The Impact of Step-Down Unit Care on Patient Outcomes

Carri W. Chan
Decision, Risk, and Operations, Columbia Business School, cwchan@columbia.edu

Linda V. Green
Decision, Risk, and Operations, Columbia Business School, lvg1@columbia.edu

Lijian Lu
Decision, Risk, and Operations, Columbia Business School, ll2755@columbia.edu

Gabriel Escobar
Division of Research, Kaiser Permanente, gabriel.escobar@kp.org

Step Down Units (SDUs) were initially introduced in hospitals in order to provide an intermediate level of care for semi-critically ill patients who are not sick enough to require intensive care but not stable enough to be treated in the general medical/surgical ward. However, there is a lack of consensus within the medical community as to how these units should be used as well as the impact of SDU care on patient outcomes. Using data from 10 hospitals from a single hospital network, we use instrumental variable approaches to estimate the impact on patient outcomes of routing patients to the SDU from the Emergency Department (ED) as well as the Intensive Care Unit (ICU). Our empirical findings suggest that SDU care is associated with better clinical outcomes for some patients – reducing in-hospital mortality by 6%-20%, shortening hospital length-of-stay (LOS) by 0.5-1.08 days or reducing ICU readmission rate by 4% and hospital readmission rate by 8%. However, inappropriately admitting patients to the SDU is associated with an increase in mortality risk by 1.60% and hospital LOS by nearly a factor of 2. Our findings suggest that an SDU may be a cost-effective way to treat patients when used as a true step down unit, i.e. for patients who are post-ICU. However, the impact of SDU care is more nuanced if and when other patients are admitted — for some patients, SDU admission is associated with substantial degradation of outcomes, while for others, it is associated with slightly improved outcomes.

Key words: healthcare, empirical operations management, congestion, quality of service

1. Introduction

Hospitals are responsible for the largest component of national health care expenditures and are therefore under pressure from government and private payers to become more cost efficient (Centers for Medicare & Medicaid Services 2016). Intensive care units (ICUs), which provide the highest level of care, are the most costly inpatient units to operate. The estimated annual cost of critical care in the U.S is between $121 and $263 billion, accounting for 17.4%-39% of total hospital costs (Coopersmith et al. 2012). Step-down units (SDUs), sometimes called transitional care or intermediate care units, have been used in many hospitals to mitigate critical care costs without jeopardizing the quality of care. SDUs provide an intermediate level of care for semi-critically ill patients who are not severe enough to require intensive care but not stable enough to be treated in the general medical/surgical ward (ward). SDUs are generally less expensive to operate than ICUs due primarily to lower nurse-to-patient ratios. While an ICU may have one nurse per one or two patients, an SDU would typically have one nurse per three to four patients. On the other hand, SDUs are more expensive than general wards where there are, generally, about 6 patients per nurse.

There is a lack of consensus within the medical community about the role of the SDU. Those who advocate the use of SDUs see them as an alternative to either maintaining larger ICUs or jeopardizing patient care due to premature, demand-driven, discharge of patients from ICUs to general care units. As the name suggests, the initial role of SDUs was to serve as a transition for patients after being discharged from the ICU. In practice, SDUs are often used to treat other patients, for example, those who might have gone to an ICU but were blocked because the ICU was full. In general, the use of SDUs has evolved without substantial evidence as to their benefits and what their role should be. Some studies argue that these units provide a safe and cost-effective environment for semi-critical patients and can serve as a "bridge from hospital to home" thereby improving patient outcomes and efficiency (Byrick et al. 1986, Harding 2009, and Stacy 2011). Other studies argue that SDUs should not be used as there is not enough evidence of their cost-effectiveness (Keenan et al. 1998 and Hanson et al. 1999). Despite the lack of consensus in the medical community surrounding the use of SDUs as well as the lack of substantive evidence to their effectiveness, many hospitals have SDUs and others are considering introducing these units. Even within a single hospital, the use of SDUs is generally not standardized. Therefore, it is very important to understand their value and how they can best be used. This paper examines whether or not SDUs are associated with improved operational and/or clinical outcomes. As SDUs are much less expensive to operate than ICUs, improvements associated with SDU care may enable reductions in hospital operating costs without sacrificing patient outcomes. Given the increasing pressures for hospitals to reduce costs, such insights can be very valuable to hospital administrators.

To the best of our knowledge, our work is the first to conduct a multi-hospital study to empirically examine the role of an SDU for patients who are discharged from the ICU as well as those who are admitted from the Emergency Department (ED). Our analyses are based on recent data from Kaiser Permanente Northern California, an integrated health care delivery system serving 3.6 million members that operates 21 hospitals, some of which do and some of which do not have SDUs. The cohort and type of data we employ have been described in previous studies (see Escobar et al. (2013), Kim et al. (2015) among others). Our data source is based on nearly 170,000 hospitalizations in a total of 10 hospitals over a course of one and half years. Each of the 10 hospitals in our study has an ICU and SDU, though the number of beds in each of the units varies across hospitals.

There are a number of challenges which arise when trying to understand the impact of SDU care on patient outcomes. One challenge is that there are limited studies regarding its efficacy and, more specifically, which patients can be appropriately admitted to the the SDU (Nasraway et al. 1998). While there is some evidence that some ICU patients who are at low risk of needing life support could be given less intensive care in an SDU with no impact on outcomes (e.g. Zimmerman et al. (1995)), there is also evidence that some critical care patients who are treated in SDUs or general wards instead of the ICU are worse off (e.g. Simchen et al. (2004)). As such, it seems that there are patients who may benefit from being cared for in an SDU rather than in a general ward, while others who are treated in an SDU rather than an ICU may suffer adverse consequences. An important empirical challenge is to be able to classify patients in order to accurately assess the impact of SDU admission on patient outcomes. To that end, we initially segregate patients who are candidates for SDU care into two broad groups: those who are discharged from the ICU and those who are admitted to an inpatient unit from the ED. Taking a data-driven approach, we then stratify patients from the ED into high and low severity groups.

In developing an understanding of SDUs, we face an important estimation challenge. The SDU admission decision may be affected by health factors which are known to the physician at the time of the decision, but are unobservable in the data. For instance, a patient's physical appearance (i.e. whether he/she appears ashen or pale) may provide evidence of early shock. Thus, a physician may determine that, despite relatively stable vital signs and lab scores, a patient who is pale and sweating will benefit from SDU care relative to being sent to the general medical ward. But because the patient is more critical than the average ward patient, he/she is also more likely to have worse outcomes. Similarly, it may be more appropriate to admit a patient to the ICU if he is cognitively impaired and not lucid. Thus, patients who are admitted to the SDU instead of the ICU may be healthier by unobservable measures. Ignoring this potential endogeneity could result in biased estimates. To address this challenge, we utilize an instrumental variable approach to identify the desired effects.

Our empirical findings suggest that SDU care is associated with substantial improvements in various patient outcomes for patients discharged from the ICU as well as low severity patients being admitted from the ED. In particular, for patients in our study cohort who comply with our instrumental variable, we find that SDU admission is associated with an average reduction in the likelihood of in-hospital death of 1.6% to 6%, remaining hospital length-of-stay (LOS) by .5 to 1.08 days, the likelihood of ICU readmission (for ICU patients) by 4%, and the likelihood of hospital readmission by up to 8%. While these findings are supportive of SDU care, we find that SDU admission is associated with worse outcomes for high severity patients coming from the ED: mortality risk, readmission risk and LOS are much higher for patients admitted to the SDU versus the ICU. Our results suggest that when SDUs are used as originally intended, as intermediary units for post-ICU care, they may result in improved outcomes relative to ward care. However, if hospital administrators wish to expand the use of SDUs beyond post-ICU care, it is important to be able to classify which patients should or should not be treated in the SDU.

The rest of the paper is organized as follows. We conclude this section with a brief summary of related papers in the literature. In Section 2, we introduce our study setting and describe our data, including the two patient cohorts we study. In Section 3, we describe our econometric model for our first cohort of patients–those being discharged from the ICU. Section 4 describes how we partition patients who are admitted from the ED into high and low severity patients and then discusses the econometric model we use for these patients. Our main results are presented in Section 5. Section 6 provides directions concluding remarks as well as discussions for future research.

1.1. Literature Review

Our work is related to existing literature in both the medical and operations management communities.

First, our work contributes to the medical literature about the role of SDUs. We note that while there have been studies on the SDU, the amount of attention SDUs have garnered is far less than has been expended on studying other care units, such as the ICU, general medical ward, emergency department, etc. On one hand, some studies argue that SDUs are a cost-effective approach to treat patients by providing a safe and less expensive environment for patients who are not quite sick enough to require treatment in the ICU, but not quite stable enough to be treated in the ward. Without an SDU, most of these patients end up being cared for in the ICU. Byrick et al. (1986) suggests that the use of the SDU could alleviate ICU congestion by reducing ICU length-of-stay (LOS) without increasing mortality rates. This reduction is possible because patients do not have to reach as high a level of stability to be discharged to an SDU rather than to a general medical-surgical ward. Other studies that have shown the cost-effectiveness of an SDU include Harding (2009), Stacy (2011), and Tosteson et al. (1996). On the other hand, a survey of studies on SDUs raises doubts about these benefits and argues that there is not enough evidence of cost-effectiveness (Keenan et al. 1998). The majority of these studies are conducted exclusively within a single hospital, whereas our study utilizes data from 10 different hospitals. Additionally, rather than conducting a before-and-after study, which may be limited by the inability to control for temporal changes such as staffing changes or closures of nearby hospitals, we utilize an instrumental variable approach to identify the impact of different care pathways (going to the SDU versus ward following ICU discharge as well as going to the SDU versus ward or ICU upon hospital admission from the ED). Our multi-center study provides compelling evidence that there are some patients for whom SDU care is associated with improved clinical outcomes, while there are others for whom SDU care is associated with worse clinical outcomes. As such, our results suggest that it would be of value for the medical community to focus more attention on developing an understanding of which patients would or would not benefit from SDU care at hospitals of varying patient mix and resource availability.

Our work is also related to a growing body of literature in the operations management community regarding ICU care. There are a number of papers, including Suter et al. (1994), Azoulay et al. (2001), Shmueli et al. (2003), Escher et al. (2004), Simchen et al. (2004) and Kim et al. (2015), which examine the impact of ICU admission decisions on patient outcomes. While we also look at the admission to ICU versus SDU versus ward decision, we take a data-driven approach to classifying patients into those who may or may not benefit from SDU care (i.e., low versus high severity patients). Additionally, a major focus of our work is the bed transfer decision upon ICU discharge, which was not considered in these prior works. Kc and

Terwiesch (2012) also examines the ICU discharge process; however, the focus is on *early* discharges from the ICU due to demand pressures. This work examines the impact of the type of unit a patient is transferred to following ICU discharge.

We also consider the admission of patients from the ED. There are a number of papers which utilize stochastic modeling and queueing approaches to study the ED to inpatient unit transfers (e.g. Mandelbaum et al. (2012), Shi et al. (2014), Huang et al. (2015)). Stowell et al. (2013), Kuntz et al. (2016) take an empirical approach to explore the impact of admitting patients to various hospital units on patient outcomes. They find that ‘off-placement’ can degrade patient outcomes. In all of these works, the focus is on admitting patients to different units *within the same level of care*. In contrast, our work empirically examines the impact of admitting patients to *different levels of care*.

Our estimation model is most related to that considered in Kim et al. (2015). Like Kim et al. (2015) and Kc and Terwiesch (2012), among others, we utilize an instrumental variable which is based on an operational measure–congestion in an inpatient unit. While the general methodology is similar, the question we are considering is wholly different. The aforementioned works focus on the ICU, while our focus is on the SDU. From an operational standpoint, it is of value to develop an understanding of how the use of the units with lower resource requirements than the ICU may be used to treat moderately severe patients. Additionally, from the viewpoint of clinicians and hospital administrators, these units are fundamentally different in their use and role. Because they serve as the site of intermediate care between the ICU and the ward, there is risk of adverse consequences in admitting a patient to the SDU who actually needs ICU care, as well as admitting patients who would do just as well on the ward. As such, we first take a data-driven approach to help identify higher and lower severity patients before estimating the impact of SDU care on patient outcomes.

2. Setting and Data

We utilize patient data from 10 hospitals from Kaiser Permanente Northern California[1], containing 165,948 hospitalizations over a course of one and a half years. We note that even within the Kaiser Permanente Northern California system, there is no consensus on how to use SDUs. Thus, some hospitals have SDUs, while others do not.

Our data contains operational and patient level information. Operational level information includes every unit to which a patient is admitted during his hospital stay along with the date and time of admission and discharge for each unit. Our objective in this work is to understand the impact of SDU care. Table 1 summarizes the distribution of where patients come from immediately preceding their SDU visit. Over 78%

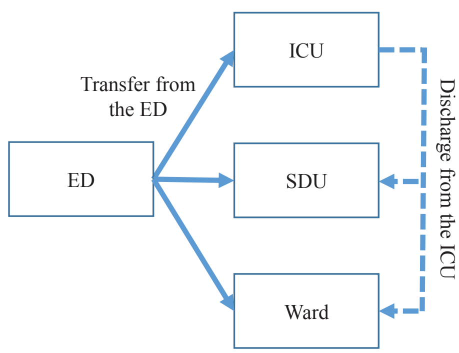
[1] This project was approved by the Kaiser Permanente Northern California Institutional Review Board for the Protection of Human Subjects, which has jurisdiction over all study hospitals, and the XXX (redacted for double-bline review) Institutional Review Board for the Protection of Human Subjects.

of patients in the SDU come from the ED or ICU. As such, our analysis will focus on these two patient cohorts. Specifically, we will focus on how transfer to the SDU impacts patients who are admitted to an inpatient unit from the ED as well as patients who are discharged from the ICU to lower levels of care. Figure 1 depicts these two transfer decisions that will be the heart of our empirical investigation.

Table 1 Distribution of Units Preceding the SDU

Unit Preceding SDU	Percentage
ED	60.93%
ICU	17.11%
Ward	13.88%
Post-Anesthesia Recovery Unit (PAR)	4.25%
Operating Room (OR)	3.58%
Other/Unknown	0.25%

Figure 1 Types of Admission Decisions



For each inpatient unit in each hospital, we use these patient flow data to derive hourly occupancy levels and we define its capacity as the maximum occupancy level over the time horizon. Table 2 summarizes the capacity for each of the different levels of inpatient care in each hospital. While each level of care may have further divisions based on specific services, e.g. medical versus surgical ICU, clinicians and administrators at the study hospitals indicate that it is widely accepted practice at their hospitals to consider the boundaries as somewhat fluid in the sense that if a medical service patient requires ICU care, but there are no medical ICU beds available, he will likely be cared for in the surgical ICU. We observe substantial heterogeneity across these hospitals; the SDU capacity varies from 11 to 32 beds and the the number of ICU beds in a given hospital ranges from one half to twice the number in the SDU.

Our dataset also contains information about patient characteristics such as age, gender, admitting diagnosis and three different severity scores. One score is based on lab results taken 72 hours preceding hospital admission and the second is based on comorbidities, such as diabetes, that may complicate patient recovery. These severity scores are assigned at hospital admission and are not updated during the hospital stay (more

Table 2 **Capacity of Various Inpatient Units**

Hosp	ICU	SDU	Ward
1	11	24	61
2	11	25	76
3	16	14	77
4	16	19	76
5	16	24	78
6	23	19	124
7	24	20	145
8	26	27	110
9	31	11	188
10	32	32	100

details on these scores can be found in Escobar et al. (2008, 2013)). The third severity score is the simplified acute physiology score 3 (SAPS3), which is a common severity score used exclusively for ICU patients (see, e.g, Strand and Flaatte (2008), Mbongo et al. (2009), Christensen et al. (2011)).

