Does Telemedicine Reduce ED Congestion? Evidence from New York State

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Abstract

Overcrowding in emergency departments (EDs) is a common yet nagging problem. It is not only costly for hospitals but also compromises care quality and patient experience. Hence, finding effective ways to improve ED efficiency is of great importance. Using a large dataset of New York State, we investigate the role of telemedicine in enhancing ED efficiency. We show that on average, ED telemedicine adoption significantly reduces patients' length of stay by 15.3% and waiting time by 9.6%. Such an effect is not a byproduct of other widely adopted health IT applications. Interestingly, the effect of telemedicine is larger for less severe patients or when the ED is at a higher occupancy level. Also, we show that the efficiency improvement does not come at the expense of care quality or patient cost. Therefore, our research points to telemedicine as a potential cost-efficient solution to alleviate ED overcrowding.

1. Introduction

Emergency Departments (EDs) (also known as Emergency Rooms) are often crowded, intimidating, expensive places to be. ED physicians constitute less than 5% of the US physician workforce, yet manage 28% of acute care encounters [1]. According to the annual National Hospital Ambulatory Medical Care Survey by Centers for Disease Control and Prevention, demand for ED is rising consistently over time. From 2000 to 2015, the number of ED visits in the United States increased by 26.76% from 108.0 million to 136.9 million, or 1.8% per year. With the sharp rise in the number of ED patients and critical shortages throughout the entire emergency medical care system, ED overcrowding continues to intensify [2]. It is not only costly for the hospital but also compromises care quality for patients. Previous research demonstrates various disturbing effects caused by congestion: poorer patient's outcome due to delayed treatment, higher dissatisfaction rate due to prolonged pain and suffering, decreased physician productivity due to overwork, and increased financial costs for unnecessary diagnostic investigation [3, 4].

Given the various adverse effects caused by ED overcrowding, finding effective ways to improve ED's operational efficiency and health care delivery becomes an urgent task for every healthcare decision maker. Researchers have investigated different interventions to reduce ED congestion from various perspectives. These approaches include: increasing resources such as ED personnel, observation units and hospital beds [5]; establishing a fast track for nonurgent patients [6]; improving patient scheduling process [7]; better work flow management [8]; revising the reimbursement scheme [9]; employing flexible labor when faced with high occupancy level [10]; etc. However, due to the complex nature of ED congestion, solutions to the problem are often complex, expensive, and debatable [3]. In addition, the majority of existing research is context specific, with few papers considering a general approach to all hospitals. Therefore, further studies and new innovations are necessary to better understand and alleviate the crisis.

To meet the challenge, this paper aims to investigate whether ED adoption of telemedicine, a type of health information technology (HIT), can reduce congestion. Definitions of telemedicine vary somewhat from one source to another, but the core concept is "the remote delivery of healthcare services and clinical information using telecommunications technology"[1]. Telemedicine differs from the widely studied HIT applications in that it focuses on delivering clinical care [11]. According to Derlet and Richards [3], the shortage of on-call specialty consultants, or lack of availability, is a key cause of ED overcrowding. With telemedicine adoption in ED, patients can quickly get access to a distant physician via video-conferencing, which may help reduce patients' waiting time for a paged physician. Despite the fact that telemedicine is an old concept,

[1] http://www.americantelemed.org/main/about/about-telemedicine /telemedicine-faqs

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existing studies regarding telemedicine center mostly on the outpatient clinic environment, with minimal studies on the effectiveness of the emergency department or inpatient settings [12]. Probably due to the lack of evidence on its effectiveness, the ED telemedicine adoption rate remains very low (see Table 1). Therefore, it is high time to provide healthcare decision makers with a clear picture of telemedicine application in ED.

