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Hospital Boarding Crises: The Impact of Urgent vs. Prevention Responses on Length of Stay

Temidayo Adepoju,[a,*] Anita L. Carson,[b] Helen S. Jin,[c] Christopher S. Manasseh[d]

[a] Rutgers Business School, Rutgers University, Newark, New Jersey 07102; [b] Questrom School of Business, Boston University, Boston, Massachusetts 02215; [c] Greater Lawrence Family Health Center, Lawrence, Massachusetts 01841; [d] Boston Medical Center, Boston, Massachusetts 02118

*Corresponding author

Contact: ta510@business.rutgers.edu, https://orcid.org/0000-0002-1858-4740 (TA); altucker@bu.edu, https://orcid.org/0000-0001-9765-7372 (ALC); jin.s.helen@gmail.com (HSJ); chris.manasseh@bmc.org (CSM)

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Abstract. Healthcare policy makers use wait-time metrics to encourage hospital managers to improve patient experience. In 2002, Massachusetts mandated that hospital managers develop processes to respond to boarding crises, which occur when emergency department (ED) patients experience long waits for inpatient beds. Performance improvement theory suggests that patients would be better served by preventing boarding crises rather than responding urgently after they occur. To empirically test this theory, we use data from a Massachusetts hospital that has two physician-based processes related to boarding and patient flow. First, to comply with the state mandate, the hospital developed processes to identify when the hospital is in a boarding crisis, a code yellow (CY), and subsequently request that physicians prioritize patient discharge (urgent response). Second, physicians can use predischarge orders, optional written communication about discharge barriers, to avoid discharge delays for patients approaching discharge (prevention response). Our data supports the existence of a trade-off between these two responses. Counter to our hypothesis, the state-mandated urgent response does not have any impact on length of stay (LOS). We also find that a CY has no impact on ED hourly occupancy, marginally decreases ED wait times, and increases boarding time. The prevention response is associated with a 26% reduction in LOS. Furthermore, we find that the urgent response reduces the likelihood of physicians' ability to use the prevention response by 27.3%. We conclude that the state policy has unintended negative consequences that stymie hospital efforts to create longer term improvement.

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1. Introduction

Hospitals frequently experience boarding crises during which demand for inpatient hospital beds exceeds supply. During a boarding crisis, admitted patients can remain in the emergency department (ED) for long periods of time (Dai and Shi 2018). In 2002, Massachusetts policy makers mandated that hospitals develop a process for dealing with ED boarding with the goal of moving boarding patients to inpatient floors within 30 minutes (Burke et al. 2013, Michael et al. 2018). We call this an "urgent" response because it deals with the immediate situation but does not attempt to prevent future occurrences (Repenning and Sterman 2001).

Performance improvement theory suggests that managers should instead invest in preventing boarding crises, which we term a "prevention" response. Theory suggests that prevention responses improve performance in the long term but are challenging to implement because they take employees' time away from current production and, therefore, exacerbate the crisis in the short term. Furthermore, the benefits emerge after a time delay (Bohn 2000, Repenning and Sterman 2001). These aspects create a "worse-before-better" dynamic that makes it unlikely that managers will invest in prevention responses (Repenning and Sterman 2001).

Healthcare scholars call for research on managers' responses to boarding crises (Fieldston et al. 2010). Managers have the ability to implement urgent and prevention responses that might reduce the frequency and negative impact of boarding crises. However, the extent to which each response performs relative to the other is unknown. Cultivating persistent use of the best response will likely require evidence of its performance, particularly if it is the prevention response. Our research aims to fill this gap.

To empirically test the effectiveness of these two types of responses, we collaborate with a Massachusetts academic medical center that we refer to by the pseudonym Omega Hospital. Omega has procedures for both urgent and prevention responses. Omega refers to its response to the state-mandated urgent response as a code yellow (CY). When a CY is activated, physicians receive a message that alerts them of the large number of patients boarding in the ED and encourages them to work on discharging inpatients. The prevention response is physicians' use of predischarge orders (PDOs) for patients within two days of being discharged. The PDO is embedded in the electronic health record (EHR) and is used at the discretion of physicians in addition to discharge orders. We provide further details on these two responses in Section 3.1.

After accounting for endogeneity using an instrumental variables (IV) approach for PDO, we find that patients with a PDO have a 26% shorter length of stay (LOS) than patients without a PDO. Conversely, using a survival analysis approach, we find that LOS is not impacted for patients who experience a CY during their hospital stay versus patients who do not. Also, we demonstrate that CY has no impact on ED hourly occupancy and marginally decreases ED wait time but increases ED boarding time. Furthermore, the urgent response crowds out the prevention response. The likelihood that physicians use PDOs decreases by 27.3% when hospital managers call a CY. Finally, we demonstrate that the use of PDOs lead to more discharges compared with CY and that using PDOs more often reduces the need for a CY activation. Our study provides empirical evidence of Repenning and Sterman's (2001) capability trap and Bohn's (2000) firefighting, in which pressure to produce results today impedes workers' efforts to improve future performance. Thus, we find that the state-mandated urgent response creates a state of chaos that weakens short-term performance and deters physicians from investing in actions that could prevent future boarding crises.

2. Literature Review and Hypotheses Development

High inpatient bed occupancy can cause admitted ED patients to remain in the ED for hours (Armony et al. 2015) and result in patients being treated in wards that are not the most appropriate for their acuity level (Kc and Terwiesch 2012, Kim et al. 2015) or medical condition (Price et al. 2011, Song et al. 2019). High occupancy is also associated with poor quality of care, including premature discharge (Anderson et al. 2011, Berry Jaeker and Tucker 2016), which, in turn, leads to higher risk of inpatient mortality (Kc and Terwiesch 2009, Kuntz et al. 2014) and readmission (Anderson et al. 2012, Kc and Terwiesch 2012).

2.1. The Discharge Process

Patient discharge is an essential component of both urgent and prevention responses. The discharge process is complex and time-consuming. It starts with the physician writing a discharge order stating that the patient is medically ready to be discharged. The physician has discretion over the timing of this decision (Abramson 1981). The discharge order is written after the physician completes a summary of the patient's visit, which includes information such as the care provided and postdischarge instructions.

Discharge requires a coordinated effort from many different disciplines. A pharmacist may be needed to reconcile the patient's (outgoing) medications with (incoming) medications; a physical therapist may be needed to assess the patient's ability to walk or swallow; and a case manager ensures that the patient has a bed in the next facility on the medical journey, such as a skilled nursing facility or rehabilitation hospital (McDermott and Venditti 2015). Advance notification from the physician that the patient will be discharged within a few days may reduce discharge delays because it can mitigate the long lead times to secure services, such as a bed in a skilled nursing facility (McDermott and Venditti 2015).

2.2. Prior Research on Improving the Discharge Process in Hospitals

An inefficient discharge process is one driver of hospital congestion. Consequently, hospitals use strategies to make discharge more efficient, such as board rounds. Board rounds are short, daily meetings on inpatient wards in which nurses, physicians, and case managers discuss which patients could be ready for discharge the next day and any barriers that would delay their discharge (Perlmutter et al. 1998, Dutton et al. 2003, Wertheimer et al. 2015). However, board rounds are limited by the need for physicians to be physically present (Song et al. 2019) and by the verbal format, which makes the discussed information unavailable to nonparticipating members of the care team, such as pharmacists.

Another strategy for improving discharge is streamlining and standardizing the process (McDermott and Venditti 2015). For example, Beck et al. (2016) finds that ED patients are discharged one hour earlier when there is a hard copy of a discharge checklist at the patient's bedside that enables the care team to see what remains to be completed. Durvasula et al. (2015) find that performing the medication reconciliation the night before the patient is expected to be discharged reduces delays.

To our knowledge, prior research has not considered the impact of using discharge strategies during boarding crises, such as a CY or the EHR-driven discharge-planning tool employed by Omega. Omega uses EPIC, one of the most common EHR systems in hospitals, and the PDO is a standard feature in EPIC. Furthermore, many acute care hospitals have some form of urgent response to alleviate boarding crises. Collectively, these common conditions make our study relevant for many hospitals.