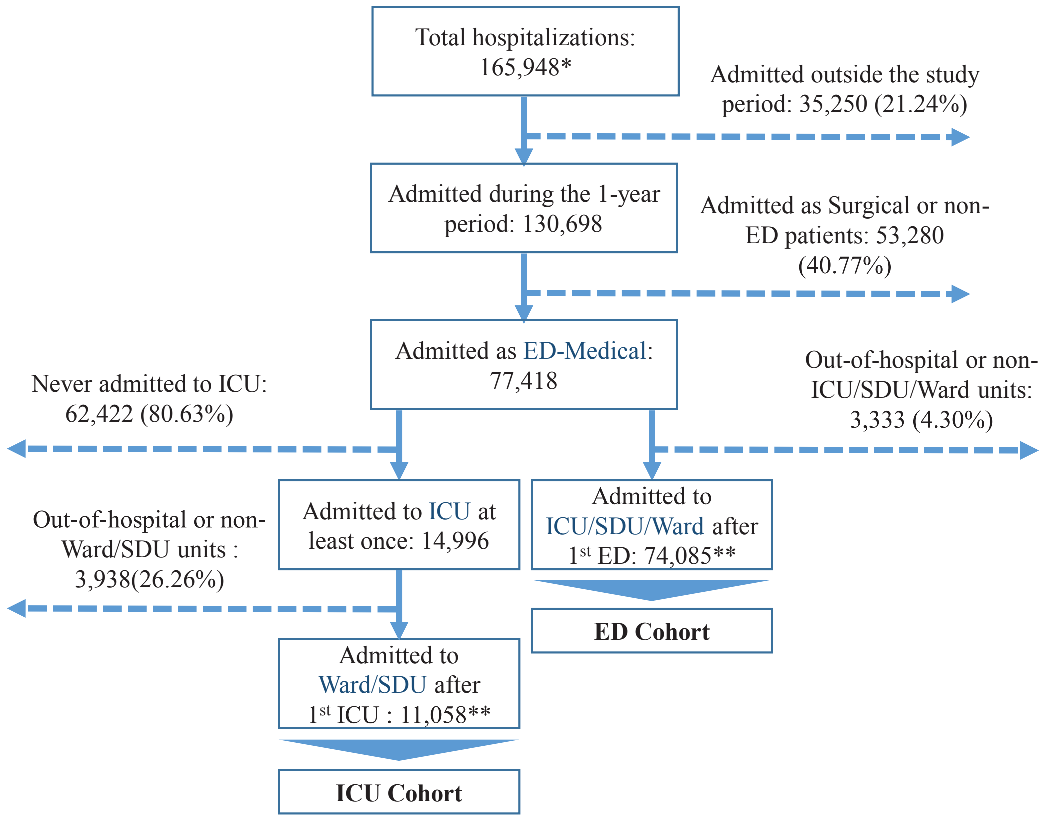
2.1. Data Selection

Since we study two different transfer decisions (from the ED and from the ICU), we form two separate patient cohorts: an ED Cohort and an ICU Cohort. Our data selection process is depicted in Figure 2. Because we use the patient flow data to determine the occupancy level (and capacity) for each unit, we first restrict both of our cohorts to the 12 months in the center of the 1.5 year time period in order to avoid censored estimates. A patient's admission category is defined as a combination of whether or not they were admitted through the ED, and whether they were admitted to a medical or surgical service resulting in 4 categories: ED-medical, ED-surgical, non-ED-medical, or non-ED-surgical. We primarily focus on patients who are admitted via the ED to a medical service for two major reasons. First, this group is the largest, consisting of about 60% of the patients treated in these hospitals, and is similar to the cohort considered in Kim et al. (2015). Second, the care pathways of surgical patients tend to be fairly standardized, especially for non-ED-surgical patients, which is the larger of the two surgical groups. In contrast, the care pathways of ED-medical patients are more variable. It is this variability we will leverage in our identification strategy (see Sections 3 and 4).

2.1.1. ED Cohort Over 60% of SDU patients are admitted from the ED. For these patients, we consider the ED to inpatient unit admission decision. The three possible units a patient can be admitted to are the ICU, the SDU, or the Ward. We exclude the less than 5% of ED-medical patients who go directly to the Operating Room (OR) or Post-Anesthesia Recovery unit (PAR) from the ED.

2.1.2. ICU Cohort Many SDUs are designed as true 'step-down units', where patients can only be admitted following ICU discharges (e.g. Eachempati et al. (2004)). Moreover, the ICU is the second most frequent unit from which SDU patients are transferred. Thus, our second cohort considers patients discharged from the ICU to either the SDU or ward. To form the ICU Cohort, we consider patients who are

Figure 2 **Data Selection**



* to determine capacity and occupancy
** patient cohorts used in our econometric model

admitted to the ICU at least once during their hospital stay. For each patient, we focus on the initial ICU admission within each hospitalization. We exclude patients who die in the ICU or are discharged directly home from the ICU, since there is no decision about whether to route these patients to the SDU or ward following ICU discharge.

Table 3 provides some summary statistics of these two cohorts.

Table 3 **Summary Statistics of Patient Demographics**

	ED Cohort				ICU Cohort			
Variable	mean	std	min	max	mean	std	min	max
Age	67.68	17.53	18	111	68.13	15.91	18	105
Male	0.47	0.50	0	1	0.55	0.50	0	1
LAPS2	74.70	37.35	0	272	75.13	49.10	0	262
COPS2	46.18	44.21	0	290	46.63	44.61	0	267
ED LOS (hrs)	1.46	2.20	0.02	118.68	1.57	2.73	0.02	118.68
ICU LOS (hrs)	N/A				61.87	84.75	0.02	2279.17
LOS before ICU (hrs)	N/A				32.99	108.88	0	4877.58

2.2. Patient Outcomes

We consider four patient outcomes: (1) in-hospital death ($Mortality$), (2) remaining hospital length-of-stay ($HospRemLOS$), (3) hospital readmission ($HospReadm$), and (4) ICU readmission ($ICUReadm$) for ICU patients.

The outcome $HospRemLOS$ is defined as the remaining time spent in the hospital following the transfer decision. Thus, for patients in the ED Cohort, this will be their total inpatient LOS; for patients in the ICU Cohort, this will be the remaining time spent in the hospital following ICU discharge.

$HospReadm_{2w}$ is defined as hospital readmission within two weeks after leaving hospital (e.g., see Doran et al. (2013) and Ouanes et al. (2012) which use these durations). In calculating hospital readmission rates, we exclude patients with in-hospital death. We also do robustness checks for different time windows for hospital readmission.

Following Brown et al. (2013) which aims to define reasonable time windows for ICU readmission, we consider $ICUReadm_{2d}$ ($ICUReadm_{5d}$) which indicate ICU readmission within two (five) days following ICU discharge. This measure is studied only for the ICU Cohort. We also do robustness checks for different time windows for ICU readmission.

Table 4 summarizes these patient outcomes for the two cohorts.

Table 4 Summary Statistics of Patient Outcomes: Mean (Number of observations or standard deviation for continuous variables)

	ED Cohort			ICU Cohort	
	ICU	SDU	Ward	SDU	Ward
Outcome	mean (N/std)	mean (N/std)	mean (N/std)	mean (N/std)	mean (N/std)
Mortality	0.12 (8,630)	0.04 (14,832)	0.03 (50,623)	0.06 (3,832)	0.07 (7,226)
HospRemLOS (days)	6.67 (11.51)	4.23 (5.89)	4.05 (5.79)	7.24 (14.76)	5.13 (10.91)
HospReadm - 2 weeks	0.12 (7,629)	0.11 (14,269)	0.10 (49,206)	0.14 (3,585)	0.13 (6,685)
ICUReadm - 2 days		N/A		0.04 (3,832)	0.05 (7,226)
ICUReadm - 5 days		N/A		0.08 (3,832)	0.06 (7,226)

3. Discharge from the ICU

We begin by explicitly stating our fundamental research question for the ICU cohort: Following ICU discharge, is SDU care associated with better patient outcomes than those for patients receiving ward care and, if so, what is the magnitude of the improvement?

3.1. Econometric Challenge: Endogeneity

Our objective is to utilize retrospective patient data to determine if ICU patients who are transferred to the SDU have better outcomes than those transferred to the ward. Because we are using retrospective data, an estimation challenge arises due to the fact that the routing decision following ICU discharge is likely correlated with patient outcomes. To highlight this challenge, we start with the following reduced form model for hospital LOS:

$$\log(HospRemLOS_i) = \beta X_i + \gamma ADMITSDU_i + \nu_{h(i)} + \epsilon_i \tag{1}$$

where X_i is a vector of control variables including patient characteristics (e.g. age) and seasonal factors (e.g, admission time of day), $ADMITSDU_i$ is an indicator variable that equals 1 if patient i is transferred directly to the SDU following ICU discharge, $h(i)$ is the hospital where patient i is treated, $\nu_{h(i)}$ is the hospital fixed effect and ϵ_i denotes the error term. (see Table 13 in Appendix A for more details on control variables). While we include controls for patient severity, unobservable patient severity measures may be correlated with both $HospRemLOS$ and $ADMITSDU$. That is, sicker patients are more likely to be transferred to the SDU than the ward, but are also more likely to have bad outcomes. As such, our estimates for γ may be biased and we may erroneously conclude that going to the SDU hurts patients. To overcome this potential endogeneity bias, we utilize an identification strategy using Instrumental Variables (IVs).

3.2. Instrumental Variable

A valid instrument should be 1) correlated with the endogenous variable, $ADMITSDU_i$, and 2) unrelated to the unobservable factors captured in ϵ_i which affect patient outcomes. We propose to use congestion in the SDU one hour before the ICU discharge as an IV. In particular, we define $SDUBusy_i$ as an indicator variable that equals one when the number of available beds in the SDU one hour prior to patient i's discharge from the ICU is less than or equal to two, and zero otherwise[2]. On average, about 11% patients are discharged from the ICU when the SDU is busy ($SDUBusy = 1$), though this varies quite a bit across hospitals (see Table 14).

When controlling for various patient characteristics in a Probit regression model, we also find at the 0.1% significance level that when the SDU is busy, patients are less likely to go to the SDU. In particular, we estimate that, on average, 21.14% percent of patients are routed to the SDU if $SDUBusy = 1$ and this percentage increases to 35.91% if $SDUBusy = 0$. Namely, a congested SDU is predicted to result in a 47% reduction in the likelihood of the SDU admission. Hence, condition 1 is satisfied.

We now consider Condition 2 and consider whether $SDUBusy_i$ is uncorrelated with unobservable factors in patient outcomes captured in ϵ_i. Since we cannot examine unobservable measures, we use patient severity, $SAPS3$, as a proxy for those unobservable factors. In particular, we perform a two-sample Kolmogorov-Smirnov test (see Gibbons and Chakraborti 2011 for details) to test the hypothesis that the

[2] We also do robustness checks in Appendix A by considering different specifications of $SDUBusy_i$: (1) different cutoffs at one, two, three, four available beds; (2) dummy variables using occupancy level with cutoffs at 80^{th} (or 85^{th}, 90^{th}, 95^{th}) percentile, i.e., $SDUBusy_i = 1$ if occupancy level is larger than the cutoff percentile and zero otherwise; (3) congestion represented by a continuous piecewise linear spline variable with knots at the 80^{th} (or 85^{th}, 90^{th}, 95^{th}) percentile; and (4) these measures 2 hours (instead of 1) prior to ICU discharge.

distribution of SAPS3 for patients who are discharged from ICU when $SDUBusy = 1$ is not statistically different to that when $SDUBusy = 0$. The p-value for the combined Kolmogorov-Smirnov test is 0.136. Thus, we can not reject the null hypothesis and believe that patients who are discharged from the ICU when $SDUBusy = 1$ are statistically similar to patients who are discharged from the ICU when $SDUBusy = 0$. For completeness, we also check this for the LAPS2 score, which is assigned at the time of hospital admission. The p-value of the combined Kolmogorov-Smirnov test is 0.334.

Kc and Terwiesch 2012 demonstrates that ICU congestion could result in early discharge, which could, in turn, affect the routing decision of ICU patients. While ICU congestion has been used as an IV in a number of hospital studies (e.g. Kc and Terwiesch 2012, Kim et al. 2015), we find that ICU congestion is not a valid IV. This is because the impact of ICU congestion does not exhibit a consistent effect on ICU routing, i.e., a congested ICU could result in both a higher and a lower percentage of patients being admitted to the SDU depending on a patient's severity score. Moreover, we find that the ICU congestion is correlated with a patient's SAPS3 and LAPS2 score.

We also considered using a number of additional instrumental variables. Specifically, we considered a measure of the average severity of other patients in the ICU, a measure of how the discharged patient compares to the severity of other patients in the ICU, and a measure of severity for the most recently discharged ICU patient. We find that all of these measures are correlated with the SAPS3 and LAPS2 scores, suggesting they may also be correlated with unobservable measures of severity, thereby invalidating these variables as potential instruments.

3.3. Econometric Model

3.3.1. Continuous outcome models We now present our estimation model for our continuous outcome, $HospRemLOS$. Since the ICU to SDU routing decision, $ADMITSDU_i$, is a binary variable, we model the ICU discharge decision via a latent variable model.

$$\begin{aligned}
ADMITSDU_i^* &= X_i\theta + \alpha SDUBusy_i + \omega_{h(i)} + \xi_i, \\
ADMITSDU_i &= \mathbf{1}\{ADMITSDU_i^* > 0\}, \\
\log(HospRemLOS_i) &= X_i\beta + \gamma \cdot ADMITSDU_i + \delta \cdot AvgOccVisited_i + \nu_{h(i)} + \varepsilon_i,
\end{aligned} \tag{2}$$

where $ADMITSDU_i^*$ is a latent variable which represents the propensity towards SDU admission; X_i is a vector of control variables for patient information; $\omega_{h(i)}$ is the hospital fixed effect; and, ξ_i represents unobservable factors that affect the routing at ICU discharge. For the outcome equation, $\nu_{h(i)}$ is the hospital fixed effect; and ε_i captures unobservable factors that affect patient outcomes.

We also control for the daily average occupancy level, denoted as $AvgOccVisited_i$, patient i experiences for all impatient units s/he is admitted to *after leaving the ICU and before leaving hospital*. Appendix A provides robustness checks for different specifications of $AvgOccVisited_i$, as well as with this control excluded. We include such a measure as Kc and Terwiesch (2012) shows that patient outcomes are affected by congestion; Kim et al. (2015) provides additional discussion.

The error terms (ξ_i, ε_i) in (2) may be correlated to model the endogeneity between the routing decision at ICU discharge and the patient outcome. We assume that (ξ_i, ε_i) follows a Standard Bivariate Normal distribution with correlation coefficient ρ. This model can be jointly estimated using a treatment effect model via via Full Maximum Likelihood Estimation (FLME) (Greene 2012). A likelihood ratio test of null $\rho = 0$ can be used to test the presence of endogeneity.

3.3.2. Discrete outcome models For the binary outcomes ($Mortality, HospReadm, ICUReadm$), we modify Eq. (2) by replacing the continuous patient outcome with a probit model. Specifically, we have:

$$\begin{aligned} ADMITSDU_i^* &= X_i\theta + \alpha SDUBusy_i + \omega_{h(i)} + \xi_i, \\ ADMITSDU_i &= \mathbf{1}\{ADMITSDU_i^* > 0\}, \\ y_i^* &= X_i\beta + \gamma \cdot ADMITSDU_i + \delta \cdot AvgOccVisited_i + \nu_{h(i)} + \varepsilon_i, \\ y_i &= \mathbf{1}\{y_i^* > 0\} \end{aligned} \tag{3}$$

where y_i^* is a latent variable which represents the propensity for the outcome. Similar to before, we assume that (ξ_i, ε_i) follows a Standard Bivariate Normal distribution with correlation coefficient ρ. This Bivariate Probit model can be jointly estimated via FLME (see Cameron and Trivedi 1998, Greene 2012, and Kim et al. 2015). The presence of endogeneity can be tested through a likelihood ratio test of null $\rho = 0$.

For ICU readmission, we modified $AvgOccVisited_i$ to be the daily average occupancy level that patient i experiences in all impatient units s/he is admitted to *between two consecutive ICU admissions*.

3.4. Demand-driven discharges

Kc and Terwiesch (2012) found evidence that when ICUs are highly congested, current ICU patients may be demand-driven discharged, in order to accommodate incoming demand of more severe patients. Kim et al. (2015) found that patients admitted to a medical service from the ED do not seem to be susceptible to such demand-driven discharges. We look at a similar group of patients to Kim et al. (2015)

One potential concern is that the cohort studied in Kim et al. (2015) includes hospitals with SDUs as well as those without. Our cohorts only include patients treated in hospitals with SDUs. Thus, it is possible that the presence of an SDU makes it more likely for medical patients who were admitted to the hospital via the ED and are being treated in the ICU to be demand-driven discharged; thus, making it possible that these types of discharges occur in our dataset. Patients who are demand-driven discharged are more critical, so are more likely to be admitted to the SDU, but also more likely to have bad outcomes. If this were the case, this could cause a downward bias of our results.

