The Effect of Discrete Work Shifts on a Nonterminating Service System

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Abstract
Hospital emergency departments (EDs) provide around-the-clock medical care and as such are generally modeled as nonterminating queues. However, from the care provider's point of view, ED care is not a never-ending process, but rather occurs in discrete work shifts and may require passing unfinished work to the next care provider at the end of the shift. We use data from a large, academic medical center ED to show that the patients' rate of service completion varies over the course of the physician shift. Further, patients that have experienced a physician handoff have a higher rate of service completion than non-handed off patients. As a result, a patient's expected treatment time is impacted by when in the physician's shift treatment begins. Lastly, we show that patients that have been handed off are more likely to revisit the ED within three days, suggesting that patient handoffs lower clinical quality.

Key Words: Healthcare Operations, Handoffs, Multitasking

1 Introduction

Businesses are increasingly running their operations around the clock. Whether it is done to speed new product development and drive down operational costs (Terwiesch and Loch 1999, Clark et al. 2013, Jain et al. 2014) or to provide customers around-the-clock access to needed services, such as healthcare or information technology support (Huckman et al. 2009, Narayanan et al. 2009, KC 2013, Batt and Terwiesch 2016), continuously run processes (i.e., nonterminating queues) create operational challenges. Although it is possible to keep a service system always open, individuals can only work continuously for a finite number of hours. As a result, in reality, nonterminating service queues consist of individuals working discrete shifts within the overall structure of the continuously operating queue. This juxtaposition of discrete shifts within a nonterminating service system has not been previously studied and has important theoretical and practical operational consequences.

Understanding and improving the operational performance of such a system requires understanding two interrelated aspects: 1) service rates over the course of a shift; 2) the effect of *handoffs* – the passing of work from one individual to another individual on the following shift. To explore these topics, we utilize the setting of a hospital emergency department (ED). The ED is an excellent setting for our purposes as the queue is nonterminating (the ED is open 24 hours a day, 7 days a week), yet individual care providers work discrete shifts (8 hours in our study setting).

We begin by examining how service rates vary over the course of a shift. In settings with terminating queues, prior work has found that individuals tend to start slowly and then speed up as they approach the end of their shift due to what has been termed the goal gradient hypothesis (Chan Jr 2015, Deo and Jain 2015). When one considers a nonterminating queue where workers can pass tasks to others rather than being forced to complete all work before leaving, it is an open and important question as to whether similar end-of-shift speedup occurs. In short, the possibility of handing off one's work at the end of the shift may reduce the impetus to speed up towards the end of the shift.

Additionally, the direct impact of handoffs on both service time and quality outcomes is an important open question. Having multiple servers work sequentially on a request may bring novel information to help address the issues at hand (Wears et al. 2003). Alternatively, with multiple parties comes the risk of inadequate information disclosure and transfer, which could lead to delays and errors (Patterson et al. 2004, Kitch et al. 2008).

We perform a detailed econometric study on 18 months of data from an academic medical center. Our study uses clinical patient-level information, detailed operational data including time-stamps of the patient care process, and physician staffing records. Using a parametric hazard model, we find that patients progress unevenly through a physician's shift, as measured by their treatment time hazard rate (i.e., hazard of treatment completion). In particular, we show that the hazard rate is lowest early in a physician shift, remains steady through the middle of the shift, and peaks toward the end of the shift. With respect to handoffs, we find evidence that handed off patients experience slightly higher hazard rates than non-handed off patients. We also show that patients that are handed off are more likely to revisit the ED than non-handed off patients, an indication of lower clinical quality.

Altogether, our paper makes three primary contributions. First, by showing the change in service rates over time within a nonterminating queue we show that the assumption of steady state behavior in nonterminating queues may be inappropriate in many settings. Second, we provide new empirical evidence on the impact of handoffs in the ED. We show that handoffs impact both the rate of service completion (accelerating) and quality (decreasing). Lastly, we show that the combined effect of service rates changing over the shift and after a handoff leads to service times being a function of when in a shift the service begins. Overall, our paper builds theory and improves practice with respect to the operations of discrete work shifts within nonterminating queues.

2 Literature Review

Our work contributes to the literature on worker productivity and quality, especially when driven by behavioral elements in the work environment. We also contribute to the literature on patient flow, and to the analysis of the emergency department as a nonterminating queuing system.

We first consider the literature that suggests that patient handoffs could improve quality of care. For example, Wears et al. (2003) observe that handing over a patient to another physician could offer the opportunity for multiple perspectives on the patient's problem, possibly leading to improved diagnosis, treatment and recovery. Moreover, workers at the end of the shift tend to be more fatigued (Kitch et al. 2008), and handing over the workload to a well-rested incoming provider can lead to more focused care and attention (e.g., KC and Terwiesch (2009) and Aiken et al. (2002)). In addition, instead of rushing through the care process and possibly cutting corners in the care process (Oliva and Sterman 2001), handing off the patient to a new physician with a longer remaining shift duration may promote a more thorough examination and treatment. Finally, a certain amount of physician workload and multitasking is beneficial for overall system-level quality outcomes (KC 2013, Narayanan et al. 2017) maintaining an ideal level of multitasking throughout the shift inevitably leads to some handoffs when the shift ends. As such, maintaining a high level of system-level quality means that some handoffs are necessary.

On the other hand, it is possible that handoffs could potentially hurt patient care. For example, Patterson et al. (2004) describe that many industries including aviation, aerospace, and nuclear power have long recognized the potential risks due to shift changes, and have instituted and documented standard process of care measures to mitigate potential pitfalls during shift handoffs. For example, Patterson and Woods (2001) study sixteen handoffs during a space shuttle mission, and observe that intense briefings and interrogation strategies were employed by flight controllers during the process in order to minimize risks of handoffs.

Healthcare delivery in general is susceptible to high error rates with serious consequences. Kitch et al. (2008) perform a survey of residents and physicians in internal medicine and general surgery and find that residents reported that 59% of patients had been harmed in their most recent rotation specifically due to handoffs. An influential study by the Institute of Medicine (IOM 2006) points out that EDs are especially subject to high rates of error. This is because the ED is a fast-paced work environment, with important pieces of information being exchanged amongst multiple providers who often perform distinct and highly specialized tasks. The patient's emergency physician is at the center of the patient's care, coordinating a number of activities. Therefore, handoffs between physicians can crucially impact patient care. In light of these considerations, Cheung et al. (2010) state that shift-change-induced handoffs are potentially hazardous in the ED.

There are several plausible reasons why handoffs may lower quality of care. For example, Anderson et al. (2014) have found that patients who arrive to the ED during periods of low resource availability experience a lower level of care. An improper handoff can similarly lead to a lack of proper continuity of care (e.g., Van Walraven et al. 2010). The likelihood of miscommunication and poor transfer of relevant information during patient handoffs may further exacerbate these risks (Arrow 1974). Relatedly, Heath and Staudenmayer (2000) find that individuals often have difficulty carrying out an organization's goals (e.g. effective care for a patients) when tasks are complex, particularly when individuals have distinct and unique perspectives on the problem. As a result, individuals frequently exhibit inadequate communication.

A number of approaches have been suggested to improve coordination. For example, Gittell (2002) suggests instituting routines in order to facilitate interactions among participants involved in the patient care process. Relatedly, Dhingra et al. (2010) suggest standardization of the sign-out or handoffs of patients to help manage the hazards of information loss. Similarly, Dubosh et al. (2014) finds that the implementation of a handoff checklist can help improve the transfer of information during shift changes. Collectively, this literature suggests that *ceteris paribus*, handoffs are generally undesirable given the increased risk of adverse patient outcomes.

In addition, excessive handing off of one's work to others might be viewed as a form of social loafing; in particular, the perception of not "pulling one's own weight" and the resulting negative externality imposed on co-workers can motivate behavioral changes (e.g. see Bandiera et al. (2010), Mas and Moretti (2009), and Song et al. (2015)). Given the possible adverse effect from handoffs, coupled with the social pressure for appearing productive, ED physicians may have a propensity to engage in fewer patient handoffs.

This desire to avoid handoffs has possible implications for ED productivity, specifically through speedups towards the end of the shift. Tasks in healthcare delivery are often discretionary and outcomes are often difficult to measure and evaluate, leading to high variability in total processing time (Hopp et al. 2007, Armony et al. 2015). For example, various system-level and worker-level factors such as workload, fatigue, and staffing schedules have been associated with changes in worker service rates (KC and Terwiesch 2009, Green et al. 2013, Shunko et al. 2017). Some of this gain in productivity may be due to changes in routines, such as early task initiation (Batt and Terwiesch 2016), or attributed to cutting corners and completing a smaller number of tasks (e.g., Oliva and Sterman 2001, Batt and Terwiesch

2016), often with adverse quality of care implications (Kc and Terwiesch 2012, Kuntz and Suelz 2013, Freeman et al. 2016).