2.3. The Urgent Response to Boarding Crises: Code Yellow

We outline a set of hypotheses related to the impact of a CY being called during a patient's hospital visit. First, we investigate the relationship between CY and patients' hospital LOS. A CY should relieve hospital occupancy pressure for three reasons. First, writing discharge orders and speaking with patients about their discharge are time-consuming tasks for physicians. Physicians typically prioritize work for newly admitted patients—who arguably are sicker and, therefore, should be treated first—over discharge-related work for healthier patients approaching the end of their hospital stay. However, this prioritization is reversed during a CY because physicians instead focus on discharging inpatients who are clinically ready to go home. Second, physicians have the discretion to determine when a patient is medically cleared for discharge (Abramson 1981). Research finds that when workload increases, workers who have discretion over their tasks reduce the time spent servicing a customer to increase throughput (Oliva and Sterman 2001, Hopp et al. 2007). As hospital occupancy increases, patients have a shorter hospital LOS because physicians discharge patients earlier than they otherwise would (Anderson et al. 2012, Berry Jaeker and Tucker 2016). Accordingly, when inpatient physicians learn via a CY that patients are boarding in the ED, they can use their discretion to begin the discharge process for inpatients closest to being medically cleared for discharge. Finally, theory suggests that, as the workload increases, staff work faster to increase throughput, improving performance in the short term (Repenning and Sterman 2001). Consequently, because urgent responses, such as CY, seem effective, workers engage in them despite the fact that they often do not help longer term performance (Repenning and Sterman 2001, Tucker and Edmondson 2003, Morrison 2015). For these reasons, we anticipate that CY is associated with a shorter inpatient LOS.

Hypothesis 1. *Patients who experience a CY during their hospital stay have a shorter LOS, on average, than patients who do not experience a CY during their stay.*

At Omega Hospital, hospital management activates CY when the ED is crowded. ED crowding is typically the result of an increase in admitted patients boarding in the ED caused by a lack of available inpatient beds (U.S. General Accounting Office 2003). Shi et al. (2016) show that early discharge policies can improve flow for patients boarding in the ED. Similarly, as previously mentioned, when CY is called, hospital management encourages physicians to discharge inpatients so that admitted ED patients can be transferred from the ED to the freed-up inpatient beds. This should reduce boarding time. Thus, we hypothesize the following.

Hypothesis 2a. *Admitted ED patients who experience a CY during their ED visit have shorter ED boarding time, on average, than admitted ED patients who do not experience a CY during their ED visit.*

CY may impact all ED patients, including those not admitted to the hospital. CY reduces the number of ED patients boarding in the ED, which should subsequently reduce ED occupancy. Thus, we hypothesize the following.

Hypothesis 2b. *ED patients who experience a CY during their ED visit experience a lower ED hourly occupancy than ED patients who do not experience a CY during their ED visit.*

A second effect of a CY is that it signals to ED physicians that they should reduce service time for all patients in order to increase throughput in the busy ED. Thus, the time that arriving ED patients have to wait to see an ED physician should reduce after a CY is called. We, therefore, hypothesize the following.

Hypothesis 2c. *ED patients who experience a CY during their ED visit have shorter ED wait time on average than ED patients who do not experience a CY during their ED visit.*

2.4. The Prevention Response: Predischarge Orders

We next hypothesize that a prevention response is associated with shorter LOS. We study the specific coordination mechanism of a PDO, a computerized tool that enables physicians to communicate asynchronously to the care team that a patient is approaching discharge. Managers in a variety of settings, such as research and development (Keller 1994), software teams (Faraj and Sproull 2000, Banker et al. 2006, Bardhan et al. 2013), and audit teams (Gupta et al. 1994), use coordination to manage interdependencies and increase efficiency. Most closely related to our study, Gittell et al. (2000) examine how relational coordination in surgical units reduces LOS and improves quality of care, whereas Faraj and Xiao (2006) study trauma centers to understand how physicians coordinate in a fast-paced environment. These studies find that coordination mechanisms that foster communication across the care team result in better outcomes.

Scholars have also examined information technology (IT)–enabled coordination. In the software industry, Banker et al. (2006) find that the use of software as a coordination tool for collaboration among project team members reduces cycle time. They attribute its effectiveness to the timely information exchange between team members. Bardhan et al. (2013) find that, when IT enables communication, it bridges information gaps between dispersed team members, especially for projects with a high level of information intensity. Similar benefits may accrue to healthcare teams who use IT to coordinate discharge, such as the PDOs in our study.

In a healthcare setting, different disciplines within the hospital can coordinate patient care by using IT to exchange information. Dobrzykowski and Tarafdar (2015) find that EHRs increase coordination across providers, which, in turn, improves patient satisfaction with provider–patient communication. We predict that PDOs can improve coordination between physicians and other clinicians and, consequently, reduce LOS because PDOs are designed to coordinate patient discharge. We, therefore, hypothesize the following.

Hypothesis 3. *Patients who receive PDO during their hospital stay have a shorter LOS on average than patients who did not receive a PDO during their stay.*

2.5. Potential "Crowding Out" Effect of the Urgent Response on the Prevention Response

Our next set of hypotheses link the urgent response of CY to a reduction in slack time that physicians need to initiate PDOs (Repenning and Sterman 2001). Prior studies at the individual-worker level find that urgent work takes time away from important but nonurgent tasks that could yield future benefits. Powell et al. (2012) demonstrate that, when physicians have a high workload, they fail to thoroughly document the care they provide to patients, resulting in lower reimbursements from insurers. Tan and Netessine (2014) show that, as the number of restaurant customers increases, wait staff reduce sales effort on profitable but optional food items. Based on these studies, we hypothesize that, during a CY, physicians are less likely to fill out PDOs because the urgent need to discharge patients today takes precedence over the optional work of filling out a PDO that might produce a faster discharge in two or three days. Thus, we hypothesize the following.

Hypothesis 4. *Patients who experience a CY in the days close to their predicted discharge are less likely to have a PDO than patients who do not have a CY in the days close to their predicted discharge.*

Research finds that congestion can affect organization-level outcomes (Kc and Terwiesch 2009, Kuntz et al. 2014). Studies show that, as workload increases, revenue decreases because workers spend less time on optional yet revenue-generating tasks, such as documenting care provided, and up-selling (Oliva and Sterman 2001, Powell et al. 2012, Tan and Netessine 2014). We draw on this literature to conjecture that, when the hospital is congested, organizational performance declines for measures that rely on optional tasks (e.g., physicians' documentation). More specifically, we anticipate that, during a CY, the number of PDOs written in the hospital decreases.

Hypothesis 5. *Fewer PDOs are completed on days when CYs are activated.*

2.6. Comparing Urgent and Prevention Response on Discharges

IT tools for coordination, such as PDOs, decrease the duration of service time (Banker et al. 2006). Similarly, Gittell et al. (2000) finds that coordination via human relationships (e.g., meetings, conversations) also reduces LOS. In our study, PDOs should reduce LOS by increasing the rate of completion of discharge-related tasks by the interdisciplinary care team. Information that the patient is going to be discharged in a few days as well as the required steps are entered into the patient's EHR. The PDO highlights to the support roles (e.g., social workers, physical therapy, pharmacy, nurses, etc.) the discharge-related tasks that need to be completed for those patients and raises their priority. The shared information also enables coordinating conversations among the team members that can smooth tasks that otherwise block discharge, such as securing a bed in a skilled nursing facility. When LOS shortens, more patients are discharged from the hospital, freeing inpatient beds. Thus, we hypothesize the following.

Hypothesis 6a. *As the number of PDOs completed for patients increases, the number of discharges increases.*

Similarly, we hypothesize that CY results in an increase in discharges on the day a CY is called. This is because, when CY is triggered, hospital physicians get the information that the organization-level priority is discharging medically ready patients in the inpatient units to make beds available for patients boarding in the ED. Thus, we hypothesize the following.