To check this, we estimated the following reduced form model:

$$\log(ICULOS_i) = \eta X_i + \kappa ICUBUSY_i + \nu_i \tag{4}$$

to explore whether ICU LOS is reduced when the ICU is busy. We estimate κ to be -0.05 with standard error 0.04. Thus, consistent with Keenan et al. (1998) and Kim et al. (2015), we do not find evidence that patients are demand-driven discharged. To dig a little deeper, we examined whether the SDU congestion had an impact on whether patients are demand-driven discharged. To do this, we enhance our regression model to include a measure of SDU congestion:

$$\log(ICULOS_i) = \eta X_i + \kappa ICUBUSY_i + \phi SDUBUSY_i + \psi\,(ICUBUSY_i \times SDUBUSY_i) + \nu_i \quad (5)$$

In particular, we would expect demand-driven discharges to be most common when the ICU is busy and the SDU is not. Table 5 summarizes these results. We find that none of the coefficients are statistically significant. Thus, we do not find any evidence suggesting that demand-driven discharges impact our ICU cohort.

Table 5 Demand-driven discharges: Effect of $ICUBusy$ and $SDUBusy$ on ICU LOS

Parameter	Estimate (SE)	ICU Busy	SDU Busy	# Observations
κ	-0.057 (0.040)	1	0	855
ϕ	-0.039 (0.039)	0	1	1,056
ψ	-0.034 (0.096)	1	1	136

Note. Standard error in parentheses. $^{+}(p < 10\%), ^{*}(p < 5\%), ^{**}(p < 1\%), ^{***}(p < 0.1\%)$.

4. Admission to Inpatient Unit

In this section, we study the routing decision regarding the ED Cohort. We aim to empirically estimate how SDU admission immediately following transfer from the ED affects patient outcomes, comparing to ED patients who are transferred to the ICU or ward. Here, a similar estimation challenge arises. Routing decisions are associated with patient severity and, thus, with patient outcomes.

Kim et al. (2015) examined this problem in the context of admitting patients to the ICU from the ED. In that paper, the goal was to estimate the impact of admitting a patient to the highest level of car, i.e. the ICU versus elsewhere. In contrast, our objective is to understand the impact of admitting patients to an intermediary level of care, the SDU. In contrast to the ICU case, it is possible that the impact of SDU care could be positive, neutral or even negative. For instance, high severity patients who should be admitted to the ICU, but are instead admitted to the SDU may experience worse outcomes as a result. On the other hand, SDU care may have no impact or even benefit low severity patients who would traditionally be cared for in the ward. There are limited objective standards for who should be treated in the ICU (see Task Force of the American College of Critical Care Medicine, Society of Critical Care Medicine (1999) and Kim et al. (2015)), let alone for the SDU (Nasraway et al. 1998). Thus, such categorizations of patients are likely to be highly varied across different physicians. As such, we take a data-driven approach to stratifying patients by severity.

4.1. Severity Categorization

In order to estimate the impact of SDU care for patients admitted from the ED, we categorize patients based on their severity and study each severity group separately. Specifically, we aim to identify a 'low severity' cohort, for which the decision is to admit patients to either the ward or SDU, and a 'high severity' cohort for which the decision is to admit to either the SDU or ICU. Certainly, it seems reasonable to expect the decision to admit a patient to the SDU will have a different impact on the low versus high severity patients.

We begin by considering how patient level characteristics influence whether a patient is admitted to the ICU, SDU or ward from the ED. Specifically, we estimate an Ordered Probit regression model using only patient characteristics.

$$Tx_i = \begin{cases} Ward, \text{ if } & Tx_i^* \leqslant t_1 \\ SDU, \text{ if } & t_1 < Tx_i^* \leqslant t_2 \\ ICU, \text{ if } & t_2 < Tx_i^* \end{cases} \text{ and } Tx_i^* = X_i'\theta + \xi_i, \tag{6}$$

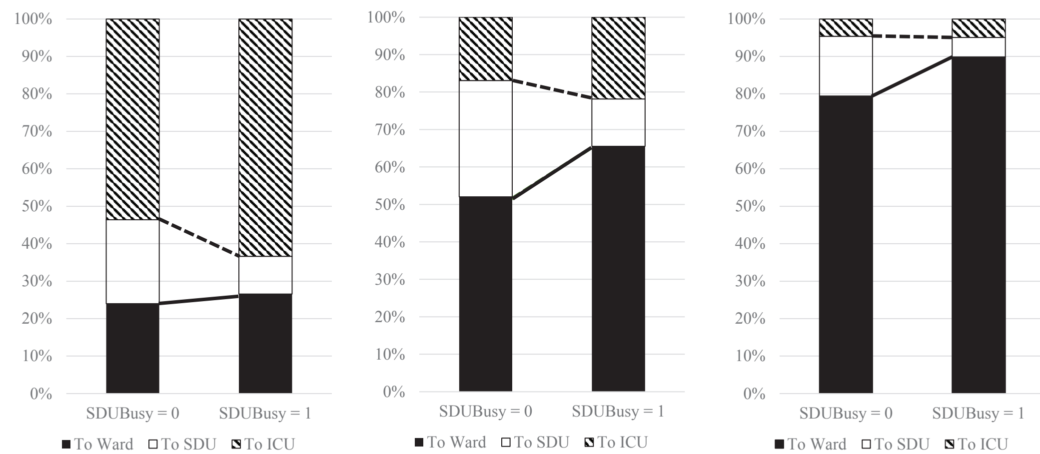
where X_i' is a vector of control variables for patient characteristics and ξ_i represents unobservable factors.

We use the observed latent variable $\widehat{Tx}_i^* = X_i'\theta$ to define each patient's severity. Intuitively, $\widehat{Tx}_i^*$ is a linear transformation of patient characteristics into a single continuous variable which can be interpreted as a measure for the desired amount of care for the patient. The larger the value of $\widehat{Tx}^*$, the more likely the patient will be routed to higher level units, e.g., the ICU; the lower the value, the more likely a patient will be routed to the ward.

We differentiate high-severity patients from low-severity patients with thresholds. In theory, t_1 and t_2 from (6) partition the Tx_i^* space into patients who will be routed to the Ward, SDU, and ICU, so that patients with $Tx_i^* \leq t_1$ could be classified as low-severity patients and patients with $Tx_i^* > t_2$ could be classified as high-severity patients. However, because we do not observe ξ_i, we are only able to observe an estimate $\widehat{Tx}_i^*$, instead of Tx_i^*. Thus, some patients with $\widehat{Tx}_i^* \leq t_1$ will be routed to the SDU, or even the ICU. Similarly, patients with $\widehat{Tx}_i^* > t_2$ may be routed to the SDU or ward. Increasing t_2 will increase the proportion of patients with $\widehat{Tx}_i^* > t_2$ who are routed to the ICU and simultaneously decrease the proportion who are routed to the ward. Similarly, decreasing t_1 will increase the proportion of patients with $\widehat{Tx}_i^* \leq t_1$ being admitted to the ward and decrease the proportion being admitted to the ICU. Of course, this also comes at the cost of reducing the number of patients which satisfy these two criteria. Thus, we define the cutoffs to balance increasing the proportion of patients in the high (low) severity group who are routed to the ICU (ward) versus maintaining large enough patient cohorts to allow for meaningful statistical analysis. We use a data-driven approach and find that setting thresholds as the 95^{th} and 60^{th} percentiles achieve this delicate balance. In Appendix A, we run robustness checks using different thresholds.

We expect that when the SDU is congested, patients will be less likely to be admitted (e.g. see Section 3). Thus, we examine where patients are admitted when the SDU is busy, defined as done in Section 3. Figure 3 shows the proportion of patients admitted to each unit, while Table 6 summarizes these results. Note that the

ICU and SDU congestion have a correlation coefficient of 0.08, so the busyness of the ICU does not factor substantially into these results. Specifically, we ran t-tests comparing the proportion of patients admitted to each level of inpatient unit when the SDU is busy versus not busy. As we can see, when the SDU is busy, low severity patients will be rerouted to the ward ($p < 0.001$), rather than the ICU ($p = 0.327$). Conversely, when the SDU is busy, high severity patients tend to be rerouted to the ICU ($p = 0.002$), rather than the ward ($p = 0.212$). These results are suggestive that these severity categorizations are reasonable for our purposes.



(a) High-severity Patients (b) Medium-severity Patients (c) Low-severity Patients

Figure 3 Proportions of ED patients who are routed to the ICU, SDU, and ward when $SDUBusy = 1$ vs $SDUBusy = 0$.

Table 6 Proportions of ED patients who are routed to the ICU, SDU, and ward when $SDUBusy = 1$ vs $SDUBusy = 0$ and results of t-tests which compare the difference in routing proportions.

	SDUBusy = 0			SDUBusy = 1			p-value of t-test		
	ICU	SDU	Ward	ICU	SDU	Ward	ICU	SDU	Ward
Low Severity	4.62%	15.97%	79.14%	4.94%	5.23%	89.93%	0.327	< 0.001	< 0.001
Medium Severity	16.90%	31.05%	52.04%	21.84%	12.64%	65.51%	0.013	< 0.001	0.001
High Severity	53.60%	22.39%	24.01%	63.38%	10.06%	26.56%	0.002	< 0.001	0.212

Remark 1 *In theory, one could also consider a 'medium severity' group. One of the challenges in trying to measure the impact of SDU care is that it may benefit some patients, while harming others. The challenge is classifying patients into groups such that the impact of SDU care is consistent within the cohort, so that one can attempt to use statistical approaches for causal inference. This is particularly challenging for a medium severity group. We see that when the SDU busy, patients may be sent to the ICU or Ward, making it difficult to assess whether SDU is beneficial or harmful. As such, we leave the exploration of these types of patients for future research.*

As summarized in Table 7, for the high severity group, 54.9% are admitted to the ICU, 20.76% to the SDU, and 24.35% to the ward. For low severity patients 4.65%, 14.73% and 80.62% are admitted to the ICU, SDU, and ward, respectively. We can see that even with our classifications, some high (low) severity patients will still be admitted to the ward (ICU). In order to focus on the impact of SDU admissions on patient outcomes, we exclude high (low) severity patients who are routed to the ward (SDU). Tables 8 and 9 report summary statistics of patient demographics and outcomes for each severity group.

Table 7 **Routing Statistics of High-severity and Low-severity Patients**

	High-Severity Patients		Low-Severity Patients	
Unit following the ED	Frequency	Percentage	Frequency	Percentage
ICU	2,034	54.90	2,067	4.65
SDU	769	20.76	6,549	14.73
Ward	902	24.35	35,836	80.62

Table 8 **Summary Statistics of Patient Demographics for ED Cohort by severity classification**

	Low Severity				High Severity			
Variable	mean	std	min	max	mean	std	min	max
Age	67.48	18.57	18	107	70.36	14.74	18	102
Male	0.43	0.49	0	1	0.57	0.50	0	1
LAPS2	59.48	26.89	0	158	155.57	31.85	16	272
COPS2	41.96	41.21	0	10 285	64.13	53.64	0	278
ED LOS (hrs)	1.38	1.99	0.02	62.73	1.66	2.92	0.02	113.50

Table 9 **Summary Statistics of Patient Outcomes for ED Cohort by severity classification: Mean (Number of observations or standard deviation for continuous variables)**

	Low Severity		High Severity	
	SDU	Ward	SDU	ICU
Outcome	mean (N/std)	mean (N/std)	mean (N/std)	mean (N/std)
Mortality	0.02 (6,549)	0.02 (35,836)	0.17 (769)	0.27 (2,034)
HospRemLOS (days)	3.97 (5.85)	3.95 (5.21)	6.68 (10.54)	9.35 (14.22)
HospReadm - 2 weeks	0.10 (6,431)	0.10 (35,258)	0.17 (636)	0.16 (1,483)

4.2. IV Justification

We are again faced with the econometric challenge of endogeneity bias. Our econometric model is very similar to that of (2) and (3). The main difference is that for low (high) severity patients, $ADMITSDU_i$ is equal to 1 if the patient is admitted to the SDU and 0 if to the ward (ICU). Detailed descriptions of the covariates are shown in Table 13 in the Appendix. Similarly, we also control for $AvgOccVisited_i$, i.e., the daily average occupancy level patient i experiences for all impatient units s/he is admitted to *after leaving the ED and before leaving hospital*.

Similar to our models for the ICU Cohort, we consider using $SDUBusy_i$ as an instrumental variable. Additionally, we consider using $ICUBusy_i$ as an instrument as Kim et al. (2015) found that it is a good instrument when studying patients who are or are not admitted to the ICU, which is similar to our High severity group. Specifically, we define $SDUBusy_i$ ($ICUBusy_i$) as an indicator variable that equals one when the number of available beds in the SDU (ICU) one hour prior to patient i's transfer from the ED is less than or equal to two, and zero otherwise[3]. On average, the proportions of patients who are transferred from the ED when the SDU is busy and the ICU is busy are approximately 12% and 6%, respectively.

As discussed previously, in order for a variable to be a valid instrument, it has to be 1) correlated with the endogenous variable, $ADMITSDU_i$, and 2) unrelated to the unobservable factors which affect patient outcomes. As seen in Table 6, when the SDU is busy, patients are less likely to be admitted to the SDU. However, we find that ICU congestion does not appear to have a monotonic effect on SDU admission for low severity patients. Specifically, we observe that when we partition the low severity patients into deciles of Tx_i^*, ICU congestion increases the percentage of SDU admissions for some patients, while it has no effect or even *decreases* the percentage of SDU admissions for other patients. Therefore, we conclude that $ICUBusy_i$ is not a valid instrument for low severity patients. We see these effects more concretely when we analyze a Probit regression model, which controls for various patient characteristics and operational controls. We find with 0.1% significance level that SDU congestion reduces the likelihood of SDU admission for both low and high severity patients, and that ICU congestion increases the chance of SDU admission for only high severity patients. The impact of ICU congestion for low-severity patients is not statistically significant.

We next examine whether our instruments are correlated with observable measures of severity. We again perform a two-sample Kolmogorov-Smirnov test to test the hypothesis that the distribution of LAPS2 is not statistically different when $SDUBusy = 1$ ($ICUBusy = 1$) from that when $SDUBusy = 0$ ($ICUBusy = 0$). For low severity patients, the p-value for the Kolmogorov-Smirnov test is 0.135, thus, we conclude that patients who leave the ED when $SDUBusy = 1$ are statistically similar to those who leave the ED when $SDUBusy = 0$. For high severity patients, the p-values are 0.141 and 0.358 for $SDUBusy$ and $ICUBusy$, respectively. Therefore, our models for low severity patients use $SDUBusy_i$ as an instrument, while both $SDUBusy_i$ and $ICUBusy_i$ are used in the models for high severity patients.

4.2.1. Additional Instruments Apart from the congestion in the ICU and the SDU, we also consider other potential behavioral IVs discussed in Kim et al. (2015). The first factor is $RecentDischarge_i^{SDU}$, which accounts for the number of all SDU discharges in the 3-hr window before patient is admission to

[3] We also do robustness checks in Appendix A by considering different specifications of $SDUBusy_i$ and $ICUBusy_i$: (1) different cutoffs at one, two, three, four available beds; (2) dummy variables using occupancy level with cutoffs at 80^{th} (or 85^{th}, 90^{th}, 95^{th}) percentile, i.e., $SDUBusy_i(ICUBusy_i) = 1$ if occupancy level is larger than the cutoff percentile and zero otherwise; (3) congestion represented by a continuous piecewise linear spline variable with knots at the 80^{th} (or 85^{th}, 90^{th}, 95^{th}) percentile; and (4) these measures 2 hours (instead of 1) prior to ICU discharge.

the first inpatient unit. The second behavioral factor, $RecentAdmission_i^{SDU}$, accounts for the number of SDU admissions in the 3-hr window before patient is admission to the first inpatient unit. To define $RecentDischarge_i^{SDU}$ and $RecentAdmission_i^{SDU}$, we normalize the number of discharges or admissions by the SDU capacity of each hospital. The third factor, $LastAdmitSeverity_i^{SDU}$, measures the severity of the last patient admitted to the SDU from the ED. We also consider $RecentDischarge_i^{ICU}$, $RecentAdmission_i^{ICU}$, $LastAdmitSeverity_i^{ICU}$, which are defined the same way but instead involve the ICU. Most of these variables demonstrate a heterogenous impact on the SDU admission decision; for instance, amongst low severity patients, $RecentAdmission_i^{SDU}$ will increase the likelihood of SDU admission, while it will decrease likelihood for other patients. We find that only $RecentAdmission_i^{ICU}$ is a valid instrument and is valid only for high-severity patients. However, we do not include this as a third IV for high-severity patients in our main specifications because the results are similar.

