues (2010) examined the impact of workload in an email contact center on agents' service times and Tan and Netessine (2014) examined the impact of workload in a restaurant chain on servers' sales efforts.

More closely related studies to this paper examined the impact of workload in ICU settings. Studies in both the operations management literature and the medical literature showed that ICU workload is an important factor affecting ICU admission decisions. That is, patients, who would have received ICU care otherwise, were not admitted to the ICU because of high workload and limited capacity (e.g., see Singer et al. (1983), Robert et al. (2012) and Kim et al. (2015)). Given that ICU care must be "rationed" at such times, studies investigated how the rationing could be done in the most effective way. For instance, a number of ICU admission policies were proposed and their performance was evaluated on optimizing various patient outcomes such as mortality and subsequent hospital LOS (Shmueli et al. 2003, Kim et al. 2015). We note that we do not examine the impact of workload on patients' admissions to ICUs in this paper; we study the impact of ICU workload on the care provided to patients *after* ICU admission.

Studies that examined the impact of ICU workload on patients already in the ICU, then, are the most relevant studies to this paper. For instance, in their influential paper in the operations management literature, Kc and Terwiesch (2012) showed that patients discharged when an ICU had high workload had a shorter ICU LOS, which in turn led to a higher chance of getting readmitted to the ICU later in their hospital stay. Their finding implied that congestion in the ICU shortened the care for some patients, which led to worse patient outcomes in the sense that these patients were more likely to need further ICU care. On a similar note, Anderson and colleagues (2011) investigated daily discharge rates from a surgical ICU and found higher discharge rates on days with high census and more scheduled surgeries. This "premature" discharge from an ICU due to high workload has been recognized as a problem in many ICUs, and models that optimize the ICU discharge process have been developed (Dobson et al. 2010, Chan et al. 2012). On the other hand, Long and Mathews (2015) separated the ICU LOS into service time and time-to-transfer, and showed that high workload led to a shorter time-to-transfer, but did not affect the service time. Their findings suggest that workload does not influence the care provided to the patients.

The medical literature has more mixed evidence for the impact of workload in ICUs. For example, Tarnow-Mordi and colleagues (2000) found that ICU patients exposed to high workload were more likely to die than patients exposed to low ICU workload. Chrusch and colleagues (2009) found that occupancy based markers of unit activity are associated with an increased likelihood of early death or ICU readmission. On the contrary, Iwashyna and colleagues (2009) found that patients admitted on high census days had the same odds of in-hospital mortality as patients admitted on average or on low census days. Also, Wagner and colleagues (2013) found no association between ICU workload and long-term outcomes, including subsequent in-hospital mortality, post-ICU discharge LOS, and hospital discharge destination.

1.2 Our Main Contributions

We now explain our main contributions, in relation to the previous literature. **First**, we show the *direct* relationship between high workload in an ICU and the health status of patients being discharged from such an ICU. Specifically, we find that more acutely ill patients are discharged from the ICU when the workload is high rather than low.

Previous studies have examined the relationships between high workload in an ICU and *proxies* for health status (e.g., ICU LOS in Kc and Terwiesch (2012), in-hospital mortality in Wagner et al. (2013), and ICU readmission in Chrusch et al. (2009)), but could not examine the direct relationship of workload and health status because they used static acuity measures that fail to track the changes in patient condition. For example, the Euroscore (2007), which measures the risk of death based on patient information before undertaking a heart operation, was used by Kc and Terwiesch (2012). Most of the severity scoring systems within ICUs—including the Acute Physiology and Chronic Health Evaluation (APACHE), Simplified Acute Physiology Score (SAPS), and Mortality Prediction Model (MPM)—are static, and are often computed within 24 hours of admission of a patient to an ICU (Strand and Flaatten 2008).

In contrast, the RI tracks patients' condition changes, and allowed us to track the acuity of the patients at discharge from the ICU. Chrusch and colleagues (2009), in fact, acknowledge such need to look at health status at discharge (on page 2756): "Consideration could be given to using a score to further adjust for patient acuity at the time of discharge, such as acute physiology scores, nursing workload measures, or organ dysfunction scores." To our knowledge, we are the first to examine the direct relationship between high workload in an ICU and the health status of patients being discharged from such an ICU. Our analysis finds a negative health impact on patients even when excluding those patients who subsequently died in the hospital. That is, this is a measurable impact that affects a broad range of patients.

Second, we introduce a new workload measure that takes into account patient acuity in addition to census and show that it is a better workload measure than census alone. We show, by dividing high census days using the percentage of acute patients in the ICU, that the effects of high census on the health status of patients discharged from an ICU are driven by the cases with a higher percentage of acute patients. That is, we find that it is not high census that affects health status at discharge; it is a high census of more acute patients. Using a simulation model we show that this effect can be explained by sampling, and not necessarily a diminished quality of care. When an ICU has many high acuity patients and space is needed, it is more likely that a patient who is healthier relative to other patients will be discharged earlier than he otherwise would have been.

Previous literature suggests that hospitals might want to avoid reaching high occupancy levels to prevent their adverse influence on patient care and outcomes. Our results suggest that it is high occupancy levels *with* many high acuity patients hospitals want to avoid, because having high occupancy levels with many low acuity patients might not be as problematic.

We note that Wagner and colleagues (2013) also included patient acuity in their ICU workload definition; they averaged the acuity of patients in the ICU, based on individual severity of illness scores calculated on the day of ICU admission. Because patients' condition changes throughout ICU stays (e.g., see Figure 1), we believe our workload measure based on patients' hourly-updated conditions gives a more accurate measure of ICU workload. In addition, Tarnow-Mordi and colleagues (2000) used patient census and nursing requirement[2] suggested by the UK Intensive Care Society based on patients' condition to define workload. However, nursing workload is only a partial view of the workload in an ICU; for instance, nursing workload does not take into account physicians' activities.[3] We believe our new measure of ICU workload is a more adequate measure of ICU workload compared to the existing measures.

Third, we show that workload has an impact on the number and timing of discharges from the ICU. In particular, we find that when workload is high, first discharge of the day tends to be earlier whereas the last one tends to be later. These empirical findings and discussions with clinicians reveal that when workload is high in the ICU, the ICU clinicians start transfers early (i.e., there is a speed up of transfer to downstream units when workload is high). On the other hand, we observe that high census in downstream units is associated with longer ICU LOS and better health status upon ICU discharge. This is contrary to the finding of Chrusch et al. (2009), which showed no interaction effect between ICU census and other unit census. Taken together these findings indicate that the interaction between ICUs and downstream units is an important consideration when improving patient flow and care. We note that Johnson and colleagues (2013) and Long and Mathews (2015) showed that downstream congestion is a major cause of delays in ICU discharges; we, in addition, are able to show that this directly influences the health status of patients at the time of discharge from the ICU.

Fourth, we show that the impact of ICU workload could differ from one ICU to another. We study two ICUs—a MICU and a SICU—in the same hospital, and show that the impact of workload in the two ICUs are different in magnitude and in how ICU workload interacts with the workload of downstream units. We speculate that these differences could be due to a number of factors including patient type (e.g., medical

[2]In fact, there have been efforts to measure nursing workload in the intensive care unit, including the Therapeutic Intervention Scoring System (TISS) and the Nursing Activities Score (NAS); see Miranda et al. (2003) for details.

[3]An instrument for measuring the physicians activities is not yet available (Miranda and Jegers 2012).

versus surgical patient), size of the ICU, different workplace culture (e.g., closed ICU versus open ICU—see more discussions in Section 4.4), and access to downstream beds. Our findings suggest that a blanket statement on the impact of workload in ICUs, which is often done in the operations management literature, could be misleading. Future work should seek to understand how different characteristics of ICUs interact with workload to influence patient care and health status.

1.3 Organization

The rest of this paper is organized as follows. In Section 2, we describe our dataset, the two ICUs we examine, and the sample we use for our analyses and introduce our new measure of workload. In Section 3, we present our hypotheses and econometric model. We present our results in Section 4. We conclude and present future research directions in Section 5.

2 Setting

2.1 Data

We collected hospitalization data for every adult patient who received care in the Medical ICU (MICU) or the Surgical ICU (SICU) at a major U.S. teaching hospital over the course of 15 months. For each hospitalization, we had the patient's age, gender, principal and secondary diagnoses (identified by the ICD-9 codes), principal and secondary procedures (identified by the ICD-9 procedures codes) and their dates, DRG classification, payor, in-hospital death, and discharge dispositions. We generated 30 comorbidity indexes (e.g., diabetes) using the ICD-9 codes and the DRG classification (Elixhauser et al. 1998). The data also included every unit the patient visited along with unit admission and discharge dates and times, including hospital admission and discharge date and time.

In addition, a key feature of our data was the availability of the patient's *Rothman Index* (RI) scores throughout each hospitalization. The RI score is a composite measure updated regularly from the electronic medical record based on changes in 26 clinical measures including vital signs, nursing assessments, Braden score, cardiac rhythms, and laboratory test results; see Rothman et al. (2013) for details. This score is independent of diagnosis, and it was developed to be used for any inpatient (i.e., medical or surgical patients including critical care patients). With a theoretical range from -91 to 100, the majority of patients on a general medical or surgical unit fall within the range from 0 to 100, with lower scores indicating poorer condition. Studies have shown that the RI score is associated with 24-hour mortality, 1-year mortality, APACHE III score, and discharge disposition (Rothman et al. 2013); 30-day hospital readmission rates (Bradley et al. 2013); post-operative complications for colorectal surgery (Tepas et al. 2013); unplanned ICU transfers (Danesh et al. 2012); and unplanned SICU readmissions (Piper et al. 2014). The RI score has also been shown to outperform the Modified Early Warning Score (MEWS)—widely used in hospitals to early detect clinical deterioration—in identifying patients who are likely to die within 24 hours (Finlay et al. 2014).

