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Increased Speed Equals Increased Wait: The Impact of a Reduction in Emergency Department Ultrasound Order Processing Time

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Working Paper

14-033

October 24, 2013

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Abstract

We exploit an exogenous process change at two emergency departments (EDs) within a health system to test the theory that increasing capacity in a discretionary work setting increases wait times due to additional services being provided to customers as a consequence of reduced marginal costs for a task. We find that an increase in physician's capacity for ordering ultrasounds (U/S) resulted in an 11.5 percentage point increase in the probability of an U/S being ordered, confirming that resource availability induces demand. Furthermore, we find that the additional U/S demand increased the time to return other radiological tests due to the higher demand placed on radiologists from the additional U/S. Consequently, the average length of stay (LOS) for patients with an abdominal complaint increased by nearly 30 minutes, and the waiting time to enter the ED increased by 26 minutes. We do not find any indications of improved performance on clinical metrics, with no statistical change in the number of admissions to the hospital or readmissions to the ED within 72 hours. Our study highlights an important lesson for process improvement in interdependent service settings: increasing process capacity at one step in the process can increase demand at that step, as well as for a subsequent shared service, and both can result in an overall negative impact on performance.

1. Introduction

Healthcare costs in the U.S. have skyrocketed since the 1980's. By 2010, healthcare expenditures accounted for 18% of the U.S. gross domestic product (Berwick and Hackbarth 2012). These high costs hinder industry competitiveness and drain financial resources away from other areas, such as education and transportation (Hussey, Eibner et al. 2009; Berwick and Hackbarth 2012; Fuchs 2012). One of the largest opportunities for reducing healthcare costs is eliminating the use of medications, tests, and treatments that do not improve patients' health (Gawande 2009; Hussey, Eibner et al. 2009; Berwick and Hackbarth 2012). Therefore, understanding factors that influence physicians' decision making can provide important levers for controlling costs. To date, misaligned financial incentives have been the primary explanation for why physicians order low-efficacy treatments. Physicians have discretion over the medical interventions prescribed for patients, which can result in overuse if they can increase their revenue by ordering more treatments (Levin and Rao 2008; Gawande 2009; Hussey, Eibner et al. 2009). However, many physician groups, such as the one in our study, are not paid for each service provided and therefore have no financial incentives to order additional tests, and yet low-efficacy treatments still occur in those settings. This suggests that other factors influence the use of these treatments.

Theory in the behavioral operations management literature provides an alternate explanation for why physicians order low-efficacy treatments: in a customer service environment where employees have high levels of discretionary task completion (DTC), service providers fill their time with work (Parkinson 1958; Debo, Toktay et al. 2008; Hasija, Pinker et al. 2010), and respond to increased capacity by *increasing* the number of services provided to their customers due to a reduction in the service's marginal cost (Hopp, Iravani et al. 2007). Applied to a hospital environment, this theory predicts that if there is a process change that makes it quicker for physicians to order a medical test—which is equivalent to increasing the physician's effective capacity for ordering a test—physicians will respond by ordering the test for more patients. The dynamic exists even in the absence of direct financial incentives because providing more services to their patients is perceived as providing higher quality service. Thus, operations management theory suggests that process improvements that reduce the time required for physicians to order a test can result in higher use of tests, even those that are low-efficacy.

We build off of this theoretical work by exploiting an exogenous process change that occurred at one of two emergency departments (EDs) within the same health system and staffed by the same physician group. The ordering process for an ultrasound (U/S), a diagnostic test, was changed for the night and weekend shifts at one of the EDs so that it was less time-consuming for a physician to order an U/S than it had been previously. Therefore, in terms of the theory, because the change reduced the time it took a physician to order an U/S, it effectively increased physicians' capacity for ordering U/S. Over a three-year period, we studied ED patients with abdominal pain, a common symptom for which an U/S is one of several diagnostic options available to ED physicians. We find that the process change reduced the LOS of an ED patient who received an U/S by 21%, or approximately 1 hour. However, the change was also associated with a 70% higher probability of receiving an U/S. The net result was an increase in ED LOS across all patients. This was due to two effects: First an U/S is a lengthy study (patients who received an U/S had a LOS that was 30% higher than patients who did not). Second, even patients who did not receive an U/S had an increase in the time for other radiographic studies to be interpreted. As a result, the overall ED LOS for all abdominal pain patients increased. The longer LOS was associated with longer ED wait times to see a provider. Thus, it appears that the overall negative impact on patient flow eroded the benefit of shortening the ordering time. In addition, we found no evidence that the increase in U/S improved two standard measures of ED quality of care: admission rate to the hospital and readmission rate to the ED within three days. The only clinical change was a small (approximately 0.25 per patient) reduction in the number of laboratory tests ordered for patients after the processing change. Therefore, the reduction in U/S ordering time resulted in a decline in the overall system performance, with a lower throughput rate, but no observed improvement in clinical quality.

Our work makes three contributions to the behavioral operations literature. First, we empirically validate that reducing the time it took physicians to order an U/S resulted in a higher probability of a patient receiving an U/S than in the past. This is consistent with Hopp, Iravani and Yuen's (2007) theory that when employees have discretion, reducing the marginal cost of providing a service will result in them giving that service to more customers. Our empirical validation of supply-induced demand highlights the importance of accounting for an increase in demand for a service, which is often thought of as exogenous, when increasing effective capacity of workers in DTC settings. Second, our study extends research on DTC settings to include the effects of changes in workers' capacity in a setting where resources are shared. We find that when increased use of the faster process placed additional demand on a shared resource (radiology), this slowed the care for other patients who used the same shared resource. These results suggest that a process improvement can inadvertently cause an increase in demand for a service as well as associated shared resources, which results in congestion, counter intuitively decreasing overall system performance. Our study thus highlights an important lesson for process improvement: reducing the cycle time of one step in a process can end up overloading a bottleneck resource (in our setting, radiology). Third, we examine the effects of changes in worker capacity on the system when incentives of individuals may not be aligned with the organization's goals. We show that while individual patients and physicians may benefit from the reduced processing time, there can be unintended consequences for overall system performance. These results illustrate how time-saving modifications to hospital processes—if they contribute to increased use—can paradoxically reduce productivity and contribute to rising costs.

2. Literature on the Impact of Worker Discretion on Operational Performance

There is a growing amount of research analytically and empirically modeling the effects of human behaviors on quality and productivity. This body of work addressed the call for research to expand our understanding of how workers behave, and how these behaviors affect the processes in which they work, particularly in service settings where workers have high levels of discretion over their tasks (Parkinson 1958; Boudreau, Hopp et al. 2003; Gino and Pisano 2007). Prior studies have shown that processes are affected by workers' behavior, suggesting that behavioral effects must be accounted for when designing service processes.

Much of the analytical research in service settings has centered on the trade-off between service quality and processing time. This body of work is directly related to our study of physician ordering behaviors as physicians balance the care of multiple concomitant patients. When a service worker performs more tasks for his or her customer, it results in a higher quality experience for that customer (Hopp, Iravani et al. 2007; Anand, Paç et al. 2011). However, this higher level of service takes more time, which means that incoming customers will wait longer for service, decreasing the quality of their experiences. Thus, service quality can be increased, but at the expense of a longer processing time (Anand, Paç et al. 2011). Analytical models have shown that to optimize performance, the service time should remain the same or decrease for each customer as the number of customers in a system rise (Stidham and Weber 1989; George and Harrison 2001). This recommendation to reduce service time maximizes the utility for all customers. However, if given the choice, each individual customer would prefer a longer service time for himself, highlighting the tension that service workers face between maximizing the satisfaction for their immediate customer versus maximizing the average satisfaction of all customers (Ha 1998). In our research setting, this work is analogous to ED physicians trying to balance providing comprehensive services (i.e. diagnostic tests, procedures, symptom relief) that patients want while also being able to quickly get to the patients who are waiting to be seen.

Empirically, studies have validated the trade-off between service quality and speed. For example, Oliva and Sterman (2001) found that when congestion increased, back-office bank workers “cut corners” by spending less time processing loan applications, which resulted in lower quality evaluations and fewer approved loans, and consequently reduced the company’s revenue. Other studies have shown that “speeding up” behavior is influenced by the visibility of the congestion (Schultz, Juran et al. 1998; Schultz, Juran et al. 1999; Song 2013), highlighting the sensitivity of human behavior to the state of the operating system. Much of the empirical work has looked at healthcare settings, perhaps because of the high levels of worker discretion and variability in treatment options (Eddy 1984). KC and Terwiesch showed that under periods of high patient load, employees worked faster (2009) and/or discharged patients earlier in order to free up bed capacity (2012). Discharging patients early is a form of reduced service quality as it has been shown to lead to readmission and rework (KC and Terwiesch 2012). Even if a patient is not discharged early, quality of care is negatively impacted by load: fewer tests are ordered (Batt, Terwiesch et al. 2012); patients have longer LOS (Berry Jaeker and Tucker 2013); and worse clinical outcomes (Kim, Chan et al. 2012; Kuntz, Mennicken et al. 2013).