Our goal in this research is to understand and to quantify the extent of telemedicine on ED efficiency improvement, and to examine the heterogeneous effect of telemedicine by patient type and ED occupancy level. We use data from several sources to link ED telemedicine adoption to patients' healthcare efficiency, as well as hospitals' and patients' characteristics from 2010 to 2014. Using a difference-in-difference model with hospital and time fixed effects, we find that adopting telemedicine achieves a significant 15.3% reduction in patient's length of stay (in hours) and 9.6% reduction in waiting time (in minutes). We then examine the heterogeneous effects by patient severity and ED occupancy level. Since several widely adopted health IT technologies prove to enhance healthcare efficiency, we further incorporate the adoption status of these health IT applications. Our results show that the effect of telemedicine is on top of these technologies in terms of efficiency improvement. We also demonstrate that such efficiency improvement does not sacrifice patient care quality and cost. Finally, to address any bias caused by reverse causality and endogeneity, we conduct a placebo test and propensity score matching as a further robustness check. All the results hold qualitatively.

2. Research Background

2.1. ED Overcrowding and Consequences

Emergency department overcrowding has become a widespread problem in hospitals across the United States. Since 1986, the Emergency Medical Treatment and Active Labor Act (EMTALA) has mandated that the ED provide care to all individuals seeking treatment for a medical condition, regardless of citizenship, legal status, or ability to pay[2]. As a result of this act, many patients refer to ED if they cannot get treatment otherwise, causing additional patient load in ED. Despite EMTALA's intention to make ED as the safety net of the healthcare system, the increasing problem of overcrowding has strained this safety net to the breaking point [4].

Among the many crucial quality indicators for monitoring the throughput process, length of stay (LOS) is the most important one since it is both the cause and the result of ED overcrowding [13]. On the one hand, LOS is an important determinant of patient satisfaction in the ED, where longer stays decrease satisfaction with emergency care [14]. Such dissatisfaction and overwork will further frustrate medical staff and negatively affect physicians' productivity, which makes the situation even worse. On the other hand, overcrowding can substantially delay patients' waiting time to get treatment, thus increasing the total LOS, and placing patients at greater risk of death [15]. Therefore, in this paper, we choose LOS as the primary outcome measure, where LOS is measured as the total time a patient spends in the ED until being admitted to the hospital or discharged (i.e., door-out time minus door-in time).

2.2. Solution to ED Overcrowding

Reducing ED overcrowding to improve operational efficiency and healthcare quality is on the top of every healthcare decision maker's to do list. A straightforward way is to increase ED capacity by adding additional personnel, observation units, and hospital beds [5]. However, this is often hard to implement due to the budget constraints and the seasonal change in patient volume. For nonurgent patients, researchers suggest that setting up a fast track can reduce their waiting time [6]. However, this is not an ultimate solution due to the limitation of the overall capacity, especially when ED becomes very crowded. To improve the scheduling process, Sinreich et al. [7] introduce two iterative heuristic algorithms for scheduling the work shifts of the ED physicians, nurses and technicians, where the algorithms account for the fact that patients being treated by multiple care providers over the course of several hours, often with interspersed waiting. There are also attempts for better flow management. For example, Imperato et al. [16] suggest that including a physician in triage improves ED patient flow in a community teaching hospital. Song et al. [8] find that while a pooled queue enables flexibility in the routing of jobs to servers, dedicated queue enables improvement in wait times and service times by enabling physicians to more actively manage the flow of patients into and out of ED beds. Several recent papers also suggest that regulators could incentivize the provider to reduce ED waiting time by changing the reimbursement scheme [17].

Existing solutions to ED congestion are often hospital or context specific, and they are subject to some constraints. Thus, it is difficult to apply these

[2] https://www.cms.gov/Regulations-and-Guidance/Legislation /EMTALA/index.html

solutions to the entire healthcare system. Accordingly, further studies and new innovations are necessary to better understand and alleviate the crisis [4].

2.3. Telemedicine

Telemedicine is designed to bridge the service divide to enhance the capabilities of service-disadvantaged segments of society, and many studies have shown that telemedicine application increases rural patients' access to better health care [18, 19]. Telemedicine also demonstrates the potential to treat patients with different diseases, ranging from telepathology [20], to tele-monitoring for chronic disease [21], and telemental health [22], etc.