We note that during our data collection period, physicians could access patients' RI scores by clicking a few buttons on the hospital's electronic medical record system. Because the RI scores were recently introduced to this hospital, the physicians did not regularly view the RI during our data collection period, and their admitting, observation, and discharge decisions were not influenced by the RI scores.

2.2 The Two Intensive Care Units

The MICU had 36 staffed beds, and the SICU had 21 staffed beds during our study period. The initial data include 3,713 MICU visits and 1,842 SICU visits during the initial 15 months period. We utilize patient flow data from all of these visits to compute the census changes in the MICU and the SICU, respectively. We then restrict our study to the one year in the center of the period, from 2/1/2013 to 1/31/2014, to avoid censored estimation of census.

Table 2 provides the summary statistics for daily arrivals, discharges, and workload for the two ICUs in our one year study period. The MICU has an average of nearly 9 new arrivals (and discharges) each day and the SICU has approximately 4. The largest source of MICU patients is the emergency room (about 50%) whereas for the SICU it is the operating room (about 40%). After ICU care, most of the patients—85% of the MICU patients and 88% of the SICU patients—are transferred out to step-down units, general wards, or discharged from the hospital.

Because we know every patient's visited units and RI trajectories, we can compute not only the census of the MICU and the SICU at any point in time, but also the RIs of the patients in the same unit at any point in time. We measure the daily *workload* of the MICU and of the SICU using the following two variables: (1) the daily average *census* and (2) the daily average percentage of *more acutely ill* patients. We define a patient to be 'more acute' if her RI is less than or equal to 50, which is approximately the average RI upon ICU admission of patients who are visiting the MICU or the SICU for the first time during their hospitalizations (see Table 3).

Table 2 shows that on average, about 32 of the 36 staffed beds in the MICU are occupied and about 17 of the 21 staffed beds in the SICU are occupied. Furthermore, for 25% of the days in our study period, the MICU has about 34 or more patients and the SICU has about 18 or more patients. We have learned that extra licensed beds in the two ICUs allow the ICUs to temporarily keep more patients than the number of the staffed beds; the maximum values of the 'Daily Avg Census' suggest that this does happen, especially in the MICU.

Table 2: Summary Statistics for Daily Arrivals, Discharges, and Workload in the MICU and the SICU. N = 365 days.

	MICU				SICU			
	Mean (Std)	Median	75th pct	Max	Mean (Std)	Median	75th pct	Max
# Daily Arrivals	8.9 (2.8)	9	11	18	4.3 (2.2)	4	6	13
from operating room	0.1 (0.3)	0	0	2	1.7 (1.4)	1	2	8
from emergency room	4.4 (2.1)	4	6	12	1.3 (1.1)	1	2	6
from step-down/wards/other ICUs	3.8 (1.7)	4	5	9	1.2 (1.1)	1	2	6
direct	0.7 (0.9)	1	1	5	0.2 (0.4)	0	0	2
# Daily Discharges	8.9 (2.7)	9	11	16	4.3 (2.0)	4	6	12
to step-down/wards/hospital discharge	7.6 (2.4)	7	9	14	3.8 (1.9)	4	5	11
in-unit death	0.99 (1.02)	1	2	5	0.21 (0.46)	0	0	3
to another ICU	0.33 (0.59)	0	1	4	0.23 (0.48)	0	0	3
to operating room*	0.04 (0.20)	0	0	2	0.04 (0.21)	0	0	2
Daily Avg Census	32.1 (3.3)	32.8	34.6	39.5	16.3 (2.7)	16.9	18.3	20.8
Daily Avg % Patients with RI $\leq$ 50	80.9 (6.2)	81.0	85.5	99.1	76.2 (9.2)	76.8	82.9	97.4

* This number includes patients who went to the operating room but was later readmitted to the ICU post-operatively. We note that clinicians would not consider such cases as ICU discharges.

We compute 'Daily Avg % Patients with RI $\leq$ 50' by tracking changes in the census and the number of patients with RI $\leq$ 50. For instance, if there are 32 patients in the MICU at 8 am and 24 of them have their RI $\leq$ 50, the percentage of more acute patients at 8 am is 75%. If one patient's RI increases from 45 to 55 at 8:40 am with other things being equal, the percentage of more acute patients drops to 72% at 8:40 am. We then compute the time-weighted average of these percentages over each day to get the 'Daily Avg % Patients with RI $\leq$ 50'. From Table 2, we observe that its average is 81% in the MICU and about 77% in the SICU. That is, on average, about 4 out of 5 patients are 'more acute' than an average first-time ICU patient. This high proportion of 'more acute' patients is due to the fact that (1) patients who are more (less) acute tend to stay longer (shorter) in the ICU, affecting the time-weighted average and that (2) patients who are not first-time ICU patients tend to be more acute than an average first-time ICU patient.

2.3 Sample Selection and Summary Statistics

In examining the impact of workload on ICU care, we attempt to eliminate possible confounding events by restricting our sample as detailed in Table 9 in the appendix. (However, all patients in our data are considered when we compute the workload measures.) There are 3,218 MICU visits and 1,556 SICU visits during our one year study period. A patient can have more than one ICU visit during a hospitalization, and we focus on only the first ICU visit. We then exclude transfers from neighboring hospitals, because we do not have enough information on what care the patient received at the previous hospital or during the transfer. We exclude MICU and SICU visits that are followed by an admission to a different ICU; the hospital we study has three additional ICUs—a cardiac ICU, a cardiac-thoracic ICU, and a neuro ICU. We have learned from the clinicians in the MICU and the SICU that these patients are usually patients with multiple complications, and that such patients are transferred to other special ICUs after the MICU or the SICU to receive additional specialized ICU care. We exclude visits whose next units are the operating room, interventional radiology, catheterization and electrophysiology (Cath/EP), or hemodialysis, because deciding when to send a patient to these next units are unlikely to be affected by the ICU workload. We exclude visits whose length-of-stays are outliers: shorter than 12 hours or longer than 21 days. We also exclude visits that are preceded by hospital stays longer than 7 days, because it is likely that such ICU visits could be due to hospital-acquired complications that might not be well explained by our data. We exclude visits that do not have any RI information. Lastly, we want to exclude the visits of the "too-sick-to-benefit" patients, i.e. patients who might be receiving "comfort measures only (CMO)". As a proxy we remove patients who die later in the hospitalization or patients who are later discharged to hospice. We exclude these patients because the way workload affects their care must be different from the way workload affects the "normal" patients. We note, however, that we find very similar results when we include these patients in our analysis.

Table 3: Summary Statistics of Patient's Health Status, ICU Care, and Workload Measures for the MICU and SICU Patients

	MICU (N=1816 patients)				SICU (N=1030 patients)			
	Mean (Std)	Min	Median	Max	Mean (Std)	Min	Median	Max
RIE_i (RI at ICU Arrival)	45.7 (20.8)	-19.4	44.7	97.1	51.9 (18.5)	-15.2	51.3	97.4
RIX_i (RI at ICU Discharge)	53.4 (20.0)	-10.2	53.2	96.8	57.6 (16.3)	8.1	57.7	98.3
$I(RIX > RIE)_i$ (Whether $RIX_i > RIE_i$)	66.5%				63.4%			
$ICULOS_i$ (ICU LOS in days)	2.9 (2.7)	0.5	1.9	20.2	3.1 (3.0)	0.5	2.0	20.0
$I(SD)_i$ (Whether next unit is a step-down)	8.6%				18.1%			
$CensusX_i$ (Avg census on discharge day)	31.8 (3.1)	18.3	32.5	39.0	16.1 (2.4)	6.0	16.7	20.4
$MoreAcuteX_i$ (Avg % more acute on discharge day)	80.9 (6.3)	61.0	81.0	97.2	75.9 (9.2)	46.5	76.6	100.0

Our final sample consists of 1,816 MICU visits and 1,030 SICU visits, whose summary statistics for the variables of interest are provided in Table 3 (see Table 10 in the appendix for the summary statistics of other variables). The mean RI at ICU arrival (RIE_i—"E" representing entry) is 45.7 in the MICU and 51.9 in the SICU, whereas the mean RI at ICU discharge (RIX_i—"X" representing exit) is 53.4 in the MICU and 57.6 in the SICU. Approximately 65% of the patients in both the MICU and the SICU have higher RI upon ICU discharge compared to the RI at ICU arrival; i.e., about 65% of the patients have improved health status after the ICU stay. Patients stay 2.9 days in the MICU and 3.1 days in the SICU on average; the ICU LOS distributions have heavy tails and the medians are approximately 2 days for both ICUs. Approximately 9% of the MICU patients and 18% of the SICU patients are transferred to a step-down (SD) unit upon ICU discharge, instead of being transferred to a general ward or being discharged from the hospital. This difference in the use of step-down units by the MICU and the SICU could be due to the inherent difference in the care for medical versus surgical patients as well as due to the number of available step-down beds; there are 15 step-down beds where the MICU patients are usually sent to and 23 step-down beds for the SICU patients.