Hypothesis 6b. *When CY is activated, the number of discharges on that day increases.*

3. Empirical Setting and Data

3.1. Prevention and Urgent Responses at Our Research Site

We gather data from Omega on prevention and urgent responses to boarding crises. For the prevention response, Omega's physicians use the EHR to write PDOs for their patients. The EHR has a screen that enables caregivers to see a list of their assigned patients. In the list view, patients with PDOs have a green circle next to their name (Online Figure A.2), and in the patient's record, there is a headline banner stating that the patient is nearing discharge and care should be prioritized

(Online Figure A.3). The PDO form has three checkboxes for potential barriers to discharge: pending labs, physical therapy clearance, and other (Online Figure A.1). If "other" is selected, the physician can enter free text to describe the barrier. The physicians on our research team coded the free text into types of barriers, including placement in another facility.

For the urgent response, when ED boarding increases, an Omega hospital manager enters information into a spreadsheet that determines whether anticipated demand for inpatient medical and surgical beds outstrips available supply. Demand information includes ED waiting room census, number of admitted ED patients who need medical and surgical inpatient beds, and anticipated ED arrivals as well as anticipated demand for medical and surgical beds from surgery, transfers, direct admits, and other procedures. Supply information includes the number of open medical and surgical inpatient beds and pending inpatient discharges. The urgent response, CY, is triggered by an algorithm that uses this supply and demand information to determine if the hospital is in a boarding crisis. When this occurs, the patient flow manager sends via phone call, email, and pager the code yellow status to physician leaders and nursing unit managers. The message states that the ED is in a state of CY and the staff should prioritize discharging patients and remain on duty to do so. Multiple services are involved in the CY discharge process, including the following: consultants to expedite patient evaluation, radiology to prioritize interventional procedures, facilities team to clean emptied rooms, food services to provide early meals so patients can be discharged, and transportation services to expedite leaving the hospital. If the critical crowding level escalates, a follow-up message is sent that states the ED remains at critical crowding levels despite previous actions and that employees and physicians must remain on duty unless released by their immediate supervisor.

3.2. Data

We use data from the hospital's EHR from June 2014 through November 2017. Omega Hospital initiated the PDO in March 2015 across all departments. We focus our analyses on patients from medical and surgical inpatient units and have data on 15,423 patient visits across 9,917 unique patients. To calculate our outcome variables, LOS, we enforce some restrictions. First, we exclude 3,688 patient visits for which patients are admitted as observation status. These are patients who are not sick enough to meet inpatient criteria but are placed in an inpatient unit because of a lack of available beds in the observation unit. Next, we exclude five patient visits with negative LOS. We retain patients who are admitted as inpatient status but who stay 24 hours or less in the inpatient unit because they contribute to the occupancy challenges. We exclude 23 patient visits with extremely high LOS, defined at the 99th percentile or higher, to remove nonrepresentative outliers. We eliminate 117 patient visits in which the patient dies during hospitalization. We further eliminate 84 patient visits that do not have attending physicians. Finally, we exclude three patient visits with no discharge date and 949 patient visits with missing acuity levels. These exclusions leave us with a final sample of 10,554 patient visits across 7,280 unique patients treated by 184 attending physicians. From our final sample, we have 3,652 patient visits (34.60%) with a PDO and 6,902 (65.40%) without a PDO. In addition, 4,290 of the patient visits (40.65%) experience a CY and 6,264 (59.35%) do not.

The data set includes patient-visit level information: the attending physician responsible for each patient, patient demographics (age, gender), department (e.g., surgical, medical), discharge disposition (e.g., discharge to home, to a skilled nursing facility, etc.), insurance type, admission/primary/secondary diagnoses, and hospital-assigned acuity level (in order of increasing acuity: nonurgent, less urgent, urgent, emergent, immediate). Note that, for the hospital-assigned acuity level, the nonurgent and less urgent categories are not included in our analyses because these categories are typically used for observation status patients. Patient severity is measured using an Elixhauser severity score constructed from patient diagnoses (Elixhauser et al. 1998). The Elixhauser method assigns each of 30 different categories of comorbidity diagnoses a weight ranging from −7 (lowest) to 12 (highest). Each patient's Elixhauser score is calculated as the sum of the weights of the diagnoses. For example, a patient diagnosed with liver disease and blood loss anemia has weights of 11 and −2, respectively, which result in an Elixhauser severity score of 9.

We also calculate hospital occupancy on each patient's days of admission and discharge. All patients are included in our calculation of occupancy, including those that were excluded in our data restriction. We follow prior research and treat weekday admissions (discharges) separately from weekend admissions (discharges) to account for staffing differences during the week versus weekends (Kuntz et al. 2014, Berry Jaeker and Tucker 2016). If a patient is admitted (discharged) on a weekday, we divide the number of occupied beds on the patient's admission (discharge) day by the maximum number of occupied beds during that quarter, excluding weekend days (Kuntz et al. 2014, Berry Jaeker and Tucker 2016). Using the maximum number of occupied beds (also known as staffed and used beds) rather than the number of licensed beds (the number of beds a hospital holds license to operate) recognizes that the number of occupied may be fewer than the number of licensed beds. This method also ensures that occupancy falls between 0% and 100%. We obtain occupancy levels that are normally distributed with a minimum of 73.61% and a maximum of 100% (Online Figure A.4).

To measure the prevention response, we collect PDO information (order time and responses to the questions in the form, including barriers to discharge). To measure the urgent response, we collect the occurrence of each CY at Omega Hospital. We have the start and stop dates and times for each CY. In total, there are 216 CY days out of 1,214 days in our data set. The median duration of a CY is 23.83 hours.

To explore the relationship between CY and ED outcomes, we obtain ED-level data from Omega's EHR from June 2014 through November 2017. We have data on 452,595 patient ED visits across 178,485 unique patients. To calculate our outcome variables—ED boarding time, ED hourly occupancy, and ED wait time, we enforce some restrictions by following Song et al. (2015). We exclude the following observations: missing acuity level; acuity level categorized as immediate; ED disposition missing or categorized as "eloped," "expired," "against medical advice," or "leave without being seen." We drop observations with missing physician assigned time and bed request time (for patients who need admission to the inpatient unit). After constructing our variables, we drop observations with negative ED wait time and ED boarding times. We trim the ED boarding time by dropping observations with boarding time greater than 48 hours. Next, we trim ED wait time at the 95th percentile. These exclusions leave us with a final sample of 354,722 patient visits across 150,297 unique patients treated by 755 physicians. From our final sample, 297,489 do not experience a CY (85.87%) and 57,233 experience a CY (16.13%). Our ED data set includes ED occupancy (admission and discharge), patient demographics (age, gender), acuity level (emergent, urgent, less urgent, and nonurgent), insurance type, severity score, ED disposition (inpatient admission, observation unit admission, discharge from ED, transfer to another healthcare facility, and transfer to same-day procedure). Unlike the inpatient data, the ED data does not include department of care. This is because patients are assigned to the respective department only after admission into an inpatient unit. We also do not have the attending physician workload as we do in the inpatient data. This is because attending physicians are not the only ones responsible for patient care in the ED, but also nurses and residents. However, in the inpatient unit, patients are assigned to a team headed by an attending physician.

To perform our main analyses, we merge patient visit– and hospital-level data into a single data set with patient visit as the level of analysis. For our ED analyses, we merge the patient visit– and ED-level data into a single data set with patient visit as the level of analysis.

3.3. Summary Statistics of Patient and Operational Characteristics

Table 1 presents the summary statistics of the variables in our models. Our key outcome variable of interest is inpatient LOS: the duration of time a patient stays in the hospital from the time of admission into an inpatient unit until the time of discharge (Oh et al. 2017). It does not include the time spent in the ED. Inpatient LOS is measured in fractions of days and is a continuous outcome measure with a right-skewed distribution. To achieve a normal distribution, we log-transform LOS. Table 1 also breaks down the summary statistics by patients who receive a PDO versus those who do not as well as patients who experience a CY during their stay versus those who do not. We test the differences between those populations using *t*-tests.