To the best of our knowledge, only a few papers investigate the effect of telemedicine usage related to ED. For example, Yeow et al. [23] and Gillespie et al. [24] study the *indirect* effect of telemedicine on ED overcrowding. They find that using telemedicine consultation in nursing homes leads to fewer ED visits. Several medical papers have discussed the *direct* effect of ED telemedicine from experimental or retrospective data [25, 26]. However, these studies focus mainly on a small sample or a short time period, and have inconclusive findings on the effect of telemedicine. Therefore, larger trials and cost-effective studies are needed [27].

This paper will examine the telemedicine application within ED and its *direct* impact on the ED congestion problem. Our paper differs from these closely related papers in several important ways: First, existing studies regarding the effectiveness of telemedicine are based on small samples with certain disease types in specific settings. Very few papers investigate the general application of telemedicine in a large population [25]. Second, most of the studies are pilot trials, and minimal papers consider the long-term or routine use of telemedicine [28]. Third, the majority of the studies regarding telemedicine focus on the outpatient clinic environment, with few papers on emergency departments or inpatient settings [12]. By collecting data from multiple sources and constructing a longitudinal dataset including all the outpatients' information and ED telemedicine adoption status for all the EDs in New York state from 2010 to 2014, this paper tries to get a more comprehensive understanding and more generalizable implications.

Overall, this paper fits in the literature on HIT and healthcare efficiency. Although there is increasing literature on HIT, findings on the efficiency improvement are inconclusive, depending on different settings or different evaluation methods [11, 29]. Therefore, this paper tries to extend the traditional realm of HIT and better quantify the direct impact of technology on ED care delivery efficiency.

3. Hypothesis Development

3.1. Telemedicine Adoption and ED Care Delivery Efficiency

Since telemedicine overcomes the distance barrier by enabling real-time interactions between physicians and patients via video conferencing and some diagnostic tools, we hypothesize that adopting telemedicine will increase ED operational efficiency through the following two mechanisms:

First, telemedicine application can improve physicians' efficiency through transportation time elimination and smoother workflow. With telemedicine adoption, patients no longer need to wait for a paged doctor to come. Moreover, a nurse practitioner or physician assistant is often available to order lab work and to conduct initial tests before connecting doctor with the patient. When a patient is taken to the treatment room, a lot of information is ready for the doctor. Therefore, doctors can treat patients in more than one hospital from their desk and pivot to their administrative tasks more quickly in between visits[3].

Second, telemedicine makes it possible for EDs to increase capacity and service rate via flexible resource allocation. Derlet and Richards [3] imply that shortage of on-call specialty consultants or lack of availability is a key cause for ED overcrowding. Through telemedicine network, EDs can rely on a much larger pool of off-site physicians and dispatch them in a more cost-efficient way, because off-site physicians can diagnose and treat patients without physically being present in the ED.

In sum, we formulate the following hypothesis:

Hypothesis 1: ED telemedicine adoption can improve ED operational efficiency by reducing patients' length of stay.

3.2. Heterogeneous Effect by Patient Severity

We believe less severe patients are more likely to benefit from telemedicine than severe patients in terms of length of stay, for two reasons.

First, anecdotal evidence[3] implies that telemedicine program started for patients with non-urgent cases. If there is any efficiency improvement, it follows naturally that less acute patients will get the benefit first. However, it is unclear whether patients with moderate or severe conditions will also benefit from

[3] https://www.wsj.com/articles/can-tech-speed-up-emergency-room-care-1490629118

the telemedicine adoption. While remote physicians can quickly diagnose patients using audio, video, and diagnostic tools through telemedicine application, they are unable to immediately perform surgical or other procedures. Therefore, telemedicine may not be applicable to very severe patients due to technological limitations.

Second, before an ED patient can be treated, a patient typically needs to see a triage nurse first, who assesses the severity of the patient and determines in what priority the emergency physicians will care for the patient. According to Song et al. [8], pooled queuing system is typical for most EDs in the United States, where all the patients in the waiting room remain in the same queue while waiting for an open bed and an assigned physician. Since acute/more severe patients are prioritized in the front of the queue, they do not have to wait long *with* or *without* telemedicine. Therefore, even if telemedicine is also applicable to more severe patients, we expect their reduction of LOS would be much smaller than less severe patients.