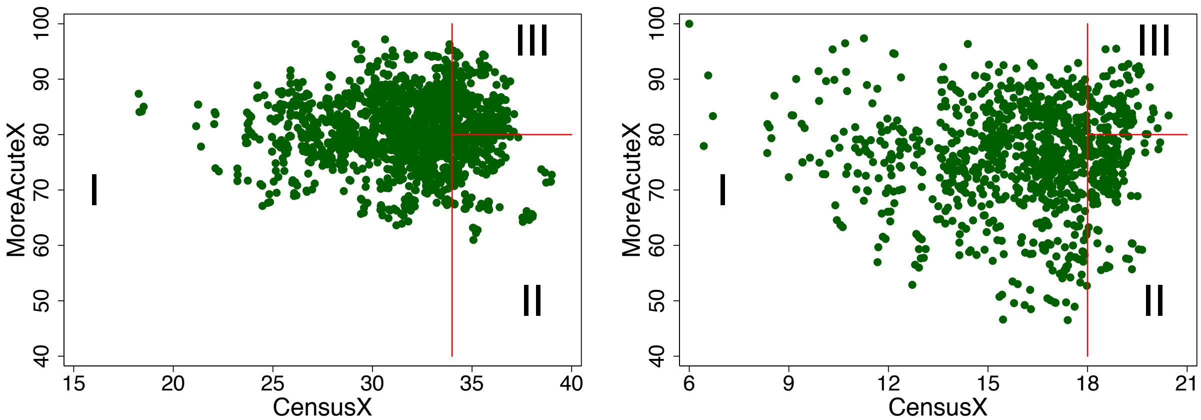
Table 3 also provides the summary statistics of our workload measures patient i experienced. We measure the daily average census on patient i's discharge day ($CensusX_i$—"X" representing exit) and the daily average percentage of more acute patients on patient i's discharge day ($MoreAcuteX_i$—"X" again representing exit). For instance, if a patient is discharged from the ICU on August 2, we track the changes in the census and the percentage of more acute patients during the 24 hours between 8/2 12:00 AM and 8/3 12:00 AM and compute the averages. $CensusX_i$ and $MoreAcuteX_i$ could be interpreted as the workload patient i is exposed to on her departure day. Note that we do not account for patient i's occupancy or RI in computing $CensusX_i$ and $MoreAcuteX_i$. Hence, two patients discharged on the same day will have different values for $CensusX_i$ and $MoreAcuteX_i$.

2.4 Defining Workload Zones in an ICU

In Section 2.3 we showed how we measure the ICU workload in two different ways using $CensusX_i$ and $MoreAcuteX_i$. We use these two variables to define workload zones used throughout this paper. First, we employ a threshold of 34 patients and 18 patients for the MICU and the SICU, respectively, to divide into 'low' census zone and 'high' census zone (this approach has been frequently used by other studies, including Kc and Terwiesch (2012) and Kim et al. (2015)). We then further divide the high census zone by whether the percentage of more acute patients is more than 80% or not. Figure 2 illustrates this idea: patients in zone I experienced low census on discharge day, patients in zone II experienced high census but smaller percentage of more acute patients, and patients in zone III experienced high census and higher percentage of more acute patients. Among the 1,816 MICU patients, 75% are in zone I, 12% in zone II, and 13% in zone III. Among the 1,030 SICU patients, 78% are in zone I, 13% in zone II, and 9% in zone III.

Previous studies have found evidence that ICU care differs in zone I versus zone II & III (e.g., see Kc and Terwiesch (2012)). Throughout this paper, we will make that comparison, but in addition will examine zone II and III separately, because we hypothesize that incorporating patient acuity in measuring workload can help us gain better understanding of the impact of workload. We have tried various other thresholds to define the workload zones; while different thresholds tell similar stories, the thresholds we choose give us a consistent definition across our two ICUs and also leaves enough data points in zones *II* and *III* for effective estimation.

Figure 2: Scatter plots of $CensusX$ and $MoreAcuteX$ and defining workload zones—I (low census), II (high census with smaller percentage of more acute patients), and III (high census with higher percentage of more acute patients)—in the MICU (left) and in the SICU (right)



3 Hypotheses Development and Econometric Model

3.1 Simulation Model for Hypotheses Development

In order to develop intuition about the impact of workload on patient discharge patterns from an ICU we propose a simple model of the operation of the unit and use discrete event Monte-Carlo simulation to generate hypotheses of what we should expect to see in our data if the model is correct. The main operating premise of our model is that the patient's health status is completely determined by the RI, that patients are discharged according to their RI which providers can perfectly discern and that new arrivals are given priority over current occupants of the ICU. None of these are completely true but give us a useful starting point for thinking about how workload affects patient flow through an ICU.

Our model operates as follows. Each day a patient stays in an ICU, the patient's RI changes by a random amount (which can be negative—i.e., the patient's health status can deteriorate). When a patient's RI exceeds a particular threshold they are ready for discharge to another less intensive unit of the hospital. We will call such patients: healthy. The implication of these assumptions is that a patient's LOS is tightly linked to the patient's RI at arrival to the unit. At the start of each day the care providers discharge all patients who are healthy. Then a random number of new patient arrivals is determined. If the number of new arrivals exceeds the number of available beds then the providers will discharge additional patients from the ICU who are not yet healthy. These additional (premature) discharges will be done in order of healthiest (highest RI) patients first. Each new arrival has an initial RI that is drawn from a distribution. Clearly the reality of an ICU is considerably more complex than the model we have described above. We elaborate on these complexities later but first explore the simple model because it will make it easier to interpret the empirical results.

3.2 Hypotheses

If the ICU operates as described we expect to see the following:

Hypothesis 1 Patients who are discharged when workload is low (workload zone I) will tend to be healthier (have higher RI) than patients discharged when the workload is high (workload zones II and III).

This is because when workload is high you are more likely to need to discharge a patient who is not yet healthy thus they have a lower RI.

Hypothesis 2 Similarly, the LOS of patients who are discharged when workload is low (workload zone I) will tend to be longer than those discharged when the workload is high (workload zones II and III).

Our model resumes that the care providers will discharge the healthiest patients available from among the current occupants even when making premature discharges. This will mitigate the impact of workload on the reduction in RI and LOS of discharged patients. We expect to see that mitigation by distinguishing between cases when a patient was discharged from an ICU that was crowded with many acute patients (workload zone III) versus one which was crowded with healthier patients (workload zone II). That is, we expect the following:

Hypothesis 3 Patients discharged in workload zone III will have lower RI and LOS than patients in zones I and II.

We conduct simulation experiments using parameter values derived from our data, and find that these hypotheses are consistent with our simulation results; the appendix provides details of the simulation experiments and their results. In practice, however, the simple operational model of an ICU behind our simulation study has a number of flaws and thus we cannot rely on it for estimates of the impact of workload on patients. First, we observe some evidence from out data that admissions to the MICU decline when workload is high (We note that Kim et al. (2015) had a similar finding). Second, in practice although the RI has been shown to be accurate it does not completely characterize patient health. Third, some patients die while in the ICU and particularly in the MICU there are patients who are too-sick-to-benefit from the ICU care and are discharged, violating the assumption that only the healthiest patients are discharged.

3.3 Econometric Model

We now describe the model we use to test our hypotheses. We are mainly interested in the following four measures: (1) RIX_i, RI at ICU discharge—this is a continuous variable with lower scores indicating poorer condition; (2) $I(RIX > RIE)_i$, whether RI at ICU discharge is greater than RI at ICU arrival—this is an indicator variable. Because the RI is a combination of many factors it is difficult to interpret the meaning of a change in RI of a few points. Therefore we also look at the probability of an improvement in the RI because it is easier to interpret as an improvement in the health status of a patient; (3) $log(ICULOS)_i$, length-of-stay in the ICU—as is standard practice, we take the logarithm of the length-of-stay in order to account for the heavy tail in its distribution; and (4) $I(SD)_i$, an indicator variable equal to 1 if the patient's next unit is a step-down unit instead of a general ward or hospital discharge.

We use the following model:

$$Y_i = \alpha WorkloadZone_i + \lambda FloorBusy_i + \beta Z_i + \epsilon_i, \tag{1}$$

where Y_i is the outcome of interest for patient i and $WorkloadZone_i$ is a categorical variable as defined in Figure 2. We apply this model separately to each ICU. In addition to $WorkloadZone_i$ that represents ICU workload, we include the variable $FloorBusy_i$ to control for the busyness of downstream units, because the availability of downstream beds could affect the care provided in the ICU (Long and Mathews 2015). To compute $FloorBusy_i$, we pool all of the beds in step-down units and general medical-surgical wards the MICU and the SICU patients, respectively, are usually transferred to and calculate their average occupancy during the 12 hours prior to patient i's discharge from the ICU. We then define $FloorBusy_i = 1$ if the average is above the 75th percentile of its distribution and $FloorBusy_i = 0$ otherwise. Z_i is a vector of control variables that include (1) patient characteristics: RI at ICU arrival, age, gender, 27 DRG group dummies, 30 Elixhauser comorbidity dummies, and 16 dummies for principal procedure classification if the principal procedure is done before ICU discharge day; (2) patient type descriptions: whether an emergency admission, payor type dummies, and dummies for the unit before ICU; and (3) seasonality dummies including ICU admission month, ICU admission time of day, and ICU discharge day of week. Lastly, ϵ_i is the error term that captures all other factors that influence Y_i other than the regressors $WorkloadZone_i$, $FloorBusy_i$, and Z_i. Table 10 in the appendix provides a comprehensive list of these control variables as well as their summary statistics.