Understanding the impact of workload on employees’ behaviors enables operations managers to allocate resources so they can better meet customers’ needs. For example, for hospitals, information about the impact of workload on performance can be used to determine the desired occupancy levels, bed allocation decisions and staffing levels (Chan, Farias et al. 2012). More generally, Hopp, Iravani and Yuen (2007) examined the effect of an increase in the effective capacity of customer service providers with high levels of task discretion on waiting times. An increase in capacity could stem from process improvements such as increased training, new equipment that reduces processing time, or increased staffing. They found that increasing service capacity lowers the marginal cost to employees of providing the service, which in turn motivates workers to provide these services to their customers. Receiving more services during their transactions increases customers' average processing times, which increases waiting times for customers queuing for service. More simply, lowering average processing times can paradoxically increase congestion in the system (Hopp, Iravani et al. 2007). Further research has taken a more prescriptive approach and examined the impact of customer demand on the number of workers that should be hired and how their behavior should change in response to changes in customer demand. For example, Armony and Gurvich (2010) developed a model of call centers that provides a recommendation of when to upsell customers versus when to provide the minimum service level. In healthcare, there are models to predict the number of hospital beds needed to meet targeted service levels and waiting times (Green and Nguyen 2001), as well as research which highlights the negative consequences of delays in care (Chalfin, Trzeciak et al. 2007) when service levels are not met. Collectively, these studies highlight the relationship between capacity and demand in a hospital and employees' behavioral response to any mismatches, as well as how this information can be used to allocate resources effectively. The studies suggest that employees will respond to available capacity by providing additional services, a theory which provides an alternate explanation for the use of low efficacy tests in healthcare: physicians might use the additional tests or treatments to improve their patients' perception of their quality of service. Our paper empirically tests these theories, as well as how changes in resource use affects shared resources in a hospital system.

3. Study Setting

We exploit an exogenous process change that impacted only one of two partner EDs, a setting where employees have a high level of discretion over the level of service they provide to patients. The process change in the ordering of U/S by ED physicians at one, but not the other ED enables us to test the impact of a reduction in processing time in the use of a resource. Specifically, we use patient-level data from the EDs of two east coast academic hospitals, which we refer to as Flagship Hospital (Flagship) and Community Hospital (Community). Flagship is the largest hospital in the state and a Level 1 Trauma Center, and Community is a community hospital located five miles away. Both EDs are part of the same healthcare system staffed by the same physician practice group, and have a large patient load, with Flagship and Community having more than 100,000 and 60,000 emergency visits per year, respectively. The physician practice group is independent and is not employed by either hospital.

Over the course of our study period (September 30, 2009 – May 31, 2012), there were 83 attending physicians (also referred to as attendings) in the physician group, with 50 attendings practicing at both hospitals. Ultimate responsibility for all testing and treatment decisions was held by the attending physicians. In some instances, resident physicians (who are physicians undergoing additional post-graduate training) or physician assistants made assessments of the patients and suggested possible treatments to the attending physician.

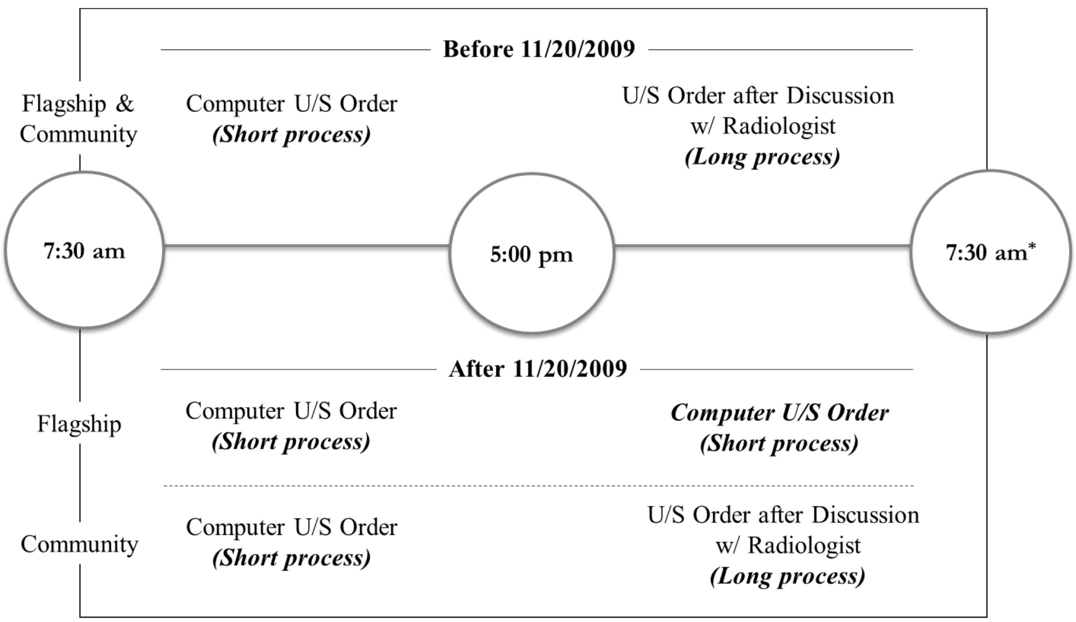
We focused our study on patients presenting to the ED with abdominal pain. We do so for several reasons. First, it is the most common chief complaint for patients who come to the ED (Pitts, Niska et al. 2008). Common diagnoses of abdominal pain include ulcers of the stomach, esophagus or small intestine; appendicitis; disorders of the gallbladder; kidney stones; inflammation of the colon; stomach or intestinal infection and constipation (Bengiamin, Budhram et al. 2009). There are also rarer but life-threatening conditions that the ED physician must rule-out, such as a ruptured aneurysm of the abdominal aorta, an intestinal obstruction, a perforated stomach ulcer, inflammation of the pancreas and occlusion of the intestinal blood vessels (Bengiamin, Budhram et al. 2009).

U/S is one of many diagnostic modalities available to the ED physician for patients with abdominal pain, thus supporting that this is a high discretion setting and the availability of a specific test might affect the demand for the test. Specifically, in addition to U/S, other common diagnostic modalities available to the ED physician include laboratory testing, and other types of imaging such as Computed Tomography (CT), or X-rays. Unlike U/S, these other tests are consistently available to the ED physician in our study group at all hours and on weekends and can be directly ordered via the electronic medical record (EMR) system.

Our interest is in how removing barriers for U/S ordering affects use. We exploit a process change that occurred at Flagship and Community: the process used by ED physicians to order an U/S was changed at Flagship and not Community. For an U/S to be completed, a radiology technician must first perform the scan, after which, the radiologist reviews the scan and interprets it. Before the process change, ED physicians who ordered an U/S at night or on the weekends at both hospitals had to discuss the particular case with the radiologist and request authorization for the study. If the radiologist approved it, then the U/S technician was called in to the hospital to perform it. In contrast, during the day, there was an U/S technician on duty in the hospital and U/S were ordered directly by the ED physician through the computerized ordering system, and no prior authorization was required.

In August 2009—which is before the September start date of our dataset—Flagship (but not Community) changed to 24/7 technician coverage so that an in-house technician would be available at night. The change was in part a response to staffing challenges that arose from having the technicians cover the overnight shift on an on-call basis: hospital and regulatory requirements restricted technicians from working the next day if they were called in at night. On November 20, 2009, Flagship switched their U/S order process so that ED doctors could place a direct order for an U/S on weekends and in the evening hours from 5:00 pm-7:30 am using the same computerized ordering system that they used during the day (See Figure 1). Prior to this change, physicians at Flagship had to complete a manual paper order for the U/S study after it was authorized by the radiologist. The net effect was that the total time required for a physician to order an U/S at Flagship decreased from 10-15 minutes to less than one minute. At Community, however, there was no change in the U/S order process. For our purposes, the reduced time to order an U/S on nights and weekends at Flagship is equivalent to increasing the physicians' capacity to order U/S because it decreased the time it took them to place an order.

Figure 1. **Timeline of Changes in U/S Ordering Process at Flagship and Community: Change in Ordering Process November 20, 2009**



**Weekends follow same procedure as night shift*

4. Hypotheses

The primary driver of whether or not the physician orders an U/S is the physician's clinical concern for a particular subset of emergent diagnoses. However, the clinical guidelines about U/S and diagnostic test usage are not clear cut, thus resulting in significant inter-physician variability in the number of tests that they order (Stiell, Wells et al. 1997). In addition, operations management research suggests that additional variability may be introduced by non-medical factors. For example, previous research has shown that physicians' medical decisions can be influenced by their environment, such as how many patients are in the hospital unit (Batt, Terwiesch et al. 2012; KC and Terwiesch 2012; Kuntz, Mennicken et al. 2013).