Following the argument, we formulate the following hypothesis:
Hypothesis 2: The effect of ED telemedicine is larger for less severe patients than for more sever patients.

3.3. Heterogeneous Effect by ED Occupancy

To understand how occupancy level moderates the effect of telemedicine, consider a simple M/M/1 queuing model with Poisson arrival rate λ and exponential service rate μ. The average response time (i.e., total time a patient spends) in the system is

$$W = \frac{1}{\mu - \lambda}, \ \mu > \lambda > 0 \tag{1}$$

Taking the derivative with respective to μ, we have:

$$\frac{\partial W}{\partial \mu} = \frac{-1}{(\mu - \lambda)^2} < 0 \tag{2}$$

Taking the derivative of $\partial W / \partial \mu$ with respective to λ, we have:

$$\frac{\partial^2 W}{\partial \mu \partial \lambda} = \frac{-2}{(\mu - \lambda)^3} < 0 \tag{3}$$

If telemedicine adoption enables timely allocation of flexible resources, then adopting telemedicine corresponds to increase in service rate μ. From Equation (2) we know that as μ increases, average response time W decreases, which can be viewed as an alternative way of motivating Hypothesis 1. From the mixed partial derivative in Equation (3), we see that as patients' arrival rate λ increases, the marginal effect of telemedicine increases since $\partial W / \partial \mu < 0$. In other words, as system load $\rho = \lambda / \mu$ increases, there should be a larger reduction in the average response time because of telemedicine adoption.

Based on the above analytical results, we hypothesize that the effect of telemedicine is larger when ED occupancy level is higher. This is intuitive if we consider two extreme scenarios: under low occupancy level, patients do not have to wait long in the first place, and accordingly there might be little reduction in patient's LOS with telemedicine application. In contrast, under high occupancy level, adopting telemedicine should lead to a significant reduction in waiting time by dispatching off-site physicians to treat ED patients remotely.

Therefore, we propose the following hypothesis:

Hypothesis 3: The effect of ED telemedicine is larger when the ED occupancy level is higher.

4. Data Description

We use the Healthcare Information and Management Systems Society (HIMSS) - Dorenfest survey, New York State Emergency Department Database (SEDD) of the Healthcare Cost and Utilization Project (HCUP), and American Hospital Association database (AHA) to construct the data. The HIMSS database provides information on telemedicine adoption status for U.S. health facilities starting from 2010. The SEDD captures discharge information on all emergency department visits that do not result in an admission. We first merge AHA and HIMSS data based on hospital's Medicare number, name, and address. Based on the resulting crosswalk between AHA and HIMSS, we further merge with HCUP SEDD to get ED patients' demographic data, visit-specific information, and hospitals' characteristics. HCUP hospitals that can't be uniquely identified and matched with HIMSS are dropped from the sample. Table 1 shows telemedicine adoption status in the U.S. and New York State. In the table, $Freq.$ is the total number of hospitals in a given year, $telemedicine(\%)$ shows the telemedicine adoption rate in any department, $tele\_ed$ is the number of hospitals that adopted telemedicine in ED in a given year, and $tele\_ed(\%)$ shows the percentage of hospitals that adopted ED telemedicine in a given year. Despite that NY has a slightly higher ED telemedicine adoption rate, the growth pattern is similar to the national average. Definitions for the key variables are shown in Tables 2 (Note: Summary Statistics are not reported due to the page limit. Results are available upon request.).

5. Empirical Analyses and Results

In this section, we conduct the empirical analyses. In our sample from 2010 to 2014, there are three types of hospitals: *always adopter* (hospitals that adopted ED telemedicine before 2010), *adopter* (hospitals that adopted ED telemedicine between 2011 and 2014), and *never adopter* (hospitals that hadn't yet adopted ED telemedicine by the end of 2014). Since the adoption time for *always adopter* is unknown, we include only *adopter* and *never adopter* in the following analyses. For all the regression results, standard errors are clustered at hospital level, t-values are shown in the parentheses.