We estimate (1) with linear regression when Y_i is a continuous variable—when $Y_i = RIX_i$ and $Y_i = log(ICULOS)_i$. When the outcome is a binary variable ($Y_i = I(RIX > RIE)_i$ and $Y_i = I(SD)_i$), we estimate (1) with logit regression. That is, the following specification is used:

$$logit(Pr(Y_i)) = ln\Big(\frac{Pr(Y_i)}{1 - Pr(Y_i)}\Big) = \alpha WorkloadZone_i + \beta Z_i. \quad (2)$$

4 Results

We present our results in this section. In Sections 4.1 and 4.2, we examine the discharge process in the MICU and the SICU in detail. In Sections 4.3 and 4.4, we examine the impact of workload using the econometric model described in Section 3 in the MICU and in the SICU, respectively.

4.1 RI and the Discharge Process

We first examine how much of a doctor's decision of whom to discharge from the ICU could be explained by the RI. That is, how often is the patient with the highest RI—the most medically stable patient according to the RI—discharged from the ICU? Because the RI scores allow us to track the changes in the RI of every patient in the ICU, for every patient i, we can extract not only patient i's RI when she was leaving the ICU (RIX_i), but also the RIs of the other patients in the ICU at the moment patient i was leaving.

We find that among the 1,816 MICU patients, approximately 14% had the highest RI in the MICU when they left the MICU. Among the 1,030 SICU patients, approximately 22% patients did. In addition, even if the patients did not have the highest RI when they were leaving the MICU or the SICU, they often had their RI higher than the majority of the patients in the ICU; on average, patients leaving from the MICU (SICU) had their RI higher than the 77th (79th) percentile of the patients currently in the MICU. This suggests that doctors are accurately taking into account the health status of the patients on deciding whom to discharge.

4.2 Impact of Workload on Discharges Times

We have shown, in Table 2, that patients can be discharged from the ICU in four different ways: to step-down/general wards/hospital discharge, in-unit death, to another ICU, or to operating room. For all of the analysis in this Section (Section 4), we only consider the transfers to step-down/general wards/hospital discharge, as they are the most likely to be affected by ICU workload.

We examine how workload in each *day* affects ICU discharges by examining the number of daily discharges and the times of the first, the median, and the last discharges of the day (see Table 4); in this subsection the unit of analysis is each day. During our study period of 365 days, there were 122 high census days (zones II & III) in the MICU and 111 high census days in the SICU. The high census days were fairly well spread across different days of the week, especially in the MICU. Among the 122 high census days in

Table 4: Mean number of daily discharges and mean discharge times by ICU workload zones.

	MICU						SICU					
Workload Zone	N	# dep	first t	median t	last t	interdep	N	# dep	first t	median t	last t	interdep
All patients going to step-down units/general wards/hospital discharge												
I, II, & III	365	7.6	8:04	15:28	20:46	1.7 hr	365	3.8	11:08	15:29	18:45	2.0 hr
I	243	7.3	8:43	15:32	20:33	1.6 hr	253	3.5	11:47	15:18	18:14	1.9 hr
II & III	122	8.2	6:46	15:22	21:12	1.8 hr	112	4.6	9:43	15:52	19:52	2.2 hr
II	53	8.5	7:10	15:45	21:46	1.7 hr	63	5.0	9:19	15:50	19:57	2.1 hr
III	69	8.0	6:27	15:04	20:46	1.8 hr	49	4.1	10:14	15:55	19:45	2.3 hr
Excluding too-sick-to-benefit patients (patients whose ultimate disposition is hospice and in-hospital mortality)												
I, II, & III	365	6.5	8:42	15:29	20:24	1.8 hr	365	3.6	11:16	15:28	18:37	2.0 hr
I	243	6.3	9:13	15:35	20:15	1.8 hr	253	3.3	11:53	15:15	18:05	1.9 hr
II & III	122	6.8	7:41	15:19	20:42	1.9 hr	112	4.3	9:57	15:56	19:44	2.3 hr
II	53	7.2	7:41	15:44	21:14	1.9 hr	63	4.6	9:50	15:52	19:51	2.2 hr
III	69	6.5	7:42	14:60	20:18	1.9 hr	49	3.8	10:07	15:60	19:35	2.5 hr

Note. Days with no discharges in the SICU are excluded when computing the mean discharge times. 'interdep' means inter-departure times.

the MICU, Fridays and Saturdays were the least presented days (14 Fridays and 14 Saturdays or 11.5%) and Tuesdays were the most presented days (22 Tuesdays or 18.0%). Among the 112 high census days in the SICU, Sundays were the least presented days (9 Sundays or 8.0%) and Wednesdays and Fridays were the most presented days (21 Wednesdays and 21 Fridays or 18.8%).

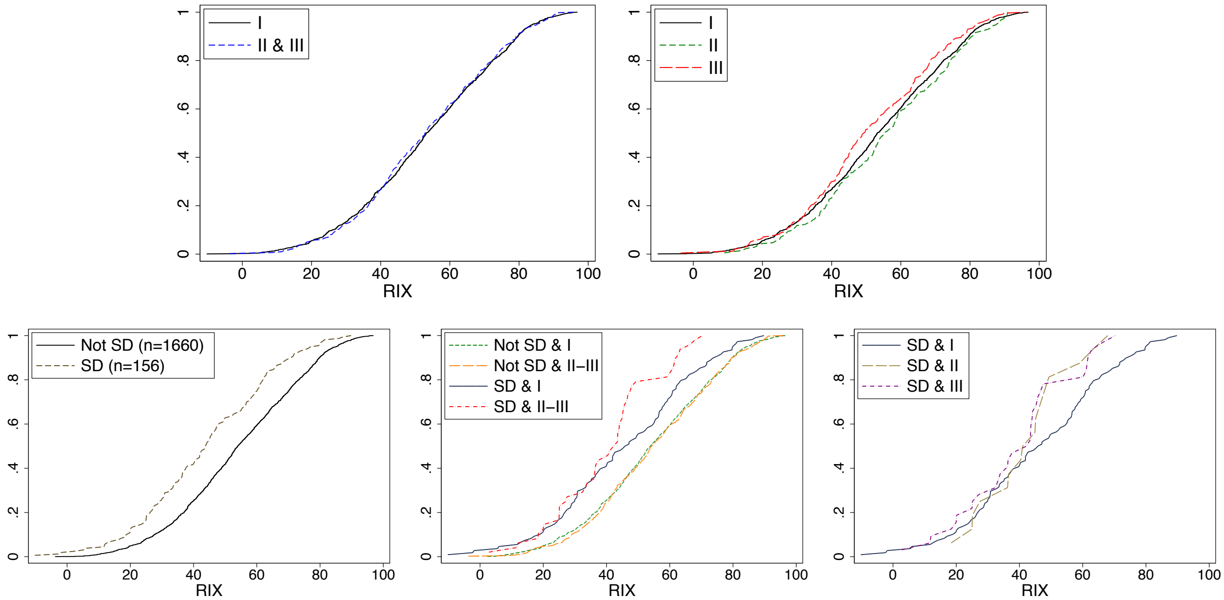
For both the MICU and SICU, comparing the row for zone I to the row for zones II & III in Table 4, we see that on average there are more discharges per day when the census is high (e.g. MICU: 8.2 average discharges in zones II & III) versus when the census is low (e.g. MICU: 7.3 average discharges in zone I). Comparing the row for zone II with the row for zone III we see fewer discharges in zone III. Both these observations make sense. When the census is high there are more patients to discharge but when patients are sicker not as many are fit to be discharged. These additional discharge takes time but we also see that the average time between discharges in zones II & III is .2 hours (12 minutes) longer than of zone I. This suggests that in addition to causing more discharges, high workload slows down the discharge processes. Furthermore, on high census days in the MICU, discharges start early (6:46 AM versus 8:43 AM) and end late (9:12 PM versus 8:33 PM). In other words, the discharges are more spread out on high census days. Figure 5 in the appendix provides further evidence to support the dependence of discharge times on workload; in both the MICU (first row of Figure 5) and the SICU (last row of Figure 5), discharges spread out when there is higher workload. The SICU shows similar results.

Based upon discussions with clinicians, we believe that three factors are at work to spread out the discharges on high census days. First, when the ICU is crowded there is more urgency to get patients out so discharges begin earlier in the day and downstream units give priority to admissions from the congested ICU. Second, the discharge process is time consuming and if ICU clinicians have many to do and the ICU is already busy due to high census, the ICU clinicians will finish the discharges later in the day. We note that more discharges also tax resources outside the ICU such as transport, janitorial, and downstream units and these units can also cause delays. Third, admissions to the ICU can come in waves based on time of day seasonality in the operation of other units of the hospital. If the ICU has low census these fluctuations can be accommodated. But if the ICU is crowded they may drive additional discharges. For example, if a group of patients unexpectedly need to be admitted later in the day the ICU will have to make room by discharging patients later in the day. This will show up in our data as the later time for last discharge of the day in zones II and III. In such case, later time for last discharge would not be the result of slower discharges.