In this paper, we consider another state-specific factor that may influence the ordering of U/S: how long it takes for a physician to place the order. There is a speed-quality tradeoff when performing tasks in service settings: spending more time performing a task for a customer increases the quality of work for that customer, but delays other customers, thus reducing their quality of service (Stidham and Weber 1989; George and Harrison 2001; Anand, Paç et al. 2011). This speed-quality tradeoff changes based on the state of the system, and workers adapt their behavior accordingly. Specifically, Hopp, Iravani and Yuen (2007) theorize that in DTC settings, quality can serve as a buffer for workload variability. When employees have a light workload, they are able to spend more time with their customers, which results in a higher quality of service. Conversely, if workers have a high workload, they may be forced to spend less time with each customer, which decreases quality, but enables more customers to be served. Moreover, if the time to complete a task is reduced, then the optimal speed-quality combination shifts since it requires less time to provide the same level of quality, and consequently, more services will be provided (Hopp, Iravani et al. 2007). In the hospital, because ED physicians provide care to multiple patients simultaneously, they face the tradeoff that spending more time on one patient's care means less time is available for other patients. Thus, if a process improvement makes a task quicker to perform the physician can achieve higher quality performance for one patient for a smaller cost to his or her other patients.

Flagship's U/S process change removed a step in the process, which reduced the time it took physicians to order an U/S, increasing the theoretical maximum number of U/S that ED physicians could order during their shift (Cachon and Terwiesch 2004). Hopp, Iravani and Yuen (2007) state that increasing capacity will encourage workers to increase the quality of service by providing additional services to customers. A different way of framing this is that the process change reduced physicians' marginal cost of ordering an U/S, thereby increasing the likelihood that physicians would choose to order U/S for more of their patients. Performing additional tests has been shown to improve a physician's confidence in her diagnosis, a desirable outcome for physicians (Abramson, Walders et al. 2000). An additional motivation for physicians to order imaging more generally is that patients are more satisfied with their experience when more diagnostic tests are performed (Sun, Adams et al. 2000). Therefore, given the reduced marginal cost of ordering an U/S, and the benefits to the physician and patient for having one performed, we expect that after the change in the U/S ordering process, there is a higher probability of an U/S being ordered, all else being equal.

HYPOTHESIS 1: *The probability a patient will receive an U/S after the change in U/S ordering procedures will be greater than for an equivalent patient before the change in the ordering process.*

Although the change in the U/S ordering process reduces the amount of time to order each U/S, patients could end up staying in the ED longer after the process change than before if the reduced marginal cost causes the physician to order an U/S that he or she otherwise would not have ordered under the old process. In general, an U/S study takes between 15-30 minutes to perform depending on the specific study ordered. In addition, there may be queuing and transport time before the study, adding to the study time. Once completed, the radiologist has to review the study and provide an interpretation for the ED physician, which takes additional time. Therefore, patients who receive an U/S have a longer ED stay than patients who do not have an U/S, all else being equal. The longer stay due to the additional U/S contributes to congestion in the ED, consistent with Hopp, Iravani and Yuen's (2007) prediction that adding capacity will result in increased congestion because servers will respond to the additional capacity by providing more services to their customers, thus increasing service time. Moreover, the increase in U/S places a higher workload on radiologists. Radiologists read U/S, x-rays, and CT scans, thus their services are shared across a wide range of ED patients. Our research setting is therefore slightly different from the setting in Hopp, Iravani and Yuen (2007), which assumes only one customer type in their model, and does not address the impact of increased service provisions on shared resources. Other research has shown that when services are shared, additional demand of one type can create congestion for all types of customers, or in this case, patients sharing that service (Chao, Zhanfeng et al. 2001; Berry Jaeker and Tucker 2013). Consequently, in our study, we expect that the increase in the number of U/S will delay radiological test results for all patients. We predict that the average LOS for ED patients will be longer after the change due to the cumulative effect of the additional time required to perform the increased number of U/S, and the increased probability of queuing for radiology services.

HYPOTHESIS 2: *The average LOS of an ED patient after the change in U/S ordering procedures will be greater than for an equivalent patient before the change in the ordering process.*

The underlying objective of process improvement changes, such as the elimination of a step in the U/S ordering process in our study, is to improve service by reducing delays in care. This could also reduce the need to expand the ED to accommodate increasing demand. In the ED, if all the beds are full, arriving patients must wait in the waiting room, delaying the start of their care, which may significantly worsen outcomes (Pines and Hollander 2008). Therefore, an important measure of a process improvement is a change in the waiting time for service. If the ED is capacity constrained, a longer average LOS for patients will increase the waiting time for patients entering the ED. The increased congestion due to waiting patients is equivalent to the increased congestion described in Hopp, Iravani and Yuen's (2007) model. The congestion occurs despite reduced service time for the service of interest because customers' *total* service times become longer. Most EDs are facing increased demand for their services (Kellermann 2006), making it likely that the EDs in our study will be capacity constrained and therefore will experience an increase in waiting time. Thus, in our study, we would expect that because the LOS of ED patients increases after the change in U/S ordering procedure, this will result in a higher probability of waiting, and an increase average waiting time for patients to the ED.

HYPOTHESIS 3: *The waiting time of an ED patient after the change in U/S ordering procedures will be greater than for an equivalent patient before the change in the ordering process.*

One of the conclusions of Hopp, Iravani and Yuen (2007) is that while the reduced processing time for a task results in more workers deciding to provide that extra service to their customers, which then leads to congestion, this process change may nevertheless be optimal because the financial benefits that the company reaps from the increased quality outweigh the costs of the additional waiting time. Our study differs from Hopp, Iravani and Yuen because the EDs treat multiple patient types and therefore, to evaluate the net effect of reducing the U/S order processing time, we must account for its impact on all ED patients, not just at the individual patient type level. For example, any benefit for the patients who receive an U/S must be compared to the costs incurred by those patients who do not. Given this, we calculate the magnitude of the benefits for the patients who were at risk of an U/S after the processing time changes. Two ED clinical quality measures are admission rate to the hospital and the percentage of ED patients who are readmitted to the ED within 72 hours.

First, we predict that increasing U/S capacity will decrease admissions to the hospital. Additional U/S capacity will enable physicians to order U/S for patients they previously would not have, providing more information for the physician to be confident in her decision that the patient does not have a serious condition and can be safely discharged to home from the ED. Without easy access to an U/S, the physician might err on the side of admitting the patient to the hospital for further observation and testing.

HYPOTHESIS 4A: *The probability of admission for an ED patient who after the change in U/S ordering procedures will be smaller than for an equivalent patient before the change in the ordering process.*

Using the same underlying logic, we expect a decrease in the readmission rate. Because we anticipate that having an U/S results in a more accurate diagnosis, the patients should receive the necessary treatment to address the medical condition. Similarly, we also expect a smaller chance of a serious condition being "missed." These two results should reduce the probability that patients who have U/S will return to the ED within three days.

HYPOTHESIS 4B: *The probability of readmission to the ED within 72 hours for an ED patient after the change in U/S ordering procedures will be less than for an equivalent patient before the change in the ordering process.*

5. Data and Econometric Specification

5.1. Data

Our data consists of patient level records for all adult ED patient visits at Flagship Hospital and Community Hospital, with a chief complaint of abdominal pain between September 30, 2009 and May 31, 2012. The beginning date of our data set is after Flagship began staffing a radiology technician in the hospital 24 hours a day, seven days a week, but before the change in the ordering process. Since our sample is restricted to abdominal pain patients, each patient has the potential to receive an U/S. For each visit, we have the patient's medical record number (MRN), demographic information (e.g. age, gender, race, insurance), emergency severity index (ESI, a measure of the patient's severity and urgency), treating physician, time of arrival, and length of service. In addition, each record has time stamped medical and procedure orders, such as medication, laboratory, and radiology orders, as well as the reason for a patient's visit (known as the primary complaint), the final diagnosis, and the disposition (e.g. admission, discharge, transfer). We also have the total number of patients seen in each ED each day. In total, we have 17,773 unique patients with 25,149 patient visits in our study period. **Table 1** provides descriptive statistics of the patients in our sample.

Since we are interested in a change in policy at one hospital that did not occur at the other, we use a difference-in-differences methodology to study the effects of the change (Angrist and Pischke 2009). The benefit of this type of model is that it controls for any unobservable trends at the hospitals. However, it also requires that the "parallel trends" assumption is met (Angrist and Pischke 2009). Specifically, other than the change of interest, both sites should have the same trend in the outcome variable over time and with no other changes during the time of the study in one, but not the other location. Therefore, we restrict our sample to only those patients who saw a physician who practices at both hospitals, thus eliminating differences between the two locations due to differences in physician behavior. We also confirmed that there was no change in patient characteristics between the two EDs over time. To do this, we ran a set of t-tests, Wilcoxon-Mann-Whitney, Chi-square, and Fisher's exact tests to compare the age, gender, ESI, and race of patients at each hospital across time (see **Appendix 1**). None of the tests were significant at the 0.05 level. Thus, we find no evidence that either hospital had a statistical change in patient types after the processing change, thus supporting that the parallel trends assumption is valid in our study.