Our paper contributes to this line of work examining behavioral implications of the work environment by specifically looking at the productivity implications stemming from the break at the end of the shift. Chan Jr (2015) examines the end-of-shift behavior amongst physicians and finds that they tend to spend a smaller amount of time on patients as the shift ends, increasing their service rate. In addition, physicians tend to order more tests, and are more likely to admit patients who are seen near the end of the shift. Similarly, Deo and Jain (2015) examine the end-of-shift effect on how physicians in an outpatient eye clinic manage their patient workload. They find that physicians start the shift by working slowly, but gradually increase their service rate as the end of their shift approaches. In their setting, the clinic operates for a predetermined period of time (8 AM to 6 PM) and the productivity changes are driven by the need to complete the existing workload; as such handing over work to other physicians is not a consideration. Both of these findings are consistent with the 'goal gradient' hypothesis that suggests individual motivation increases as a goal draws near, in this case finishing one's work allows the individual to go home (Heilizer 1977). What distinguishes our work from the aforementioned papers is that in our setting the work need not be finished by the end of the work shift. Rather, the patient can be handed off at the end of the shift. In addition, ours is the first paper to empirically examine the quality implications of handoffs in the ED.

3 Empirical Setting

3.1 Clinical Context and Process Flow

Our study is based on data from a mid-sized academic medical center with 31 ED treatment rooms and an average of 4,000 adult ED visits per month. The patient treatment process is similar to many EDs across the United States (KC 2013, Song et al. 2015, Batt and Terwiesch 2016). Arriving patients first check in with a greeter and shortly thereafter go through a triage process administered by a triage nurse. The triage nurse records the chief complaint, measures vital signs, and performs a brief assessment of the patient. The triage nurse also assigns a triage acuity score, which serves as a general indicator of priority for treating the patient. The hospital uses a five-level Emergency Severity Index (ESI) scale with 1 being the most acute and 5 being the least acute (Gilboy et al. 2011).

Patients then wait in the waiting room until they are assigned and escorted to a treatment room in the treatment area of the ED. Patients are generally assigned treatment rooms in first-come-first-served order by triage level. Each of these process steps is recorded and time stamped in the hospital electronic health record (EHR) system. Patients arriving via emergency transport (i.e., ambulance, helicopter) as well as those who obviously have immediately life-threatening conditions generally skip the check-in and triage steps and are placed in a treatment room immediately or after a brief wait.

Once a patient is in a treatment room, they wait to be selected or “picked up” by a physician. Patient pick-up happens at the physicians’ discretion.[1] Physicians periodically check a digital track board to see the list of patients that have been roomed but not picked up. While physicians can access any patient information in the EHR prior to picking up a patient, they typically just review the information on the digital dashboard which includes the patient’s name, gender, age, chief complaint, triage level, and elapsed time since check in (Patterson et al. 2016). If the physician chooses to pick up a patient, she indicates this by assigning herself to the patient in the EHR. This creates the “pickup” time stamp, which we use as the indication of the start of treatment. Generally, physicians go see the patient for the first time soon after indicating pickup in the EHR, however if the physician is quite busy it might be up to 30 or 40 minutes before the physician visits the patient.[2]

[1] Note that this patient selection method is different from another common patient-physician matching method used in the United States in which the physician is responsible for a fixed group of rooms and treats whatever patient is assigned to her room (Batt and Terwiesch 2016).

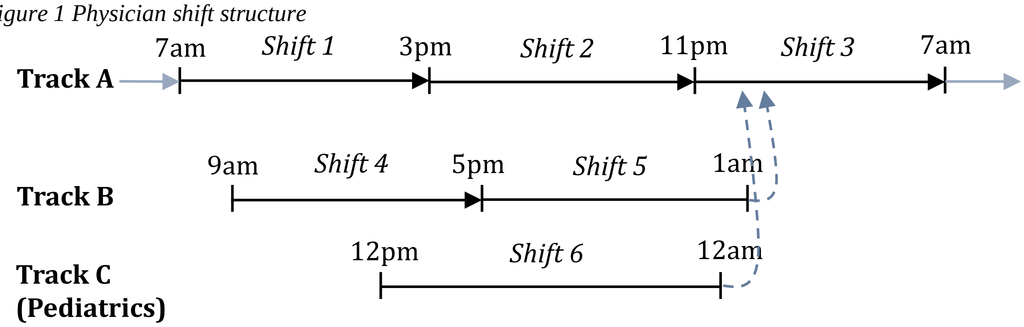
[2] For some severe patients, such as trauma cases, treatment begins immediately upon arrival and the pickup timestamp is not entered until later when the physician has a free moment. We do not include trauma patients in our analysis, except for their contribution to census and handoff counts.

Once the physician has taken responsibility for a patient, the treatment process proceeds under the physician's direction and generally involves cycles of interactions with the physician, laboratory or radiology testing, medication administration, consultation with specialists, waiting, and so on. Eventually, the physician decides that the patient is ready to leave the ED, either to be admitted to the hospital or to be discharged home. The physician indicates this decision in the EHR by changing the status of the patient to either "ready to admit" or "ready to discharge." The "ready" timestamp indicates that the physician is done with the patient, and we use this timestamp to define the end of the treatment phase of the patient's ED visit.

The patient generally remains in the ED for a little while after the "ready" declaration to receive discharge instructions (for those being discharged) or to await a transfer to an inpatient bed (for those being admitted, commonly referred to as "boarding"). This part of the patient encounter is not the focus of this paper.

For some patients, the care process is interrupted by the physician coming to the end of her shift. Patients that have not been designated as "ready" by the end of the physician's shift must be "handed off" to another physician. This involves a face-to-face meeting between the outgoing and incoming resident and attending physicians (and sometimes other members of the care team such as nurses) wherein the outgoing physician describes the patient's condition, status, and recommended plan of action. For some patients, this can be quite simple and clear. For example, "We're just waiting on the lab result for Mr. Smith. If it comes back negative, send him home. Otherwise, admit him." For others, it can be more complex or ambiguous. For example, "Mrs. Jones has non-specific abdominal pain with nausea. I ordered several labs, but they all came back normal. We gave her some anti-emetics and are waiting to see how she responds to that." Depending on how many patients are being handed off, the hand-off meeting generally takes from 5 to 30 minutes and occurs at the beginning of the new shift (e.g., from 3:00pm to 3:15pm). The incoming physician then takes responsibility for the patient and the outgoing physician leaves the ED. We refer to patients that have been handed off as "inherited" patients and patients that a physician starts herself as "new" patients.

Figure 1 Physician shift structure



The study ED has a stable shift schedule for physicians with fixed protocols of who hands off to whom at the end of each shift. Figure 1 depicts the physician shift schedule, which is the same for all days of the week. The schedule can be viewed as three tracks. Track A is made up of three shifts, which we refer to as Shifts 1, 2, and 3, respectively: 7:00am to 3:00pm, 3:00pm to 11:00pm, and 11:00pm to 7:00am. At the end of each of these shifts, the outgoing physician hands off to the incoming physician. Thus, the Shift 1 physician hands off to the Shift 2 physician at 3:00pm. The Shift 2 physician hands off to the Shift 3 physician at 11:00pm, and so on. Track B contains Shifts 4 and 5, which run from 9:00am to 5:00pm and 5:00pm to 1:00am, respectively. The Shift 4 physician receives no hand off, but hands off to the Shift 5 physician at 5:00pm. The Shift 5 physician hands off to the Shift 3 physician at 1:00am (mid-shift for the Shift 3 physician). Lastly, Track C is a single 12:00pm to 12:00am pediatrics shift.[3] The Track C physician hands off to the Shift 3 physician at 12:00am.[4] Thus, depending on the hour of day, the ED is staffed by one, two, or three attending physicians.

At the study ED, physician pay is largely fixed; physicians do have some variable compensation that is based on meeting a number of both academic and clinical metrics, and is not a direct function of the

[3] Sometimes the pediatric shift is split into two six hour shifts.
[4] Because pediatric patients can require quite different clinical care than adult patients, even with the same chief complaint, we do not include the approximately 14,000 pediatric patients (less than eighteen years old) in our analysis, except for their contributions to census and handoff counts.

number of patients treated by the physician each shift. However, the physicians do receive personal performance metrics each month including number of patients seen and billing generated. The physicians also receive limited patient satisfaction survey results. It is important to note that generally the physician that starts a patient's treatment (i.e., picks up the patient) remains the physician of record even if a handoff occurs. In other words, all performance metrics for a given patient accrue to the starting physician. Thus, it is possible that physicians have an incentive to devote more effort to patients started oneself than to patients inherited at handoff.

3.2 Data Description

This study uses data extracted from the hospital EHR system and includes all ED patient encounters between July 1, 2012 and December 31, 2013, consisting of approximately 70,000 patient encounters. The data include patient level information for each encounter such as age, gender, triage level, chief complaint, and physician identifier. Each record also includes the time stamps of the major milestones of the patient encounter such as check in, triage, placed in room, picked up by physician, ready to discharge or admit, and departure.