We see that zone III is driving much of the earliness in departure times. Discussions with the clinicians revealed that this difference in the zones II and III could be largely due to the difference in the care given to the too-sick-to-benefit patients. Because clinicians have to take care of the patients with limited capacity for recovery when workload is high, they look at the value added of their care, and identify patients who are too-sick-to-benefit early. (We note that Freeman and colleagues (2015) had a similar finding: in a study of a maternity unit, they found that when the workload is low, the midwives had a tendency to provide more service features.) Indeed, when we exclude the too-sick-to benefit patients, the difference between zones II and III with respect to early discharge times disappears. (In addition, in Figure 5 we show the distribution of discharge times for patients whose ultimate disposition is hospice; only in zone III do their discharge times appear noticeably earlier than other patients.) We note that the results for the SICU do not change much when we exclude the too-sick-to-benefit patients due to the small number of too-sick-to-benefit patients in the SICU.

The data in Table 4 of discharge times support the idea that when the ICU is crowded the stays are shortened as ICU clinicians try to transfer patients out of the ICU early. In addition, it suggests that the speed-up is happening in the transfer process and not necessarily in a way that impacts the health of the patient, because there is no reason to assume that expediting the transfer of a patient to another unit by a few hours will impact the care received by that patient. That is, it is more of a logistical issue. In the next section we explore if there is evidence that the health status of patients is impacted by the workload.

Figure 3: CDFs of RIX for the Medical ICU Patients



4.3 Impact of Workload for the Medical ICU Patients

In this subsection, the unit of analysis is individual MICU patient. We first compare the distributions of RIX by workload zones: see Figure 3. If workload does not have any impact on ICU discharge practices, the RIX cumulative probability functions (cdfs) of the different workload zones will look alike. Whereas the top left graph suggests that the RIX distribution does not depend on census (i.e., low census versus high census), the top right graph suggests that more acute patients are discharged from zone III compared to zone II. (The p-value for the two-sample Kolmogorov-Smirnov (KS) test for equality of distribution functions is 0.059—the distributions of RIX are statistically different at the 0.10 significance level.) In other words, the top right graph suggests that patients discharged when others are more acute tends to be more acute. For instance, the probability that RIX is smaller than or equal to 40 is 0.23 in zone II, and the same probability is 0.30 in zone III.

The three graphs on the bottom row of Figure 3 show that the RIX distribution depends on patients' next unit as well. After ICU stays, depending on the condition of the patients and the care path, patients can be either transferred to the step-down units, transferred to the general medical-surgical wards, or discharged from the hospital.[4] Because step-down units provide a higher level of care compared to general wards, the least medically stable patients are transferred to a step-down unit. Hence, we expect the RI of patients going

[4]Note that we excluded ICU visits whose next units are the operating room, interventional radiology, catheterization and electrophysiology (Cath/EP), hemodialysis, or in-unit death because deciding when to send a patient to these next units are unlikely to be affected by the ICU workload; see Section 2.3.

to the step-down units to be lower, as we see in the bottom left graph of Figure 3.

More interestingly, the bottom middle graph of Figure 3 suggests that census affects RIX even among the patients who go to a step-down unit. That is, more acute patients are sent to step-down units when the census is high (The p-value for the KS test is 0.012—the RIX distribution is statistically different at the 0.10 significance level). Lastly, the bottom right graph of Figure 3 further compares zones II and III for only the patients that are transferred to the step-down units. Note that the cdfs are not as smooth as the others because of the small sample sizes in each group—for instance, there are 18 patients in the "SD & II" group. We find that more acute patients are sent to step-down units from zone III compared to zone I (p-value 0.042), but there is no statistical difference in the RIX distributions in zone II compared to zone I at the 0.10 significance level.

Table 5: Effect of Workload Zones on RIX, $I(RIX > RIE)$, $log(ICULOS)$, and $I(SD)$ for the Medical ICU Patients

Workload Zone	RIX		$I(RIX > RIE)$		$log(ICULOS)$		$I(SD)$	
I	(Reference)	(Reference)	(Reference)	(Reference)	(Reference)	(Reference)	(Reference)	(Reference)
II & III	-0.29		-0.08		-0.15***		0.47*	
	(0.85)		(0.14)		(0.04)		(0.22)	
II		1.52		0.10		-0.12*		0.08
		(1.18)		(0.21)		(0.05)		(0.33)
III		-1.83+		-0.23		-0.18***		0.73**
		(1.08)		(0.17)		(0.05)		(0.27)
FloorBusy	1.16	0.88	0.17	0.14	0.05	0.05	-0.85**	-0.79**
	(0.89)	(0.90)	(0.15)	(0.16)	(0.04)	(0.04)	(0.29)	(0.30)
Observations	1816	1816	1808	1808	1816	1816	1788	1788
(Pseudo) R^2	0.524	0.526	0.181	0.182	0.309	0.310	0.185	0.187

Note. Robust standard errors in parentheses. $^+$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Next, we use the econometric model described in Section 3 to examine the impact of workload on RIX as well as other outcomes defined in Section 3 when we control for other factors including patient characteristics and seasonality factors: see Table 5. In summary, in zone III (compared to zone I), RIX drops by 1.83 points on average, ICU LOS drops by 16.4% ($= 1 - e^{-0.18}$), and the odds ratio of being transferred to a SD increases by a factor of 2.1 ($= e^{0.73}$). In addition, if downstream units are busy it lowers the odds of being transferred to a SD, but it does not affect the rest of the outcomes.

Our finding of shortened ICU LOS in a congested MICU agrees with the findings of Kc and Terwiesch (2012) in a cardiac ICU. In addition, using our new workload measure, we find that the ICU LOS is even more reduced in zone III (decreases by 16%), but less so in zone II (decreases by 10%). This pattern applies to most of results in Table 5. That is, if we used the traditional workload measure only (zones II and III combined), we would have observed either no statistically significant impact of workload (on RIX) or smaller impact of workload (on $log(ICULOS)$ and $I(SD)$). The results using our workload measure reveal that zone III is driving much of the impact of workload.

In addition, whereas we cannot separate the ICU LOS into service time and time-to-transfer as Long and Mathews (2015) did due to a lack of data, our results provide evidence that shortening ICU LOS is not a matter of shortening the time-to-transfer, contrary to Long and Mathews (2015). Our results indicate that high workload shortens ICU LOS and also lowers RIX. If only the time-to-transfer is shortened, then it should not have any health effect. However, our evidence of lower RIX in zone III indicates that there indeed is some health effect.

Lastly, we examine the interaction between ICU workload and floor census: see Table 6. We observe that including the interaction effects strengthens the effect of zone III. The coefficients of the interactions terms in the RIX models show that busy floor, together with high workload in the ICU, leads ICUs to discharge less acute patients. This suggests that when there is no room on the floor, the impact of ICU workload is mitigated because the MICU cannot discharge as many patients as it would have if there were more rooms available downstream. This is consistent with assumptions underlying our simulation model. We can imagine that the patients are ordered from highest to lowest RI and the doctors discharge the patients from top to bottom in this list. If the ICU is crowded they need to make room by going deeper into this list and thus patients with lower RI values. If the downstream unit is crowded there is a limit to how deep into the list they can go and thus the average RI of a discharged patient is higher than if they could go deeper into the list.

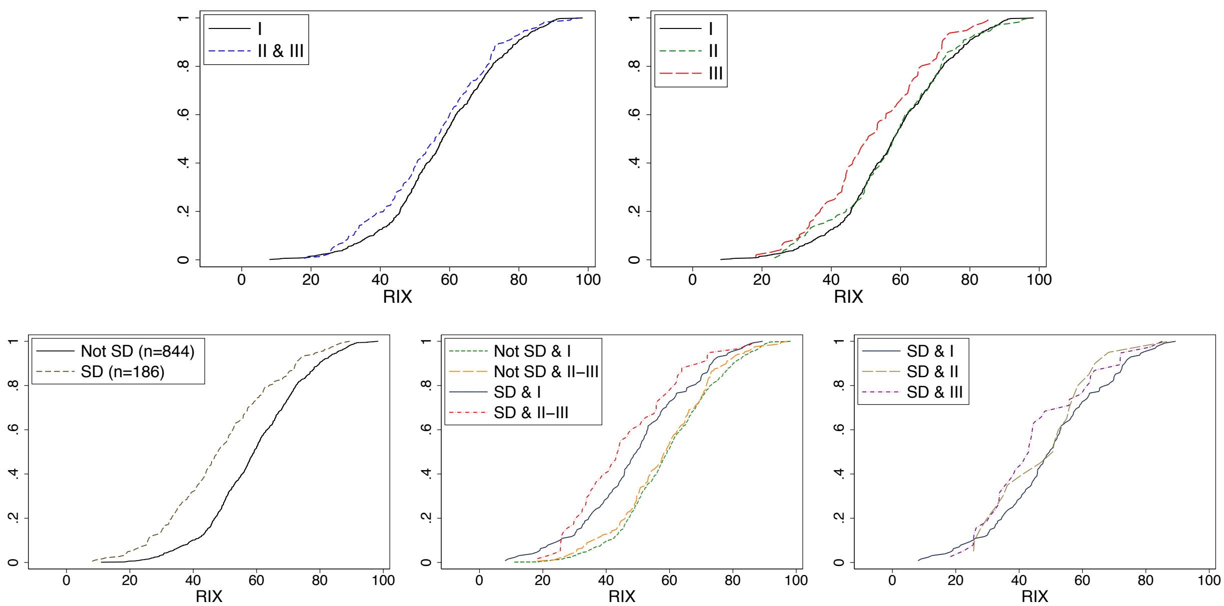
Table 6: Effect of Workload Zones on RIX, $I(RIX > RIE)$, $log(ICULOS)$, and $I(SD)$ for the Medical ICU Patients: With Interaction Terms for Workload Measures