Table 1: Summary Statistics

Hospital	Flagship		Community	
Abdominal Patient Visits				
*Before Change**	429		355	
After Change	9404		6950	
Beds	99**		42	
Average daily U/S performed:				
Weekday				
Before Change	1.098	(1.043)	0.761	(0.929)
After Change	1.485	(1.270)	0.834	(0.886)
Night/Weekend				
Before Change	0.429	(0.587)	0.344	(0.538)
After Change	1.603	(1.385)	0.468	(0.702)
Primary Insurance (% of Total)				
Private	50.5%		62.3%	
Medicare	11.0%		11.5%	
Medicaid	21.0%		15.2%	
Free care/Uninsured	14.8%		10.0%	
Other	2.7%		1.0%	
Race (% of total)				
White	71.8%		60.2%	
Black	15.0%		17.5%	
Other	13.2%		22.3%	
Severity Score (% of total)				
ESI 2	21.0%		4.4%	
ESI 3	72.0%		92.4%	
Other	7.0%		3.2%	
Average LOS in ED (Service time, in minutes)	267.9	(120.8)	253.2	(114.6)
Average Wait time to enter ED (in minutes)	90.2	(93.6)	30.2	(46.5)
Average ED Occupancy	83.1%	(7.64)	79.2%	(8.87)
% Admitted to hospital	23.2%		25.3%	
% Readmitted				
Within 72 hours	2.26%		2.53%	
Within 7 days	4.12%		4.46%	
% of cases Resident present	79.2%		12.3%	

*Before Change = September 20, 2009-November 20, 2009; After Change = November 21, 2009-May 31, 2012; **Includes 20 psychiatric beds; Std. deviations in parentheses

5.2. Main Model for Hypothesis 1

Hypothesis 1 predicts that Flagship night and weekend patients will have a higher probability of having an U/S after the process change than before. To test this hypothesis, we model the probability of U/S as follows:

$$\Pr\left(U/S_{i,h}\right) = \beta_0 + \beta_1 Controls_i + \beta_2 PrimComplaint_i + \beta_3 Flagship_i + \beta_4 NightWeekend_i + \beta_5 PostNW_i + \beta_6 Flagship_i * PostNW_i + \varepsilon_{i,h} \quad (1)$$

$Pr(U/S_{i,h})$ is the probability of an U/S for patient *i* at hospital *h*. Since our variable of interest is binary, we use robust logistic regression, with standard errors clustered by physician (in all models), to predict the probability that a patient will receive an U/S. We employ a difference-in-differences methodology, taking advantage of the process change that occurred at Flagship. To do this, we control for the underlying differences between Flagship and Community with a binary variable $Flagship_i$, which is equal to one if the patient is treated at Flagship. In addition, we control for any trend that occurs at both hospitals after the processing change. However, the U/S ordering change only directly affected some patients, specifically those who arrived on the weekend or at night, therefore we control for the fact that these patients are predicted to have a different effect from the weekday patients. To account for these patients, we introduce $PostNW_i$, which is a binary variable equal to one if patient *i* is treated at night or on the weekend after the change in U/S policy. We define night as arrival between 5pm and 5am because this corresponded to the times during which physician had to get radiologist approval before the change in the U/S ordering policy. It should be noted that the actual night hours went until 7:30 am, but we truncate the night definition as a patient who arrives closer to 7:30 am has a high probability of overlapping with the daytime hours. $Flagship*PostNW_i$ is a binary variable equal to one if patient *i* arrives to Flagship at night or on the weekend after the U/S policy change. We are interested in β_6, the coefficient on $Flagship*PostNW_i$, as this represents the additional probability of ordering an U/S for patients who were affected by the U/S policy change.

We control for several observable variables, while underlying patient physiological differences are captured in our error term. $Controls_i$ is a vector of control variables that includes age, age squared, primary and secondary insurance, race, gender, arrival at night or on the weekend, the quarter of the year (for seasonal effects), and year (for trend). Given the high autonomy of physicians, as well as their highly variable training styles and personal skills, there can be large variation in practicing styles, particularly in the use of tests and medications (Stiell, Wells et al. 1997). Therefore, in addition to the primary complaint and demographics of a patient, we control for the attending physician. We also control for the presence of a resident or mid-level provider as they are present on some, but not all, cases and may influence decision making.

We also control for the daily census of hospital *h*'s ED in which patient *i* was treated. Previous work has shown that inpatient occupancy can affect the LOS of a patient and the use of resources (KC and Terwiesch 2012; Kuntz, Mennicken et al. 2013). To account for similar relationships between occupancy and resource use in the ED, we control for ED census. Since our EDs are different sizes, we convert the daily census into an occupancy percentage (between 0 and 100%) so that we can compare across our two study sites. ED capacity is not defined by the number of rooms because most EDs (including Flagship and Community), use hallway beds and boarding areas to provide flexibility in ED bed capacity. Therefore, following Kuntz, Mennicken and Scholtes (2013), we create an occupancy based on the census of each day divided by the maximum daily census, where the maximum daily census is the 99th percentile of daily censuses.

Finally, $PrimComplaint_i$, is a vector of symptom variables, described in more detail in the section below, where each symptom is binary with one meaning patient *i*'s primary complaint includes that symptom and zero meaning it does not. This vector controls for the impact of the patient's underlying medical condition on the probability of receiving an U/S.

5.3. Complaints and Symptoms Associated with U/S

Some patients with abdominal pain are more likely to receive an U/S than others. Specifically, the likelihood of an U/S is dependent on the clinician's level of suspicion that the patient has a condition for which an U/S is considered diagnostic, which is dependent on the patient's symptoms, gender, age, and other characteristics. As an example, U/S is a first-line choice for disorders of the gallbladder, however it is not considered as useful for disorders of the colon. However, due to limitations of the EMR, we do not have access to the particular disorders or conditions that the physician was considering when ordering specific tests or studies. Instead, we only have the patient's stated complaints, which are typically symptom-based rather than diagnosis-based. For certain complaints, such as "Right-upper quadrant abdominal pain," we might expect a higher likelihood of an U/S since right-upper quadrant abdominal pain is a symptom that is often associated with a disorder of the gallbladder.

To account for primary complaint in predicting U/S usage, we constructed an index, $PrimComplaint_i$, of patients' symptoms/complaints. We first compiled a list of conditions where U/S is considered a useful diagnostic modality, based on the American College of Emergency Physician's (ACEP) policy statement (American College of Emergency Physicians 2008) (see **Appendix 2**). Next, we used the MedlinePlus database, an online medical encyclopedia produced by the U.S. National Library of Medicine and the National Institutes of Health (2013) to provide a list of symptoms or symptom categories associated with the U/S sensitive diagnoses identified in step one (see **Appendix 3**). This approach resulted in 59 symptom categories (e.g., nausea, vomiting, and flank pain). In addition to typical symptoms, such as abdominal pain or a cough, a patient's primary complaint could also include any recent surgeries or history of past medical illnesses that may be relevant to the use of U/S. For example, if a patient complains of flank pain and they had previous kidney stones, they would be more likely to receive an U/S than a patient complaining of general abdominal pain. As another example, the primary complaint could contain a note about a suspected disease, such as appendicitis, that either a referring doctor or the triage nurse believes to be the cause of the symptoms. These examples indicate that for some of the patients there was additional patient information, which although not a physical symptom, was related to the conditions in the ACEP guidelines for which an U/S would be appropriate. Therefore, we incorporate this information by adding 12 additional "symptom" categories to the list of conditions where U/S is a useful diagnostic modality that account for any history or previous medical judgment related to the conditions in the ACEP guidelines. Finally, there are some symptoms or complaints, such as alcohol abuse, which are not described in the ACEP guidelines, but could change the likelihood of an U/S being performed. These conditions add an additional nine categories. All 80 symptom categories used are shown in **Appendix 3**. Each of our symptom 80 categories is a binary variable equal to one if the patient's primary complaint (which can include multiple symptoms) includes that symptom and zero otherwise. For example, a patient's primary complaint could be three symptoms: nausea, vomiting, and abdominal pain, which would be coded as one for each of those symptoms, and zero for the other 77. One can consider these symptom categories as analogous to comorbidity categorizations, such as Elixhauser's comorbidity measures (Elixhauser, Steiner et al. 1998), to predict LOS and the probability of mortality within the hospital. In our sample, there were 5,509 unique primary complaints, with 1.54 U/S-related symptoms per patient on average, for a total of 38,722 symptom complaints. The first author categorized the symptoms associated with each of the 5,509 unique primary complaints into the 80 symptom categories described above. In our study, we used these variables to predict, in addition to patient demographics, the propensity for an U/S to be used.

There were numerous free-texted complaints that did not exactly match one of the clinical symptoms, but were nevertheless similar to one. To ensure that our results were not impacted by our interpretation of the free text symptoms, we went through the 38,722 symptoms and separated them into two categories: those that clearly fell into a symptom category and those that required interpretation. Almost all (99.8%) of the symptom complaints fell cleanly into one of the 80 symptom categories. The remaining 0.2% of symptoms was less clear, so we used the context to make our final categorization. For example, a primary complaint of "Constipation – cramping" does not explicitly say abdominal cramping, but given the context, we coded that symptom as abdominal cramping. The first author and a research assistant both coded the 77 symptoms that were less clear and achieved a 0.66 ($p<0.01$) kappa value, which indicates a substantial inter rater reliability (Landis and Koch 1977).