5.1. Baseline Analysis

To test whether telemedicine can improve ED efficiency (**Hypothesis 1**), we conduct the following baseline regression

$$\begin{aligned} Y_{ijt} =& \beta_0 + \beta_1 tele\_ed_{jt} + \gamma X_{ijt} + \delta Z_{jt} + \\ & HosFE_j + TimeFE_t + \epsilon_{ijt} \end{aligned} \tag{4}$$

where Y_{ijt} corresponds to patient i's length of stay in hospital j at time t; $tele\_ed_{jt}$ is an indicator for hospital j's telemedicine adoption status in ED at time t; X_{ijt} include visit-specific control variables for patient i in hospital j at time t; Z_{jt} include time-variant controls for hospital j at time t (e.g., *ptraffic*, *NofBeds*, *NofFTE*, and other health IT adoptions (*ehr*$_{jt}$, *edis*$_{jt}$, *IEInitiative*$_{jt}$)); $HosFE_j$ is the hospital fixed effect; $TimeFE_t$ is the time fixed effect (year, seasonality on a quarterly basis, patient's admission hour and discharge hour).

Table 6 (see the last page) reports the regression results. From columns 1 & 5, we can see that the coefficient estimates for $tele\_ed$ are significantly negative, suggesting that the adoption of telemedicine in ED results in a significant reduction of 0.025 days or 0.634 hours in average patients' length of stay. This corresponds to a decrease in *los* by 25.0% and *duration* by 15.3% on average.

Since several other HIT applications also prove to improve healthcare efficiency in previous research, we further incorporate hospital's adoption of health information exchange ($IEInitiative$), electronic health record (ehr), and ED information system ($edis$) as control. In columns 2-4 and 6-8, the coefficient estimates of $tele\_ed$ are still significantly negative. This suggests that the effect of telemedicine is on top of the most widely adopted HIT applications that might also affect timely information availability. Note that the reduction in the number of observations in columns 2 & 6 is due to the missing variable $IEInitiative$ in HIMSS 2011 database.

5.2. Heterogeneous Effect by Patient Severity

We analyze the heterogeneous effect of telemedicine usage by incorporating the interaction term of patient's severity level and the telemedicine adoption status (**Hypothesis 2**). Since HCUP SEDD does not provide patients' Emergency Severity Index, we proxy patient's severity level using num_dx (total number of ICD-9-CM diagnoses for the visit) and num_proc (total number of procedures performed on the patient for the visit). The representative regression model is as follows[4]:

$$\begin{aligned} Y_{ijt} =& \beta_0 + \beta_1 tele\_ed_{jt} + \beta_2 severity_{ijt} + \\ & \beta_3 tele\_ed_{jt} \times severity_{ijt} + \gamma X_{ijt} + \\ & \delta Z_{jt} + HosFE_j + TimeFE_t + \epsilon_{ijt} \end{aligned} \tag{5}$$

In table 7 (see the last page), columns 1-2 and 3-4 use "num_dx", "num_proc" to proxy patient's acuity level, respectively. The coefficient estimates for $tele\_ed$ are significantly negative, and the interaction term $tele\_ed \times num\_dx$ and $tele\_ed \times num\_proc$ are positive and significant. This suggests that less severe patients benefit more from ED telemedicine adoption in terms of a larger reduction in *los* and *duration*, which supports **Hypothesis 2**. At the mean severity level num_dx (2.28), adopting telemedicine in ED significantly reduces *los* by 0.045 days, and *duration* by 1.207 hours. At the mean severity level num_proc (5.88), adopting telemedicine in ED significantly reduces *los* by 0.036 days, and *duration* by 0.934 hours.

In our sample, 75% of the patients have significant reduction in *los* and *duration*. The results make sense based on the anecdotal evidence. Initially, ED telemedicine program is designed for less acute patients as a fast track, which can reduce the usually long hours of wait. Since there is one queue in ED and patients share the same group of healthcare providers, moderately severe patients also enjoy the spillover effect due to the efficiency improvement for less acute patients. However, for very severe patients with the highest priority, they do not have to wait before getting treatment even without telemedicine. Therefore, the reduction in length of stay is not so significant as that of the less acute patients.