In Table 2, we present the summary statistics of our ED variables of interest. We define our outcome variables as follows: ED boarding time is the difference in time between when an inpatient bed is requested by an ED physician for a patient and when the patient departs the ED. Note that not all patients need to be admitted; thus, we calculate boarding time by focusing on only those patients who need to be admitted to the inpatient unit. ED hourly occupancy is measured by calculating the number of patients in the ED by the hour, accounting for both arrivals and departures within the hour. ED wait time is the difference between the time a patient arrives to the ED and the time a patient is assigned an ED physician. ED boarding time and ED wait time are continuous variables that are right-skewed. Therefore, to achieve a normal distribution, we log-transform these variables. To understand whether CY improves ED outcomes, we investigate the impact on ED outcomes after a CY is called. Thus, we define our key independent variable as *CY After*, which is a one from the time CY is called until it is cleared and zero otherwise. To illustrate, if CY occurs on June 13, 2014, at 3:00 p.m., *CY After* returns one for any patient present in the ED from 3:00 p.m. until that CY ends.

4. Econometrics Approach

4.1. Survival Analysis: CY on Inpatient LOS

CY can occur any day during a patient's hospitalization. For example, a patient hospitalized for five days may experience CY on days 2 and 5 of the stay (e.g., $0, 1, 0, 0, 1$). In other words, CY can take on different values (e.g., 0 or 1) in different time periods of a patient's hospitalization. Because of the time-varying nature of CY, to test Hypothesis 1, we use discrete-time survival analysis, which enables the risk of the occurrence of an event (i.e., hazard) to change for each time period (Singer and Willett 2003). In our study, inpatient discharge is the event. Given that a patient can experience CY on different days during the stay, the risk of discharge changes during each time period. It is important to note that, whereas the values of the risk of discharge vary in different time periods for CY and no CY patients, the effect remains identical in every time period. Our analysis begins on day 1 when the patient

Table 1. Summary Statistics of Main Variables of Interest

Variables	Mean (all patients)	Minimum	Maximum	Standard deviation	Mean (PDO)	Mean (no PDO)	Difference	Mean (CY)	Mean (no CY)	Difference
Discharge occupancy, %	88.64	73.61	100	5.19	88.71	88.59	0.12	90.32	87.48	2.83***
Admission occupancy, %	88.21	72.56	100	5.15	87.81	88.41	−0.60***	89.20	87.52	1.68***
Age, years	55.19	9	116	16.52	56.20	54.65	1.55***	55.84	54.74	1.10***
Insurance, %										
Medicaid	44.69	0	100	49.72	44.91	44.58	0.33	44.55	44.80	−0.25
Medicare	36.45	0	100	48.13	37.68	35.80	1.88+	37.13	35.98	1.15
Private	14.42	0	100	35.13	13.14	15.10	−1.96**	13.64	14.96	−1.32+
Uninsured	0.76	0	100	8.67	0.77	0.75	0.02	0.75	0.77	−0.02
Others	3.68	0	100	18.82	3.50	3.78	−0.28	3.94	3.50	0.44
Severity score	7.42	−14	52	9.39	8.05	7.08	0.97***	8.43	6.72	1.71***
Female, %	41.98	0	100	49.36	42.22	41.86	0.36	42.73	41.48	1.25
Acuity level, %										
Immediate	2.66	0	100	16.1	2.35	2.83	−0.48	3.52	2.08	1.44***
Emergent	45.94	0	100	49.84	49.21	44.20	5.01***	45.17	46.46	−1.29
Urgent	51.40	0	100	49.98	48.44	52.97	−4.53***	51.31	51.47	−0.16
Postacute care	41.77	0	100	49.32	42.03	41.63	0.4	47.02	38.17	8.85***
Attending physician workload, number of patients)	7.48	0	24	3.68	7.66	7.38	0.28***	7.73	7.30	0.42***
Surgical, %	11.50	0	100	31.91	11.31	11.61	−0.3	12.77	10.63	2.14***
CY, %	40.65	0	100	49.12	37.24	42.45	−5.21***	40.65	59.35	—
PDO, %	34.60	0	100	47.57	34.60	65.40	—	31.70	36.59	−4.89***
LOS, days	5.21	0.005	79.07	5.93	6.15	4.71	1.44***	6.99	3.98	3.01***
Observations		10,554			3,652	6,902		4,290	6,264	

Notes. $N = 10{,}554$. Difference is the difference between both means. Table includes controls used in the main analyses.
$^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

is admitted and ends on day 80, which includes the maximum LOS in our data set of 79.07 days. Capturing the event occurrence (i.e., inpatient discharge time) for all patients minimizes right-censoring. The sample size starts to drop toward the end of our observation period, which can exaggerate the discharge risk. However, we perform a robustness check by excluding data beyond the 99th percentile and find our results are robust.

Our data to perform Hypothesis 1 analysis is set up using a patient-period data set in which a row represents a time period t of patient i's hospitalization. This increases the sample size in our person-period data set to 68,894.[1] We estimate the discrete-time hazard, which is the probability that the patient experiences discharge in time t, conditional on the patient not experiencing discharge at an earlier time. The hazard function is given as

$$h_{it} = Pr[T_i = t | T_i \geq t], \quad t = 1, \ldots, 80, \tag{1}$$

where T_i is patient i's discharge time. Given that T is characterized by its conditional probability density function for the values of our discrete time hazard, we estimate Hypothesis 1 using a logit specification:

$$\begin{aligned} logit\ Y_{it} = {} & [\alpha_1 D_{1it} + \alpha_2 D_{2it} + \cdots + \alpha_T D_{Tit}] \\ & + [\beta_1 CY_{it} + \beta_2 X_{it} + \beta \vartheta_{it} + \beta \theta_{j(i)} + \mu_{ijt}], \end{aligned} \tag{2}$$

where Y_{it} is the observed binary variable that returns a one if patient i is discharged in time period t and zero otherwise. D_{1it} to D_{Tit} are time indicators that represent each time period in our data set. Each time indicator returns one for the specific time period it represents and zero otherwise. The corresponding parameter estimates, α_1 to α_T, give the baseline hazard in each time period. CY_{it} is a time-varying covariate with a value of one if patient i experiences CY in time period t and zero otherwise. X_{it} is a vector of patient- and hospital-level control variables. At the patient level, we control for patient i's gender, linear and squared term of age, insurance, Elixhauser severity score, department (surgical/nonsurgical), acuity level, and whether the patient is discharged to a postacute care facility (= 1) or not (= 0). We also account for the workload of the attending physician by using the total number of patients under the attending physician's care during patient i's visit.

At the hospital level, we control for both the linear and squared term of occupancy in the hospital on each day. We follow prior studies (Berry Jaeker and Tucker 2016; Freeman et al. 2017, 2020) that examine inpatient LOS and control for time trends and seasonality using day of the week, quarter, and year fixed effects (FE), represented by ϑ_{it}. We perform a robustness check

Table 2. Summary Statistics of ED Variables of Interest

Variable	Mean (all patients)	Minimum	Maximum	Standard deviation	Mean (CY after)	Mean (no CY after)	Difference
ED discharge occupancy, %	63.65	0	100	14.80	68.43	62.73	5.70***
ED admission occupancy, %	63.30	0	100	14.81	68.30	62.34	6.00***
Age, years	42.78	9	117	18.48	43.02	42.74	0.28***
Insurance, %							
Medicaid	52.44	0	100	49.94	52.21	52.49	−0.28
Medicare	16.29	0	100	36.93	16.71	16.21	0.50**
Private	17.06	0	100	37.61	16.63	17.14	−0.50**
Uninsured	3.50	0	100	18.38	3.80	3.44	0.35***
Others	10.70	0	100	30.92	10.65	10.72	−0.07
Female, %	50.00	0	100	50.00	50.24	49.96	0.28
Severity score	1.13	−16	56	4.69	1.18	1.12	0.06**
Acuity level, %							
Emergent	16.53	0	100	37.15	17.00	16.44	0.56**
Urgent	50.06	0	100	50.00	49.73	50.12	−0.39$^+$
Less urgent	29.14	0	100	45.44	29.09	29.15	−0.06
Non urgent	4.27	0	100	20.22	4.18	4.29	−0.11
ED disposition, %							
Inpatient admission	10.27	0	100	30.36	10.21	10.28	−0.07
Discharged home	81.65	0	100	38.71	81.15	81.74	−0.59***
Observation admission	6.40	0	100	24.48	6.78	6.33	0.45***
Transfer to Another facility	1.66	0	100	12.76	1.81	1.62	0.19**
Transfer same-day procedure	0.01	0	100	1.06	0.01	0.02	−0.01
ED wait time, hours	1.83	0.01	12.11	1.89	2.09	1.78	0.30***
ED boarding time, hours	3.43	0.001	46.19	2.28	4.36	3.25	1.10***
ED hourly occupancy	148.16	7	289	45.19	160.15	145.85	14.30***
CY after, %	19.85	0	100	39.30	14.74	85.26	
Observation	354,722				57,233	297,489	