5.4. Models for Hypotheses 2, 3 and 4

To test Hypothesis 2, we analyze whether the change in the U/S ordering process increased the LOS for evening and weekend Flagship Hospital ED patients. We measure LOS as the time from the start of care to the time care is completed (in minutes). In our regression, we use the log LOS, since LOS is exponentially distributed. We perform a robust OLS regression using the following model to test whether the process change impacted LOS.

$$\begin{aligned}\mathrm{Ln(LOS)} = {} & \beta_0 + \beta_1 Controls_i + \beta_2 PrimComplaint_i + \beta_3 Flagship_i + \beta_4 NightWeekend_i \\ & + \beta_5 PostNW_i + \beta_6 Flagship_i * PostNW_i + \beta_7 U/S_i + \beta_8 U/S * NW_i + \beta_9 U/S \\ & * PostNW_i + \beta_{10} U/S * Flagship * PostNW_i + \varepsilon_{i,h}\end{aligned} \tag{2}$$

If Hypothesis 2 is supported, $\beta_6$will be positive and significant. In addition, since an U/S is likely to increase the LOSs for those patients who have one, we include a dummy variable that is one if the patient had an U/S. We also include variables for whether the U/S was performed on a night or weekend, before or after the change in process, and whether it was performed at Flagship.

As a result of the hypothesized increase in U/S use and service time in the ED, we predicted that ED patients' waiting time would be greater at Flagship after the process change (Hypothesis 3). We defined waiting time as the time between arrival/check-in and time brought to a bed. In our dataset, there are a significant number of patients with zero wait. Therefore, we use a count model, and since the variance is much greater than the mean, we use a negative binomial regression model. When a patient is waiting, he cannot have an U/S that would affect his waiting time, so we do not need to include that in our model, which leaves us with

$$\begin{aligned}Wait\ Time_{i,h} = {} & \beta_0 + \beta_1 Controls_i + \beta_2 PrimComplaint_i + \beta_3 Flagship_i + \beta_4 NightWeekend_i \\ & + \beta_5 PostNW_i + \beta_6 Flagship_i * PostNW_i + \varepsilon_{i,h}\end{aligned} \tag{3}$$

If Hypothesis 3 is supported, β_6 will be positive and significant.

We predicted that Flagship ED patients who receive an U/S after the process change will be less likely to be admitted to the hospital (Hypothesis 4a) and less likely to be readmitted to the ED within three days (Hypothesis 4b). More specifically, we have:

$$\begin{aligned}\Pr\left(Event_{j,i,h}\right) = {} & \beta_0 + \beta_1 Controls_i + \beta_2 PrimComplaint_i + \beta_3 Flagship_i + \beta_4 NightWeekend_i \\ & + \beta_5 PostNW_i + \beta_6 Flagship_i * PostNW_i + \varepsilon_{i,h}\end{aligned} \tag{4}$$

where $Event_{j,i,h}$ is event j occurring to patient i in hospital h, where j is admission to the hospital or readmission to the ED within three days. For the models described in Eq. 5, we again use a logistic regression model. The outcome variable is one if a CT (or admission or readmission) was performed, and zero otherwise. If H4a is supported, then β_6 will be negative and significant, and it will also be negative and significant if H4b is supported.

5.5. Additional Analyses

We conduct additional analyses to deepen our understanding of the impact of the ordering policy change, as well as to run robustness checks. Given that we predict more U/S, we are interested in seeing if the additional load for radiologists affects the time it takes to complete other radiological studies, which can contribute to the change in LOS. To do this, we measure the time between a radiology test being ordered, excluding U/S, and when the results of the test are returned. If the patient had more than one radiological study, we take the maximum time for returning the results. As with our LOS model, we take the log of this value given the exponential distribution of the time to test return. We regress the controls and difference-in-differences variables on this logged time using a robust OLS model, to get the following:

$$\begin{aligned} Ln(RadTestReturnTime_{i,h}) &= \beta_0 + \beta_1 Controls_i + \beta_2 PrimComplaint_i + \beta_3 Flagship_i + \beta_4 NightWeekend_i \\ &+ \beta_5 PostNW_i + \beta_6 Flagship_i * PostNW_i + \varepsilon_{i,h} \end{aligned} \tag{5}$$

If the policy change impacts the time required for radiology to return test results, β_6 will be positive and significant.

To test if reducing the barrier for an U/S changes the use of other resources, we measure the number of laboratory tests ordered and the likelihood of having a CT ordered after the processing change. To measure the number of laboratory tests ordered for a patient, we use a count model, and since the variance is roughly equal to the mean, we use a Poisson regression. We control for whether the patient had an U/S or not as in Eq. (4).

$$\begin{aligned} \text{NumLabTests} &= \beta_0 + \beta_1 Controls_i + \beta_2 PrimComplaint_i + \beta_3 Flagship_i + \beta_4 NightWeekend_i \\ &+ \beta_5 PostNW_i + \beta_6 Flagship_i * PostNW_i + \beta_7 U/S_i + \beta_8 U/S * NW_i + \beta_9 U/S \\ &* PostNW_i + \beta_{10} U/S * Flaghsip * PostNW_i + \varepsilon_{i,h} \end{aligned} \tag{6}$$

If the policy change reduces the number of lab tests, β_6 will be negative and significant. For the CT probability, we use a logit model as follows:

$$\begin{aligned} \Pr(Event_{j,i,h}) &= \beta_0 + \beta_1 Controls_i + \beta_2 PrimComplaint_i + \beta_3 Flagship_i + \beta_4 NightWeekend_i \\ &+ \beta_5 PostNW_i + \beta_6 Flagship_i * PostNW_i + \varepsilon_{i,h} \end{aligned} \tag{7}$$

If the policy reduces CT use, β_6 will be negative and significant.

6. Results

Table 2 shows the results from an OLS regression testing the impact of the process change on the LOS of patients who received an U/S (Eq. 2). We ran this equation first to verify that the process change reduced the time required for patients to receive an U/S. As shown in Model 1, we find that the LOS for Flagship ED patients who received an U/S during the night or weekend after the ordering process change was shorter (β = -0.210, $p<0.01$) than before the change. Since this is an OLS with a log transform of the dependent variable, this is equivalent to a 21.0% decrease in LOS for a patient who receives an U/S on the night/weekend after the change at Flagship, when compared to the same patient receiving an U/S an night/weekend before the change. This change represents a reduction of more than one hour in the LOS in the ED. Therefore, these results suggest that—given that a patient received an U/S before the change—the ordering process change reduced the ED LOS.

Next, we look if this reduction in processing time is associated with an increase in U/S orders at Flagship (Hypothesis 1). In **Table 2**, in Model 2, the base model (not including the difference-in-differences time effects) that predicts the probability of an U/S, we control for patient characteristics and show that there is a significant increase in the number of U/S performed at Flagship (β = 0.659, $p<0.01$), with a patient at Flagship having a 7.9 percentage points higher predicted probability of receiving an U/S than patients at Community. When we refine our analysis to include controls for the change in U/S ordering process (Model 3), the coefficient for Flagship patients on nights and weekends after the change is significant and positive (β=0.965, $p<.01$), providing support for Hypothesis 1. The average marginal effect (AME) indicates that Flagship ED patients on nights and weekends after the ordering process change have an 11.5 higher percentage point probability of having an U/S ordered than patients at Community on nights and weekends after the change. The U/S ordering process change results in an increase in the average predicted probability of a night/weekend patient at Flagship receiving an ultrasound from 9.4% to 20.3%. This result confirms our expectation that when U/S are quicker to order, physicians order more of them.

Hypothesis 2 predicted that the U/S policy change would be associated with an increase in ED LOS (Eq. 2). Model 1 of **Table 2** presents the effect on LOS before and after the change in policy on patients who receive an U/S (as described above), as well as those who do not. Model 1 shows that there was an 11.0% ($p<0.01$) increase in LOS, or around 26 minutes, within the ED for all Flagship abdominal pain patients seen at night or on the weekend after the change in the U/S ordering process, supporting Hypothesis 2. To explain how the average ED LOS increases when the time it takes to receive an U/S at Flagship decreases, we see that in general, receiving an U/S increases ED LOS by 30.3% ($p<0.01$), and an additional 15.9% ($p<0.01$) on the nights and weekends. Since more U/S are ordered after the change, the net effect on LOS is an increase.