5. Results

We now present our main results for the three different groups of patients we study. We find that the effect of SDU admission varies substantially across these different patient types.

5.1. ICU Cohort

We start by exploring the impact of SDU care on patients being discharged from the ICU. Because we jointly estimate the SDU admission decision and patient outcomes, using FMLE, the impact of $SDUBusy_i$ may vary slightly for different outcomes. That said, we observe that the differences are very minor. For illustrative purposes, we note that the coefficient for the impact of $SDUBusy_i$ in the Mortality model is -0.5110 with standard error 0.0503 and p-value $< 0.1\%$.

As we are primarily interested in estimating the causal effects of SDU admission on patient outcomes, we report only the coefficient of SDU admission on the patient outcomes, i.e., γ in (2) and (3).

Table 10 Effect of SDU Admission Following ICU discharge (γ) on Patient Outcomes

	With IV					Without IV
Outcome	γ (SE)	Predicted Outcome $\hat{P}_{SDU}$	Predicted Outcome $\hat{P}_{Ward}$	ρ (SE)	Test $\rho=0$	γ (SE)
$Mortality$	-0.60** (0.22)	3.96%	10.26%	0.26+ (0.14)	0.07	-0.18*** (0.05)
$\log(HospRemLOS)$	-0.35*** (0.10)	2.48	3.56	0.44*** (0.05)	0.00	0.38*** (0.02)
$ICUReadm_{2d}$	-0.51** (0.20)	2.34%	6.62%	0.32* (0.12)	0.02	0.01 (0.05)
$ICUReadm_{5d}$	-0.51** (0.18)	3.93%	10.10%	0.36** (0.11)	0.05	0.09* (0.04)
$HospReadm_{2w}$	-0.43* (0.21)	8.66%	17.08%	0.21+ (0.12)	0.09	0.05 (0.04)

Note. Standard error in parentheses. $^{+}(p<10\%),^{*}(p<5\%),^{**}(p<1\%),^{***}(p<0.1\%)$.
Predicted outcome: $\hat{P}_{SDU}$ - Average predicted outcome if all patients could be routed to the SDU
and $\hat{P}_{Ward}$ if no SDU and everyone is rerouted to Ward.
Predicted $HospRemLOS$ (days) is shown instead of $\log(HospRemLOS)$

Table 10 summarizes the relationship between SDU admission right after ICU discharge and patient outcomes. The sign of SDU admission is negative and statistically significant in all outcome measures, suggesting that routing an ICU discharge to the SDU is associated with improved patient outcomes. To get a rough estimate of the magnitude of the effects we've estimated, we also use our estimation results to predict patient outcomes under two extreme scenarios: (i) the SDU has ample capacity so that all patients will be routed to the SDU (referred to as $\hat{P}_{SDU}$) versus (ii) the hospital does not have an SDU and all patients will be routed to the ward (referred to as $\hat{P}_{Ward}$). We find that, on average, SDU care is associated with significant improvements in patient outcomes: the relative reduction is 72% in the likelihood of in-hospital death, 34% in the hospital remaining length-of-stay, 67.7% (63.9%) in the likelihood of ICU readmission within 2 (5) days, and 52% in the likelihood of hospital readmission within 2 weeks.

We note that the large effect on mortality rate is under the hypothetical (and extreme) comparison of sending all patients to the SDU versus ward. In practice, if there were no SDU, this could likely impact the ICU discharge decision, so that, e.g. patients would have to reach a higher level of stability before being discharged to the ward. Moreover, these estimates are based on rerouting *all* patients to the ward, while our estimates (as with all instrumental variables estimates) are for the subset of patients who 'comply' with the IV. That is, our estimates are an average treatment effect for the patients who the SDU versus ward routing decision may be impacted by SDU congestion. As it is difficult to ascertain exactly which patients comprise this subset, we provide marginal estimates assuming the average treatment effect is consistent across our entire cohort.

Another factor which could be impacting our results is "do not resuscitate (DNR)" orders, which are patients' end-of life wishes not to undergo Cardiopulmonary resuscitation (CPR) or advanced cardiac life support if their heart were to stop or they were to stop breathing. In speaking with intensivists, we learned it is possible that patients with DNRs are more likely to be sent to the ward, but also may be more likely to die, resulting in an overestimate of the effect of SDU care. Unfortunately, we do not have access to patients' DNR status, so cannot control for this. That said, DNR orders only represent 9% of ICU patients (Jayes et al. 1993), so this is likely to affect only a small percentage of patients. Additionally, there is evidence that DNR orders do not change the quality of care (Baker et al. 2003). We do not expect DNR orders to impact our results for hospital readmission since we exclude patients who died in hospital in this model. For remaining LOS, we find that our results are robust to including and excluding patients who died.

Our empirical findings also suggest strong evidence of an endogeneity bias between the routing following ICU discharge and patient outcomes. The p-value of the likelihood ratio test with null hypothesis $\rho = 0$ is small, as seen in Table 10, implying a strong correlation between the routing at ICU discharge and patient outcomes. Ignoring this endogeneity tends to result in underestimates of the benefit of SDU care and could result in a qualitatively different insight; see the column titled with "Without IV".

5.2. ED Cohort

We now consider the impact of SDU admission on patients being admitted to an inpatient unit from the ED.

5.2.1. High Severity We find that a busy SDU is associated with a decrease in likelihood of SDU admission for high severity patients, while a busy ICU is associated with an increase in likelihood of SDU admission. For the mortality model, the coefficient on $SDUBusy_i$ is -0.6325 with standard error 0.1043 and p-value $< .1\%$; for $ICUBusy_i$, the coefficient is 0.4072 with standard error 0.1352 and p-vale $< .1\%$. The results are similar for the other patient outcome models. Table 11 summarizes the impact of SDU admission after ED transfer on the various patient outcomes for these patients.

Table 11 **Effect of SDU Admission Following the ED (γ) on Patient Outcomes for High Severity Patients**

	With IV					Without IV
Outcome	γ (SE)	Predicted Outcome $\hat{P}_{SDU}$	$\hat{P}_{ICU}$	ρ (SE)	Test $\rho = 0$	γ (SE)
$Mortality$	0.75* (0.33)	42.08%	20.86%	-0.48* (0.18)	0.03	-0.05 (0.07)
$\log(HospRemLOS)$	0.45*** (0.12)	8.31	5.32	-0.57*** (0.07)	0.00	-0.32*** (0.04)
$HospReadm_{2w}$	1.27** (0.40)	49.17%	11.51%	-0.78* (0.20)	0.04	-0.08 (0.08)

Note. Standard error in parentheses. $^{+}(p < 10\%), ^{*}(p < 5\%), ^{**}(p < 1\%), ^{***}(p < 0.1\%)$.
Predicted outcome: $\hat{P}_{SDU}$ - Average predicted outcome if all patients will be routed to the SDU
and $\hat{P}_{ICU}$ if everyone is routed to the ICU.
Predicted $HospRemLOS$ (days) is shown instead of $\log(HospRemLOS)$

For high severity patents, being admitted to the SDU appears to be associated with worse outcomes, as seen in the sign of SDU admission coefficient, which is positive and statistically significant in all outcome measures. We also present the predicted patient outcomes under two extreme scenarios: (i) the ICU has no available capacity but the SDU has ample capacity so all patients will be routed to the SDU ($\hat{P}_{SDU}$) and (ii) the ICU has ample capacity and all patients will be routed to the ICU ($\hat{P}_{ICU}$). Our results suggest that being admitted to the SDU instead of the ICU is associated with substantial degradation in patient outcomes. SDU admission is, on average, associated with an increase of 91.60% in in-hospital death and 28.21% in hospital remaining length-of-stay. SDU care also increases the likelihood of hospital readmission within 2 weeks by 2.93 times. As with the ICU cohort, the marginal effects estimates are based on the estimated treatment effect, which is averaged across all patients who comply with the instruments. Thus, one should interpret our results as demonstrating substantive and rigorous evidence to the statistical significance and direction of the treatment effect. Again, we see evidence of a correlation between the SDU admission decision and patient outcomes.

The results for LOS and hospital readmissions are consistent with Kim et al. (2015). Interestingly, we find that being admitted to the SDU is associated with an increase in mortality risk, while Kim et al. (2015) did not find an impact of non-ICU care on mortality. One potential explanation is that Kim et al. (2015) considered all patients admitted from the ED to a medical service, while we stratify our analysis to focus on only the high severity patients. As such, the results of Kim et al. (2015) may be distorted as SDU care may improve mortality risk for some patients within their cohort while also degrading mortality risk for other patients, thereby cancelling each other out. In contrast, since we focus on patients who are more likely to be admitted to the ICU (i.e. 54.90% compared to 11% in Kim et al. (2015)), we are able to provide a cleaner estimate.

5.2.2. Low Severity We now consider the impact of SDU admission on low severity patients. For low severity patients, a busy SDU is associated with a decrease in likelihood of SDU admission. For the mortality model, the coefficient on $SDUBusy_i$ is -0.5117 with standard error 0.0376 and p-value $< .1\%$. The results are similar for the other patient outcome models.

Table 12 summarizes our results. We find that although SDU care is associated with worse outcomes for high severity patients, it may actually benefit low severity patients. Specifically, we find that SDU care is associated with lower mortality rate and shorter hospital remaining length-of-stay, as seen in the positive sign of SDU admission coefficient. We again use our estimation results to predict the patients outcomes under two extreme cases: (i) the SDU has ample capacity and all patients will be routed to the SDU ($\hat{P}_{SDU}$) and (ii) the hospital does not have an SDU and all patients will be admitted to the Ward ($\hat{P}_{Ward}$). Our results indicate that, on average, SDU care is associated with a reduction in mortality by 78.60% and hospital remaining length-of-stay by 19.90%. As with the ICU cohort and the high severity patients, these marginal estimates are based on the assumption that the SDU effects apply to all patients according to the average treatment effect, so may overestimate the potential benefits of SDU care for non-compliers. We do not find a statistically significant relationship between SDU care and the likelihood of hospital readmission within 2 weeks.

Table 12 Effect of SDU Admission Following the ED (γ) on Patient Outcomes for Low Severity Patients

<table>
<tr><th rowspan="3">Outcome</th><th colspan="5">With IV</th><th>Without IV</th></tr>
<tr><th rowspan="2">γ (SE)</th><th colspan="2">Predicted Outcome</th><th rowspan="2">ρ (SE)</th><th>Test</th><th rowspan="2">γ (SE)</th></tr>
<tr><th>$\hat{P}_{SDU}$</th><th>$\hat{P}_{Ward}$</th><th>$\rho = 0$</th></tr>
<tr><td>$Mortality$</td><td>-0.55** (0.28)</td><td>0.64%</td><td>2.24%</td><td>0.33^{+} (0.17)</td><td>0.07</td><td>0.06 (0.06)</td></tr>
<tr><td>$\log(HospRemLOS)$</td><td>-0.20*** (0.04)</td><td>2.37</td><td>2.89</td><td>0.18*** (0.03)</td><td>0.00</td><td>0.03* (0.01)</td></tr>
<tr><td>$HospReadm_{2w}$</td><td>-0.13 (0.12)</td><td>-</td><td>-</td><td>0.09 (0.07)</td><td>0.21</td><td>0.02 (0.03)</td></tr>
</table>

Note. Standard error in parentheses. $^{+}(p < 10\%), ^{*}(p < 5\%), ^{**}(p < 1\%), ^{***}(p < 0.1\%)$.
Predicted outcome: $\hat{P}_{SDU}$ - Average predicted outcome if all patients could be routed to the SDU
and $\hat{P}_{Ward}$ if no SDU and everyone is routed to the Ward.
Predicted $HospRemLOS$ (days) is shown instead of $\log(HospRemLOS)$

5.3. Robustness Checks

We now describe a number of robustness checks for our main results. First, we tried different specifications of control variables. Recall that, some of our control variables – age, severity scores (LAPS2, COPS2, SAPS3), length-of-stay at ICU, and length-of-stay before ICU admission – are modeled as spline variables to account their possible non-linear effects on the ICU to SDU and ED to SDU routings and patient outcomes. We repeated the analysis with different specifications, including changing the number of cutoffs and values of these cutoffs. Our results are qualitatively similar to these changes.

The second robustness check we did is with respect to the length of time window for readmission. For ICU readmission, we varied the time window of the ICU readmission from time of ICU discharge from 2 to 7 days and also during any time frame during the same hospital stay. For hospital readmission, we consider hospital readmission within 1 week, 2 weeks, and 30 days after a patient is discharged from the hospital. We found that our main results are similar to those in Tables 10, 11, and 12 with slight quantitative changes. For example, the effects of the ICU to SDU and ED to SDU routings are *weaker* when the elapsed time between two consecutive hospital stays is longer. We provide the detailed estimation results in Tables 19, 28, and 21 in the Appendix.

For ICU readmission, we also checked alternative specifications of $AvgOccVisited$. In the paper, we define $AvgOccVisited$ for ICU readmission as the average occupancy for all units a patients is admitted to between two consecutive ICU admissions. We considered three alternatives: 1) the average occupancy for all units a patient is admitted to in *the remaining hospital stay before leaving hospital*; 2) the average occupancy for all units a patient is admitted to *within 3 days* after the ICU discharge and before the next ICU admission; and 3) excluding a control for $AvgOccVisited$. While these three specifications yield similar results, there are slight differences in the significance level – the first is the strongest and the last is the weakest, see Table 18 in the Appendix.

For the LOS models, we also considered the robustness of our results to including patients with in-hospital death. We find that for the ICU cohort and for the low-severity patients in the ED Cohort, our results are very robust. However, as seen in Table 17, when including patients with in-hospital mortality in the high-severity ED Cohort, the sign of γ is negative and statistically significant. This raises questions as to the robustness of our LOS results for the high-severity group. However, we believe the main results as reported are more likely to be aligned with the true effect direction and size of SDU admission as it has been well established in the medical literature to exclude patients with in-hospital death for LOS models (e.g. Rapoport et al. (1996), Norton et al. (2007)).

5.3.1. Severity categorizations In our severity categorizations for the ED Cohort, we took a data-driven approach and used thresholds on Tx_i^* to partition the patients into Low and High Severity groups. We varied the thresholds for these categorizations and examined the estimation results in the Appendix.

Table 16 presents the results for the low severity patients. As with our main specification, we do not find statistically significant results for the Hospital Readmission models. We find that the results for $HospRemLOS$ is very robust in magnitude and statistical significance to different specifications of the the low severity threshold. While the mortality results are robust to lowering the threshold, which reduces the sample size, we lose statistical significance when increasing the threshold. This may be because as the sample size is increased, more medium severity patients whose mortality risk may suffer with SDU admission are included in the cohort. When examining the LOS results more closely, we see that as the threshold is increased, the magnitude of the coefficient decreases, suggesting that the low severity cohort is including more patients for which SDU care is detrimental.

Table 15 presents the results for the high severity patients. We see that, in some cases, increasing the threshold for high severity patients results in some of the regressions not converging. This is likely because the size of the cohort is being made smaller and smaller, and there are not enough samples to solve the FMLE optimization. Our tests suggest that the hospital readmission results are not very robust. On the other hand, the $HospRemLOS$ results are quite robust to changes in the threshold. Similar to our observations for the low severity patients, we see that as the threshold decreases, the magnitude of the coefficient decreases. This may be because medium severity patients who benefit from SDU care are entering into the high severity cohort as the threshold is decreased. A similar argument can be made for the mortality results.

5.3.2. Definitions of 'Busy' We also vary the definition of a busy SDU and a busy ICU by considering different cutoffs for the number of available beds, ranging from one bed to four. On average, the percentage of patients, who are discharged from the ICU when the SDU is congested, varies from 34% to 3% when the cutoff is decreased from four beds to one (Table 14). While the quantitative effect of a busy SDU and ICU varies for these different specifications, the main results do not change–being admitted to the SDU following ICU discharge is associated with better patient outcomes, and being admitted to the SDU from the ED is associated with better and worse patient outcomes for low severity patients and high severity patients, respectively. See Tables 19, 20, 21, and 28. We also considered alternative measures of SDU (ICU) congestion based on percentiles of the SDU (ICU) occupancy level. We did this using a binary variable indicating whether the occupancy level exceeds a threshold percentile as well as a piece-wise linear spline. The estimation results are similar to our results obtained in the other specifications. See Tables 22 - 30. We find that our results are very robust to different specifications of our instrumental variables.