We also make use of physician shift schedule records to identify which physician is working which shift each day. This is important for two reasons. First, by knowing which shift a physician is working, we can identify which hour of the shift the physician is in when she makes pickup and discharge decisions. Second, because the physician receiving a patient at handoff is not always recorded in the EHR, knowing the shift assignments allows us to identify which physician receives a patient at handoff.

We use the above data to construct hourly workload metrics. For each hour of the study period we calculate the mean number of patients in treatment for each physician (what KC (2013) refers to as the "multitasking level"). We decompose this workload metric into the number of new patients, (patients that the focal physician picked up), and the number of inherited patients (patients that the focal physician received from another physician at a handoff).

Lastly, we use the patient encounter records to create binary variables indicating if the patient was handed off and if the patient returned to the ED within 72 hours of discharge.

Table 1 provides summary statistics for the key patient encounter variables used in the analysis. The values are calculated on all patients age 18 and older who are treated in the main ED (rather than the Fast Track) and who were either admitted or discharged (rather than being transferred, leaving before completion of treatment, or dying).

Table 1 Patient summary statistics

	All Complaints
Age	49.6
	(0.09)
Female (%)	54.0
	(0.002)
ESI 2 (%)	27.2
	(0.002)
ESI 3 (%)	61.0
	(0.002)
ESI 4 (%)	10.3
	(0.001)
Treatment Time (hr.)	2.99
	(0.01)
Handed off (%)	20.3
	(0.002)
Admitted to Hospital (%)	37
	(0.002)
Revisit within 3 days† (%)	5.6
	(0.001)
N	49,568

† Conditional on being discharged from the ED
Means shown. Standard errors in parentheses.

Table 2 provides summary statistics of the workload measures by shift. Note that the New Patients and Inherited Patients values are for a single physician working the indicated shift. The Other Patients column is the time-averaged total number of patients in process by all physicians other than the focal physician over the course of the focal physicians shift. For example, on average a physician working the 7am to 3pm shift is simultaneously working 5.76 new patients and 1.13 inherited patients. The average number of patients being worked on by all other physicians (the 9am-5pm physician and the pediatric specialist that starts at noon.) over that same 7am to 3pm window is 4.95 patients.

Table 2 Time-averaged mean workload (patients in process) by shift

	Focal Physician		Non-Focal Physicians
Shift	New Patients	Inherited Patients	Other Patients
1: 7am-3pm	5.76	1.13	4.95
	(0.006)	(0.003)	(0.008)
2: 3pm-11pm	5.95	1.60	10.08
	(0.005)	(0.004)	(0.006)
3: 11pm-7am	4.74	1.99	1.86
	(0.005)	(0.004)	(0.007)
4: 9am-5pm	6.66	*NA*	8.19
	(0.006)		(0.007)
5: 5pm-1am	5.43	1.22	10.12
	(0.005)	(0.003)	(0.007)

Means shown. Standard errors in parentheses.

4 Empirical Analysis of Treatment Time

4.1 Model Specification

The purpose of this analysis is to determine the impact of the discrete shift structure on the length of time patients spend in the treatment portion of the ED encounter. We hypothesize that such impacts may occur via two mechanisms: systematic changes in physicians' processing rate over the shift, and handoffs. Because these factors potentially change during the treatment time being measured, we need a model that can handle covariates that change during the analysis time. A parametric proportional hazard model with time varying covariates does precisely that. It models duration (treatment time) as the result of a baseline hazard model that is modified by a collection of covariates that may change over time.

More specifically, we estimate a model of the form

$$h\left(t \mid \mathbf{x}_{i,t}\right) = h_0\left(t\right)\exp\left(\mathbf{x}_{i,t}\boldsymbol{\beta}\right) \qquad 1$$

where $h_0(t)$ is the baseline hazard rate model and $\mathbf{x}_{i,t}\boldsymbol{\beta}$ is the linear combination of covariates and related estimated coefficients for patient *i* at time *t*. This model is well suited to our purposes because the instantaneous hazard rate that is modeled can be interpreted as the instantaneous processing speed, or rate at which the patient is moving toward completion. Further, covariate coefficients can be interpreted as the proportional effect a given covariate has on the patient processing speed. For example, if patient age has a negative coefficient, this would be interpreted as older patients having a reduced hazard rate and therefore longer treatment times.

We test several functional forms for the baseline hazard model and find the Weibull distribution to provide the best fit, although other distributions provide qualitatively similar results. For the Weibull distribution, the baseline hazard is parameterized as $h_0(t) = pt^{p-1}\exp(\beta_0)$, where p is an ancillary shape parameter and $\exp(\beta_0)$ is the scale parameter, both of which are estimated via maximum likelihood from the data. One advantage of the Weibull distribution is that it is quite flexible in that it allows for a variety of monotonically increasing or decreasing shapes of the hazard function (Greene 2012, Sec. 19.4.3).

To allow for time varying covariates (e.g., hour of shift, workload), we preprocess the raw encounter data such that each encounter is split into multiple observations at time points where the covariates change values. Because hour of shift changes at the top of each hour, we create the encounter split points at the top of each hour. For example, an encounter that begins at 1:45 pm and ends at 3:20pm is split into three segments, as shown in Table 3, and the time varying covariates can change values for each segment. When the model is estimated, the first segment is treated as right censored (no observed "failure"), the middle segments are treated as both left and right censored (neither the start nor the failure is observed), and the final segment is treated as left censored (only the failure is observed) (Cleves 2016, Ch. 5).

Table 3 Example patient encounter data

Patient	Start	Stop	Shift	HOS	Work_New	Work_Inherit	Work_Other	Handoff
1	13:45	14:00	1	7	6	1	8	0
1	14:00	15:00	1	8	5	0	7	0
1	15:00	15:20	2	1	3	2	8	1

Despite our rich set of patient covariates, it is possible that there is unexplained heterogeneity in hazard rates across patients. This can lead to biased hazard estimates because as time passes, the patient population shifts as those with inherently higher hazard rates finish quickly leaving behind those with inherently lower hazard rates. To control for this possibility, we incorporate a "frailty" in the hazard model, which is the survival model equivalent of random-effects linear models (Duchateau and Janssen 2007). Thus, the model we estimate is a modified version of Equation 1:

$$h\left(t \mid \mathbf{x}_{i,t}, \alpha_i\right) = \alpha_i h_0\left(t\right) \exp\left(\mathbf{x}_{i,t}\boldsymbol{\beta}\right) \qquad 2$$

The individual-specific frailty term α follows a gamma distribution with mean of one and variance θ, and is estimated as an auxiliary parameter of the hazard model.

4.2 Hour of Shift Effect

We first focus on how the hazard rate changes over the course of the physician shift. Based on conversations with emergency department physicians and observation of the ED, we expect the hazard rate to be higher toward the end of the shift as physicians rush to get patients finished and reduce the number of patients that must be handed off at the end of the shift. To measure this hour of shift effect we define $\mathbf{x}_{i,t}\boldsymbol{\beta}$ as

$$\mathbf{x}_{i,t}\boldsymbol{\beta} = \beta_0 + HOS_{i,t}\boldsymbol{\beta}_1 + \mathbf{P}_i\boldsymbol{\beta}_P + \mathbf{W}_{i.t}\boldsymbol{\beta}_W + \mathbf{Z}_{i.t}\boldsymbol{\beta}_Z \qquad 3$$

$HOS_{i.t}$ is a vector of binary variables indicating the hour of the shift that patient *i*'s physician is engaged in at time *t*. $\mathbf{P}_i$ is a vector of patient-encounter specific covariates including age, gender, chief complaint, and triage level. $\mathbf{W}_{i,t}$ is a vector of workload variables including the hourly mean workload of new and inherited patients for patient *i*'s physician at time *t*, and the hourly mean workload of all other physicians at time *t*. $\mathbf{Z}_{i,t}$ is a vector of fixed effects controlling for physician, month, weekend, and shift.

Model 1 of Table 4 presents the results of estimating Equation 2 with $\mathbf{x}_{i,t}\boldsymbol{\beta}$ defined as shown in Equation 3.[5] We first note that $p>1$, indicating a monotone increasing hazard function, and θ is significantly different from zero, suggesting that there is indeed unexplained patient heterogeneity for which our frailty model is controlling.