Table 2: Impact of process change on probability of U/S

	(1) *OLS Log ED LOS*	(2) *Probability of U/S Logit Base Model*		(3) *Probability of U/S Logit Diff-in-Diffs*	
		Coefficient	AME	Coefficient	AME
Flagship	-0.059**	0.659**	0.079**	0.180*	0.021*
	(0.019)	(0.072)	(0.009)	(0.081)	(0.010)
Night/Weekend	0.049	-0.284**	-0.034**	-0.779**	-0.093**
	(0.036)	(0.057)	(0.007)	(0.200)	(0.024)
Night/Weekend After Change	-0.133**	-	-	-0.141	-0.017
	(0.032)	-	-	(0.221)	(0.026)
Flagship Night/Weekend After Change	0.110**	-	-	0.965**	0.115**
	(0.022)	-	-	(0.107)	(0.013)
U/S ordered	0.303**	-	-	-	-
	(0.013)	-	-	-	-
U/S ordered Night/Weekend	0.159**	-	-	-	-
	(0.051)	-	-	-	-
U/S ordered Night/ Weekend After Change	0.026	-	-	-	-
	(0.052)	-	-	-	-
U/S ordered Flagship Night/ Weekend After Change	-0.210**	-	-	-	-
	(0.030)	-	-	-	-
Constant	5.082**	-0.881*	-	-0.528	-
	(0.055)	(0.413)	-	(0.405)	-
Controls	Yes	Yes	Yes	Yes	Yes
Primary Complaint	Yes	Yes	Yes	Yes	Yes
Number of Obs.	17,118	17,000	17,000	17,000	17,000
R^2	0.16	-	-	-	-
Adjusted R^2	0.15	-	-	-	-
Degrees of Freedom	49	-	-	-	-
Pseudo R^2	-	0.11	-	0.12	-

OLS model of the LOS within the ED, controlling for whether a patient receives an U/S (1). Logistic regression models of the probability of U/S, where the base model (2) is w/o the processing change and the diff-in-diffs model (3) is with it. The logistic regressions include regression coefficients and average marginal effects (AME).

Note: Controls include gender, age, age^2, year, quarter of the year, attending, presence of a resident primary insurance, secondary insurance, ESI severity score and race; Robust standard errors clustered by attending in ( )

$^+p<0.1$; $*p<0.05$; $**p<0.01$

In addition to analyzing the time spent in the ED for treatment, we also modeled the effect of the policy change on the waiting time of patients in the ED (Eq. 3). Waiting time better reflects the impact of the process change on the ED's flow rate independent of whether the patient waiting ends up with an U/S. We present these results in **Table 3**, Model 1. Given that we had to use a negative binomial count model, we cannot easily interpret the effect sizes associated with the coefficients. Therefore, we also present the marginal effects for patients seen at Flagship on the nights and weekends after the change, and find that for these patients, the policy change results in an average predicted increase in waiting time from 52 to 78 minutes ($p<0.01$), in support of Hypothesis 3. To provide more insight into why the change in U/S ordering process increases ED LOS and waiting time, we also analyzed if there was a change in the time to return radiological tests (Eq. 5) given that radiology services are shared among all ED patients. Our results, presented in Model 2 of **Table 3** show that there is a 27.1% ($p<0.01$), or approximately 30 minute increase in the time it takes to return radiology tests (other than U/S) after the change, which is consistent in explaining the increased LOS and waiting times in the Flagship ED.

Table 3: Impact of Process Change on Waiting Times

	(1) *Negative Binomial ED Wait Time*		(2) *OLS Log Rad. Test Return Time*
	Coefficient	AME	Coefficient
Flagship	0.753**	49.241**	0.041
	(0.060)	(4.398)	(0.029)
Night/Weekend	0.235**	15.349**	0.288**
	(0.085)	(5.564)	(0.086)
Night/Weekend After Change	-0.301**	-19.663**	-0.407**
	(0.089)	(5.789)	(0.089)
Flagship Night/Weekend After Change	0.400**	26.172**	0.271**
	(0.073)	(4.700)	(0.035)
Occupancy	0.040**	2.632**	0.003*
	(0.003)	(0.187)	(0.001)
Constant	-0.808*	-	4.687**
	(0.392)	-	(0.125)
Ln Alpha Constant	0.406**	-	-
	(0.020)	-	-
Controls	Yes	Yes	Yes
Primary Complaint	Yes	Yes	Yes
Number of Obs.	17,121	17,121	6,859
R^2	-	-	0.09
Adjusted R^2	-	-	0.06
Degrees of Freedom	-	-	49

Negative binomial regression of wait time to enter ED (3). OLS regression predicting time to return radiology tests (4)
Robust standard errors clustered by attending in ( )
$^{+}p<0.1$; $^{*}p<0.05$; $^{**}p<0.01$

Next, we analyzed if the U/S policy change was associated with a change in clinical quality measures, as measured by admission to the hospital and readmission to the ED within 72-hours (we also include within 7 days for robustness) (Eq. 4), and we present the results in **Table 4**, Models 1-3. We do not find any statistical support for an improvement in clinical quality measures, as measured by a change in admission rate or readmission to the ED, and thus we cannot reject the nulls for Hypotheses 4a and 4b.

Finally, to understand any other consequences as a result of the change in ordering process, we tested if there was a change in the number of laboratory tests performed (Eq. 6, **Table 5**, Model 1) or the probability of receiving a CT (Eq. 4, **Table 5**, Model 2). We find that the predicted number of medical laboratory tests for night/weekend patients at Flagship drops from 7.86 to 7.60 ($p<0.01$). However, we find that the average marginal effect of the ordering process change is to increase the probability of a CT scan by 4.5% ($p<0.01$) with the predicted probability increasing from 50.1% to 54.6%. We discuss the implications of these results in the next section.

Table 4: Impact of Process Change on Clinical Quality Measures

	(1) *Logit Admission*		(2) *Logit Readmit - 72 hours*		(3) *Logit Readmit - 7 days*	
	Coefficient	AME	Coefficient	AME	Coefficient	AME
Flagship	-0.387**	-0.056**	-0.208	-0.005	-0.273+	-0.011+
	(0.075)	(0.011)	(0.207)	(0.005)	(0.144)	(0.006)
Night/Weekend	0.158	0.023	-0.781+	-0.019+	-0.731+	-0.030+
	(0.163)	(0.023)	(0.431)	(0.011)	(0.387)	(0.016)
Night/Weekend After Change	-0.119	-0.017	0.858+	0.021+	0.599	0.025
	(0.180)	(0.026)	(0.473)	(0.012)	(0.400)	(0.016)
Flagship Night/ Weekend After Change	0.032	0.005	-0.215	-0.005	0.093	0.004
	(0.090)	(0.013)	(0.192)	(0.005)	(0.168)	(0.007)
Occupancy	-0.005+	-0.001+	-0.004	-0.000	-0.009	-0.000
	(0.003)	(0.000)	(0.008)	(0.000)	(0.006)	(0.000)
Constant	-3.302**	-	-3.976**	-	-2.947**	-
	(0.288)	-	(0.714)	-	(0.598)	-
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Primary Complaint	Yes	Yes	Yes	Yes	Yes	Yes
Number of Obs.	17,073	17,073	15,627	15,627	16,557	16,557
Pseudo R^2	0.19	-	0.07	-	0.05	-

Logistic regression models of the probability of Admission to the hospital (1), Readmission to the ED within 72 hours (2), and Readmission to the ED within 7 days (3)
Robust standard errors clustered by attending in ( )
$^{+}p<0.1$; $^{*}p<0.05$; $^{**}p<0.01$

Table 5: Impact of Process Change on Use of Other Medical Tests

	(1) *Poisson Lab Test Count*		(2) *Logit CT Scan*	
	Coefficient	AME	Coefficient	AME
Flagship	-0.032**	-0.247**	-0.287**	-0.063**
	(0.011)	(0.087)	(0.074)	(0.016)
Night/Weekend	0.006	0.049	0.450**	0.098**
	(0.017)	(0.128)	(0.120)	(0.026)
Night/Weekend After Change	0.013	0.102	-0.488**	-0.106**
	(0.017)	(0.131)	(0.126)	(0.027)
Flagship Night/Weekend After Change	-0.033**	-0.254**	0.209**	0.045**
	(0.010)	(0.081)	(0.062)	(0.013)
Occupancy	0.000	0.001	-0.001	-0.000
	(0.000)	(0.003)	(0.002)	(0.000)
U/S ordered	0.076**	0.589**	-	-
	(0.010)	(0.078)	-	-
U/S ordered Night/Weekend	0.116*	0.898*	-	-
	(0.056)	(0.433)	-	-
U/S ordered Night/Weekend After Change	-0.111*	-0.860*	-	-
	(0.055)	(0.422)	-	-
U/S ordered Flagship Night/ Weekend After Change	0.005	0.037	-	-
	(0.023)	(0.174)	-	-
Constant	1.951**	-	-1.294**	-
	(0.045)	-	(0.205)	-
Controls	Yes	Yes	Yes	Yes
Primary Complaint	Yes	Yes	Yes	Yes
Number of Obs.	17,138	17,138	17,119	17,119
Pseudo R^2	0.03	-	0.10	-

Poisson count model of number of laboratory tests ordered (1). Logistic regression model of the probability of a CT scan (2).
Robust standard errors clustered by attending in parentheses.
$^+p<0.1$; $*p<0.05$; $**p<0.01$

7. Robustness Check

In addition to showing that the change in U/S orders affects radiological test return time, which provides support that the increase in LOS was due to the processing change, we also performed a further robustness check to provide additional evidence that the changes in U/S orders were a function of the change in ordering process, and not due to some other underlying trend. Specifically, we re-ran the original logistic regression, restricting our analysis to patients seen in 2010 or later. We also interacted the Flagship*NW effect with the years 2011 and 2012, thus Flagship*NW in 2010 is the baseline effect. If the processing change explains the increase in U/S use, then the greatest difference in U/S use should occur in 2010 and thus show up in the baseline, with no other effect in 2011 and 2012. Our results confirm this; the only statistically significant change in U/S use occurred in 2010 (See **Table 6**).