Notes. $N = 354{,}722$. Difference is the difference between both means. Table includes variables used in the ED analyses. For ED boarding time, CY after sample size is 5,829 and no CY after is 30,536.
$^+p < 0.10$, $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

using month-year fixed effects (Powell et al. 2012, Kim et al. 2015, Song et al. 2018). We include physician FE represented by $\theta_{j(i)}$, which indicates patient i's attending physician j. Physician FE account for unobserved time-invariant heterogeneity between physicians. We clustered our robust standard error term, $\mu_{j(i)t}$, by patient i's attending physician j in time period t. Clustering by attending physician accounts for within-cluster correlation in the error term for patients treated by the same attending physician because observations within each group are not independent and identically distributed (Angrist and Pischke 2008).

4.2. IV Approach: CY on ED Outcomes

To test the impact of CY on ED outcomes—ED boarding time (Hypothesis 2a), ED hourly occupancy (Hypothesis 2b), and ED wait time (Hypothesis 2c)—we use an IV because of endogeneity bias as a result of omitted variables. To the best of our knowledge, there is no prior work that examines CY policy in hospitals. Consequently, we do not have any precedents for potential IVs and must instead rely on discussion with our partner physicians and the bed controller to construct our IVs.

We use the average minimum and maximum temperature[2] during a patient's hospitalization as our IV. The intuition behind using these IVs is that warm days increase the number of trauma cases in the ED (Ou et al. 2005, Wilson et al. 2018). On warm days, more people engage in outdoor leisure activities, increasing the likelihood of accidents (Ou et al. 2005, Pape-Köhler et al. 2014, Wilson et al. 2018). For example, Wilson et al. (2018) find that average daily temperature significantly increases the volume of trauma cases in the ED. As accidents increase, the ED becomes crowded, increasing the likelihood of CY activation.

Omega Hospital is located in South Boston. We use weather data from that specific geographic area from June 2014 to November 2017. The weather data includes the minimum and maximum temperature for each hour, which we average to obtain the average minimum and maximum temperature for each day. We use both minimum and maximum temperature to allow us account for the variation in weather change throughout the day regardless of the season. We anticipate that, during minimum temperature, the likelihood of CY activation will be low, whereas maximum temperature results in a higher likelihood of CY activation.

Table 3. Impact of Urgent and Prevention Responses on Inpatient LOS

Variables	Model 1 Logit LOS	Model 2 OLS Log LOS	Model 3 2SLS (first stage) PDO	Model 4 2SLS (second stage) Log LOS
Hypothesis	1	3	3	3
CY	−0.058^			
	(0.039)			
PDO		0.345***		−0.260*
		(0.021)		(0.118)
Attending physician's number of PDO use			0.011***	
			(0.001)	
Controls	Yes[a]	Yes[b]	Yes[b]	Yes[b]
Day of week FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Attending physician FE	Yes	Yes	Yes	Yes
Log pseudo-likelihood	−26,535.633	—	—	—
R^2	—	0.1415	0.2496	0.0912
Observations	68,894	10,554	10,554	10,554

Note. Standard errors, in parentheses, are clustered by attending physician.
[a]Controls include occupancy (linear and squared), age (linear and squared), insurance (Medicaid, Medicare, private, uninsured, others), severity score, female, acuity level (immediate, emergent, urgent), postacute care, surgical, and attending physician workload.
[b]Controls include discharge occupancy (linear and squared), admission occupancy, age (linear and squared), insurance (Medicaid, Medicare, private, uninsured, others), severity score, female, acuity level (immediate, emergent, urgent), postacute care, surgical, and attending physician workload.
$\hat{}p > 0.10$, $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Our IVs must meet the relevance and exclusion restriction conditions (Wooldridge 2010). The relevance condition assumes that the IVs are correlated with CY. We find that average minimum temperature during a patient's hospitalization decreases the likelihood that a patient experiences CY by 0.6% or less (p-value < 0.001), and maximum temperature increases the likelihood that a patient experiences CY by 0.4% or less (p-value < 0.001). We test the weakness of the IV using the Kleibergen–Paap Wald rk F test. We find that the IV is not weak ($F = 46.212$). Next, for the exclusion restriction, we assume that the IVs are uncorrelated with the error term. In other words, our IVs can only be correlated with the outcome variable through the relationship with CY. Because this condition cannot be tested formally, we perform analyses to rule out violation of the condition. One potential explanation that can violate the exclusion restriction is that weather increases the number of inpatient admissions (Chan et al. 2013). As inpatient admission increases, ED occupancy levels also increase. Thus, we control for occupancy level in our model. Furthermore, we check the correlation between our IVs (minimum and maximum temperature) and occupancy levels and find that the values are

Table 4. Impact of Urgent Response on ED Outcomes

Variables	Model 1 2SLS (second stage) Log ED boarding time	Model 2 2SLS (second stage) ED hourly occupancy	Model 3 2SLS (second stage) Log ED wait time
Hypothesis	2a	2b	2c
CY after	0.892***	−7.408	−0.239+
	(0.173)	(7.130)	(0.133)
Controls	Yes	Yes	Yes
Day of week FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes
R^2	0.0272	0.7410	0.0808
Observations	36,365	354,722	354,722

Notes. Standard errors, in parentheses, are clustered by physician. Controls include ED discharge and arrival occupancy, age, female, severity score, insurance (Medicaid, Medicare, private, uninsured, others), acuity level (emergent, urgent, less urgent, nonurgent), ED disposition (inpatient admission, observation admission, discharge home, transfer to another facility, transfer same day procedure). For abbreviation purposes, see the online appendix for OLS and first stage results.
$^+p < 0.10$, $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

low with the highest being 0.12. Specifically, we test Hypotheses 2a–2c using the following two-stage least squares (2SLS) model:

$$CY\_After_{ijt} = \alpha_0 + \alpha_1 Z_{it} + \delta W_{it} + \vartheta_t + \theta_j + e_{ijt}, \tag{3}$$

$$Y_{ijt} = \alpha_0 + \alpha_1 \widehat{CY\_After}_{ijt} + \delta W_{it} + \vartheta_t + \theta_j + \varepsilon_{ijt}, \tag{4}$$

where $CY\_After_{it} = 1$ if a patient experienced CY during the ED stay and zero otherwise. Z_{it} represents the IVs, average minimum and maximum temperature. W_{it} is a vector of patient- and ED-level control variables. ϑ_t and θ_j represent time and physician fixed effects, respectively. Y_{ijt} represents our outcome variables: ED boarding time, ED hourly occupancy, and ED wait time.

Despite our binary endogenous variable, we choose to estimate the first stage of the 2SLS using a linear probability model rather than a nonlinear model for two reasons. First, we run the risk of specification error if we run the first stage using a nonlinear model and plug the predicted values obtained from the first stage into a linear model in the second stage (Angrist and Krueger 2001, Wooldridge 2010). Second, a linear model accommodates the FE in our model, which is typically difficult in nonlinear models (Greene 2004).