Table 4 Survival model results

	(1)		(2)	
HoS 1	-1.091***	(0.032)	-1.120***	(0.034)
HoS 2	-0.383***	(0.023)	-0.399***	(0.024)
HoS 3	-0.084***	(0.019)	-0.090***	(0.019)
HoS 4	0.000	(.)	0.000	(.)
HoS 5	0.008	(0.018)	0.013	(0.018)
HoS 6	0.026	(0.019)	0.034+	(0.019)
HoS 7	0.070***	(0.019)	0.080***	(0.020)
HoS 8	0.345***	(0.018)	0.358***	(0.019)
Handoff			0.074**	(0.024)
Age	-0.004***	(0.000)	-0.004***	(0.000)
Female	-0.131***	(0.012)	-0.132***	(0.012)
Work_New	-0.184***	(0.003)	-0.184***	(0.003)
Work_Inhert	-0.105***	(0.005)	-0.110***	(0.005)
Work_Other	0.012***	(0.001)	0.012***	(0.001)
Shift fixed effect	Y		Y	
Physician fixed effect	Y		Y	
Chief complaint fixed effect	Y		Y	
ESI fixed effect	Y		Y	
Month fixed effect	Y		Y	
Weekend fixed effect	Y		Y	
p	2.151***	(0.015)	2.145***	(0.015)
θ	0.337***	(0.011)	0.347***	(0.013)
N	48,738		48,738	
BIC	80,871		80,873	

Standard errors in parentheses

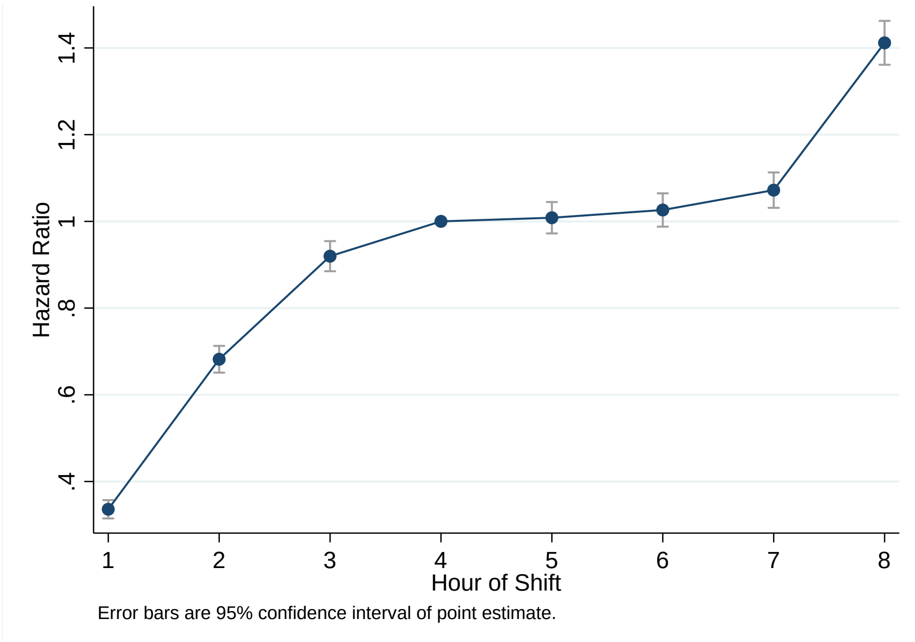
+ p<0.100, * p<0.050, ** p<0.010, *** p<0.001

Turning to the hour of shift effect, the fourth hour (*HOS4*) is the omitted category, and thus the other HOS coefficients indicate changes in the hazard rate relative to *HOS4*. We see that *HOS1*, *HOS2*, and *HOS3* have hazard rates significantly lower than *HOS4*, while *HOS7* and *HOS8* have significantly higher

[5] Please see Appendix 1 for a results table displaying all estimated coefficients

hazard rates. A Wald test indicates that the seven *HOS* variables are jointly significantly different from zero. Exponentiating the coefficients provides hazard ratios or hazard rate multipliers. Thus *HOS1* has a hazard rate that is only 34% of *HOS4* (exp(-1.091)=0.34), and *HOS8* has a hazard rate that is 41% higher than *HOS4* (exp(0.345)=1.41). Figure 2 displays the hazard ratios for all hours of the shift.

Figure 2 Relative hazard ratios of completion by hour of shift



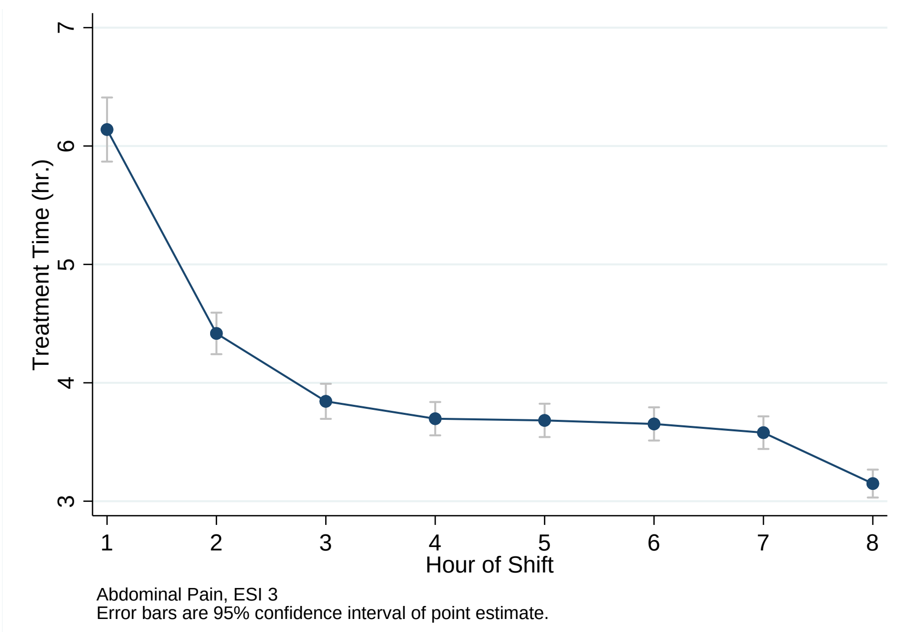
These results show that indeed physicians are more likely to discharge a patient in the latter hours of the shift. In addition, we see that physicians are less likely to discharge patients in the first hour of the shift. This is likely at least partly due to the time it takes an on-coming physician to have the handoff meeting, read over the notes, and familiarize herself with the current patients before becoming fully productive. It is important to recognize that the model is controlling for how long the patient has already been in treatment and for the physician's workload. Thus, the hour of shift effect is not simply an artifact of patients being started near the beginning of the shift, staying for a few hours, and then being discharged near the end of the shift. The baseline hazard function controls for that phenomenon. The hour of shift effects observed are proportional shifts of the hazard rate regardless of whether the patient has been in treatment for 10 minutes or 10 hours.

To get a sense of the magnitude of these differences in hazard rates on treatment times, we estimate predicted treatment times for a "typical" abdominal pain[6] patient, holding hour of shift constant (which cannot happen in reality, but provides a useful hypothetical benchmark). The expected duration of a random variable with survival function *S(t)* is calculated as $\mu = \int_0^\infty S(t)dt$, where *S(t)* for our Weibull hazard model with gamma shared frailty is

$$S(t \mid \mathbf{x}) = \left\{1 + \theta \exp\left(\mathbf{x}\boldsymbol{\beta}\right) t^{p}\right\}^{-1/\theta} \quad 4$$

Figure 3 shows the predicted treatment times for an abdominal pain patient under the hypothetical assumption of constant hour of shift. The range in predicted times is quite large. Our estimates show that a patient that is treated under perpetual *HOS1* conditions has an expected treatment time of more than 6.1 hours, while the same patient treated under perpetual *HOS8* conditions has an expected treatment time of

Figure 3 Expected treatment time under fixed hour-of-shift behavior



[6] Abdominal pain is the most common chief complaint, occurring in 9% of patients.

just over 3.2 hours. Thus, we see that the rate of treatment varies greatly over the course of the work shift.

4.3 Handoff Effect

To estimate a handoff effect, we modify the linear predictor from Equation 3 to include a binary variable indicating if the patient has been handed off.

$$\mathbf{x}_{i,t}\boldsymbol{\beta} = \beta_0 + HOS_{i,t}\boldsymbol{\beta}_1 + \beta_2 HANDOFF_{i,t} + \mathbf{P}_i\boldsymbol{\beta}_P + \mathbf{W}_{i.t}\boldsymbol{\beta}_W + \mathbf{Z}_{i.t}\boldsymbol{\beta}_Z \qquad 5$$

As shown in the example in Table 3, the *HANDOFF* variable equals zero until a patient's treatment encounter crosses over a shift change and the patient has been handed off.[7] It is not obvious ex ante what sign β_2 will take. As mentioned previously, in the study ED, patients that are inherited at handoff do not impact the performance metrics of the receiving physician. Thus, with little extrinsic incentive to focus on the inherited patients, physicians may devote less time and energy to them, leading to lower hazard rates and longer treatment times for inherited patients. Conversely, physicians may prefer to complete those inherited patients that are closer to being done as quickly as possible so they can fully focus on their own patients. (Amar et al. (2011) show evidence of a similar response in consumers that deviate from normative behavior by focusing on reducing the number of outstanding debt accounts.) This would lead to increased hazard rates for inherited patients.