Table 6: Impact of Process Change on U/S use across years

	Probability of U/S *Logit Model*	
	Coefficient	Std. Err.
Flagship	0.192*	(0.080)
Night/Weekend	-0.954**	(0.113)
Night/Weekend_2011	0.064	(0.119)
Night/Weekend_2012	0.081	(0.190)
Flagship Night/Weekend	0.851**	(0.116)
Flagship Night/Weekend_2011	0.158	(0.129)
Flagship Night/Weekend_2012	0.169	(0.203)
Constant	-0.100	(0.372)
Controls	Yes	-
Primary Complaint	Yes	-
Number of Obs.	15,562	-
Pseudo R^2	0.12	-

Logistic regression model of the probability of U/S, for patients seen during or after 2010.
Robust standard errors clustered by attending in parentheses.
$^+p<0.1$; $*p<0.05$; $**p<0.01$

Finally, to provide further evidence that making U/S easier to order increased the probability that physicians would order low efficacy U/S, we tested whether there was a difference in propensity to order an U/S between patients whose symptoms were clearly linked to a need—or not—for an U/S versus for patients whose symptoms were more ambiguous as to the need of an U/S. Specifically, some complaints, such as abdominal cramping—the primary complaint for patients with cholecystitis—and pelvic pain—for ectopic pregnancies—are conditions which strongly indicate the need for an U/S. Other conditions, such as fainting, are clear in not needing an U/S. The left hand column of **Table 7** contains eight such symptoms that are clear about the need, or not, for an U/S. Conversely, other complaints, such as abdominal pain, are more ambiguous about whether or not an U/S is warranted. For example, abdominal pain is a symptom for many conditions, most of which do not require an U/S, but can also be associated with cholecystitis or other acute conditions which warrant an U/S. The right hand side of **Table 7** lists eight symptoms for which the need for an U/S is ambiguous.

To test for a difference in the use of U/S between patients with clear versus ambiguous symptoms for an U/S, we run logistic regressions for each primary complaint of interest on only those patients seen after the change, and we look at the effect of being seen at Flagship compared to Community. **Table 7** shows that the coefficients for Flagship are not significant for the patients whose symptoms clearly warrant an U/S (or not, as in the case of the shaded symptoms). In contrast, the coefficients for Flagship are significant for the ambiguous symptoms. These findings support our explanation that ambiguous cases—which are "low efficacy uses of U/S"—are responsible for the increase in use of U/S at Flagship after the order process change.

Table 7: Impact of Process Change on U/S use across complaints

Stable, Frequent (Rare) Use of U/S				Varying Use of U/S			
Complaint	***Propensity for U/S at Flagship***		***N=***	**Complaint**	**Propensity for U/S at Flagship**		**N=**
	Coefficient	Std. Error			Coefficient	Std. Error	
Abd. Cramps	0.790	(0.565)	103	Abd. Pain	0.768**	(0.053)	12,300
Vaginal Bleeding	-0.182	(0.632)	53	Flank (side) Pain	0.784**	(0.190)	806
Pelvic Pain	0.506	(0.437)	93	Nausea	0.773**	(0.127)	2,490
Ascites	2.025+	(1.073)	157	Vomiting	0.788**	(0.128)	2,602
Swelling (not abd.)	1.625	(1.087)	71	Back Pain	0.844**	(0.221)	692
Biliary Indication	0.154	(0.759)	66	Chest Pain	0.580**	(0.221)	806
Fainting/ Syncope	-0.470	(0.642)	102	Rt Upper Quad Abd Pain	1.073*	(0.441)	95
Abnormal Stool	0.363	(0.712)	149	Fever	0.604*	(0.295)	346

Logistic regression of U/S propensity by primary complaint comparing Flagship and Community after processing change. Note: All coefficients are for a logistic regression predicting U/S use; Conditions in gray rarely associated with U/S use; +p<0.1, *p<0.05, **p<0.01

8. Discussion

We examined the impact of a change in the ordering process for U/S on nights and weekends for ED patients with abdominal pain at two hospitals within the same health system and staffed by the same ED physicians between 2009 and 2012. We found that the change—which decreased the time it took for ED physicians to order an U/S—decreased the LOS for patients who receive an U/S by 21%, or about an hour. However, the reduction in U/S processing time was associated with an 11.5 percentage point increase in the probability of a patient receiving an U/S. Although the processing change reduced the LOS of patients who had U/S, having an U/S compared to not having an U/S increased the LOS of ED patients by 30% with an additional 15.9% increase when ordered on the night or weekends. Thus, the cumulative effect was a net increase in the LOS in the ED. Furthermore, the expected waiting time for patients entering the ED increased by approximately 26 minutes. Although part of the increased LOS was from the additional U/S that were ordered, we also found that after the process change there was a delay in getting other radiological test results, such as CT, back from the now busier radiologists. Specifically, we found that the time to return non-U/S radiological tests increased by 27.1%, or approximately 30 minutes.

Unfortunately, it does not appear that patients' clinical quality measures improved as a result of the additional U/S. More specifically, we did not see a change in the admission rates of ED patients to the hospital or in the 3 or 7-day readmission rates to the ED. A curious finding was that the number of CT scans in Flagship on nights and weekends after the process change increased by 4.5%. Overall, the number of CT scans over time was decreasing, with a 10.6 percentage point decrease in the probability of receiving one on the night or weekend after the change, suggesting that in general, physicians were not ordering more scans. Instead, we suspect that physicians used CT scans in combination with U/S to be sure of an appropriate diagnosis if the U/S results were uncertain or negative, because if the leading explanation for the patients' symptoms were ruled out by the U/S, physicians might need a CT to understand what else might be causing the patients' symptoms.

Combined, these results have major implications for the research and implementation of operational improvements in DTC settings. Prior research and policies have focused on removing waste, either physical or labor, from a system in order to improve its performance. However, we find that removing what appears to be a wasteful step in a process (i.e., getting approval for a test from an additional doctor) actually creates additional inefficiencies in the system. These results suggest that behavioral responses to a system must be incorporated when trying to improve the efficiency of a system.

8.1. Implications for Research

Our study empirically validates that increasing servers' capacity to provide a service could result in an overall increase in congestion because workers with discretion over their tasks will use their additional capacity to provide more services to their individual customers. The additional services that are provided to customers increases their service time, which makes incoming customers' waits longer. Moreover, we show that the increase in service time also spilled over to patients who did not receive an U/S due to a shared external resource, radiology. This shared resource creates interdependencies between all patients who have any kind of radiological test. Our work shows that the interdependency between servers' decisions and the load on the shared resource causes an increase in service time to patients who do not actually receive the additional service. Given the occurrence of this amplification of cost across patients, the effects must be included when considering the cost versus benefit of process changes that increase capacity.

Another contribution is that our study includes the impact of incentives on discretionary behavior. In our paper, the incentives of the physicians are not necessarily in alignment with the incentives of the hospital. Specifically, a physician orders a test, such as an U/S, to improve the certainty of her diagnosis for her patient. However, the hospital is incentivized to increase throughput, while ensuring an appropriate level of care (i.e. avoiding a costly readmission to the ED, which is a sign that a diagnosis was “missed’), and thus might not want the physician to order additional U/S if they increase waiting times and LOS without increasing quality metrics.

Finally, our paper contributes to the literature on cost efficiency in healthcare by including a non-financially-driven motivation that explains why physicians order medical interventions that do not improve their patients’ health. By decreasing the time required for a physician to order an U/S, the marginal cost to the physician of ordering an U/S is reduced, while the benefits to the physician remain the same. Specifically, the additional information provided by the U/S provides information to the physician which helps her diagnosis her current patient, and may bring additional satisfaction to a patient who generally believes more medical care is better. However, it is likely difficult for physicians to perceive that their higher rate of ordering U/S places an additional load on radiology that ultimately decreases all patients’ experiences in the ED by increasing their wait times and LOS without providing a noticeable benefit in clinical quality measures.