4.3. IV Approach: PDO on Inpatient LOS

To test Hypothesis 3, we rely on an IV approach to address potential selection of physicians' decisions to use PDOs for some patients and not others. The PDO selection process creates an endogeneity concern because of the possibility of unobserved variables that influence a physician's decision to complete a PDO for a patient. For example, if a physician anticipates a patient will have a difficult discharge because of a complex medical condition, the physician may use a PDO, but the complex medical condition may also drive a longer LOS. This biases our results toward finding that patients who receive a PDO have longer LOS. Failing to account for this selection bias results in an inconsistent estimate (Wooldridge 2010, Ho et al. 2017), leading to underestimating the effect of PDOs.

To address the endogeneity, we use an IV approach using a 2SLS model. To construct our IV, we draw on the Bavafa et al. (2018) study that uses physician intensity of electronic visit usage as an instrument for a patient adopting an electronic visit. They argue that, if a physician has a high use of electronic visits overall, it may influence a patient's decision to use the technology to communicate with the physician. In our study, we similarly use the attending physician's number of PDOs written in a given quarter-year (ignoring the focal patient) as an instrument for whether that patient will receive a PDO. This instrument relies on variation among the physician's other patients in a given quarter-year, leaving out the focal patient (Bavafa et al. 2018). We perform additional robustness checks by aggregating at the month level and find our results are robust. Specifically, we estimate using the following 2SLS model:

$$PDO_{it} = \alpha_0 + \alpha_1 Attending\ physician's\ no.\ of\ PDO\ use_{ijt} + \delta X_{it} + \vartheta_t + \theta_j + e_{ijt}, \tag{5}$$

$$ln(INPATIENT\_LOS)_{ijt} = \alpha_0 + \alpha_1 \widehat{PDO}_{ijt} + \delta X_{it} + \vartheta_t + \theta_j + \varepsilon_{ijt}, \tag{6}$$

where PDO_{it} is a binary variable that is one when patient i has a PDO during visit t and zero otherwise. We include all the same controls, X_{it}, and fixed effects, ϑ_t and θ_j.

Our IV meets the two conditions, relevance and exclusion restriction, required of an IV (Wooldridge 2010). To test the relevance condition, we rely on the result from our first stage. Our IV positively correlates with our endogenous variable ($\alpha_1 = 0.011$, p-value $<$ 0.001). Next, we test the weakness of the IV using the Kleibergen–Paap Wald rk F test. We find that the IV is not weak ($F = 250.273$). All of these analyses demonstrate that our IV meets the relevance criteria (Wooldridge 2010). For the exclusion restriction, we rely on an explanation to rule out violations in which our IV (physician PDO use) directly impacts our variable of interest (LOS). One way that attending physician PDO use can be associated with a patient's LOS is that PDO use could be impacted by physician busyness, which, in turn, can ultimately impact LOS. Hence, we control for attending physician workload in our model. Furthermore, we check the correlation between our IV and attending physician workload and find that the value is low at 0.15. We perform a regression of the IV on LOS and find no association (p-value $>$ 0.9). Given these results, we conclude that our IV meets the exclusion criteria condition.

4.4. IV Approach: Crowding Effect of CY on PDO

For Hypothesis 4, we want to understand if CY crowds out physicians' use of PDOs. Our dependent variable is PDO_{ijt}. The PDO is completed, on average, two days before a patient is discharged. Therefore, we are only interested in CYs that occur on the day the PDO is supposed to be completed. We test Hypothesis 4 using an IV approach rather than ordinary least squares (OLS) because, during a CY, physicians can decide which patients receive a PDO. We do not use survival analysis because we are not interested in patients' survival time.

We follow the work of Song et al. (2019) to test the impact of a binary endogenous variable on a binary outcome variable by using a control function approach of the two-stage residual inclusion (2SRI) model (Terza et al. 2008, Wooldridge 2014).[3] The 2SRI model slightly deviates from the same approach as the 2SLS in the first

Table 5. Impact of Urgent Response on Prevention Response (Hypothesis 4)

Variables	Model 1 Probit PDO	Model 2 2SRI (first stage) CY two days	Model 3 2SRI (second stage) PDO
CY two days	−0.055***		−0.273**
	(0.015)		(0.098)
Average minimum temperature		−0.011***	
		(0.003)	
Average maximum temperature		0.009**	
		(0.003)	
Controls	Yes	Yes	Yes
Day of week FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Attending physician FE	Yes	Yes	Yes
Log pseudo likelihood	−5,268.46	−3,999.82	−5,268.56
Observations	10,554	9,915	8,666

Notes. Standard errors, in parentheses, are clustered by attending physician. Standard errors in parenthesis. We report the average marginal effect for all models. The reduced sample in the nonlinear model is because there are no changes in the outcome variable (PDO) for some attending physicians (i.e., the outcome may be all zeros or ones for these attending physicians).

$^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

stage. Rather than replace the second stage with the predicted values obtained from the first stage, it adds the first stage residuals as an additional variable in the second stage (Terza et al. 2008). Thus, we estimate the following model:

$$Prob(CY\_two\_days_{it} = 1|X_{it}) = \Phi(\beta_0 + \beta_1 Z_{it} + \delta X_{it} + \vartheta_t + \theta_j), \quad (7)$$

$$Prob(PDO_{ijt} = 1|X_{it}) = \Phi(\beta_0 + \alpha_1 CY\_two\_days_{it} + \delta X_{it} + \vartheta_t + \theta_j + \upsilon_{ijt}), \quad (8)$$

where $CY\_two\_days_{it} = 1$ if a patient experiences CY two days before discharge and zero otherwise. Z_{it} represents IVs as described in Section 4.2. υ_{ijt} is defined as $\upsilon_{ijt} = PDO_{ijt} - Prob(PDO_{ijt} = 1|X_{it})$. Here, α_1 captures the unbiased 2SRI estimator of the impact of CY two days before discharge on the likelihood of completing a PDO.

4.5. IV Approach: CY on PDO Count

For Hypothesis 5, we are concerned with the impact of CY on the number of PDOs per day. We, therefore, rely on a day-level rather than patient-visit analysis. We use an IV approach and employ a control function using a 2SRI model with the first stage estimated using a probit model and the second stage using a negative binomial model because the number of PDOs per day, PDO_count_d, is an over-dispersed count data. The likelihood ratio test, $X^2 = 1970.35$, is not equal to zero, which confirms that a negative binomial distribution is appropriate. Specifically, we estimate the following model:

$$CY_d = \alpha_0 + \alpha_1 Z_d + Y_d + \vartheta_m + e_{dm}, \quad (9)$$

$$PDO\_count_d = \alpha_0 + \alpha_1 \widehat{CY_d} + Y_d + \vartheta_m + \varepsilon_{dm}, \quad (10)$$

where PDO_count_d is the total number of patients who received a PDO on day d. CY_d is a binary variable that returns one if CY occurred on day d and zero otherwise. Z_d is our IV as described in Section 4.2. We use only the average minimum temperature per day in our first stage and do not include average maximum temperature because it did not meet the relevance condition. Y_d is a vector of hospital-level control variables for day d that includes $Occupancy\_level_d$, $Occupancy\_level_d^2$, and $average\_severity\_score_d$. We calculate $average\_severity\_score_d$ by taking the average severity score of all patients on day d. ϑ_m is the month and year fixed effect, and ε_{dm} is the robust standard error.