Workload Zone	RIX		$I(RIX > RIE)$		$log(ICULOS)$		$I(SD)$	
I	(Reference)	(Reference)	(Reference)	(Reference)	(Reference)	(Reference)	(Reference)	(Reference)
II & III	-1.95*		-0.32^{+}		-0.12**		0.54*	
	(0.98)		(0.16)		(0.05)		(0.24)	
II		-0.47		-0.26		-0.07		0.08
		(1.51)		(0.26)		(0.07)		(0.39)
III		-2.79*		-0.35^{+}		-0.16**		0.77**
		(1.16)		(0.19)		(0.05)		(0.29)
FloorBusy	-0.41	-0.39	-0.07	-0.07	0.08	0.08^{+}	-0.72*	-0.73*
	(1.02)	(1.02)	(0.18)	(0.18)	(0.05)	(0.05)	(0.36)	(0.36)
II & III x FloorBusy	5.86**		0.88**		-0.10		-0.39	
	(1.85)		(0.31)		(0.09)		(0.59)	
II x FloorBusy		4.92*		0.91*		-0.13		-0.06
		(2.23)		(0.40)		(0.10)		(0.71)
III x FloorBusy		5.39^{+}		0.68		-0.13		-0.37
		(3.04)		(0.45)		(0.15)		(0.86)
Observations	1816	1816	1808	1808	1816	1816	1788	1788
(Pseudo) R^2	0.527	0.528	0.185	0.185	0.310	0.311	0.185	0.188

Note. Robust standard errors in parentheses. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

4.4 Impact of Workload for the Surgical ICU Patients

Figure 4: CDFs of RIX for the Surgical ICU Patients



In this subsection, we repeat the analyses of Section 4.3 for the SICU patients. Figure 4 compares the SICU Patients' RIX distributions by workload zones. The two graphs on the top row suggest that the RIX distribution depend on the census (p-value 0.059—the distributions of RIX are statistically different at the 0.10 significance level), and that this difference is driven by zone III (p-value 0.001—between zones I and III). As expected, the bottom left graph of Figure 4 shows that the RI of patients going to the step-down units tend to be lower. The bottom middle graph shows that more acute patients are sent to step-down units when the census is high (p-value 0.097—statistically different at the 0.10 significance level). Furthermore, more acute patients are sent to step-down units from zone III compared to zone I (p-value 0.021), but there is no statistical difference in the RIX distributions in zone II compared to zone I at the 0.10 significance level.

Table 7 shows that in zone III (compared to zone I), RIX drops by 5.29 points on average, the log-odds of RI improvement decreases by 1.07, ICU LOS drops by 15.0% ($= 1 - e^{-0.16}$), and the odds ratio of being transferred to a SD increases by a factor of 5.6 ($= e^{1.73}$). As we have seen for the MICU patients, we observe that zone III is driving much of the impact of workload. In addition, busy floor increases RIX and lowers the odds of being transferred to a SD, but does not affect the other two outcomes. This makes sense because the downstream units include step-down units and when the downstream units are busy only the healthier patients are discharged.

Table 7: Effect of Workload Zones on RIX, $I(RIX > RIE)$, $log(ICULOS)$, and $I(SD)$ for the Surgical ICU Patients

Workload Zone	RIX		$I(RIX > RIE)$		$log(ICULOS)$		$I(SD)$	
I	(Reference)	(Reference)	(Reference)	(Reference)	(Reference)	(Reference)	(Reference)	(Reference)
II & III	-3.21**		-0.61**		-0.07		0.86**	
	(1.18)		(0.23)		(0.06)		(0.30)	
II		-2.10		-0.36		-0.02		0.21
		(1.35)		(0.26)		(0.07)		(0.39)
III		-5.29**		-1.07**		-0.16+		1.73***
		(1.80)		(0.37)		(0.09)		(0.41)
FloorBusy	2.42*	2.31*	0.22	0.20	0.02	0.01	-0.77*	-0.70*
	(1.06)	(1.06)	(0.21)	(0.21)	(0.05)	(0.05)	(0.31)	(0.31)
Observations	1030	1030	1023	1023	1030	1030	944	944
(Pseudo) R^2	0.424	0.426	0.306	0.308	0.381	0.382	0.334	0.344

Note. Robust standard errors in parentheses. $^+$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

When we include the downstream census interaction with the SICU workload zones, we find that the impact on patient health status of being discharged in zone III is weakened. This is different than what we saw for MICU patients: see Table 8. There are many differences between the MICU and the SICU that could play a role in explaining the difference in the effect of the downstream unit. Some key differences are the patients in the two units (e.g., medical versus surgical patient), the sizes of the ICUs (the MICU has 36 staffed beds whereas the SICU has 21), and the approaches to using step down units. MICU patients tend to be sicker and more complex cases than SICU patients who tend to have a better defined care path. There is also greater variance in RI for MICU patients which we see both at arrival to the unit and at departure (see Table 3). From queueing theory we know that system size impacts performance under heavy workloads. So the fact that the MICU is significantly larger than the SICU means that we should not expect identical performance across the two ICUs. The MICU is more of a closed ICU while the SICU is more open leading to different interactions with step-down units[5] and different access to step-down beds (e.g., in the hospital we study, there are 15

[5]The MICU is a "closed" ICU whereas the SICU is an "open" ICU in the hospital we study. An ICU is "closed" if all care in the ICU is directed by intensivists. On the other hand, an ICU is "open" if the intensivists are consultants without primary responsibility for the patient and separate attending physicians direct the patient's care. (In the medical literature, studies have examined the advantages and drawbacks of having a closed ICU versus an open ICU: see Brilli et al. (2001), Pronovost et al. (2002), and Pronovost et al. (2006).) This means that in the MICU we study, only the MICU intensivists are treating the patients while the patients are in the ICU and when the patients leave the MICU, the MICU intensivists hand-off the care to other physicians. We believe that this leads the MICU intensivists to be less flexible about discharging a patient to another unit if the patients have not achieved a sufficient health status and thus ceteris paribus they discharge less acute patients. In the SICU we study the patients' attending physicians are their surgeons, and the surgeons follow the patients throughout their stay in the hospital. As a result the surgeons know that they can keep an eye on the patients even after the patients leave the SICU. We suggest that this leads them to be more flexible about discharging a patient from the SICU.

step-down beds where the MICU patients are usually sent to and 23 step-down beds for the SICU patients).

Table 8: Effect of Workload Zones on RIX, $I(RIX > RIE)$, $log(ICULOS)$, and $I(SD)$ for the Surgical ICU Patients: With Interaction Terms for Workload Measures

Workload Zone	RIX		$I(RIX > RIE)$		$log(ICULOS)$		$I(SD)$	
I	(Reference)	(Reference)	(Reference)	(Reference)	(Reference)	(Reference)	(Reference)	(Reference)
II & III	-2.00		-0.70**		-0.05		0.96**	
	(1.36)		(0.27)		(0.07)		(0.31)	
II		-0.56		-0.43		-0.03		0.40
		(1.64)		(0.34)		(0.09)		(0.40)
III		-4.20*		-1.12**		-0.11		1.72***
		(2.06)		(0.41)		(0.11)		(0.43)
FloorBusy	3.47**	3.50**	0.13	0.14	0.03	0.03	-0.63+	-0.61+
	(1.24)	(1.24)	(0.25)	(0.25)	(0.06)	(0.06)	(0.34)	(0.34)
II & III x FloorBusy	-3.64		0.29		-0.04		-0.42	
	(2.29)		(0.44)		(0.12)		(0.60)	
II x FloorBusy		-4.14		0.20		0.02		-0.66
		(2.70)		(0.53)		(0.15)		(1.01)
III x FloorBusy		-4.26		0.19		-0.17		0.05
		(3.38)		(0.63)		(0.16)		(0.63)
Observations	1030	1030	1023	1023	1030	1030	944	944
(Pseudo) R^2	0.426	0.428	0.306	0.308	0.381	0.383	0.334	0.345

Note. Robust standard errors in parentheses. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

5 Conclusion

In this study, we have examined the impact of ICU workload on the health status and the care path of patients discharged from ICUs. In doing so, we use a detailed patient dataset of two ICUs at a major U.S. teaching hospital and a novel measure of patient acuity, the Rothman Index (RI). Whereas previous studies have examined the impact of ICU workload only using proxies of the health status of patients—due to the absence of a dynamic measure of patient acuity—the RI allows us to examine the direct relationship between workload and the health status of patients in this study: more acute patients are discharged when the ICU has high workload. Furthermore, leveraging the RI, we measure the workload using not only the census (as is traditionally done) but using also the acuity of the patients currently in the ICU. By studying the impact of this severity-adjusted workload on the health status and the care path of patients discharged from the ICUs, we show that it is not just the census that drives the changes in patient flow but also the mix of patients.

At its heart patient flow in a hospital is about which patients get which resources and when. Given the high utilization and expense of intensive care units there will be continued interest in understanding patient flow through ICUs. Our study provides insights into how researchers should proceed in studying ICU patient flow. We saw that not accounting for the acuity adjusted workload of the unit could hide the impact of workload on the health of patients discharged from the units. Additionally, we found that excluding the very sickest patients including those what died in hospital also gave a clearer picture of the impact of workload on patient health status at discharge. We also found that in addition to patient acuity and ICU census the downstream unit census must be accounted for to get a good understanding of patient flow.