6. Conclusions and Managerial Insights

This paper studies the role of a hospital step-down unit (SDU) in the care of patients. To that end, we consider a fundamental question regarding the SDU: Does admitting a patient to the SDU improve or degrade patient outcomes and, if so, what is the magnitude of these effects? Our work represents an important first step towards answering this question. We find that while the answer for patients discharged from the ICU (its original purpose) is fairly clear, for those admitted from the ED, it is quite nuanced – some patients will benefit, while others will not. Moreover, the impact of SDU care can be substantial, so it is essential to be able to carefully identify which patients are appropriate for SDU care.

Using patient data from 10 hospitals, we use econometric models to estimate the impact of SDU care. Our empirical results suggest that using SDUs according to their original intent — as a true step down unit from the ICU — is associated with substantial improvements in patient outcomes relative to discharge to a ward. Under the hypothetical comparison that all patients can be discharged to the SDU rather than all patients being discharged to the ward, we find that the SDU is associated with a reduction in in-hospital mortality rate of 70%, ICU readmission rate of 67.7%, hospital readmission rate of 52%, and hospital length-of-stay of 34%. As such, we find compelling evidence that there are measurable benefits to having an SDU for these patients. It is important to note that our findings for patients being discharged from the ICU provide guidelines and demonstrate the potential for using SDUs in a way that not only results in better clinical outcomes, but also can result in significant cost savings for hospitals. Because SDUs are significantly less expensive to operate than ICUs, and have the potential to significantly decrease ICU and hospital readmissions as well as remaining hospital LOS, properly used they can result in decreased hospital bed utilization and staffing costs. In the current healthcare environment in which hospitals are under increasing pressure to be more cost-effective, findings like the ones in this paper can be very valuable in achieving that goal.

Though the role of an SDU was originally intended for post-ICU care, its use has expanded and patients are often admitted from non-ICU units. For patients admitted to an inpatient unit from the ED, the impact of an SDU is much more nuanced. We take a data-driven approach to partition patients in to high and low severity groups. We find that low severity patients may benefit from the additional monitoring provided in the SDU. However, off-placing high severity patients who should be admitted to the ICU into the SDU is associated with substantial adverse consequences with regard to mortality risk and hospital LOS. While there appear to be potential benefits associated with SDUs, if used inappropriately, they could degrade patient outcomes and increase costs. As such, it is essential to identify which patients can be safely admitted to the SDU and those who cannot. If such classification proves too challenging (e.g unavailability of relevant clinical data such as those from tests and imaging), our results suggest that it may be better to restrict use of the SDU to function as a true step-down unit and only allow admission of patients from the ICU. Of course, this may require additional capacity in the ICU.

Our work complements the results of Armony et al. (2013). When ICU and SDU capacity is limited, Armony et al. (2013) provides insights into how to allocate resources between the two units depending on the relative costs of abandonment of critical patients and bumping of semi-critical patients. This work is a first step towards estimating the impact of bumping semi-critical patient from the SDU to the ward on patient outcomes, thereby providing insights into the bumping cost component which drives the capacity allocation decision.

There are a number of opportunities for future work. Our empirical analysis relies on the variation in patient routings following ICU discharge or following admission from the ED due to SDU and/or ICU capacity constraints. Consequently, our estimates fundamentally apply to patients whose SDU admission comply with our instrumental variables. As such, it is not possible to make any statements about the impact of SDU care for patients whose care pathway is invariant to SDU (or ICU) bed availability. While it is difficult to extrapolate our results to make inferences on the precise magnitude of the effect of the SDU on individual patients, our results demonstrate strong evidence as to the directional impact of an SDU. Because SDUs go in and out of favor at individual hospitals, there may be opportunities for natural experiments to make such inferences without requiring an instrumental variable analysis. Alternatively, at a hospital system such as Kaiser Permanente, it might be possible to conduct a controlled randomized trial by randomizing which hospitals have SDUs. Of course, such a study would require substantial buy-in from hospital administrators and staff. The purpose of our work is to measure the relationship between SDU care and patient outcomes rather than to build a predictive model to determine the role of SDU care for each individual patient. In such a setting, a split-validation approach would be useful to verify the out of sample predictive power of such a model.

Our empirical setting focuses on patients admitted to the hospital via the ED to a medical service. A number of studies in the medical literature consider the impact of SDUs on surgical patients (e.g. Eachempati et al. (2004)). The impact of SDU congestion is likely very different for surgical patients, where surgical procedures and schedules often dictate the precise care pathway for these patients. Hence, an alternative identification strategy is likely needed.

From a stochastic modeling point of view, it would be interesting to study the optimal control policies regarding where to transfer patients from the ED or following ICU discharge in the presence of an SDU. This would provide a system-level view that would capture the potential benefits of an SDU, including externalities on other patients, beyond the estimates of individual patients estimated in this work. Additionally, given the findings of this work, one could consider how to determine the capacity of the SDU relative to the ICU given patient mix and arrival rates. One factor which would significantly impact this decision is whether to restrict use of the SDU to be a true step-down versus allowing admission of patients from non-ICU units, such as the ED.

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Appendix A: Supplementary Tables

Table 13 Control variables for patient characteristics and hospital care

Variable	Description	ICU Cohort	ED Cohort
Gender	Dummy variable: Males were coded 1 and females 0	✓	✓
Age	Continuous variable: Coded as piecewise linear spline variables with knots at its 50^{th} and 80^{th} percentiles (65 and 81)	✓	✓
LAPS2	Laboratory-based Acute Physiology Score; measures physiologic derangement at admission and is mapped from 14 laboratory test results, such as arterial pH and white blood cell count, obtained 72 hours preceding hospitalization to an integer value that ranges from 0 to 262 in our data set(higher scores indicate poorer condition); coded as piecewise linear spline variables with knot at its 50^{th} and 80^{th} percentiles (94 and 134)	✓	✓
COPS2	Comorbidity Point Score; measures the chronic illness burden and is based on 41 comorbidities, such as diabetes, to which patients are categorized using outpatient and inpatient data from the 12 months preceding hospitalization. It ranges from 0 to 267 in our data set, a higher score indicates a higher comorbid illness burden, it was coded as piecewise linear spline variables with knot at its 50^{th} and 80^{th} percentiles (33 and 87)	✓	✓
SAPS3	Simplified Acute Physiology Score; measures the severity of illness and predict vital status at hospital discharge based on ICU admission data. SAPS3 score is associated with each ICU admission and is calculated based on data obtained within on hour of ICU admission. SAPS3 ranges from 14 to 100 in our data set; coded as piecewise linear spline variables with knot at its 50^{th} and 80^{th} percentiles (52 and 61)	✓	
Admitting diagnosis	A way of classifying ICD9 codes. This clinical classification system was developed by HCUP and buckets ICD9's into about 200 groups. A further grouping of the variable HCUP developed by Gabriel Escobar to condense the HCUP grouping into 38 groups so it could be used in a similar fashion as PRIMCOND3.	✓	✓
Seasonality	Month/day-of-week/time-of-day; Category variable for each month and day-of-week. For time-of-day, we use category variables for nurse shifts happening three times a day at 7am, 15pm, and 23pm.	✓	✓
Previous unit	Category variable to track impatient unit a patient is admitted to immediately before ICU admission.	✓	
LOS before ICU	Continuous variable that is the total lengh-of-stay (hrs) prior to the ICU admission. It measures how long a patient has been in hospital before being admitted to the ICU, coded as piecewise linear spline variables with knot at its 50^{th} and 80^{th} percentiles (2 and 31).	✓	
ICU LOS	Continuous variable that is the lengh-of-stay (hrs) at the first ICU. It measures how long a patient has been taking care of at ICU, coded as piecewise linear spline variables with knot at its 50^{th} and 80^{th} percentiles (38 and 83).	✓	
ED LOS	Continuous variable that is the lengh-of-stay (hrs) at the first ED. It measures how long a patient has been taking care of at ED.		✓

Table 14 **ICU Cohort: Percentage of patients who are discharged from ICU when SDU is busy**

		% when number of available SDU beds			
Hosp	SDU Size	≤ 1	≤ 2	≤ 3	≤ 4
1	24	0.93	3.57	7.80	12.17
2	25	0.66	2.95	7.54	12.46
3	14	0.56	7.94	24.29	45.63
4	19	3.17	12.68	27.07	41.59
5	24	0.28	1.54	3.93	7.87
6	19	0.82	3.34	6.76	15.37
7	20	0.00	2.84	16.74	36.77
8	27	2.81	9.34	18.80	31.74
9	11	9.76	37.72	63.94	80.34
10	32	0.34	2.66	6.19	12.71
All hosp		2.52	10.64	21.70	34.00

Table 15 Estimation Results for Patient Outcomes: Different High Severity Thresholds as specified by percentiles of Tx_i^*.

Percentile of Tx_i^*	Estimate (SE)	AME	ARC	ρ (SE)	Test $\rho = 0$
			$Mortality$		
90^{th} and above	0.35 (0.23)	-	-	-0.26$^+$ (0.13)	0.05
91^{th} and above	0.35 (0.24)	-	-	-0.27$^+$ (0.14)	0.07
92^{th} and above	0.36 (0.30)	-	-	-0.28 (0.17)	0.12
93^{th} and above	0.51$^+$ (0.29)	0.13	71.24%	-0.37* (0.16)	0.04
94^{th} and above	0.52$^+$ (0.31)	0.14	73.19%	-0.36$^+$ (0.18)	0.06
95^{th} and above	0.75* (0.33)	0.21	91.60%	-0.48* (0.18)	0.03
96^{th} and above	0.96* (0.46)	0.28	116.71%	-0.57$^+$ (0.25)	0.08
97^{th} and above	0.80 (0.59)	-	-	-0.47 (0.31)	0.20
			$\log(HospRemLOS)$		
90^{th} and above	-0.01 (0.22)	-	-	-0.23 (0.17)	0.19
91^{th} and above	0.23 (0.16)	-	-	-0.41*** (0.11)	0.00
92^{th} and above	0.25 (0.17)	-	-	-0.42*** (0.12)	0.00
93^{th} and above	0.36** (0.13)	0.36	23.93%	-0.50*** (0.09)	0.00
94^{th} and above	0.35** (0.13)	0.35	22.54%	-0.51*** (0.09)	0.00
95^{th} and above	0.45*** (0.12)	0.45	28.21%	-0.57*** (0.07)	0.00
96^{th} and above	0.48** (0.14)	0.48	29.01%	-0.56*** (0.08)	0.00
97^{th} and above	0.51* (0.21)	0.51	29.09%	-0.65*** (0.11)	0.00
			$HospReadm_{1w}$		
90^{th} and above	-0.27 (0.56)	-	-	0.15 (0.34)	0.67
91^{th} and above	0.19 (0.69)	-	-	-0.13 (0.42)	0.77
92^{th} and above	0.33 (0.57)	-	-	-0.21 (0.34)	0.54
93^{th} and above	0.45 (0.59)	-	-	-0.31 (0.34)	0.40
94^{th} and above	0.53 (0.74)	-	-	-0.36 (0.42)	0.24
95^{th} and above	1.27* (0.59)	0.32	390.23%	-0.77 (0.26)	0.11
96^{th} and above	Does not converge			Does not converge	
97^{th} and above	Does not converge			Does not converge	
			$HospReadm_{2w}$		
90^{th} and above	-0.33 (0.45)	-	-	0.22 (0.28)	0.44
91^{th} and above	0.07 (0.62)	-	-	-0.02 (0.38)	0.75
92^{th} and above	0.29 (0.50)	-	-	-0.16 (0.30)	0.59
93^{th} and above	0.63 (0.65)	-	-	-0.39 (0.38)	0.35
94^{th} and above	0.72$^+$ (0.59)	0.20	165.56%	0.47$^+$ (0.34)	0.09
95^{th} and above	1.27** (0.40)	0.38	293.70%	-0.78* (0.20)	0.04
96^{th} and above	Does not converge			Does not converge	
97^{th} and above	Does not converge			Does not converge	
			$HospReadm_{30d}$		
90^{th} and above	-0.16 (0.35)	-	-	0.07 (0.21)	0.76
91^{th} and above	0.14 (0.37)	-	-	-0.11 (0.22)	0.64
92^{th} and above	0.15 (0.35)	-	-	-0.12 (0.21)	0.56
93^{th} and above	0.39 (0.36)	-	-	-0.29 (0.21)	0.21
94^{th} and above	0.56 (0.40)	-	-	-0.42 (0.23)	0.11
95^{th} and above	0.97** (0.31)	0.31	278.71%	-0.65** (0.17)	0.01
96^{th} and above	Does not converge			Does not converge	
97^{th} and above	Does not converge			Does not converge	

Note. Standard error in parentheses. $^+(p < 10\%)$, $^*(p < 5\%)$, $^{**}(p < 1\%)$, $^{***}(p < 0.1\%)$.
AME - Average Marginal Effect; ARC - Average Relative Change.

Table 16 Estimation Results for Patient Outcomes: Different Low Severity Thresholds as specified by percentiles of Tx_i^*.

Percentile of Tx_i^*	Estimate (SE)	AME	ARC	ρ (SE)	Test $\rho = 0$
			Mortality		
85^{th} and below	-0.35 (0.35)	-	-	0.22 (0.22)	0.32
80^{th} and below	-0.46 (0.34)	-	-	0.30 (0.21)	0.18
75^{th} and below	-0.51 (0.33)	-	-	0.33 (0.20)	0.12
70^{th} and below	-0.52 (0.31)	-	-	-0.33 (0.20)	0.11
65^{th} and below	-0.52 (0.30)	-	-	-0.33 (0.19)	0.11
60^{th} and below	-0.55** (0.28)	-0.02	-78.60%	0.33^{+} (0.17)	0.07
55^{th} and below	-0.58** (0.23)	-0.02	-80.82%	0.34* (0.14)	0.03
50^{th} and below	-0.58** (0.24)	-0.02	-80.81%	0.33* (0.14)	0.03
45^{th} and below	-0.58^{+} (0.31)	-0.02	-81.40%	0.34^{+} (0.19)	0.09
			$\log(HospRemLOS)$		
85^{th} and below	-0.08* (0.04)	-0.08	-8.55%	0.11*** (0.03)	0.00
80^{th} and below	-0.14*** (0.04)	-0.14	-14.35%	0.14^{+} (0.03)	0.09
75^{th} and below	-0.14*** (0.04)	-0.14	-14.65%	0.15*** (0.03)	0.00
70^{th} and below	-0.15*** (0.04)	-0.15	-15.15%	-0.16*** (0.03)	0.00
65^{th} and below	-0.17*** (0.04)	-0.17	-16.87%	0.16*** (0.03)	0.00
60^{th} and below	-0.20*** (0.04)	-0.20	-19.90%	0.18*** (0.03)	0.00
55^{th} and below	-0.21*** (0.04)	-0.21	-20.26%	0.18*** (0.03)	0.00
50^{th} and below	-0.22*** (0.04)	-0.22	-21.46%	0.18*** (0.03)	0.00
45^{th} and below	-0.22*** (0.05)	-0.22	-21.67%	0.19*** (0.03)	0.00
			$HospReadm_{1w}$		
85^{th} and below	-0.04 (0.12)	-	-	0.04 (0.07)	0.57
80^{th} and below	0.00 (0.14)	-	-	0.01 (0.08)	0.88
75^{th} and below	-0.03 (0.14)	-	-	0.02 (0.08)	0.80
70^{th} and below	-0.03 (0.14)	-	-	0.16 (0.08)	0.80
65^{th} and below	-0.03 (0.14)	-	-	0.05 (0.08)	0.81
60^{th} and below	-0.03 (0.15)	-	-	0.02 (0.08)	0.78
55^{th} and below	0.00 (0.15)	-	-	0.00 (0.09)	0.99
50^{th} and below	-0.03 (0.18)	-	-	0.00 (0.10)	0.94
45^{th} and below	-0.11 (0.21)	-	-	0.05 (0.11)	0.67
			$HospReadm_{2w}$		
85^{th} and below	-0.04 (0.10)	-	-	0.04 (0.07)	0.50
80^{th} and below	-0.02 (0.11)	-	-	0.03 (0.07)	0.69
75^{th} and below	-0.06 (0.12)	-	-	0.04 (0.07)	0.52
70^{th} and below	-0.08 (0.12)	-	-	0.04 (0.07)	0.45
65^{th} and below	-0.11 (0.14)	-	-	0.05 (0.07)	0.25
60^{th} and below	-0.15 (0.12)	-	-	0.09 (0.07)	0.18
55^{th} and below	-0.16 (0.13)	-	-	0.09 (0.07)	0.20
50^{th} and below	-0.10 (0.14)	-	-	0.06 (0.08)	0.43
45^{th} and below	-0.10 (0.17)	-	-	0.07 (0.09)	0.45
			$HospReadm_{30d}$		
85^{th} and below	-0.04 (0.09)	-	-	0.04 (0.05)	0.41
80^{th} and below	-0.02 (0.10)	-	-	0.03 (0.06)	0.57
75^{th} and below	-0.07 (0.10)	-	-	0.05 (0.06)	0.34
70^{th} and below	-0.10 (0.11)	-	-	0.06 (0.06)	0.30
65^{th} and below	-0.09 (0.12)	-	-	0.05 (0.06)	0.27
60^{th} and below	-0.10 (0.11)	-	-	0.07 (0.06)	0.23
55^{th} and below	-0.09 (0.11)	-	-	0.06 (0.06)	0.32
50^{th} and below	-0.09 (0.12)	-	-	0.06 (0.07)	0.36
45^{th} and below	-0.12 (0.14)	-	-	0.08 (0.07)	0.29

Note. Standard error in parentheses. $^{+}(p<10\%),^{*}(p<5\%),^{**}(p<1\%),^{***}(p<0.1\%)$.
AME - Average Marginal Effect; ARC - Average Relative Change.