8.2. Implications for practice

Our results have significant implications for practice. As we described above, we find that at least in an ED setting, a process improvement that reduces the processing time for providing a particular service can actually increase demand for that service, which results in increased congestion in the system and longer overall throughput time. Our study highlights an important lesson for process improvement: increasing process capacity at one step in a service delivery process can change the demand for that service in discretionary settings, and can even decrease performance by further overloading a downstream bottleneck resource that has to process the larger volume of demand (in our setting, radiology). Therefore, improvement initiatives should seek to optimize performance at the system—rather than local—level. Although it was not implemented as a process improvement project, a similar dynamic occurred when Starbucks introduced the time-consuming, but popular Frappuccino beverage without adding worker capacity. As a result, waiting times for all customers sharply increased, driving away customers who ordered drinks with shorter processing times (e.g., espresso), which reduced overall revenue (Adamy 2006). Another example is related to transportation. In many metro areas, highway congestion contributes to pollution and wasted worker productivity. Although a reasonable solution would seem to be to widen roads to increase highway capacity, state transportation department officials recognize that increasing capacity on roadways will encourage more people to drive on these roads, quickly causing congestion again (Emmett Brady 1993). Therefore, the net result will be the same high congestion, but this time at a higher load which causes even higher levels of pollution and more people stuck in gridlock. This example helps illustrate an important concept for practitioners: it may be optimal to have longer service times if this reduces overall demand, preventing additional costly delays in service. In our ED setting, it may be optimal to have a less efficient U/S ordering process with radiology as a gatekeeper to minimize low efficacy U/S orders. Given that clinical quality measures did not increase with the additional U/S orders, our results suggest that while the original process was more difficult for the ED attendings, when necessary, patients still received an U/S.

8.3 Limitations

As with any study, ours has limitations, which we have done our best to address. First, our dataset is limited in the pre-process change period due to a change in the hospital's data collection software that reduced the availability of data. We are therefore unable to separately analyze the effect of the increased availability of the technician. Second, we only have data from abdominal pain ED patients and therefore cannot comment on the impact of the process change on all ED patients. However, there is no reason to think that abdominal pain patients would have a different ED wait time than non-abdominal pain patients. Third, we control for physician effects to account for inter-physician variability. However, it is possible that a patient's care spreads across two physician shifts. In these situations, we used the first attending assigned to the patient, who is typically the one responsible for the care plan, including the orders and disposition. If a second attending physician was involved, the standard practice for this physician group is that the second physician would do their best to execute the care plan as originally conceived. There may be instances where the physician to whom the patient was "signed-out" to may exercise discretion in changing the plan. We are unable to identify the frequency of this but we believe it is not significant based on observing the practice habits of the physician group. Fourth, we do not study the financial cost to insurance company and profit to hospital associated with the change in resource use. We recognize that Flagship might benefit from the additional payment from U/S, and these profits might outweigh the cost on LOS. However, the ordering physicians do not benefit financially from increased U/S as they are independent of the hospital and the radiology group who are paid for the service. Additionally, the ED physicians at both Flagship and Community are salaried with no change in compensation for additional tests ordered. In addition to financial benefit to the hospital, we are unable to assess if the additional U/S increase patient satisfaction, which might bring more future revenue to the hospital. We leave it to future research to examine these effects more closely. Finally, we recognize that our study is limited to two EDs at one health system. We have tried to control for any population factors, such as insurance, age, and other demographics, but of course we cannot prove that these results replicate at other institutions. Nevertheless, we feel that results have significant implications for both research and practice.

9. Conclusions

Our work empirically shows that increasing resource capacity in an ED *increases*—rather than decreases—throughput time due to an increase in resource use to provide additional service. These results highlight the importance of accounting for endogenous changes in demand due to capacity changes in service settings, and suggest that due to behavioral responses to resource availability, what appears to be a wasteful step may not actually be inefficient. In healthcare, this is very important as our results provide an explanation for some of the ever increasing costs. Furthermore, we show that in the complex, interconnected system or hospitals, changes in resource capacity impact not just the patients who receive the additional resources, but other patients who share a resource. Our study suggests an operations-based solution of increasing the cost/difficulty of ordering discretionary but sometimes low-efficacy treatments to address the rise in healthcare spending. We show that, paradoxically, to improve hospital performance, it could be optimal to put into place "inefficiencies" to curb the desire to increase service that does not actually improve outcomes.

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Appendix 1. Confirmation that patient characteristics did not change pre-/post-change

	Flagship		Community	
	Pre Change	***Post Change***	***Pre Change***	***Post Change***
Age (Mean)	40.8	41.1	44.2	45.1
	*T-test**	*p=0.824*	*T-test**	*p=0.5182*
Sex				
Female	137	3,360	124	2,723
Male	87	1,886	68	1,385
	Chi-square	*p=0.378*	*Chi-square*	*p=0.626*
Race				
White	148	3,168	139	2,917
Black	30	895	27	643
Other	46	1,183	26	548
	Fisher's exact	*p=0.209*	*Fisher's exact*	*p=0.861*
ESI				
1	0	6	0	1
2	58	1,186	6	177
3	163	3,783	182	3,794
4	3	96	4	94
5	0	7	0	8
	Fisher's exact	*p=0.811*	*Fisher's exact*	*p=0.849*
Day of Week				
Sunday	37	1,186	44	963
Monday	61	1,524	58	1,102
Tuesday	70	1,448	63	1,044
Wednesday	70	1,399	51	983
Thursday	75	1,328	59	961
Friday	67	1,342	39	961
Saturday	49	1,177	41	936
	Chi-square	*p=0.082*	*Chi-square*	*p=0.317*
Visit times				
Weekday	205	4,158	163	2,842
Night/Weekend	224	5,246	192	4,108
	Chi-square	*p=0.145*	*Chi-square*	*0.061*

Comparison of patient characteristics before and after processing change. All but Day of Week and Visit times were run for night/weekend patients only (Day of Week and Visit times run on all patients at each hospital), but similar results were obtained when using all patients. Other than Age, each analysis compares number of patients in each category. *Also ran using Wilcoxon-Mann-Whitley test, with similar results.

Appendix 2: Categories and medical indications, as described by the American College of Emergency Physicians, for which an emergency U/S is warranted

U/S Category	Medical Indications
Abdominal Aortic Aneurysm (AAA)	AAA
Biliary	Cholelithiasis
	Cholecystitis
	Common bile duct abnormalities
	Liver abnormalities
	Portal vein abnormalities
	Abnormalities of the pancreas
	Other gallbladder abnormalities
	Unexplained jaundice, ascites
Echocardiography	Pericardial effusion and/or tamponade LV systolic function
	RV function and/or acute pulmonary hypertension w/unexplained chest pain
	Dyspnea or hemodynamic instability
Pelvic	Intrauterine/ectopic pregnancy
	Ovarian cysts
	Fibroids
	Tobu-ovarian abscess
Renal	Obstructive uropathy and/or urinary retention
	Acute hematuria
	Renal failure
	Infection/abscesses
	Bladder and prostate abnormalities
Trauma	Fluid in peritoneal, pericardial, and pleural cavities
	Pneumothorax
	Solid organ injury
Venous Thrombosis	Acute proximal DVT in lower extremities
	Chronic DVT
	Distal DVT
	Superficial venous thrombosis
	Lower extremity swelling/pain
	Cellulitis
	Abscess
	Muscle hematoma
	Fasciitis
	Baker's cyst
	Upper extremity venous thrombosis

Appendix 3: Symptoms associated with U/S

Abdominal Cramping
Abdominal Pain/Pressure
Abdominal Swelling (ascites)
Abnormal films/CT
Abnormal Vaginal Bleeding
Alcohol/Drug
Anxiety/nervousness
Back pain/cramps
Blood in Stool/Abnormal Stool Color or smell
Blood in Urine
Chest Pain/Tightness
Chills
Confusion/Altered Mental Status/Unresponsive
Cough
Crohn's Disease
Decreased amount of urine
Diarrhea
Difficulty breathing/SOB
Diminished Appetite
Dizziness
Double or Blurred Vision
Easy Bruising
Fainting/LOC
Fast/Rapid HR/ Palpitations/Pounding Heartbeat
Fatigue
Feeling Faint
Fever
Flank Pain
Foot Pain/Swelling
Frequent Urge to Urinate
Gaseous
Groin Pain
Headache
Hernia
History of liver, pancreas, gallbladder issues
History of renal/Post-op
Hyper- or hypoglycemia
Hypertension
Hypotension
Inability to urinate
Itching
Joint Pain/Swelling/Stiffness
Leg Pain
Lump (mass) in abdomen
Malaise/Not Feeling Well
Muscle aches and pains/Body Aches
Nausea
Neck Pain
Numbness
Other GI History
Pain or Burning with urination
Pelvic Pain
Post Choley/Gallbladder removal
Post Surgery
Post-op renal
Rule out (R/o) AAA
R/o Biliary
R/o DVT or U/S guided procedure
R/o DVT/US guided procedure- abscess
R/o echo
R/o pelvic
R/o renal
R/o trauma
Rib Pain
RUQ Abdominal Pain
Seizure
Shakiness
Shoulder Pain
Skin sore or rash
Small Bowel Obstruction/Constipation/BM Pain
Sweating
Swelling of extremities
Tube issues
Vomiting
Vomiting Blood
Warm tissue
Weakness
Weight gain
Weight loss
Yellowing of skin (Jaundice)