Model 2 of Table 4 presents the results from estimating Equation 2 with $\mathbf{x}_{i,t}\boldsymbol{\beta}$ defined as shown in Equation 5. The coefficient for *HANDOFF* is positive and significant (β_2 =0.074, p<0.010) indicating that patients that are handed off (inherited) have hazard rates that are 8% (exp(0.074)=1.08) higher than non-handed off patients (new). Stated differently, a patient that has been handed off has a shorter expected remaining treatment time than does an equivalent patient that has not been handed off. The

[7] We allow a short buffer at the end of each shift such that patients that receive a "ready" timestamp within the first 30 minutes after a shift change are considered *not* handed off. We do this because it is unlikely that the on-coming physician had any interaction or influence on such a patient, but rather the outgoing physician simply did not get to entering the "ready" timestamp until after the start of the new shift. Our results are qualitatively similar if we adjust this window to 15 minutes.

magnitude of this effect on expected treatment time depends on the other covariates of the patient, but is on the order of five to ten minutes for a typical patient.

4.4 Combined Effect on Treatment Time

Because our parametric proportional hazard model is non-linear and estimates hazard rates rather than durations, it is difficult to directly interpret estimated coefficients in terms of marginal effects on treatment time. Further, because the baseline hazard is monotone increasing and the effects of all independent variables are proportional (multiplicative), the magnitude of marginal effects varies with when in a patient's treatment a change in an independent variable occurs. For example, a patient that is early in his treatment has a relatively low baseline hazard, and thus any change in the state of the system (e.g., hour of shift, workload) has a small absolute impact on the hazard rate. In contrast, a patient late in treatment has a higher baseline hazard, and changes in the state of the system have a larger absolute effect on the hazard rate. Because of this, the net impact of the hour of shift and handoff effects on treatment time will be different depending on when they occur in a patient's encounter. Stated differently, a patient's expected treatment time will be different depending on when in the physician's shift treatment is started.

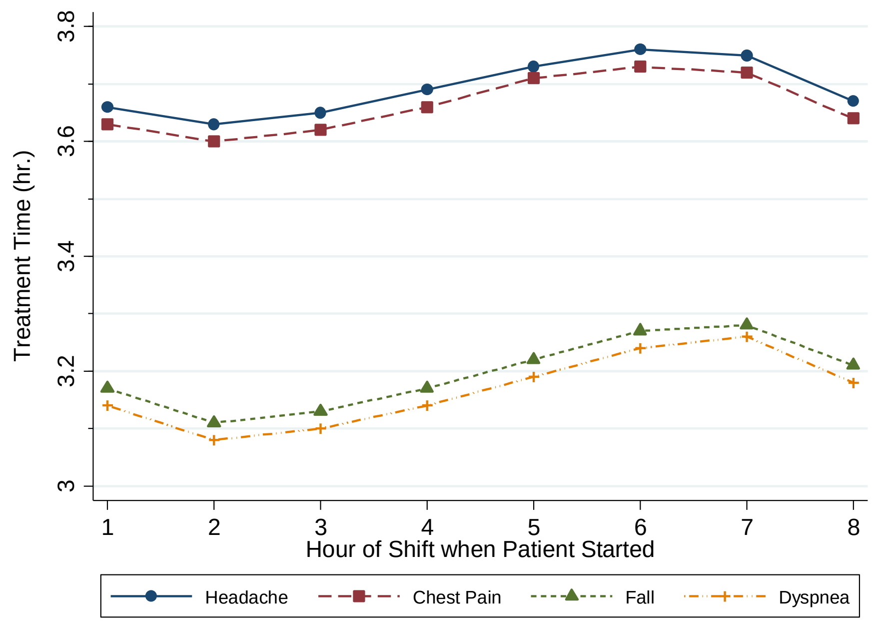
To see this effect, we estimate the mean treatment time for a few common chief complaints as a function of when in the shift the physician starts the patient. For the purposes of this analysis, we define a typical patient as a 48 year-old female, triage level ESI 3. We set workload levels to typical daytime levels of *WORK_NEW*=6, *WORK_INHERIT*=1, and *WORK_OTHER*=8.

As described in Section 4.3, mean treatment times are estimated by integrating the survival function from zero to infinity. However, because we now want to allow some covariates to change over time, we must break the integral into pieces for each hour and do piecewise integration. Further, rather than integrating an infinite number of parts of the integral, after a suitably long number of parts (48), we allow the last integral to go to infinity. Because the survival function approaches 0 as t goes to infinity, this gives a reasonable approximation of the infinite sum. Thus, the integral we calculate is

$$\mu_i = \int_0^\infty S(t \mid x_{i,t}\beta)dt = \int_0^1 S(t \mid x_{i,1}\beta)dt + \int_1^2 S(t \mid x_{i,2}\beta)dt + \ldots + \int_{48}^\infty S(t \mid x_{i,48}\beta)dt \qquad 6$$

Figure 5 shows the results of these calculations. The x-axis indicates the hour of shift when the hypothetical patient starts treatment (assuming treatment starts at the top of the indicated hour), and each set of connected points represents a chief complaint. For example, a chest pain patient that begins treatment at the start of the first hour of the shift has an expected treatment time of 3.63 hours, while the

Figure 4 Expected treatment time by hour and shift when treatment started



expected treatment time for an identical patient that starts treatment in the sixth hour is 3.73 hours.

The results in Figure 5 highlight multiple interesting insights. The difference in expected treatment time from minimum (starting treatment in HOS 2) to maximum (starting treatment in HOS 6 or 7) is only a few minutes (e.g., 9 minutes for Headache, 11 minutes for Dyspnea), which is somewhat surprising given the large change in hazard rates over the hours. Because most patients spend several hours in treatment, only a portion of their treatment occurs during the hours when the hazard rates are most severe (HOS 1 and HOS 8). This also explains why the effect of Hour of Shift of treatment start is larger for chief complaints with shorter average treatment times (e.g., Dyspnea).

The roughly sinusoidal pattern of expected treatment time seen in of Figure 5 is caused by the Hour of Shift effects reported in Table 4 and Figure 2. For patients that start early (Hour of Shift 1 or 2) or late (Hour of Shift 8), the slow hazard rates of Hour 1 and 2 occur either early enough or late enough in the patient encounter so as to have only a muted effect on expected treatment time. In contrast, patients that start treatment in the middle hours of a shift are likely to experience the low Hour 1 and Hour 2 hazard rates in the middle of their encounter when these proportional coefficients have a large impact on the expected treatment time. Thus, for these patients the retarding effects of Hour of Shift 1 and 2 overpower the accelerating effect of Hour of Shift 8 and the mild acceleration of being handed off.

To summarize, the results of Section 4 show that the rate of treatment varies over the course of each shift, being lowest early in the shift and being highest in the last hour. This causes expected treatment time to be a function of when in a shift a patient starts treatment. We also find that patients that are handed off experience a slightly higher hazard rate from those that have not been handed off.

5 Empirical Analysis of Revisit Rate

Section 4 focused on the effects of discrete shifts and handoffs on treatment time, which has a direct effect on ED productivity. In this section, we analyze the effects of discrete shifts and handoffs on a quality measure, ED revisits. If handoffs have a negative impact on quality, then patients that experience a handoff should be more likely to revisit the ED. A “revisit” is defined as an ED discharged patient returning to the ED for treatment within a given time window from discharge from the ED. Revisits are commonly used as a measure of ED quality both in the medical literature (Keith et al. 1989, Martin-Gill and Reiser 2004, Wu et al. 2010), as well as in the Operations Management literature (KC 2013, Song et al. 2015). Following common practice (e.g., Keith et al. 1989, Song et al. 2015), we study revisits that occur within 72 hours of discharge from the ED. As noted in Table 1, 5.6% of all discharged patients return within 72 hours.

For this analysis, the dependent variable is the binary variable *REVIST* which equals one if a discharged patient returned to the ED within 72 hours, and zero otherwise. The main independent variable of interest is the variable *HANDOFF*, which indicates if the patient was handed off at a shift change, just as in the analysis in Section 4.

Given this basic design, one empirical approach is to use a standard probit model to estimate the effect of *HANDOFF* on *REVIST*. However, a concern with such a model is endogeneity of the handoff decision. For example, if sicker patients are both more likely to be handed off (perhaps due to long treatment times) and are more likely to revisit the ED, then the *HANDOFF* variable will be correlated with the error term of the probit model leading to biased coefficient estimates. This is referred to as an "endogenous treatment" problem because the treatment for which we are trying to estimate a causal effect (handoff) is potentially correlated with the treatment assignment (Wooldridge 2010).

There are various models available to address the endogenous treatment concern depending on whether the treatment assignment is *conditionally* independent of the outcome or not.[8] Treatment assignment is conditionally independent if no unobserved variable is correlated with both treatment assignment and the outcome. Stated differently, assignment is conditionally independent if treatment assignment is explained by the observed variables. If this is the case, several modeling options are available including regression adjustment, nearest neighbor matching, and propensity score matching. We return to this below.