Table 17 Effect of SDU Admission Following the ED (γ) on $HospRemLOS$ When Including Patients with In-Hospital Death

Cohort	γ (SE)	Predicted Outcome $\hat{P}_{SDU}$	$\hat{P}_{ICU}/\hat{P}_{Ward}$	ρ (SE)	Test $\rho=0$
ED Cohort - High Severity	-1.83** (0.07)	1.33%	8.31% ($\hat{P}_{ICU}$)	0.81*** (0.02)	0.00
ED Cohort - Low Severity	-0.20*** (0.04)	2.38	2.92 ($\hat{P}_{Ward}$)	0.18*** (0.03)	0.00

Note. Standard error in parentheses. $^{+}(p<10\%),^{*}(p<5\%),^{**}(p<1\%),^{***}(p<0.1\%)$.
Predicted outcome: $\hat{P}_{SDU}$ - Average predicted outcome if all patients could be routed to the SDU and $\hat{P}_{ICU}$ ($\hat{P}_{Ward}$) if no SDU and everyone is routed to the ICU (Ward).
Predicted $HospRemLOS$ (days) is shown instead of $\log(HospRemLOS)$

Table 18 ICU Cohort Robustness Test on ICU Readmissions: Alternative Specifications for $AvgOccVisited$

$AvgOccVisited$	Estimate (SE)	AME	ARC	ρ (SE)	Test $\rho=0$
	$ICUReadm_{2d}$				
Before next ICU admission (Baseline)	-0.51** (0.20)	-0.04	-68%	0.32* (0.12)	0.02
Before hospital discharge	-0.62*** (0.19)	-0.05	-74%	0.38** (0.11)	0.00
3 days before next ICU admission	-0.50** (0.20)	-0.04	-67%	0.31* (0.12)	0.02
$AvgOccVisited$ not included	-0.40* (0.20)	-0.03	-58%	0.25* (0.12)	0.05
	$ICUReadm$				
Before next ICU admission (Baseline)	-0.24 (0.20)	-	-	0.25* (0.12)	0.05
Before hospital discharge	-0.40* (0.18)	-0.06	-53%	0.34** (0.11)	0.00
3 days before next ICU admission	-0.23 (0.20)	-	-	0.24^{+} (0.12)	0.06
$AvgOccVisited$ not included	-0.15 (0.20)	-	-	0.19 (0.12)	0.11

Note. Standard error in parentheses. $^{+}(p<10\%),^{*}(p<5\%),^{**}(p<1\%),^{***}(p<0.1\%)$.
AME - Average Marginal Effect; ARC - Average Relative Change.

Table 19 ICU Cohort Robustness Test on Patient Outcomes: Binary $SDUBusy$ Based on Number of Available Beds

$SDUBusy = \mathbf{1}$	Estimate (SE)	AME	ARC	ρ (SE)	Test $\rho = 0$
	$Mortality$				
$SDUFreeBeds <= 4$	-0.56* (0.27)	-0.06	-70%	0.23 (0.17)	0.17
$SDUFreeBeds <= 3$	-0.47* (0.23)	-0.05	-64%	0.17 (0.14)	0.22
$SDUFreeBeds <= 2$	-0.60** (0.22)	-0.06	-72%	0.26^{+} (0.14)	0.07
$SDUFreeBeds <= 1$	-0.69*** (0.25)	-0.07	-77%	0.31^{+} (0.16)	0.06
	$\log(HospRemLOS)$				
$SDUFreeBeds <= 4$	-0.42*** (0.03)	-0.42	-37%	0.47*** (0.05)	0.00
$SDUFreeBeds <= 3$	-0.38*** (0.10)	-0.38	-36%	0.46*** (0.05)	0.00
$SDUFreeBeds <= 2$	-0.35*** (0.10)	-0.35	-34%	0.44*** (0.05)	0.00
$SDUFreeBeds <= 1$	-0.36*** (0.12)	-0.36	-34%	0.44*** (0.06)	0.00
	$ICUReadm_{2d}$				
$SDUFreeBeds <= 4$	-0.70*** (0.20)	-0.06	-78%	0.43*** (0.12)	0.00
$SDUFreeBeds <= 3$	-0.76*** (0.17)	-0.07	-81%	0.47*** (0.10)	0.00
$SDUFreeBeds <= 2$	-0.51** (0.20)	-0.04	-68%	0.32* (0.12)	0.02
$SDUFreeBeds <= 1$	-0.39 (0.27)	-	-	0.24 (0.17)	0.16
	$ICUReadm_{3d}$				
$SDUFreeBeds <= 4$	-0.30 (0.31)	-	-	0.21 (0.19)	0.28
$SDUFreeBeds <= 3$	-0.52* (0.22)	-0.05	-67%	0.35* (0.13)	0.02
$SDUFreeBeds <= 2$	-0.45* (0.20)	-0.05	-61%	0.31* (0.12)	0.02
$SDUFreeBeds <= 1$	-0.18 (0.35)	-	-	0.14 (0.21)	0.53
	$ICUReadm_{5d}$				
$SDUFreeBeds <= 4$	-0.41 (0.27)	-	-	0.30^{+} (0.16)	0.08
$SDUFreeBeds <= 3$	-0.55** (0.20)	-0.07	-67%	0.39*** (0.12)	0.00
$SDUFreeBeds <= 2$	-0.51** (0.18)	-0.06	-64%	0.37*** (0.10)	0.00
$SDUFreeBeds <= 1$	-0.15 (0.29)	-	-	0.14 (0.18)	0.42
	$ICUReadm$				
$SDUFreeBeds <= 4$	-0.28 (0.25)	-	-	0.27^{+} (0.15)	0.08
$SDUFreeBeds <= 3$	-0.35^{+} (0.20)	-0.05	-48%	0.32** (0.12)	0.01
$SDUFreeBeds <= 2$	-0.24 (0.20)	-	-	0.25* (0.12)	0.05
$SDUFreeBeds <= 1$	-0.02 (0.27)	-	-	0.11 (0.16)	0.49
	$HospReadm_{1w}$				
$SDUFreeBeds <= 4$	-0.49* (0.25)	-0.07	-62%	0.24 (0.15)	0.12
$SDUFreeBeds <= 3$	-0.27 (0.25)	-	-	0.10 (0.15)	0.49
$SDUFreeBeds <= 2$	-0.22 (0.23)	-	-	0.07 (0.13)	0.60
$SDUFreeBeds <= 1$	-0.34 (0.31)	-	-	0.15 (0.18)	0.43
	$HospReadm_{2w}$				
$SDUFreeBeds <= 4$	-0.26 (0.22)	-	-	0.10 (0.13)	0.46
$SDUFreeBeds <= 3$	-0.32 (0.22)	-	-	0.14 (0.13)	0.30
$SDUFreeBeds <= 2$	-0.43* (0.21)	-0.08	-52%	0.21^{+} (0.12)	0.09
$SDUFreeBeds <= 1$	-0.79*** (0.21)	-0.15	-74%	0.43*** (0.13)	0.00)
	$HospReadm_{3w}$				
$SDUFreeBeds <= 4$	-0.22 (0.20)	-	-	0.11 (0.12)	0.35
$SDUFreeBeds <= 3$	-0.18 (0.20)	-	-	0.09 (0.12)	0.45
$SDUFreeBeds <= 2$	-0.39* (0.19)	-0.09	-45%	0.22^{+} (0.11)	0.06
$SDUFreeBeds <= 1$	-0.70*** (0.20)	-0.16	-66%	0.41*** (0.12)	0.00
	$HospReadm_{30d}$				
$SDUFreeBeds <= 4$	-0.18 (0.20)	-	-	0.08 (0.12)	0.49
$SDUFreeBeds <= 3$	-0.20 (0.21)	-	-	0.09 (0.12)	0.45
$SDUFreeBeds <= 2$	-0.44* (0.20)	-0.11	-47%	0.24^{+} (0.12)	0.05
$SDUFreeBeds <= 1$	-0.71*** (0.23)	-0.18	-64%	0.41** (0.14)	0.01

Note. Standard error in parentheses. $^{+}(p < 10\%)$, $^{*}(p < 5\%)$, $^{**}(p < 1\%)$, $^{***}(p < 0.1\%)$.
AME - Average Marginal Effect; ARC - Average Relative Change.

Table 20 ED Cohort Robustness Test on Patient Outcomes: Binary $SDUBusy$ Based on Number of Available Beds. High Severity Patients.

$SDUBusy = \mathbf{1}$	Estimate (SE)	AME	ARC	ρ (SE)	Test $\rho = 0$
	$Mortality$				
$SDUFreeBeds <= 4$	0.45 (0.40)	-	-	-0.30 (0.22)	0.19
$SDUFreeBeds <= 3$	0.62^{+} (0.34)	0.17	86%	-0.40^{+} (0.19)	0.06
$SDUFreeBeds <= 2$	0.75* (0.33)	0.21	92%	-0.48* (0.18)	0.03
$SDUFreeBeds <= 1$	0.61 (0.41)	-	-	-0.39 (0.23)	0.12
	$\log(HospRemLOS)$				
$SDUFreeBeds <= 4$	0.48*** (0.12)	0.48	31%	-0.58*** (0.07)	0.00
$SDUFreeBeds <= 3$	0.49*** (0.11)	0.49	32%	-0.59*** (0.06)	0.00
$SDUFreeBeds <= 2$	0.45*** (0.12)	0.45	28%	-0.57*** (0.07)	0.00
$SDUFreeBeds <= 1$	0.48*** (0.12)	0.48	31%	-0.58*** (0.07)	0.00
	$HospReadm_{1w}$				
$SDUFreeBeds <= 4$	0.99 (1.12)	-	-	-0.62 (0.58)	0.44
$SDUFreeBeds <= 3$	0.32 (1.23)	-	-	-0.25 (0.72)	0.74
$SDUFreeBeds <= 2$	1.27* (0.59)	0.32	390%	-0.77 (0.26)	0.11
$SDUFreeBeds <= 1$	1.11 (0.81)	-	-	-0.68 (0.40)	0.26
	$HospReadm_{2w}$				
$SDUFreeBeds <= 4$	1.01 (0.95)	-	-	-0.64 (0.51)	0.38
$SDUFreeBeds <= 3$	1.02 (1.08)	-	-	-0.45 (0.62)	0.53
$SDUFreeBeds <= 2$	1.27** (0.40)	0.38	294%	-0.78* (0.20)	0.04
$SDUFreeBeds <= 1$	1.19* (0.57)	0.35	283%	-0.74^{+} (0.29)	0.09
	$HospReadm_{30d}$				
$SDUFreeBeds <= 4$	0.51 (0.77)	-	-	-0.38 (0.45)	0.44
$SDUFreeBeds <= 3$	0.42 (0.70)	-	-	-0.33 (0.41)	0.46
$SDUFreeBeds <= 2$	0.97** (0.31)	0.31	279%	-0.65** (0.17)	0.01
$SDUFreeBeds <= 1$	0.94** (0.37)	0.30	163%	-0.63* (0.20)	0.03

Note. Standard error in parentheses. $^{+}(p<10\%),^{*}(p<5\%),^{**}(p<1\%),^{***}(p<0.1\%)$.
AME - Average Marginal Effect; ARC - Average Relative Change.

Table 21 ED Cohort Robustness Test on Patient Outcomes: Binary $SDUBusy$ Based on Number of Available Beds. Low Severity Patients.

$SDUBusy = \mathbf{1}$	Estimate (SE)	AME	ARC	ρ (SE)	Test $\rho = 0$
			$Mortality$		
$SDUFreeBeds <= 4$	-0.66* (0.34)	-0.02	-85%	0.40 (0.21)	0.09
$SDUFreeBeds <= 3$	-0.59* (0.27)	-0.02	-80%	0.35* (0.16)	0.05
$SDUFreeBeds <= 2$	-0.54** (0.27)	-0.02	-78%	0.33^{+} (0.17)	0.07
$SDUFreeBeds <= 1$	-0.21 (0.25)	-	-	0.12 (0.15)	0.41
			$\log(HospRemLOS)$		
$SDUFreeBeds <= 4$	-0.22*** (0.04)	-0.22	-22%	0.19*** (0.03)	0.00
$SDUFreeBeds <= 3$	-0.21*** (0.04)	-0.21	-21%	0.18*** (0.03)	0.00
$SDUFreeBeds <= 2$	-0.20*** (0.04)	-0.20	-20%	0.17*** (0.03)	0.00
$SDUFreeBeds <= 1$	-0.22*** (0.04)	-0.22	-22%	0.19*** (0.03)	0.00
			$HospReadm_{1w}$		
$SDUFreeBeds <= 4$	-0.01 (0.15)	-	-	0.00 (0.09)	0.99
$SDUFreeBeds <= 3$	-0.06 (0.14)	-	-	0.03 (0.08)	0.71
$SDUFreeBeds <= 2$	-0.03 (0.15)	-	-	0.02 (0.08)	0.78
$SDUFreeBeds <= 1$	-0.12 (0.17)	-	-	0.07 (0.10)	0.45
			$HospReadm_{2w}$		
$SDUFreeBeds <= 4$	-0.12 (0.13)	-	-	0.08 (0.07)	0.27
$SDUFreeBeds <= 3$	-0.11 (0.12)	-	-	0.07 (0.07)	0.29
$SDUFreeBeds <= 2$	-0.15 (0.12)	-	-	0.09 (0.07)	0.18
$SDUFreeBeds <= 1$	-0.21 (0.14)	-	-	0.13^{+} (0.08)	0.10
			$HospReadm_{30d}$		
$SDUFreeBeds <= 4$	-0.09 (0.11)	-	-	0.06 (0.06)	0.31
$SDUFreeBeds <= 3$	-0.07 (0.11)	-	-	0.06 (0.06)	0.35
$SDUFreeBeds <= 2$	-0.10 (0.11)	-	-	0.07 (0.06)	0.23
$SDUFreeBeds <= 1$	-0.14 (0.11)	-	-	0.09 (0.06)	0.15

Note. Standard error in parentheses. $^{+}(p<10\%), ^{*}(p<5\%), ^{**}(p<1\%), ^{***}(p<0.1\%)$.
AME - Average Marginal Effect; ARC - Average Relative Change.