4.6. IV Approach: CY and PDO on Discharges

In Hypotheses 6a and 6b, we compare whether increasing the number of PDOs or calling a CY, respectively, results in a larger number of additional discharges in a given day beyond what is expected on average. To test Hypothesis 6a, we are concerned with the number of PDOs per day rather than the impact of a patient receiving a PDO on LOS. Thus, we do not treat the number of PDOs as an endogenous variable. Using a negative binomial model, we estimate the number of PDOs per day on additional discharges using the following model:

$$Additional\_discharges_d = \alpha_0 + \alpha_1 PDO\_count_d + Y_d + \vartheta_m + \varepsilon_{dm}, \quad (11)$$

where $Additional\_discharges_d$ is the total number of discharges minus the expected number of discharges in a day, d. We calculate expected number of discharges by multiplying the percentage of patients discharged[4] by the occupancy on each day. If the total number of discharges is less than the expected number of discharges, we assume there were no additional patients discharged and assign zero as the value.[5]

To test Hypothesis 6b, we follow the same approach as Hypothesis 5 and employ a control function using the 2SRI model (Terza et al. 2008, Wooldridge 2014). Specifically, we estimate the following model using a negative binomial model:

$$CY_d = \alpha_0 + \alpha_1 Z_d + Y_d + \vartheta_m + e_{dm}, \qquad (12)$$

$$Additional\_discharges_d = \alpha_0 + \alpha_1 \widehat{CY}_d + Y_d + \vartheta_m + \varepsilon_{dm}. \qquad (13)$$

$Additional\_discharges_d$ is count data and is over-dispersed relative to Poisson (Cameron and Trivedi 1998). The likelihood ratio test, $X^2 = 825.76$ and $X^2 = 1851.99$, for the models used in Hypotheses 6a and 6b, respectively, is not equal to zero, which confirms that the distribution is not Poisson and the negative binomial is an appropriate distribution (Gutierrez et al. 2001).

5. Results

We perform all our analysis with STATA version 15. Model 1 in Table 3 shows the results for the discrete-time hazard model that tests Hypothesis 1 with the *logit* command. CY has no impact on the risk of discharge (p-value = 0.140), providing no support for Hypothesis 1. We explore possible explanations for the lack of impact of CY on LOS in Section 6.2. The discrete-time hazard model relies on the proportionality assumption, which states that the effect of a predictor is identical in every time period. In other words, the effect of CY should be identical in each time period of the patient's hospitalization. We test the proportionality assumption following the method in Kuntz et al. (2014) and find that it holds. To provide more detail, we divide the time period into two different epochs using the mean (approximately six days) of the time indicators as the dividing point. We create a binary variable, *LATE*, that returns zero for time periods t1–t6 (i.e., early stay) and one for time period of t7 and above (i.e., late stay). Using *LATE* as the time indicator, we reestimate Equation (2), including a new term that interacts *LATE* with CY. The additional term allows the effect of CY to vary in each epoch (Singer and Willett 2003). We perform a Wald test to determine whether the effect is identical in both epochs and find that we cannot reject the null hypothesis that the terms are identical (p-value = 0.113). (The estimated coefficient in the early stay is 0.10 (p-value = 0.113) for when CY occurs and −2.06 (p-value = 0.372) for when no CY occurs. In the late stay, the estimated coefficient is −4.51 (p-value = 0.252) for when CY occurs and −4.50 (p-value = 0.253) for when no CY occurs).

Models 1a, 2a, and 3a in Online Table A.8 show the results of testing the impact of CY on ED outcomes using a linear model with the *reg* command. This model, which does not account for endogeneity, finds that CY does not improve the ED outcomes of the boarding time (Hypothesis 2a), hourly occupancy (Hypothesis 2b), and wait time (Hypothesis 2c). We account for endogeneity using IVs using the *ivreg2* command. The first stage results are shown in Models 1b, 2b, and 3b in Online Table A.8. We report the second stage result in Table 4. We find CY significantly increases boarding time by 89.2% (Model 1), providing no support for Hypothesis 2a. Hypothesis 2b is also not supported (Model 2). Model 3 shows that CY marginally decreases ED wait time by 23.9%, providing weak support for Hypothesis 2c.

Table 3, Models 2–4 report the results from testing Hypothesis 3, the impact of PDO on LOS. Model 2 estimates the linear model in Hypothesis 3 using *reg*, and Models 3 and 4 estimate the IV model using the *ivreg2* command. As expected, without accounting for endogeneity, we find that the use of a PDO is associated with an increase in inpatient LOS (α_1 = 0.345, p-value < 0.001). Model 3 shows the first stage results of the IV. The attending physician's number of PDO use is significantly associated with the patient receiving a PDO. Model 4 corrects the bias using our IV. In support of Hypothesis 3, we find that a PDO is associated with a 26% decrease in inpatient LOS (p-value < 0.05). In other words, the use of the prevention response is associated with an approximately 1.4-day shorter inpatient LOS.

Table 5 reports the results for Hypothesis 4. Model 1 estimates a nonlinear model for Hypothesis 4 using *probit*, whereas Models 2 (first stage) and 3 (second stage) use a 2SRI model to test Hypothesis 4 via the *glm* command. Model 3, which accounts for endogeneity, shows that CY decreases the likelihood of getting a PDO by 27.3% (p-value < 0.01). In other words, when there is a CY, physicians are substantially less likely to complete PDOs.

Table 6 tests Hypothesis 5 using a 2SRI model (*glm* command). Model 1 reports the first stage and Model 2 the second stage. As shown in Model 2, when the hospital calls a CY, the rate of the number of PDO completion decreases by a factor of 0.36 (p-value < 0.05). In other words, for every 10 PDOs completed per day, when a CY is activated, the number of PDOs written reduces by approximately 4.

Table 6, Model 3, reports the results of a negative binomial model (*nbinomial* command) for Hypothesis 6a. We use incidence rate ratios (IRRs) to interpret the coefficient and find that a unit increase in PDOs leads to 1.29 times more additional discharges (p-value < 0.001). A PDO can be completed for each patient; therefore, the effect of PDOs can be scaled up. In other words, the more frequently hospital physicians use PDOs, the higher the number of patients who get discharged faster.

Table 6. Impact of CY on PDO Count and Additional Discharges

Variables	Model 1 2SRI (first stage) CY	Model 2 2SRI (second stage) PDO count	Model 3 negative binomial additional discharges	Model 4 2SRI (first stage) CY	Model 5 2SRI (second stage) additional discharges
Hypothesis	5	5	6a	6b	6b
Average minimum temperature	−0.011* (0.007)			−0.011* (0.006)	
CY		[0.355] −1.037** (0.347)			[0.240] −1.429* (0.708)
PDO count			[1.29] 0.257*** (0.015)		
Control	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Log likelihood	−448.36	−2,709.96	−1,976.98	−448.36	−2,199.08
Observations	1,214	1,214	1,214	1,214	1,214

Notes. Bootstrap standard errors in parenthesis replicated 50 times. IRRs in square brackets. Controls include occupancy (linear and squared) and average severity score.
$^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Models 4 (first stage) and 5 (second stage) show the findings for Hypothesis 6b using a 2SRI model (*glm* command). When a CY is activated, it leads to approximately 0.24 times fewer additional discharges (p-value < 0.05). Collectively, the results of these two hypotheses show that the prevention response of PDOs has greater potential to increase discharges—and, thus, free beds—compared with the urgent response of a CY. We run Wald tests to compare the coefficients from both regressions and find that we can reject the equality hypothesis (p-value < 0.05).

Controls include discharge occupancy (linear and squared), admission occupancy, age (linear and squared), insurance (Medicaid, Medicare, private, uninsured, others), severity score, female, acuity level (immediate, emergent, urgent), postacute care, surgical, and attending physician workload.

5.1. Counterfactual Analysis: Comparing the Impact of CY vs. PDO

To quantify whether the use of PDOs could reduce the need to call CYs, we conduct a counterfactual analysis by calculating how many CY events could have been avoided if all patients received a PDO two days before their expected discharge. In this analysis, we focus on day level rather than patient-visit level. We use all patients in our data set to determine, on average, the total number of patients discharged from the hospital per day, the total number of patients per day who receive a PDO, and the total number per day who do not receive a PDO. Recall that patients who receive a PDO are discharged approximately 1.4 days earlier. We perform our analysis using a counterfactual discharge date two days earlier than when the patient was actually discharged. We use two days because 1.4 days is the minimum LOS decrease from using a PDO based on our main results and robustness check analyses.