If treatment assignment is not conditionally independent, then we can use the control-function regression adjustment method described by Wooldridge (2010, Sec. 21.4). This is a two-step procedure in which treatment assignment is estimated with a probit model to obtain predicted treatment probabilities and associated residuals. These values are then used in second-stage probit models to estimate the probability

[8] This condition is also referred to as "ignorability of treatment" (Rosenbaum and Rubin 1983) and "selection on observables" (Heckman and Robb 1985, Moffitt 1996)

of a binary outcome (revisit, in our case) under both the treatment and control condition. From these probabilities, average treatment effects are calculated. With this method, a Wald test can be used to explicitly test for correlation between the unobservables of the treatment-assignment and the outcome models. (Guajardo et al. (2012) use a similar control-function regression model but with a continuous outcome variable rather than a binary outcome.)

The covariates included in both the treatment and outcome models are all the patient, physician, and time variables from vectors **P** and **Z** included in Equation 3. Further, while not strictly necessary, we use the hour of day when a patient is put in a treatment bed (*BED_HOUR*) as an exogenous predictor of *HANDOFF*. This is reasonable, since the time of patient arrival is independent of the shift start and end times of individual physicians.

Table 5 Average treatment effect (ATE) of a handoff on 72 hour revisit rate

	Average Treatment Effect
Endogenous Treatment Model	0.008
	(0.013)
Propensity Score Matching	0.016*
	(0.007)
Nearest Neighbor Matching	0.013*
	(0.005)
N	30,886

* p<0.050, ** p<0.010, *** p<0.001

The first row of Table 5 shows that the endogenous treatment model (control-function regression adjustment model) estimates the average treatment effect (ATE) of undergoing a handoff to be 0.8 percentage points, however the effect is not statistically significant. While this suggests that being handed off does not have a significant effect on revisit rate, a Wald test of the residual correlation terms shows that there is not significant correlation between the treatment-assignment equation and the outcome equations. That indicates that we can use treatment models that assume conditional independence of treatment assignment, and these will likely have smaller standard errors.

As mentioned above, there are several treatment models that work under the assumption of conditionally independent treatment assignment. We present results from propensity score matching (PSM) and nearest neighbor matching (NNM) here.

In propensity score matching, first proposed by Rosenbaum and Rubin (1983), a probit or logit model is used to estimate a probability of receiving treatment (a propensity for treatment score) for all observations as a function of a collection of covariates. Observations that did receive treatment are then paired with observations with similar propensity scores that did not receive the treatment. Average treatment effects are then estimated as the mean difference between matched observations. Nearest neighbor matching is similar to propensity score matching, however the matching is done nonparametrically (Wooldridge 2010, Sec. 21.3.5). The "distance" between two observations is determined by a weighted function of the covariates, and then matching is done to minimize this Mahalanobis distance. As with the endogenous treatment effect model above, we include *BED_HOUR* and all the patient, physician, and time variables of vectors **P** and **B** into the PSM and NNM. (See Levine and Toffel (2010), Gray et al. (2015), and Gopal et al. (2013) for examples of PSM and NNM in other Operations Management settings.)

Table 5 shows the results of the propensity score and nearest neighbor matching models.[9] The estimated ATEs are quite similar in magnitude to each other at 1.6 and 1.3 percentage points, and both estimates are statistically significant. Thus, we find that discharged patients that experience a shift-change handoff are more likely to return to the ED within 72 hours than are similar patients that did not experience a handoff.

6 Discussion and Conclusion

Given continuous demand for service, such as emergency care, many service processes operate as nonterminating queues. However, given physiological constraints, individual workers who provide these services operate under durations of fixed shifts. This leads to operational challenges in deciding how

[9] To verify that the matching balances the control and treatment groups, we provide tables of standardized differences of means (Austin 2011) for all matching variables for both the PSM and NNM models in the appendix. Note that in the NNM we force an exact match on chief complaint while the remainder of the matching is done to minimize the Mahalanobis distance.

work should be allocated across individuals over time. Our investigation of these dynamics in a hospital emergency department permits us to make three unique contributions to theory.

First, we examine how service rates change over time in a nonterminating queue. Prior work commonly assumes that nonterminating queues exhibit steady state behavior. Although empirical work has challenged this assumption in a context of terminating queues with fixed shifts (Chan Jr 2015, Deo and Jain 2015), we believe that we are the first to investigate it in a nonterminating queue setting.

Second, we examine the impact of handoffs within a nonterminating queue. Because workers cannot work forever and some patients take longer to treat than can be accomplished within a shift, understanding the operational implications of handoffs is important. We are aware of no empirical evidence that has explored the impact of handoffs in the emergency department context. Thus, we are the first to consider both the efficiency and quality implications of handoffs. Our empirical results show that handed off patients have slightly shorter treatment times, but also have statistically significant higher probability of returning to the ED within 72 hours.

Lastly, we show that the combined effect of the hour of shift effect and the handoff effect leads to patient treatment times being a function of when in the physician's shift the patient's treatment begins.

6.1 Managerial Implications

Our paper yields multiple important implications for managers. As we have seen through discussions with physicians, each of our empirical findings is important for the practice of medicine. The fact that physicians alter their behavior over the course of the shift and with handed off patients is important to consider in the assignment of work. With respect to the former, we see that hazard rates increase over a physician's shift, regardless of how long the patient has been in treatment. Some difference between first hour and last hour productivity can be explained by differences in the job – for example, at the start of a shift a physician must ramp up and learn about new patients, however this is controlled for in the hazard model. The observed hour of shift effect differences are likely a function of the physician's actions. Maintaining Hour 8 productivity is unlikely to be realistic for an entire shift, however, that does not mean that it cannot be continued for longer portions of the shift. Both physicians and administrators should study the differences in how physicians act and make decisions in the early and later parts of a shift. Studying the differences may identify best practices (Song et al. 2017). In addition, making physicians aware of this difference and then providing them ongoing feedback on their hourly performance may help. In addition, our findings create opportunities to think more carefully about shift staggering. Combining more creative shift start times and different patient pickup rules may aid productivity. Finally, it may be that the eight-hour shift structure is not ideal. Our results suggest that longer shifts may be useful. Further work is needed to consider how much longer and the tradeoffs this introduces with tiring workers. This could involve field experiments or simulation (e.g., Buell et al. 2017, Kasaie et al. 2017).

Second, our findings suggest that management may want to consider how best to manage workload through handoffs. Managers may wish to consider a cutoff policy for when physicians stop taking on new patients. Although limiting a doctor from taking on new patients might at first seem to hurt operational performance, by avoiding handoffs the overall system might be better off. When considering cutoff policies, the hospital would need to consider what outcome variable is most important to prioritize –wait time, throughput time, or quality. It seems likely that depending on this choice, different cutoff policies might be in order. This is a question that both managers and academics should consider more fully. In addition to considering cutoff policies, other policy changes might also help. For example, a policy whereby the finishing physician only takes patients with simple complaints, while leaving the more complex cases to the other physician might be a viable choice in order to avoid cutoffs, but still take advantage of available capacity. Finally, shift scheduling (staggered shifts), along with differential rules for who picks up when might also help a hospital administrator to deliver efficient, high quality care.

6.2 Limitations and Future Work

We note some limitations to our work. First, although our data provide excellent detail about a nonterminating queue over an extended period of time, it is from one hospital. We are able to control for many factors, but we cannot control for any hospital-specific effects. Future work should seek to expand our findings to other hospitals that permit handoffs and operate queues around the clock. Second, there are many important outcome variables to consider when investigating the healthcare context. Here we are able to investigate the time to treat as well as revisit rate, an established measure of quality. Future work should seek to study additional measures of performance including patient satisfaction and clinical outcomes (Bartel et al. 2017). Third, our empirical examination of handoffs helps us to identify the effect on both of our outcome measures. We are able to examine econometrically the effect with our selection model and matching models. However, future work should seek to implement field experiments to precisely identify the effect of handoffs, if possible, as well as the other measures we study. Creating an intervention with handoffs may not be organizationally practical and so future work should seek to find natural experiments where patients are exogenously treated.

Future work should seek to unpack the productivity effects of handoffs in more detail. What are the characteristics of physicians and patients that lead to changes in operational performance due to handoffs? Anecdotally, emergency physicians pride themselves on the ability to maintain productivity while producing an “easy handoff” for the oncoming team, and based on our analysis it is not clear that actions taken to minimize or modify handoffs would necessarily improve overall system productivity. An interesting set of questions to consider include examining whether physicians learn over time and so are better able to manage handoffs with experience. Alternatively, it is possible that experience may exacerbate the problem as physicians are less aware of their actions and so experience ends up being maladaptive (Ibanez et al. 2017, Staats et al. 2017).

Finally, future research could examine why handoffs lead to quality problems. Our findings show that it is not a challenge of overall delay, but it is possible that there is delay in some key step. Alternatively, it is possible that knowledge problems arise due to poor transfer of information. Moreover, more work should be done to understand how to better hand off patients, since eliminating the need for hand offs is unrealistic in many settings.