Table 22 ICU Cohort Robustness Test on Patient Outcomes: Binary $SDUBusy$ Based on Occupancy Percentile

	With IV				
$SDUBusy = \mathbf{1}$	Estimate (SE)	AME	ARC	ρ (SE)	Test $\rho = 0$
	$Mortality$				
$SDUOcc >= 80^{th} percentile$	-0.55* (0.27)	-0.06	-70%	0.23 (0.17)	0.19
$SDUOcc >= 85^{th} percentile$	-0.72** (0.29)	-0.08	-78%	0.33^{+} (0.18)	0.09
$SDUOcc >= 90^{th} percentile$	-0.72** (0.27)	-0.08	-78%	0.33^{+} (0.17)	0.07
$SDUOcc >= 95^{th} percentile$	-0.81*** (0.27)	-0.09	-82%	0.39* (0.17)	0.04
	$\log(HospRemLOS)$				
$SDUOcc >= 80^{th} percentile$	-0.50*** (0.08)	-0.50	-43%	0.51*** (0.04)	0.00
$SDUOcc >= 85^{th} percentile$	-0.47*** (0.09)	-0.47	-42%	0.50*** (0.04)	0.00
$SDUOcc >= 90^{th} percentile$	-0.42*** (0.09)	-0.42	-39%	0.48*** (0.05)	0.00
$SDUOcc >= 95^{th} percentile$	-0.42*** (0.10)	-0.42	-37%	0.47*** (0.05)	0.00
	$ICUReadm_{2d}$				
$SDUOcc >= 80^{th} percentile$	-0.63*** (0.20)	-0.05	-75%	0.39*** (0.11)	0.00
$SDUOcc >= 85^{th} percentile$	-0.55* (0.23)	-0.05	-71%	0.34* (0.14)	0.02
$SDUOcc >= 90^{th} percentile$	-0.38 (0.30)	-	-	0.24 (0.18)	0.20
$SDUOcc >= 95^{th} percentile$	-0.54* (0.24)	-0.05	-70%	0.33* (0.14)	0.03
	$ICUReadm_{3d}$				
$SDUOcc >= 80^{th} percentile$	-0.44 (0.27)	-	-	0.30^{+} (0.17)	0.09
$SDUOcc >= 85^{th} percentile$	-0.19 (0.32)	-	-	0.14 (0.20)	0.47
$SDUOcc >= 90^{th} percentile$	-0.05 (0.38)	-	-	0.06 (0.23)	0.80
$SDUOcc >= 95^{th} percentile$	-0.24 (0.33)	-	-	0.17 (0.20)	0.40
	$ICUReadm_{5d}$				
$SDUOcc >= 80^{th} percentile$	-0.54*** (0.22)	-0.07	-66%	0.38*** (0.13)	0.01
$SDUOcc >= 85^{th} percentile$	-0.40 (0.26)	-	-	0.30^{+} (0.16)	0.08
$SDUOcc >= 90^{th} percentile$	-0.19 (0.32)	-	-	0.16 (0.19)	0.41
$SDUOcc >= 95^{th} percentile$	-0.36 (0.26)	-	-	0.27 (0.15)	0.10
	$ICUReadm$				
$SDUOcc >= 80^{th} percentile$	-0.54*** (0.18)	-0.08	-64%	0.43*** (0.11)	0.00
$SDUOcc >= 85^{th} percentile$	-0.49** (0.19)	-0.07	-60%	0.40*** (0.12)	0.00
$SDUOcc >= 90^{th} percentile$	-0.12 (0.26)	-	-	0.18 (0.16)	0.28
$SDUOcc >= 95^{th} percentile$	-0.29 (0.23)	-	-	0.27^{+} (0.14)	0.06
	$HospReadm_{1w}$				
$SDUOcc >= 80^{th} percentile$	-0.37 (0.23)	-	-	0.27^{+} (0.14)	0.06
$SDUOcc >= 85^{th} percentile$	-0.55** (0.22)	-0.08	-65%	0.38** (0.13)	0.01
$SDUOcc >= 90^{th} percentile$	-0.06 (0.25)	-	-	0.08 (0.15)	0.58
$SDUOcc >= 95^{th} percentile$	-0.54* (0.23)	-0.08	-65%	0.38** (0.14)	0.01
	$HospReadm_{2w}$				
$SDUOcc >= 80^{th} percentile$	-0.23 (0.23)	-	-	0.17 (0.14)	0.24
$SDUOcc >= 85^{th} percentile$	-0.37^{+} (0.23)	-0.07	-47%	0.26^{+} (0.14)	0.00
$SDUOcc >= 90^{th} percentile$	-0.18 (0.22)	-	-	0.14 (0.14)	0.33
$SDUOcc >= 95^{th} percentile$	-0.71*** (0.21)	-0.14	-70%	0.47*** (0.13)	0.00
	$HospReadm_{3w}$				
$SDUOcc >= 80^{th} percentile$	-0.14 (0.22)	-	-	0.12 (0.13)	0.37
$SDUOcc >= 85^{th} percentile$	-0.22 (0.22)	-	-	0.17 (0.13)	0.20
$SDUOcc >= 90^{th} percentile$	-0.20 (0.22)	-	-	0.16 (0.13)	0.25
$SDUOcc >= 95^{th} percentile$	-0.67*** (0.20)	-0.16	-65%	0.45*** (0.12)	0.00
	$HospReadm_{30d}$				
$SDUOcc >= 80^{th} percentile$	-0.06 (0.23)	-	-	0.07 (0.14)	0.63
$SDUOcc >= 85^{th} percentile$	-0.08 (0.22)	-	-	0.08 (0.13)	0.53
$SDUOcc >= 90^{th} percentile$	-0.13 (0.24)	-	-	0.11 (0.14)	0.45
$SDUOcc >= 95^{th} percentile$	-0.69*** (0.23)	-0.18	-63%	0.45** (0.14)	0.01

Note. Standard error in parentheses. $^{+}(p<10\%),^{*}(p<5\%),^{**}(p<1\%),^{***}(p<0.1\%)$.
AME - Average Marginal Effect; ARC - Average Relative Change

Table 23 ED Cohort Robustness Test on Patient Outcomes: Binary $SDUBusy$ Based on Occupancy Percentile. High Severity Patients.

$SDUBusy = \mathbf{1}$	Estimate (SE)	AME	ARC	ρ (SE)	Test $\rho = 0$
	$Mortality$				
$SDUOcc >= 80^{th} percentile$	0.56^{+} (0.33)	0.15	84%	-0.37^{+} (0.18)	0.07
$SDUOcc >= 85^{th} percentile$	0.61^{+} (0.36)	0.17	86%	-0.40^{+} (0.20)	0.08
$SDUOcc >= 90^{th} percentile$	0.75* (0.33)	0.21	92%	-0.47* (0.18)	0.03
$SDUOcc >= 95^{th} percentile$	0.64^{+} (0.37)	0.18	86%	-0.41^{+} (0.20)	0.07
	$\log(HospRemLOS)$				
$SDUOcc >= 80^{th} percentile$	0.38* (0.15)	0.38	24%	-0.53*** (0.09)	0.00
$SDUOcc >= 85^{th} percentile$	0.41** (0.14)	0.41	26%	-0.54*** (0.08)	0.00
$SDUOcc >= 90^{th} percentile$	0.45*** (0.13)	0.45	29%	-0.56*** (0.07)	0.00
$SDUOcc >= 95^{th} percentile$	0.44** (0.13)	0.44	28%	-0.56*** (0.07)	0.00
	$HospReadm_{1w}$				
$SDUOcc >= 80^{th} percentile$	0.93 (0.86)	-	-	-0.60 (0.45)	0.33
$SDUOcc >= 85^{th} percentile$	0.92 (1.00)	-	-	-0.59 (0.52)	0.40
$SDUOcc >= 90^{th} percentile$	1.10^{+} (0.68)	0.26	379%	-0.68 (0.33)	0.18
$SDUOcc >= 95^{th} percentile$	1.01 (1.07)	-	-	-0.63 (0.54)	0.41
	$HospReadm_{2w}$				
$SDUOcc >= 80^{th} percentile$	0.82 (0.72)	-	-	-0.54 (0.40)	0.29
$SDUOcc >= 85^{th} percentile$	1.04 (0.77)	-	-	-0.6 (0.41)	0.28
$SDUOcc >= 90^{th} percentile$	1.26** (0.42)	0.37	290%	-0.77^{+} (0.23)	0.07
$SDUOcc >= 95^{th} percentile$	1.16^{+} (0.67)	0.34	280%	-0.72 (0.35)	0.21
	$HospReadm_{30d}$				
$SDUOcc >= 80^{th} percentile$	0.54 (0.49)	-	-	-0.41 (0.28)	0.20
$SDUOcc >= 85^{th} percentile$	0.77^{+} (0.42)	0.25	151%	-0.54^{+} (0.24)	0.07
$SDUOcc >= 90^{th} percentile$	0.94** (0.34)	0.31	279%	-0.64* (0.19)	0.02
$SDUOcc >= 95^{th} percentile$	0.86* (0.43)	0.28	164%	-0.59^{+} (0.24)	0.07

Note. Standard error in parentheses. $^{+}(p < 10\%), ^{*}(p < 5\%), ^{**}(p < 1\%), ^{***}(p < 0.1\%)$.
AME - Average Marginal Effect; ARC - Average Relative Change.

Table 24 ED Cohort Robustness Test on Patient Outcomes: Binary $SDUBusy$ Based on Occupancy Percentile. Low Severity Patients.

$SDUBusy = \mathbf{1}$	Estimate (SE)	AME	ARC	ρ (SE)	Test $\rho = 0$
	$Mortality$				
$SDUOcc >= 80^{th} percentile$	-0.67* (0.30)	-0.02	-85%	0.41 (0.19)	0.06
$SDUOcc >= 85^{th} percentile$	-0.84** (0.25)	-0.03	-89%	0.51** (0.16)	0.01
$SDUOcc >= 90^{th} percentile$	-0.93** (0.21)	-0.03	-90%	0.57** (0.13)	0.01
$SDUOcc >= 95^{th} percentile$	-0.42 (0.29)	-	-	0.25 (0.18)	0.17
	$\log(HospRemLOS)$				
$SDUOcc >= 80^{th} percentile$	-0.22*** (0.04)	-0.22	-22%	0.19*** (0.03)	0.00
$SDUOcc >= 85^{th} percentile$	-0.22*** (0.04)	-0.22	-22%	0.19*** (0.03)	0.00
$SDUOcc >= 90^{th} percentile$	-0.22*** (0.04)	-0.22	-22%	0.20*** (0.03)	0.00
$SDUOcc >= 95^{th} percentile$	-0.22*** (0.04)	-0.22	-22%	0.20*** (0.03)	0.00
	$HospReadm_{1w}$				
$SDUOcc >= 80^{th} percentile$	-0.01 (0.15)	-	-	0.02 (0.08)	0.77
$SDUOcc >= 85^{th} percentile$	-0.02 (0.15)	-	-	0.01 (0.09)	0.87
$SDUOcc >= 90^{th} percentile$	-0.01 (0.15)	-	-	0.01 (0.09)	0.91
$SDUOcc >= 95^{th} percentile$	-0.10 (0.17)	-	-	0.06 (0.09)	0.51
	$HospReadm_{2w}$				
$SDUOcc >= 80^{th} percentile$	-0.10 (0.12)	-	-	0.07 (0.07)	0.34
$SDUOcc >= 85^{th} percentile$	-0.13 (0.13)	-	-	0.08 (0.07)	0.26
$SDUOcc >= 90^{th} percentile$	-0.09 (0.11)	-	-	0.07 (0.06)	0.27
$SDUOcc >= 95^{th} percentile$	-0.20 (0.13)	-	-	0.13+ (0.08)	0.10
	$HospReadm_{30d}$				
$SDUOcc >= 80^{th} percentile$	-0.05 (0.11)	-	-	0.04 (0.06)	0.49
$SDUOcc >= 85^{th} percentile$	-0.07 (0.11)	-	-	0.05 (0.06)	0.39
$SDUOcc >= 90^{th} percentile$	-0.10 (0.11)	-	-	0.07 (0.06)	0.23
$SDUOcc >= 95^{th} percentile$	-0.14 (0.11)	-	-	0.10 (0.06)	0.13

Note. Standard error in parentheses. $^{+}(p < 10\%)$, $^{*}(p < 5\%)$, $^{**}(p < 1\%)$, $^{***}(p < 0.1\%)$.
AME - Average Marginal Effect; ARC - Average Relative Change.

Table 25 ICU Cohort Robustness Test on Patient Outcomes: Continuous $SDUBusy$ Modeled as a Spline Variable

	With IV				
SDUOcc. as piece-wise linear spline	Estimate (SE)	AME	ARC	ρ(SE)	Test $\rho = 0$
	$Mortality$				
With knot at 80^{th} pct	-0.79*** (0.25)	-0.08	-81%	0.38* (0.16)	0.03
With knot at 85^{th} pct	-0.79*** (0.25)	-0.08	-81%	0.38* (0.16)	0.03
With knot at 90^{th} pct	-0.77*** (0.25)	-0.08	-81%	0.37* (0.16)	0.04
With knot at 95^{th} pct	-0.83*** (0.26)	-0.09	-83%	0.40* (0.16)	0.03
	$\log(HospRemLOS)$				
With knot at 80^{th} pct	-0.44*** (0.09)	-0.44	-44%	0.49*** (0.04)	0.00
With knot at 85^{th} pct	-0.42*** (0.09)	-0.42	-42%	0.48*** (0.05)	0.00
With knot at 90^{th} pct	-0.40*** (0.10)	-0.40	-38%	0.46*** (0.05)	0.00
With knot at 95^{th} pct	-0.35*** (0.11)	-0.35	-34%	0.43*** (0.06)	0.00
	$ICUReadm_{2d}$				
With knot at 80^{th} pct	-0.43^{+} (0.24)	-0.04	-61%	0.26^{+} (0.15)	0.09
With knot at 85^{th} pct	-0.40 (0.26)	-	-	0.25 (0.16)	0.14
With knot at 90^{th} pct	-0.42 (0.26)	-	-	0.26 (0.16)	0.11
With knot at 95^{th} pct	-0.50* (0.24)	-0.04	-67%	0.31* (0.15)	0.05
	$ICUReadm_{3d}$				
With knot at 80^{th} pct	-0.06 (0.31)	-	-	0.06 (0.19)	0.74
With knot at 85^{th} pct	-0.02 (0.33)	-	-	0.04 (0.20)	0.85
With knot at 90^{th} pct	-0.05 (0.34)	-	-	0.06 (0.20)	0.78
With knot at 95^{th} pct	-0.12 (0.34)	-	-	0.10 (0.20)	0.62
	$ICUReadm_{5d}$				
With knot at 80^{th} pct	-0.23 (0.27)	-	-	0.19 (0.16)	0.25
With knot at 85^{th} pct	-0.18 (0.28)	-	-	0.16 (0.17)	0.35
With knot at 90^{th} pct	-0.20 (0.28)	-	-	0.17 (0.17)	0.33
With knot at 95^{th} pct	-0.31 (0.26)	-	-	0.24 (0.15)	0.14
	$ICUReadm$				
With knot at 80^{th} pct	-0.24 (0.21)	-	-	0.25^{+} (0.13)	0.07
With knot at 85^{th} pct	-0.15 (0.23)	-	-	0.19 (0.14)	0.18
With knot at 90^{th} pct	-0.07 (0.25)	-	-	0.14 (0.15)	0.34
With knot at 95^{th} pct	-0.12 (0.25)	-	-	0.17 (0.15)	0.26
	$HospReadm_{1w}$				
With knot at 80^{th} pct	-0.37^{+} (0.22)	-0.05	-51%	0.27^{+} (0.14)	0.05
With knot at 85^{th} pct	-0.33 (0.23)	-	-	0.25^{+} (0.14)	0.09
With knot at 90^{th} pct	-0.29 (0.25)	-	-	0.23 (0.15)	0.14
With knot at 95^{th} pct	-0.45^{+} (0.23)	-0.06	-58%	0.33* (0.14)	0.03
	$HospReadm_{2w}$				
With knot at 80^{th} pct	-0.38^{+} (0.21)	-0.07	-47%	0.26^{+} (0.13)	0.06
With knot at 85^{th} pct	-0.39^{+} (0.21)	-0.08	-49%	0.27^{+} (0.13)	0.05
With knot at 90^{th} pct	-0.42^{+} (0.23)	-0.08	-51%	0.29^{+} (0.14)	0.05
With knot at 95^{th} pct	-0.63*** (0.21)	-0.12	-65%	0.42*** (0.13)	0.00
	$HospReadm_{3w}$				
With knot at 80^{th} pct	-0.30 (0.20)	-	-	0.22^{+} (0.12)	0.09
With knot at 85^{th} pct	-0.34^{+} (0.21)	-0.08	-41%	0.25^{+} (0.12)	0.06
With knot at 90^{th} pct	-0.40^{+} (0.21)	-0.09	-46%	0.28* (0.13)	0.04
With knot at 95^{th} pct	-0.55** (0.20)	-0.13	-57%	0.37** (0.12)	0.01
	$HospReadm_{30d}$				
With knot at 80^{th} pct	-0.24 (0.22)	-	-	0.17 (0.13)	0.19
With knot at 85^{th} pct	-0.29 (0.22)	-	-	0.21 (0.13)	0.13
With knot at 90^{th} pct	-0.39^{+} (0.23)	-0.10	-43%	0.27^{+} (0.14)	0.07
With knot at 95^{th} pct	-0.60** (0.22)	-0.16	-58%	0.40** (0.14)	0.01

Note. Standard error in parentheses. $^{+}(p < 10\%)$,* $(p < 5\%)$,** $(p < 1\%)$,*** $(p < 0.1\%)$.
AME - Average Marginal Effect; ARC - Average Relative Change

Table 26 ED Cohort Robustness Test on Patient Outcomes: Continuous $SDUBusy$ Modeled as a Spline Variable. High Severity Patients.