[4]Since $IEInitiative$ is unavailable for all hospitals in 2011, hereafter HIT_{jt} includes only ehr and $edis$. Incorporating $IEInitiative$ does not change the results qualitatively. Results are available upon request.

5.3. Heterogeneous Effect by ED Occupancy

To test the interaction effect of ED telemedicine with ED occupancy level (**Hypothesis 3**), we run the following regression:

$$\begin{aligned} Y_{ijt} = \beta_0 + \beta_1 tele\_ed_{jt} + \beta_2 EDCong_{jt} + \\ \beta_3 tele\_ed_{jt} \times EDCong_{jt} + \gamma X_{ijt} + \\ \delta Z_{jt} + HosFE_j + TimeFE_t + \epsilon_{ijt} \end{aligned} \quad (6)$$

where $EDCong_{jt}$ is constructed following literature [30]. It is the normalized occupancy level for hospital j at time t that accounts for hospital seasonality. The higher the value of this variable, the higher the occupancy level.

In Table 7 (see the last page), columns 5-6 report the regression results. The effect of ED telemedicine is stronger when ED occupancy level increases, as can be seen from the significantly negative coefficient of $tele\_ed \times EDCong$. At the average level of $EDCong$ (0.61), adopting telemedicine significantly reduces *los* by about 0.027 days, and significantly reduces *duration* by about 0.644 hours. This corresponds to 27.0% and 15.5% decrease in *los* and *duration*. The result supports **Hypothesis 3**, implying that the efficiency improvement is more salient during peak hours.

5.4. Telemedicine & ED Care Quality

If the increase in ED efficiency is a sacrifice of the healthcare quality, we can not jump to the conclusion that adopting telemedicine in ED is operationally efficient. Therefore, we further test the change of care quality in terms of readmission rate, mortality rate, and cost for ED patients. Specifically, we generate the dummies indicating whether a patient is readmitted into the hospital within 7 days ($read\_7$) or 30 days ($read\_30$), and whether a patient dies in the following hospital visits within 7 days ($mort\_7$) or 30 days ($mort\_30$). Following is the representative estimating equation:

$$\begin{aligned} Y_{ijt} = & \beta_0 + \beta_1 tele\_ed_{jt} + \gamma X_{ijt} + \delta Z_{jt} + \\ & HosFE_j + TimeFE_t + \epsilon_{ijt} \end{aligned} \quad (7)$$

where Y_{ijt} corresponds to one of patient i's outcome measures ($read\_7$, $read\_30$, $mort\_7$, $mort\_30$, $totchg$) in hospital j at time t, and all other variables follow the same definitions as in the previous sections.

Table 3 reports the regression results. Columns 1-4 show the logistic regression results. It is evident that hospital readmission and mortality rate do not increase after telemedicine adoption. This suggests that telemedicine adoption does not trade care quality for efficiency improvement. Column 5 shows the ordinary least squares regression result using patient's total charge for the visit as the dependent variable. Instead of going up, patients' cost significantly decrease with the adoption of telemedicine in ED. From previous analyses, we know that telemedicine adoption reduces patients' length of stay. Since LOS is an important risk factor for hospital-acquired conditions (HAC) [31], the reduction in LOS will avoid unnecessary HACs and payment penalty by Medicare & Medicaid.[5] Therefore, adopting telemedicine in ED is actually cost-efficient for both patients and hospitals.

5.5. Telemedicine & ED Waiting Time

In this paper, we do not observe patient's waiting time in ED. Instead, we use patient's length of stay as the measure of ED operational efficiency. From previous analysis, we know that adopting telemedicine is associated with a significant reduction in patient's length of stay. However, it is not clear how patient's actual waiting time changes.