We assume that if non-PDO patients had received a PDO, their discharge day would be two days earlier. Thus, the new total number of patients discharged on a particular day becomes the sum of PDO patients discharged on that day, plus the non-PDO patients discharged two days later because we assume—had they had a PDO—they would have been discharged on that day. For example, on February 18, 2015, there were 13 patients discharged in total—7 PDO and 6 non-PDO patients—and on February 20, 2015, 4 PDO and 7 non-PDO were discharged. Using the approach described, the counterfactual total number of patients discharged on February 18, 2015, would be 14 patients (7 PDO patients from February 18 plus 7 non-PDO patients from February 20). The 6 non-PDO patients from February 18 are added to the discharge count for February 16 in addition to the PDO patients on that day. Taken together, the new total number of patients discharged captures the expected number if all patients had received a PDO, $Expected\_Dx\_CountA_d$.

$Expected\_Dx\_CountA_d$ is a proxy for the total number of beds freed in the hospital. Because of the high priority given to surgical patients, we subtract from the number of open beds the number of patients admitted from surgery and other procedures. Please note that Omega's CY algorithm also subtracts the total number of those patients from the number of open beds. The remaining beds can be occupied by the patients waiting in the ED, $Free\_beds_d$.

To determine the number of patients boarding in the ED, ED_Admits_d, we sum up patients per day with ED LOS greater than zero and who were transferred to an inpatient bed with inpatient LOS greater than zero days. We do this to avoid including ED patients who do not get transferred to an inpatient bed. We subtract ED_Admits_t from $Free\_beds_d$ to calculate the number of patients waiting in the ED after all free beds are occupied. A positive value indicates the hospital still has free beds after all of the ED admit patients occupy the available beds. A negative value means patients are still waiting in the ED after all free beds are occupied. Following the CY algorithm, we focus only on the scenario in which patients are still in the ED when there are inpatient beds unavailable, which is indicative of ED congestion. We refer to these patients as $Remaining\_Patients\_ED_d$. Next, we check whether $Remaining\_Patients\_ED_d$ is greater than or equal to the average number of remaining patients who wait in the ED for an inpatient bed on a CY day, which we find to be approximately four. In other words, when the hospital has four or more patients waiting in the ED after all beds are occupied, the hospital typically calls a CY. Finally, we determine whether $Remaining\_Patients\_ED_d$ is greater than or equal to four. If yes, then our counterfactual analysis assumes that the hospital will call a CY. If less than four, then there is no CY. We find that CY days in our time frame reduce by 44.9% ((216 − 119)/216) from 216 days to 119 days, thus reducing the number of potential boarding crises.

6. Discussions and Conclusion

Using data from a large academic hospital, we investigate the impact on inpatient LOS of two managerial responses to boarding crises. We find no impact on LOS from the government-mandated urgent response of calling a CY that prompts physicians to discharge patients. Our result suggests physicians may not behave any differently with respect to discharging patients when there is a CY versus no CY. Furthermore, physicians are less likely to use PDOs to coordinate patient discharge when a CY is called. Our study also shows that CY increases ED boarding time, has no impact on ED hourly occupancy, and only marginally decreases ED wait times. On the other hand, the prevention response of physicians writing PDOs for their patients is associated with an LOS that is 1.4 days shorter, on average, and increases the number of discharges per day compared with CY, providing more incentive for using PDOs. Finally, the frequent use of PDO has the potential to reduce CY activations in the hospital.

6.1. Implications for Theory

Our study has implications for healthcare operations management theory. We contribute to the body of research that uncovers specific avenues through which IT improves hospital performance. Dobrzykowski and Tarafdar (2015) show that IT can facilitate physician-to-physician coordination. We extend their findings by demonstrating that IT also successfully conveys discharge-related information, which enables cross-disciplinary coordination that shortens LOS. Relatedly, our results contribute to the findings of Song et al. (2019), who speculate that IT-enabled solutions might help with planning the discharge of off-service patients. Our study points to PDOs as a potential IT solution because they enable physicians to communicate discharge plans about off-service patients asynchronously.

We also contribute to the body of research that investigates the impact of high hospital occupancy on inpatient LOS. Prior literature does not have detailed information about what physicians do differently during high occupancy that affects LOS (Kc and Terwiesch 2012, Kuntz et al. 2014, Berry Jaeker and Tucker 2016). To the best of our knowledge, no study has data on both boarding crises behavior (e.g., CY) and hospital occupancy. Our study finds that, when the hospital goes into a state of urgent alert, managers respond by increasing work pressure on workers via a CY. The focus is on today's tasks that are perceived to yield immediate gains (i.e., encouraging discharges). However, as workers become saturated with work and overwhelmed from work pressure, they reduce secondary tasks that may yield system improvements in the long run (i.e., PDOs). The dynamic of crisis-mode behaviors driving out effective coordination echoes Repenning and Sterman's (2001) theory of capability traps and might partially explain findings that LOS increases when hospital occupancy is extremely high (Kc and Terwiesch 2009, Berry Jaeker and Tucker 2016).

6.2. Implications for Policy and Practice

Our research also has implications for policy and practice. We do not find positive results from the Massachusetts Department of Public Health policy that requires hospitals to deploy hospital staff with the goal of moving all admitted patients out of the ED within 30 minutes. Given our result in Hypothesis 1 that inpatient LOS is not impacted when CY is active means that patients are not getting discharged in the inpatient units; thus, CY is not creating empty beds to reduce boarding time in the ED. CY might be ineffective at reducing LOS because it does not reengineer the discharge process, which is time-consuming and requires significant effort from multiple services. Furthermore, CY is triggered often, leading to CY burnout in which workers do not alter their behavior. In our data set, nearly one out of every five days is a CY. Our physician partners suggest that CY counterproductively creates a chaotic environment, uneasiness among care teams, and provokes unnecessary squabble. The discharge process during CY is not systematic and calls for the discharge of "any" patient ready for discharge rather than specific patients. The Shi et al. (2021) research to identify how many and which specific patients should be discharged during a boarding crisis may be a more productive approach. In contrast to the ineffectiveness of CY, our findings provide evidence that the PDO is successful at conveying discharge-related information, which enables cross-disciplinary coordination that shortens LOS. Policy makers should be aware of these dynamics and incentivize solutions proven to improve patient flow.

6.3. Limitations

Our study has several limitations. Our data comes from a single U.S. hospital, which limits the generalizability of our results. Given that the PDO used by Omega Hospital is a standard component of the EPIC hospital IT system, a study with a large number of hospitals that differ in size, teaching status, and ownership type would increase confidence that PDO's benefits persist under a variety of settings. Furthermore, such a study could also help disentangle whether CY failed because of being a flawed policy or flawed implementation by Omega Hospital. A larger sample size could yield insights about heterogenous effects by type of hospital unit and patient conditions, such as medical versus surgical. A second limitation is that physicians decide which patients get a PDO, which creates endogeneity. Therefore, a field experiment that randomly selects which patients receive a PDO would provide stronger causal evidence of PDO's effectiveness. We hope that our results provide promising evidence that can justify a study with patient randomization. Finally, our data does not reveal the exact time when physicians decide that a patient is medically ready to be discharged. This limits our ability to precisely measure the difference between the time of a physician's discharge decision to the time of actual discharge.

7. Conclusions

Hospitals frequently face boarding crises when admitted ED patients have long waits for inpatient beds. In an effort to reduce waiting time, Massachusetts imposed a well-intended policy that required hospital managers to use an urgent response. Our findings suggest that this policy has no impact at shortening average LOS or improving ED performance measures and also results in crowding out the effective preventive response of using IT to coordinate patient discharge. Our study underscores the importance of changing processes and developing policies that instead encourage managers to persevere through the worse-before-better dynamic that occurs when improving performance over the longer term.

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Endnotes

[1] The person-period data set of N = 68,894 comes from the total sum of the number of patients in the hospital in each time period. The number of patients in the hospital in time period t does not include patients discharged in period $t - 1$.

[2] Our weather data were obtained from openweathermap.org.

[3] The 2SRI approach allows a nonlinear regression model in the two stages (e.g., probit) and provides valid coefficients with minimal bias (Terza et al. 2008).

[4] The percentage of patients discharged is the average number of discharges divided by average occupancy in our data period.

[5] We rerun the analysis including the negative values using OLS and find the results remain robust.

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