6.3 Conclusion

Increasingly, operations must function around the clock. However, even when production occurs continuously the individuals doing the work must change. Both of these statements are true in the healthcare context that we study. Therefore, it is important to understand the operational implications of nonterminating queues with fixed work shifts. In this paper, we do just that. We use data from an emergency department to explore how service time varies as a function of when within a shift a patient starts. We also investigate the impact of handoffs. Our empirical results provide important insights for both the academy and practice. Overall, our results highlight that modeling nonterminating queues as systems in steady state is likely to diverge from reality. Finally, if managers want to increase the productivity of emergency departments, then they should challenge conventional wisdom and consider changes to the way that work is structured.

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7 Appendices

7.1 Appendix 1

Table 6 replicates Table 4 but includes all estimated coefficients.

Table 6 Survival Model Estimates (full list)

	(1)		(2)	
HoS 1	-1.091***	(0.032)	-1.120***	(0.034)
HoS 2	-0.383***	(0.023)	-0.399***	(0.024)
HoS 3	-0.084***	(0.019)	-0.090***	(0.019)
HoS 4	0.000	(.)	0.000	(.)
HoS 5	0.008	(0.018)	0.013	(0.018)
HoS 6	0.026	(0.019)	0.034+	(0.019)
HoS 7	0.070***	(0.019)	0.080***	(0.020)
HoS 8	0.345***	(0.018)	0.358***	(0.019)
Handoff			0.074**	(0.024)
Work_New	-0.184***	(0.003)	-0.184***	(0.003)
Work_Inhert	-0.105***	(0.005)	-0.110***	(0.005)
Work_Other	0.012***	(0.001)	0.012***	(0.001)
Shift 2	0.084***	(0.019)	0.085***	(0.019)
Shift 3	0.401***	(0.021)	0.401***	(0.021)
Shift 4	0.053**	(0.020)	0.058**	(0.020)
Shift 5	0.059**	(0.019)	0.060**	(0.019)
Age	-0.004***	(0.000)	-0.004***	(0.000)
Female	-0.131***	(0.012)	-0.132***	(0.012)
ESI 2	0.127***	(0.015)	0.128***	(0.015)
ESI 4	0.928***	(0.023)	0.933***	(0.024)
Month 2	0.097**	(0.036)	0.097**	(0.037)
Month 3	0.115**	(0.035)	0.115**	(0.036)
Month 4	0.163***	(0.035)	0.163***	(0.036)
Month 5	0.084*	(0.035)	0.084*	(0.036)
Month 6	0.126***	(0.035)	0.126***	(0.035)
Month 7	0.073*	(0.031)	0.072*	(0.031)
Month 8	0.053+	(0.031)	0.052+	(0.031)
Month 9	0.077*	(0.031)	0.077*	(0.031)
Month 10	0.081**	(0.031)	0.080*	(0.031)
Month 11	0.037	(0.031)	0.036	(0.031)
Month 12	0.008	(0.031)	0.008	(0.031)
Weekend	0.004	(0.013)	0.004	(0.013)
Chief Complaint 2	1.174***	(0.066)	1.184***	(0.067)
Chief Complaint 3	1.112***	(0.069)	1.118***	(0.070)
Chief Complaint 4	0.499***	(0.054)	0.505***	(0.055)
Chief Complaint 5	0.915***	(0.080)	0.921***	(0.081)

Chief Complaint 6	0.613***	(0.110)	0.616***	(0.111)
Chief Complaint 7	0.300***	(0.042)	0.305***	(0.042)
Chief Complaint 8	1.967***	(0.099)	1.980***	(0.100)
Chief Complaint 9	0.373***	(0.029)	0.377***	(0.029)
Chief Complaint 10	0.913***	(0.064)	0.922***	(0.065)
Chief Complaint 11	1.456***	(0.097)	1.467***	(0.098)
Chief Complaint 12	0.502***	(0.079)	0.507***	(0.079)
Chief Complaint 13	0.749***	(0.083)	0.754***	(0.083)
Chief Complaint 14	0.385***	(0.045)	0.391***	(0.045)
Chief Complaint 15	0.690***	(0.033)	0.696***	(0.034)
Chief Complaint 16	1.306***	(0.142)	1.321***	(0.144)
Chief Complaint 17	1.049***	(0.075)	1.059***	(0.076)
Chief Complaint 18	0.669***	(0.034)	0.675***	(0.034)
Chief Complaint 19	0.545***	(0.068)	0.553***	(0.069)
Chief Complaint 20	0.554***	(0.043)	0.560***	(0.043)
Chief Complaint 21	0.872***	(0.086)	0.876***	(0.086)
Chief Complaint 22	0.431***	(0.046)	0.435***	(0.047)
Chief Complaint 23	0.806***	(0.091)	0.813***	(0.092)
Chief Complaint 24	1.120***	(0.078)	1.127***	(0.078)
Chief Complaint 25	0.358***	(0.037)	0.361***	(0.037)
Chief Complaint 26	0.852***	(0.065)	0.860***	(0.065)
Chief Complaint 27	0.592***	(0.082)	0.598***	(0.082)
Chief Complaint 28	1.041***	(0.056)	1.047***	(0.056)
Chief Complaint 29	0.592***	(0.060)	0.597***	(0.060)
Chief Complaint 30	0.619***	(0.069)	0.626***	(0.070)
Chief Complaint 31	1.213***	(0.046)	1.223***	(0.047)
Chief Complaint 32	0.242***	(0.046)	0.244***	(0.046)
Chief Complaint 33	0.412***	(0.082)	0.417***	(0.083)
Chief Complaint 34	0.737***	(0.022)	0.744***	(0.023)
Chief Complaint 35	0.749***	(0.075)	0.754***	(0.076)
Chief Complaint 36	0.768***	(0.067)	0.775***	(0.068)
Chief Complaint 37	0.323***	(0.056)	0.326***	(0.056)
Chief Complaint 38	1.206***	(0.104)	1.218***	(0.105)
Chief Complaint 39	0.962***	(0.062)	0.972***	(0.062)
Chief Complaint 40	0.389***	(0.060)	0.394***	(0.060)
Chief Complaint 41	0.931***	(0.073)	0.937***	(0.074)
Chief Complaint 42	0.812***	(0.078)	0.819***	(0.079)
Chief Complaint 43	0.452***	(0.054)	0.456***	(0.054)
Chief Complaint 44	0.670***	(0.054)	0.677***	(0.055)
Chief Complaint 45	1.615***	(0.081)	1.624***	(0.082)
Chief Complaint 46	0.426***	(0.085)	0.432***	(0.085)
Chief Complaint 47	1.021***	(0.081)	1.030***	(0.081)
Chief Complaint 48	0.380***	(0.058)	0.385***	(0.059)
Chief Complaint 49	0.481***	(0.055)	0.486***	(0.056)
Chief Complaint 50	0.871***	(0.084)	0.879***	(0.085)

Physician 2	0.079*	(0.039)	0.082*	(0.039)
Physician 3	-0.209***	(0.043)	-0.211***	(0.044)
Physician 4	0.200+	(0.117)	0.202+	(0.118)
Physician 5	0.320***	(0.033)	0.323***	(0.034)
Physician 6	-0.052	(0.046)	-0.052	(0.046)
Physician 7	0.285**	(0.110)	0.288**	(0.110)
Physician 8	-0.255***	(0.046)	-0.254***	(0.046)
Physician 9	0.404***	(0.049)	0.406***	(0.049)
Physician 10	-0.147**	(0.046)	-0.146**	(0.046)
Physician 11	0.031	(0.222)	0.030	(0.223)
Physician 12	-0.278***	(0.064)	-0.278***	(0.065)
Physician 13	0.027	(0.037)	0.028	(0.037)
Physician 14	0.073+	(0.037)	0.076*	(0.038)
Physician 15	0.161***	(0.036)	0.162***	(0.036)
Physician 16	0.273***	(0.032)	0.274***	(0.032)
Physician 17	0.102**	(0.033)	0.104**	(0.033)
Physician 18	-0.123***	(0.033)	-0.123***	(0.034)
Physician 19	-0.234***	(0.033)	-0.234***	(0.033)
Physician 20	-0.064+	(0.038)	-0.063+	(0.038)
Physician 21	-0.159***	(0.032)	-0.159***	(0.033)
Physician 22	-0.181**	(0.062)	-0.179**	(0.062)
Physician 23	-0.095+	(0.055)	-0.094+	(0.055)
Physician 24	-0.001	(0.031)	-0.002	(0.031)
Physician 25	-0.218***	(0.037)	-0.217***	(0.037)
Physician 26	0.098*	(0.048)	0.098*	(0.049)
Physician 27	0.000	(.)	0.000	(.)
Physician 28	-0.029	(0.059)	-0.031	(0.059)
Physician 29	0.271***	(0.047)	0.273***	(0.047)
Physician 30	0.072	(0.046)	0.071	(0.046)
Physician 31	-0.234***	(0.051)	-0.235***	(0.051)
Physician 32	-0.092*	(0.046)	-0.092*	(0.046)
Constant	-3.073***	(0.045)	-3.081***	(0.046)
p	2.151***	(0.015)	2.145***	(0.015)
θ	0.337***	(0.011)	0.347***	(0.013)
N	48,738		48,738	
BIC	80,871		80,873	

Standard errors in parentheses

+ p<0.100, * p<0.050, ** p<0.010, *** p<0.001

7.2 Appendix 2

Section 5 presents results from propensity score matching and nearest neighbor matching models. When the matching process is working well, the control and treatment groups should have similar covariate means, known as balance. We present here standardized differences of the means of all covariates used in the matching models. The standardized difference is a measure of the difference of the means of the control and treatment groups normalized by the pooled standard deviation (Austin 2011). There is no universally accepted threshold for “acceptable” imbalance. Many papers use an absolute value of 0.1 or 0.2 as the benchmark (Cohen 1988, Normand et al. 2001).