SDUOcc. as piece-wise linear spline	Estimate (SE)	AME	ARC	ρ (SE)	Test $\rho = 0$
			$Mortality$		
With knot at 80^{th} pct	0.54 (0.38)	-	-	-0.36 (0.21)	0.12
With knot at 85^{th} pct	0.66 (0.39)	-	-	-0.37 (0.22)	0.13
With knot at 90^{th} pct	0.71^{*} (0.32)	0.19	91%	-0.46^{*} (0.17)	0.04
With knot at 95^{th} pct	0.71^{+} (0.36)	0.18	87%	-0.47^{+} (0.21)	0.06
			$\log(HospRemLOS)$		
With knot at 80^{th} pct	0.40^{**} (0.14)	0.40	25%	-0.54^{***} (0.08)	0.00
With knot at 85^{th} pct	0.42^{**} (0.13)	0.42	27%	-0.55^{***} (0.08)	0.00
With knot at 90^{th} pct	0.43^{***} (0.13)	0.43	27%	-0.55^{***} (0.08)	0.00
With knot at 95^{th} pct	0.46^{***} (0.12)	0.46	30%	-0.58^{***} (0.07)	0.00
			$HospReadm_{1w}$		
With knot at 80^{th} pct	0.93 (1.04)	-	-	-0.60 (0.54)	0.41
With knot at 85^{th} pct	1.03 (0.96)	-	-	-0.65 (0.49)	0.36
With knot at 90^{th} pct	1.20^{*} (0.58)	0.26	377%	-0.69 (0.25)	0.15
With knot at 95^{th} pct	1.05 (0.95)	-	-	-0.66 (0.48)	0.25
			$HospReadm_{2w}$		
With knot at 80^{th} pct	1.11 (0.73)	-	-	-0.70 (0.38)	0.25
With knot at 85^{th} pct	1.25^{*} (0.57)	0.37	289%	-0.77 (0.28)	0.14
With knot at 90^{th} pct	1.26^{*} (0.56)	0.37	290%	-0.78^{+} (0.23)	0.09
With knot at 95^{th} pct	1.14 (0.76)	-	-	-0.71 (0.40)	0.28
			$HospReadm_{30d}$		
With knot at 80^{th} pct	0.77^{+} (0.47)	0.25	150%	-0.54 (0.27)	0.11
With knot at 85^{th} pct	0.87^{*} (0.43)	0.25	151%	-0.59^{+} (0.24)	0.06
With knot at 90^{th} pct	0.87^{*} (0.44)	0.28	222%	-0.60^{+} (0.25)	0.07
With knot at 95^{th} pct	0.70 (0.71)	-	-	-0.50 (0.41)	0.31

Note. Standard error in parentheses. $^{+}(p < 10\%), ^{*}(p < 5\%), ^{**}(p < 1\%), ^{***}(p < 0.1\%)$.
AME - Average Marginal Effect; ARC - Average Relative Change.

Table 27 ED Cohort Robustness Test on Patient Outcomes: Continuous $SDUBusy$ Modeled as a Spline Variable. Low Severity Patients.

SDUOcc. as piece-wise linear spline	Estimate (SE)	AME	ARC	ρ (SE)	Test $\rho = 0$
	$Mortality$				
With knot at 80^{th} pct	-0.61* (0.26)	-0.02	-82%	0.37* (0.16)	0.04
With knot at 85^{th} pct	-0.60** (0.26)	-0.03	-89%	0.36* (0.16)	0.04
With knot at 90^{th} pct	-0.54* (0.27)	-0.02	-78%	0.32+ (0.17)	0.07
With knot at 95^{th} pct	-0.24 (0.25)	-	-	0.14 (0.15)	0.33
	$\log(HospRemLOS)$				
With knot at 80^{th} pct	-0.21*** (0.04)	-0.21	-21%	0.18*** (0.03)	0.00
With knot at 85^{th} pct	-0.21*** (0.04)	-0.21	-21%	0.19*** (0.03)	0.00
With knot at 90^{th} pct	-0.21*** (0.04)	-0.21	-21%	0.19*** (0.03)	0.00
With knot at 95^{th} pct	-0.22*** (0.04)	-0.22	-22%	0.19*** (0.03)	0.00
	$HospReadm_{1w}$				
With knot at 80^{th} pct	-0.09 (0.16)	-	-	0.06 (0.09)	0.53
With knot at 85^{th} pct	-0.11 (0.16)	-	-	0.07 (0.09)	0.45
With knot at 90^{th} pct	-0.13 (0.17)	-	-	0.08 (0.10)	0.41
With knot at 95^{th} pct	-0.14 (0.17)	-	-	0.09 (0.10)	0.38
	$HospReadm_{2w}$				
With knot at 80^{th} pct	-0.16 (0.12)	-	-	0.12 (0.17)	0.15
With knot at 85^{th} pct	-0.19 (0.13)	-	-	0.12 (0.07)	0.11
With knot at 90^{th} pct	-0.21 (0.13)	-	-	0.13+ (0.07)	0.08
With knot at 95^{th} pct	-0.22 (0.13)	-	-	0.14+ (0.08)	0.08
	$HospReadm_{30d}$				
With knot at 80^{th} pct	-0.06 (0.10)	-	-	0.05 (0.06)	0.38
With knot at 85^{th} pct	-0.10 (0.11)	-	-	0.07 (0.06)	0.24
With knot at 90^{th} pct	-0.11 (0.11)	-	-	0.08 (0.06)	0.18
With knot at 95^{th} pct	-0.15 (0.11)	-	-	0.10 (0.06)	0.12

Note. Standard error in parentheses. $^{+}(p < 10\%), ^{*}(p < 5\%), ^{**}(p < 1\%), ^{***}(p < 0.1\%)$.
AME - Average Marginal Effect; ARC - Average Relative Change.

Table 28 ED Cohort Robustness Test on Patient Outcomes: Binary $ICUBusy$ Based on Number of Available Beds. High Severity Patients.

$ICUBusy = \mathbf{1}$	Estimate (SE)	AME	ARC	ρ (SE)	Test $\rho = 0$
	$Mortality$				
$ICUFreeBeds <= 4$	0.63^{+} (0.35)	0.18	84%	-0.41^{+} (0.23)	0.06
$ICUFreeBeds <= 3$	0.68* (0.32)	0.19	86%	-0.44* (0.18)	0.03
$ICUFreeBeds <= 2$	0.75* (0.33)	0.21	92%	-0.48* (0.18)	0.03
$ICUFreeBeds <= 1$	0.69* (0.34)	0.19	86%	-0.44* (0.19)	0.04
	$\log(HospRemLOS)$				
$ICUFreeBeds <= 4$	0.42*** (0.13)	0.42	27%	-0.55*** (0.08)	0.00
$ICUFreeBeds <= 3$	0.43*** (0.13)	0.43	27%	-0.55*** (0.08)	0.00
$ICUFreeBeds <= 2$	0.45*** (0.12)	0.45	28%	-0.57*** (0.07)	0.00
$ICUFreeBeds <= 1$	0.56* (0.24)	0.56	30%	-0.46*** (0.07)	0.00
	$HospReadm_{1w}$				
$ICUFreeBeds <= 4$	1.19^{+} (1.68)	0.29	390%	-0.73 (0.32)	0.18
$ICUFreeBeds <= 3$	1.15 (0.73)	-	-	-0.71 (0.35)	0.21
$ICUFreeBeds <= 2$	1.27* (0.59)	0.32	390%	-0.77 (0.26)	0.11
$ICUFreeBeds <= 1$	1.19^{+} (0.62)	0.29	388%	-0.73 (0.29)	0.14
	$HospReadm_{2w}$				
$ICUFreeBeds <= 4$	1.35** (0.36)	0.41	297%	-0.83* (0.17)	0.02
$ICUFreeBeds <= 3$	1.28** (0.35)	0.38	293%	-0.79* (0.17)	0.02
$ICUFreeBeds <= 2$	1.27** (0.40)	0.38	294%	-0.78* (0.20)	0.04
$ICUFreeBeds <= 1$	1.18** (0.43)	0.35	283%	-0.73* (0.22)	0.05
	$HospReadm_{30d}$				
$ICUFreeBeds <= 4$	1.01** y(0.28)	0.33	281%	-0.68** (0.15)	0.01
$ICUFreeBeds <= 3$	0.98** (0.27)	0.32	277%	-0.66** (0.15)	0.01
$ICUFreeBeds <= 2$	0.97** (0.31)	0.31	279%	-0.65** (0.17)	0.01
$ICUFreeBeds <= 1$	0.90** (0.35)	0.29	270%	-0.62* (0.19)	0.02

Note. Standard error in parentheses. $^{+}(p < 10\%),^{*}(p < 5\%),^{**}(p < 1\%),^{***}(p < 0.1\%)$.
AME - Average Marginal Effect; ARC - Average Relative Change.

Table 29 ED Cohort Robustness Test on Patient Outcomes: Binary $ICUBusy$ Based on Occupancy Percentile. High Severity Patients.

$ICUBusy = \mathbf{1}$	Estimate (SE)	AME	ARC	ρ (SE)	Test $\rho = 0$
	$Mortality$				
$ICUOcc >= 80^{th} percentile$	0.51 (0.37)	-	-	-0.34 (0.21)	0.13
$ICUOcc >= 85^{th} percentile$	0.56 (0.36)	-	-	-0.37^{+} (0.20)	0.09
$ICUOcc >= 90^{th} percentile$	0.58* (0.38)	0.17	90%	-0.35^{+} (0.21)	0.09
$ICUOcc >= 95^{th} percentile$	0.60^{+} (0.35)	0.17	86%	-0.39^{+} (0.20)	0.08
	$\log(HospRemLOS)$				
$ICUOcc >= 80^{th} percentile$	0.42** (0.13)	0.42	27%	-0.55*** (0.08)	0.00
$ICUOcc >= 85^{th} percentile$	0.40** (0.14)	0.40	25%	-0.54*** (0.08)	0.00
$ICUOcc >= 90^{th} percentile$	0.49** (0.13)	0.49	30%	-0.54*** (0.08)	0.00
$ICUOcc >= 95^{th} percentile$	0.39*** (0.15)	0.39	23%	-0.56*** (0.07)	0.00
	$HospReadm_{1w}$				
$ICUOcc >= 80^{th} percentile$	1.09^{+} (0.65)	0.26	375%	-0.69 (0.32)	0.16
$ICUOcc >= 85^{th} percentile$	1.15* (0.52)	0.28	388%	-0.71^{+} (0.25)	0.08
$ICUOcc >= 90^{th} percentile$	1.14^{+} (0.63)	0.27	380%	-0.71 (0.31)	0.15
$ICUOcc >= 95^{th} percentile$	1.12^{+} (0.68)	0.27	383%	-0.70 (0.33)	0.18
	$HospReadm_{2w}$				
$ICUOcc >= 80^{th} percentile$	1.24** (0.41)	0.36	286%	-0.77* (0.24)	0.04
$ICUOcc >= 85^{th} percentile$	1.27** (0.31)	0.38	293%	-0.79** (0.15)	0.01
$ICUOcc >= 90^{th} percentile$	1.29*** (0.37)	0.38	294%	-0.80* (0.18)	0.03
$ICUOcc >= 95^{th} percentile$	1.22** (0.41)	0.36	287%	-0.76* (0.21)	0.04
	$HospReadm_{30d}$				
$ICUOcc >= 80^{th} percentile$	1.05** (0.24)	0.34	287%	-0.70** (0.13)	0.01
$ICUOcc >= 85^{th} percentile$	1.01** (0.25)	0.33	285%	-0.68** (0.14)	0.01
$ICUOcc >= 90^{th} percentile$	0.97** (0.28)	0.32	280%	-0.66** (0.15)	0.01
$ICUOcc >= 95^{th} percentile$	0.94** (0.30)	0.31	279%	-0.64** (0.16)	0.01

Note. Standard error in parentheses. $^{+}(p < 10\%), ^{*}(p < 5\%), ^{**}(p < 1\%), ^{***}(p < 0.1\%)$.
AME - Average Marginal Effect; ARC - Average Relative Change.

Table 30 **ED Cohort Robustness Test on Patient Outcomes: Continuous $ICUBusy$ Modeled as a Spline Variable. High Severity Patients.**

$ICUBusy = \mathbf{1}$	Estimate (SE)	AME	ARC	ρ (SE)	Test $\rho = 0$
	$Mortality$				
With knot at 80^{th} pct	0.60$^+$ (0.34)	0.17	90%	-0.39$^+$ (0.19)	0.07
With knot at 85^{th} pct	0.63$^+$ (0.33)	0.18	90%	-0.41* (0.18)	0.05
With knot at 90^{th} pct	0.68* (0.32)	0.19	91%	-0.44* (0.18)	0.03
With knot at 95^{th} pct	0.72* (0.30)	0.20	91%	-0.46* (0.17)	0.02
	$\log(HospRemLOS)$				
With knot at 80^{th} pct	0.42** (0.13)	0.42	27%	-0.55*** (0.08)	0.00
With knot at 85^{th} pct	0.42** (0.13)	0.42	27%	-0.55*** (0.08)	0.00
With knot at 90^{th} pct	0.42** (0.13)	0.42	26%	-0.54*** (0.08)	0.00
With knot at 95^{th} pct	0.43** (0.13)	0.43	27%	-0.55*** (0.07)	0.00
	$HospReadm_{1w}$				
With knot at 80^{th} pct	1.18* (0.54)	0.29	388%	-0.73$^+$ (0.25)	0.09
With knot at 85^{th} pct	1.22* (0.54)	0.28	388%	-0.75$^+$ (0.25)	0.08
With knot at 90^{th} pct	1.24* (0.54)	0.27	380%	-0.76$^+$ (0.24)	0.08
With knot at 95^{th} pct	1.29* (0.50)	0.32	392%	-0.78$^+$ (0.22)	0.07
	$HospReadm_{2w}$				
With knot at 80^{th} pct	1.24** (0.36)	0.36	286%	-0.77* (0.18)	0.02
With knot at 85^{th} pct	1.26** (0.37)	0.38	293%	-0.78* (0.18)	0.02
With knot at 90^{th} pct	1.27** (0.37)	0.38	295%	-0.79* (0.18)	0.03
With knot at 95^{th} pct	1.27** (0.37)	0.38	294%	-0.79* (0.18)	0.02
	$HospReadm_{30d}$				
With knot at 80^{th} pct	0.98** (0.27)	0.32	279%	-0.66** (0.15)	0.01
With knot at 85^{th} pct	0.97** (0.28)	0.33	285%	-0.65** (0.14)	0.01
With knot at 90^{th} pct	0.98** (0.29)	0.32	280%	-0.66** (0.15)	0.01
With knot at 95^{th} pct	0.99*** (0.28)	0.32	287%	-0.67** (0.15)	0.01

Note. Standard error in parentheses. $^+(p < 10\%), ^*(p < 5\%), ^{**}(p < 1\%), ^{***}(p < 0.1\%)$.
AME - Average Marginal Effect; ARC - Average Relative Change.

Table 31 **ED Cohort Estimation Results for Patient Outcomes with $RecentAdmission_i^{ICU}$ Included as an Additional Instrument. High Severity Patients**

Outcome	Estimate (SE)	AME	ARC	ρ (SE)	Test $\rho = 0$
$Mortality$	0.73* (0.33)	0.20	92.81%	-0.49$^+$ (0.29)	0.08
$\log(HospRemLOS)$	0.46*** (0.13)	0.46	29.55%	-0.59*** (0.08)	0.00
$HospReadm_{1w}$	1.16 (0.46)	0.38	353.41%	-0.79* (0.20)	0.05
$HospReadm_{2w}$	1.21* (0.39)	0.34	240.98%	-0.79$^+$ (0.25)	0.09
$HospReadm_{30d}$	0.92* (0.30)	0.29	233.60%	-0.65 (0.38)	0.13

Note. Standard error in parentheses. $^+(p < 10\%), ^*(p < 5\%), ^{**}(p < 1\%), ^{***}(p < 0.1\%)$.
AME - Average Marginal Effect; ARC - Average Relative Change.