In addition, we found evidence that (1) discharges are sped up through shorter transfer times to downstream units when ICU workload is high, (2) high workload leads to patients with lower health status being discharged, (3) downstream unit census mitigates this negative effect because patients are blocked from leaving the ICU prematurely, and (4) the discharge patterns are consistent with our relatively simple conceptual model of the ICU. Taken together, our findings have two implications. First, the Rothman Index is consistent with provider assessments of patient health status. That is, it is the patients with the higher RI values that get discharged first from an ICU, which provides support for the Rothman Index as a measure of severity. It also provides validation for our findings on health impact. While previous studies of workload effects on patients have looked at readmission rates or mortality, these phenomenon fortunately affect relatively few patients; our study provides a measurement of the health impact of ICU workload on all discharged patients, even those that do not die or bounce back to the ICU. This finding, on the other hand, also indicates that at least in units of this particular hospital in which clinicians fairly consistently discharge healthier patients first, the Rothman Index may not provide added value to provider assessments of patient health status around the time of ICU exit. Second, we see that the reduction in health status at discharge caused by the workload is driven by a sampling bias, and not necessarily a deterioration in care. That is, a patient cohabiting an ICU with many high acuity patients will be more likely to get discharged from the ICU than a patient in a lower workload ICU.

Traditionally, the census has been the sole tool to determine the workload in ICUs (more broadly, hospital units). It is often said that "What gets measured is what is improved". Our results show the value of measuring the patient mix in addition to census. We believe that (1) ICUs need to track the changes in patient acuity in addition to census in order to use such information to prevent reaching high occupancy with many high acuity patients, and that (2) future studies of ICU workload should take patient acuity into account in measuring the workload because this study shows that patient acuity in combination with census are affecting who is discharged from the ICU and when.

This study also shows that the impact of workload in ICUs can differ across ICUs within a single hospital. While we have speculated on a number of factors that could be causing the difference, further study is needed. It is also natural to ask how these impacts of ICU workload on ICU care *eventually* affect patients' hospital care and hospitals' resource usage. That is, will patients who are discharged from the ICU with worse health status be still more acute at hospital discharge? Could they be even healthier upon hospital discharge because they went to a step-down unit instead of a general unit and hence received a higher level of care after the ICU? Do hospitals end up using more resources because of how ICU workload alters ICU care for some patients? These are important questions that we plan to explore in future studies. The discharge process is another area for further study. Our results show that workload can influence the number and timing of discharges from ICUs and there may be potential to modify the hospital discharge process to take workload into account. Given that we have shown that very high workload does have a negative effect on patient health it is natural to look for ways to reduce workload without reducing the access to care. The theoretical analysis in Dobson et al. (2010) model shows the potential for reducing patient bumping by smoothing the arrival process.

Lastly, while our new measure of ICU workload is shown to have a great advantage over the traditional workload measure that takes into account only patient census, it is questionable whether it is the *best* workload measure one can use. As Halpern (2009) claimed, we need to continue looking for the most parsimonious measure of ICU workload that can capture the differences in care: "Development of an appropriately accurate and parsimonious measure of ICU capacity strain may augment the precision of future critical care outcomes research by reducing unexplained variance attributable to temporal fluctuations in ICU-level factors; elucidate organizational characteristics that make some ICUs better able to withstand high capacity strain without substantive degradations in quality; and enhance the transparency of critical care rationing while helping to improve its equity and efficiency, thereby promoting the ethics of this inevitable practice (page 648 of Halpern (2009))."

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A Additional Tables and Figures

Table 9: Sample Selection

Sample	MICU Obs	MICU % prior	MICU % initial	SICU Obs	SICU % prior	SICU % initial
All ICU visits from 2/1/2013 to 1/31/2014	3218	NA	100.0	1556	NA	100.0
Excluding non-first-time ICU	2748	85.4	85.4	1372	88.2	88.2
Excluding those that died during the ICU stay	2469	89.8	76.7	1307	95.3	84.0
Excluding transfers from neighboring hospitals	2460	99.6	76.4	1306	99.9	83.9
Excluding those whose next unit is another ICU or the operating room	2344	95.3	72.8	1228	94.0	78.9
Excluding those who left against medical advice or unknown discharge destinations	2319	98.9	72.1	1222	99.5	78.5
Excluding ICU length of stays shorter than 12 hours or longer than 21 days	2172	93.7	67.5	1172	95.9	75.3
Excluding those preceded by hospital stays that are longer than 7 days	2060	94.8	64.0	1130	96.4	72.6
Excluding those with no Rothman Index	2053	99.7	63.8	1068	94.5	68.6
Excluding those with in-hospital mortality	1939	94.4	60.3	1049	98.2	67.4
Excluding those whose discharge destination is hospice	1816	93.7	56.4	1030	98.2	66.2

Figure 5: Discharge hour histograms for patients going to step-down units/general wards/hospital discharge by workload zones

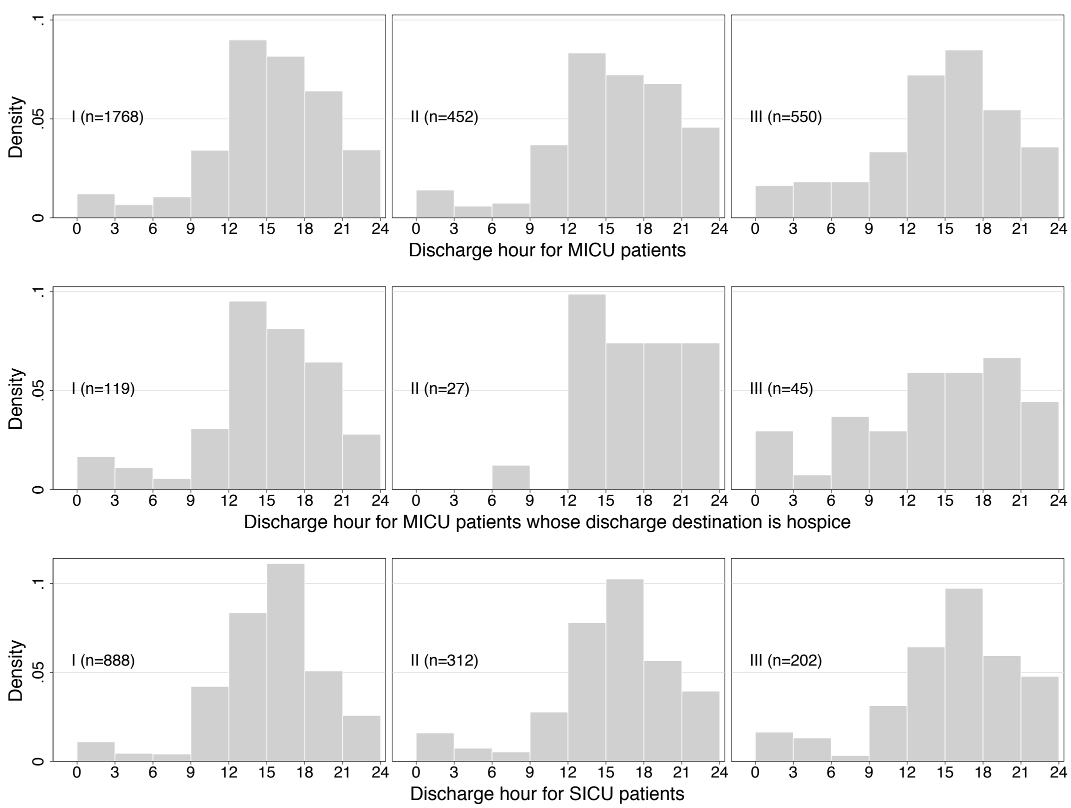

Table 10: Control Variables: Descriptions and Summary Statistics (Means only)