Table 7 shows the standardized differences for the raw and matched data under PSM and NNM. Overall, the matching is quite good with all but one variable in the PSM and two in the NNM having standardized differences greater than 0.2. This is likely due to the large number of categorical variables with many categories (e.g., hour of day, physician, chief complaint). We note that for the NNM model, the standardized difference for Chief Complaint is precisely zero because we forced exact matching on Chief Complaint

Table 7 Standardized differences of means of control and treatment groups

	Propensity Score Matching		Nearest Neighbor Matching	
	Raw	Matched	Raw	Matched
Age	0.12	0.05	0.12	0.10
ESI 2	0.16	0.03	0.16	0.06
ESI 4	-0.35	-0.07	-0.35	-0.29
Female	0.06	0.04	0.06	0.08
Shift 2	-0.01	-0.02	-0.01	-0.01
Shift 3	-0.09	0.07	-0.09	-0.22
Shift 4	0.05	-0.03	0.05	-0.02
Shift 5	-0.19	-0.05	-0.19	-0.06
Hour of Day 1	-0.15	0.01	-0.15	-0.05
Hour of Day 2	-0.06	0.07	-0.06	-0.04
Hour of Day 3	-0.02	0.00	-0.02	-0.02
Hour of Day 4	0.12	-0.02	0.12	0.00
Hour of Day 5	0.23	0.01	0.23	0.02
Hour of Day 6	0.11	0.22	0.11	-0.01
Hour of Day 7	-0.19	0.03	-0.19	-0.09
Hour of Day 8	-0.22	-0.01	-0.22	-0.15
Hour of Day 9	-0.25	0.05	-0.25	-0.16
Hour of Day 10	-0.13	0.00	-0.13	-0.05
Hour of Day 11	0.02	-0.02	0.02	0.07
Hour of Day 12	0.18	0.00	0.18	0.13

Hour of Day 13	0.31	-0.03	0.31	0.17
Hour of Day 14	0.17	-0.05	0.17	0.08
Hour of Day 15	0.02	-0.09	0.02	0.02
Hour of Day 16	-0.15	-0.06	-0.15	-0.10
Hour of Day 17	-0.29	-0.03	-0.29	-0.19
Hour of Day 18	-0.20	0.02	-0.20	-0.10
Hour of Day 19	-0.10	0.04	-0.10	-0.06
Hour of Day 20	0.08	-0.02	0.08	0.05
Hour of Day 21	0.18	-0.03	0.18	0.11
Hour of Day 22	0.12	-0.05	0.12	0.06
Hour of Day 23	-0.04	-0.07	-0.04	0.00
Month 2	-0.02	0.02	-0.02	-0.05
Month 3	-0.03	-0.03	-0.03	-0.07
Month 4	0.00	-0.03	0.00	-0.04
Month 5	-0.01	0.02	-0.01	-0.05
Month 6	-0.03	0.02	-0.03	-0.07
Month 7	-0.01	-0.01	-0.01	0.02
Month 8	0.04	0.01	0.04	0.05
Month 9	0.03	0.01	0.03	0.02
Month 10	0.00	0.05	0.00	0.02
Month 11	0.01	-0.03	0.01	0.02
Month 12	0.00	-0.01	0.00	0.00
Weekend	-0.06	-0.02	-0.06	-0.08
Chief Complaint 2	-0.01	-0.04	-0.01	0.00
Chief Complaint 3	-0.04	-0.02	-0.04	0.00
Chief Complaint 4	0.02	0.00	0.02	0.00
Chief Complaint 5	-0.03	0.03	-0.03	0.00
Chief Complaint 6	-0.01	0.01	-0.01	0.00
Chief Complaint 7	-0.01	0.01	-0.01	0.00
Chief Complaint 8	-0.03	-0.04	-0.03	0.00
Chief Complaint 9	0.14	0.09	0.14	0.00
Chief Complaint 10	-0.06	-0.01	-0.06	0.00
Chief Complaint 11	-0.11	-0.03	-0.11	0.00
Chief Complaint 12	0.00	0.01	0.00	0.00
Chief Complaint 13	-0.03	0.03	-0.03	0.00
Chief Complaint 14	0.01	0.04	0.01	0.00
Chief Complaint 15	0.03	-0.01	0.03	0.00
Chief Complaint 16	-0.04	-0.05	-0.04	0.00
Chief Complaint 17	-0.05	0.00	-0.05	0.00
Chief Complaint 18	0.02	0.00	0.02	0.00
Chief Complaint 19	0.01	0.01	0.01	0.00
Chief Complaint 20	0.02	0.02	0.02	0.00
Chief Complaint 21	-0.01	-0.03	-0.01	0.00
Chief Complaint 22	0.01	-0.01	0.01	0.00
Chief Complaint 23	-0.02	-0.01	-0.02	0.00

Chief Complaint 24	-0.05	-0.02	-0.05	0.00
Chief Complaint 25	0.02	-0.02	0.02	0.00
Chief Complaint 26	-0.01	-0.03	-0.01	0.00
Chief Complaint 27	-0.03	-0.01	-0.03	0.00
Chief Complaint 28	-0.07	-0.04	-0.07	0.00
Chief Complaint 29	0.00	-0.03	0.00	0.00
Chief Complaint 30	-0.01	-0.04	-0.01	0.00
Chief Complaint 31	-0.03	0.04	-0.03	0.00
Chief Complaint 32	0.02	0.00	0.02	0.00
Chief Complaint 33	0.01	-0.01	0.01	0.00
Chief Complaint 34	-0.14	-0.02	-0.14	0.00
Chief Complaint 35	0.03	0.03	0.03	0.00
Chief Complaint 36	-0.03	-0.03	-0.03	0.00
Chief Complaint 37	0.01	-0.02	0.01	0.00
Chief Complaint 38	-0.07	-0.02	-0.07	0.00
Chief Complaint 39	-0.02	-0.04	-0.02	0.00
Chief Complaint 40	0.02	-0.01	0.02	0.00
Chief Complaint 41	-0.06	-0.03	-0.06	0.00
Chief Complaint 42	0.05	0.03	0.05	0.00
Chief Complaint 43	0.03	-0.01	0.03	0.00
Chief Complaint 44	-0.01	-0.02	-0.01	0.00
Chief Complaint 45	0.02	-0.01	0.02	0.00
Chief Complaint 46	-0.01	0.05	-0.01	0.00
Chief Complaint 47	-0.04	-0.02	-0.04	0.00
Chief Complaint 48	0.01	-0.03	0.01	0.00
Chief Complaint 49	0.04	0.03	0.04	0.00
Chief Complaint 50	-0.02	-0.03	-0.02	0.00
Physician 2	0.06	0.01	0.06	-0.01
Physician 3	0.01	-0.01	0.01	-0.01
Physician 4	-0.08	-0.01	-0.08	-0.05
Physician 5	-0.03	0.01	-0.03	-0.02
Physician 6	-0.06	-0.02	-0.06	-0.03
Physician 7	0.06	0.03	0.06	-0.02
Physician 8	-0.08	-0.04	-0.08	-0.04
Physician 9	0.03	0.03	0.03	-0.01
Physician 10	0.05	0.01	0.05	-0.01
Physician 11	0.01	-0.03	0.01	-0.02
Physician 12	-0.02	0.01	-0.02	-0.01
Physician 13	-0.03	0.02	-0.03	-0.01
Physician 14	-0.04	-0.03	-0.04	0.00
Physician 15	-0.05	-0.04	-0.05	-0.01
Physician 16	0.01	0.02	0.01	0.00
Physician 17	0.10	0.00	0.10	0.07
Physician 18	0.01	0.02	0.01	0.00
Physician 19	0.00	0.00	0.00	0.03

Physician 20	-0.01	0.02	-0.01	-0.02
Physician 21	0.01	-0.02	0.01	-0.02
Physician 22	0.02	0.01	0.02	0.05
Physician 23	0.05	0.04	0.05	-0.01
Physician 24	-0.03	-0.01	-0.03	-0.02
Physician 25	0.06	0.00	0.06	0.05
Physician 26	0.00	-0.01	0.00	-0.02
Physician 27	-0.08	-0.04	-0.08	-0.04
Physician 28	0.04	0.01	0.04	-0.01
Physician 29	0.01	0.04	0.01	-0.02
Physician 30	0.03	0.01	0.03	-0.01