Measure	Description and Coding	MICU (n=1816)	SICU (n=1030)
RI at ICU Arrival	Coded as piecewise linear spline variables with knots at 40 and 65	45.7	51.9
Age	Coded as piecewise linear spline variables with knots at 45 and 65	60.9	58.8
Gender	Females were coded 1 and males 0	0.48	0.42
Principal procedure classification	Included if the principal procedure is done before ICU discharge day. The classification (e.g., operations on the eye) is provided by the Clinical Classification Software (CCS) codes. See http://www.hcup-us.ahrq.gov/toolssoftware/ccs/ccs.jsp for details. Categorical variable to denote operations on (nervous system, endocrine system, eye, ear, nose/mouth/pharynx, respiratory system, cardiovascular system, hemic and lymphatic system, digestive system, urinary system, male genital organs, female genital organs, Obstetrical procedures, musculoskeletal system, integumentary system, miscellaneous, none)	(0.012, 0.000, 0.001, 0.000, 0.001, 0.034, 0.135, 0.001, 0.110, 0.067, 0.000, 0.001, 0.000, 0.009, 0.008, 0.360, 0.263)	(0.061, 0.020, 0.007, 0.003, 0.041, 0.040, 0.092, 0.016, 0.228, 0.051, 0.005, 0.019, 0.006, 0.135, 0.034, 0.110, 0.133)
Major Diagnostic Category (MDC)	Formed by categorizing the DRG codes into 27 mutually exclusive diagnosis areas. The first group is pre-MDC (surgical transplant) and the last group is invalid and ungroupable DRGs. See http://health.utah.gov/opha/IBIShelp/codes/MDC.htm for details.	(0.008, 0.022, 0.001, 0.007, 0.209, 0.100, 0.113, 0.047, 0.018, 0.003, 0.065, 0.044, 0.001, 0.002, 0.002, 0.000, 0.014, 0.009, 0.194, 0.000, 0.042, 0.083, 0.000, 0.003, 0.000, 0.008, 0.006)	(0.077, 0.190, 0.005, 0.022, 0.037, 0.048, 0.100, 0.109, 0.107, 0.013, 0.021, 0.039, 0.005, 0.018, 0.010, 0.000, 0.005, 0.018, 0.032, 0.001, 0.000, 0.037, 0.000, 0.003, 0.088, 0.002, 0.015)
ER admission	Coded 1 if the hospitalization started from the emergency room and 0 otherwise	0.85	0.52
Payer	Categorical variable to denote (Medicare, Managed Medicare, Medicaid, Managed Care—includes Blue Cross and Commercial Managed Care, Other)	(0.46, 0.10, 0.25, 0.18, 0.01)	(0.34, 0.09, 0.20, 0.34, 0.03)
Previous unit	The unit patient was in right before ICU. Categorical variable to denote (step-down unit, general ward unit, none (direct hospital admission to the ICU), operating room, emergency room, various tests)	(0.06, 0.19, 0.09, 0.01, 0.64, 0.01)	(0.04, 0.13, 0.04, 0.45, 0.32, 0.02)
ICU admission month	Categorical variable to denote (Feb 2013, Mar 2013, Apr 2013, May 2013, June 2013, July 2013, Aug 2013, Sept 2013, Oct 2013, Nov 2013, Dec 2013, Jan 2014)	(0.08, 0.09, 0.09, 0.08, 0.08, 0.09, 0.07, 0.08, 0.09, 0.09, 0.08, 0.08)	(0.07, 0.09, 0.09, 0.08, 0.09, 0.09, 0.10, 0.06, 0.07, 0.10, 0.09, 0.09)
ICU admission hour of day	Categorical variable to denote ([12am, 3am), [3am, 6am), [6am, 9am), [9am, 12pm), [12pm, 3pm), [3pm, 6pm). [6pm, 9pm), [9pm, 12am))	(0.13, 0.09, 0.06, 0.10, 0.13, 0.17, 0.18, 0.14)	(0.10, 0.08, 0.06, 0.06, 0.15, 0.20, 0.19, 0.15)
ICU discharge day of week	Categorical variable to denote (Sunday, Monday, Tuesday, Wednesday, Thursday, Friday, Saturday)	(0.14, 0.13, 0.16, 0.14, 0.16, 0.15, 0.12)	(0.13, 0.11, 0.14, 0.17, 0.16, 0.16, 0.14)
Downstream bed occupancy	The average occupancy of downstream beds during the 12 hours prior to the focal patient's discharge from the ICU. The average was 275.3 and 169.2 for the MICU and SICU patients, respectively. Binary variable to denote whether the average is above the 75th percentile of its distribution (285.6 and 183.2 for the MICU and SICU patients, respectively)	0.25	0.25

Note. Summary statistics of 30 Elixhauser comorbidity indexes, computed from the ICD-9 codes and the DRG, are not provided due to space limitations.

B Supplementary Materials for Section 3

In Section 3, we propose a simple model of the operation of the ICU to generate hypotheses of what we should expect to see in our data if the model is correct. The main operating premises of our model are that the patient's health status is completely determined by the RI, that patients are discharged according to their RI which providers can perfectly discern and that new arrivals are given priority over current occupants of the ICU. Here we provide a detailed description of the simulation model and results of numerical experiments using realistic parameter values.

For each day, d, a patient i stays in an ICU, the patient's RI, RI_i, changes by a random amount $RIC_{i,d}$ drawn from a normal distribution with mean μ_{RIC} and standard deviation σ_{RIC}. When RI_i exceeds a threshold $Healthy$, patient i is ready for discharge to another less intensive unit of the hospital. We will call such patients: healthy. The implication of these assumptions is that a patient's LOS is tightly linked to the patient's RI at arrival to the unit. At the start of the day (d) the care providers discharge all patients who are healthy. Then a random number of new patient arrivals, NEW_d, from a Poisson distribution with mean λ is determined. If NEW_d exceeds the number of available beds, then the care providers will discharge additional patients from the ICU who are not yet healthy. These additional (premature) discharges will be done in order of healthiest (highest RI) patients first. Each new arrival j has an initial RI, RIE_j, drawn from a normal distribution with mean μ_{RIE} and standard deviation σ_{RIE}.

Using the aforementioned framework, we simulate the MICU and the SICU separately, with parameter values derived from our data: see Table 11. Recall that our final sample has 1,816 MICU visits and 1,030 SICU visits. In order to derive the parameter values from only the "normal" stays that are not affected by workload, we exclude patients who are discharged from zones II and III and patients who are discharged to step-down units. We then compute the mean and standard deviation of their RIE to set the values for μ_{RIE} and σ_{RIE}. To set the values for μ_{RIC} and σ_{RIC}, we divide ($RIX - RIE$) for each patient by the length-of-stay, and compute the mean and standard deviation. We choose the values for NEW_d and $Healthy$ close to what we observe in the data (e.g., $Healthy$ close to the mean of RIX), but adjust them to make the simulated ICU occupancy and patients' length-of-stay close to what we observe in the data.

For each parameter set, we run 100 replications where each replication is run for 1,000 days. To get rid of any initial effects, we use the last 2000 patients of each replication for our analysis. We assign workload zones to the 2000 patients in each replication in the following way. First, we define a patient j to be $MoreAcute$ if RI_j is less than or equal to μ_{RIE}, which is 46 in the MICU and 53 in the SICU. At the beginning of the day patient i is discharged from the ICU (before any discharges happen), we count the number of patient in the ICU other than patient i, and the percentage of the $MoreAcute$ patients among them.

Table 11: Parameters Selected for the MICU and SICU Simulation Experiments

Parameter	Description	MICU	SICU
NumBeds	Number of ICU beds	36	21
New_d	Number of new patient arrivals in day d. Drawn from a Poisson distribution with mean λ	8	4
RIE_i	Patient i's initial RI. Drawn from a Normal distribution with $(\mu_{RIE}, \sigma_{RIE})$	(46, 21)	(53, 18)
$RIC_{i,d}$	Patient i's change in RI in day d. Drawn from a Normal distribution with $(\mu_{RIC}, \sigma_{RIC})$	(4, 11)	(4, 11)
$Healthy$	Patient i is health if RI_i exceeds this threshold	50	57

We use a threshold of 35 patients and 18 patients for the MICU and the SICU, respectively, to divide into low census zone (workload zone I) and high census zone (workload zones II and III). We then further divide the high census zone into workload zones II and III by whether the percentage of more acute patients is less than or equal to 72% for the MICU and 70% for the SICU. These thresholds are deliberately selected to assign approximately 75% patients to zone I, 12.5% to zone II, and 12.5% to zone III. However, because of the integrality of the occupancy, we have on average 63% of the MICU patients in zone I, 17% in zone II, and 20% in zone III and 66% of the SICU patients in zone I, 15% in zone II, and 19% in zone III.

To test the impact of workload zones on RIX, we run linear regressions with RIX as the dependent variable and workload zone and RIE as the independent variables. To test the impact of workload zones on patients' length-of-stay, LOS, we run Poisson regressions with LOS as the dependent variable and workload zone and RIE as the independent variables, because, given the design of the simulation, LOS is a count variable. (In Section 3.3, we use linear regressions for $log(LOS)$ because LOS in our data is measured in seconds. For comparison, we also provide the results of linear regressions for $log(LOS)$ below, but we note that this models fails the assumption of normally distributed errors.) Because we do 100 replications of the MICU or the SICU simulation, we have 100 different coefficients for workload zones and 100 corresponding p-values. We present their median values in Table 12.

The results presented in Table 12 are consistent with our hypotheses 1, 2 and 3 in Section 3. The results are also consistent with the outcome of the econometric analysis. We have conducted extensive simulation experiments with varying parameter values (e.g., varying μ_{RIE}, σ_{RIE}, μ_{RIC} and σ_{RIC}, NumBeds, and λ) and the results provide robust support for our hypotheses.

Table 12: Regression Results from Simulation Experiments: The medians of workload zones' coefficients and their corresponding p-values (in parentheses) from 100 replications are reported.

	MICU						SICU					
Workload Zone	RIX		$log(ICULOS)$		LOS		RIX		$log(ICULOS)$		LOS	
I	(Ref)	(Ref)	(Ref)	(Ref)	(Ref)	(Ref)	(Ref)	(Ref)	(Ref)	(Ref)	(Ref)	(Ref)
II & III	-1.73		-0.11		-0.10		-0.96		-0.06		-0.07	
	(0.00)		(0.00)		(0.00)		(0.03)		(0.06)		(0.00)	
II		-0.49		-0.08		-0.08		-0.12		-0.05		-0.05
		(0.33)		(0.06)		(0.01)		(0.52)		(0.30)		(0.04)
III		-2.74		-0.12		-0.12		-1.61		-0.08		-0.07
		(0.00)		(0.00)		(0.00)		(0.00)		(0.06)		(0.01)