Starting from 2012, Centers for Medicare & Medicaid Services provide measure "OP-20" in Hospital Compare database. "OP-20" is the average time (in minutes) patients spent in the emergency department before they were seen by a healthcare professional. As a robustness check, we conduct the following regression:

$$\begin{aligned} Y_{jt} = \beta_0 + \beta_1 tele\_ed_{jt} + \delta Z_{jt} + \\ HosFE_j + TimeFE_t + \epsilon_{jt} \end{aligned} \quad (8)$$

where Y_{jt} is the ED waiting time measure OP-20, $tele\_ed_{jt}$ stands for hospital j's ED telemedicine adoption status in year t, Z_{jt} are hospital control variables including the adoption statuses of other health IT applications. The panel includes all hospitals in the U.S. from 2012 to 2014.

Table 4 reports the regression results. Under different estimation models, the coefficient estimate for $tele\_ed$ is always significantly negative, suggesting that adopting telemedicine indeed reduces patients' waiting time in ED. From full specification model (column 3), ED telemedicine adoption reduces waiting time by 2.849 minutes. This corresponds to 9.6% reduction in waiting time (the mean of OP-20 is 29.55 minutes).

Since hospitals have to ensure high care quality to get reimbursement, physicians do not have the incentive to reduce treatment time at the risk of lowering care quality. Furthermore, we have verified that the efficiency improvement through telemedicine adoption does not compromise care quality. Therefore, we argue

[5] https://www.cms.gov/Medicare/Medicare-Fee-for-Service-Payment/AcuteInpatientPPS/HAC-Reduction-Program.html

that the reduction in length of stay comes from shorter waiting time rather than shorter service time. In fact, previous research shows that physicians will not reduce treatment time even when the ED becomes very crowded [32].

6. Robustness Check

Clearly, adoption of telemedicine in ED is an endogenous decision, which many be correlated with other factors that could also impact healthcare efficiency. If such endogeneity exists, then the causal interpretation of our results may be dubious. In the previous empirical analyses, we address these concerns by including (1) hospital and time fixed effects that control for the impact of time trends and time-invariant differences among hospitals, (2) clustered robust standard errors on hospital level that account for the interdependence for patients within the same ED, (3) time-varying hospitals' characteristics such as their health IT efforts that also affect healthcare efficiency, (4) patients' demographic and visit-specific information that capture potential shift of patient population within healthcare facilities over time. To further evaluate the validity of the causal interpretation of our empirical finding, we conduct further robustness tests.

Since there might be systematic differences between *adopter* and *never adopter* in our sample, we reconstruct a subsample of hospitals that more closely mimics the randomized assignment of ED telemedicine adoption using propensity score matching (PSM) [33]. We choose matching variables prior to 2011 (2009 Hospital Compare data) to make sure that these variables are not affected by the adoption decision. Using PSM with nearest neighbors specified as 3 and a caliper of 0.25 standard deviations of the propensity score [34], we end up with 22 hospitals in the control and 9 hospitals in the treatment group. We then merge patient-level data with the matched hospital sample that satisfies common support, and run the following two regression equations:

$$\begin{aligned} Y_{ijt} =& \beta_0 + \beta_1 treated_j + \gamma X_{ijt} + \delta Z_{jt} + \\ & TimeFE_t + \epsilon_{ijt} \end{aligned} \tag{9}$$

$$\begin{aligned} Y_{ijt} =& \beta_0 + \beta_1 tele\_ed_{jt} + \gamma X_{ijt} + \delta Z_{jt} + \\ & HosFE_j + TimeFE_t + \epsilon_{ijt} \end{aligned} \tag{10}$$

In Table 5, columns $1-2$ and $3-4$ show the regression results corresponding to equation (9) and (10). The coefficient for $treated$ is not significantly different from zero, while the coefficient for $tele\_ed$ is negative and significant. Since $treated$ differs from $tele\_ed$ only for *adopter*, the results here suggest that the efficiency improvement is caused by telemedicine adoption rather than the unobservable characteristics of the *adopter*.

7. Conclusion

Utilizing a large dataset constructed from multiple sources, we examine the potential of telemedicine in improving ED operational efficiency. We found that ED telemedicine program can significantly reduce patients' length of stay. We identify the heterogeneous effect of telemedicine with respect to patients' severity and ED occupancy level. In particular, the effect of telemedicine is stronger when patient severity level decreases, or when ED occupancy level increases. In addition, we found that the effect of ED telemedicine is on top of several other widely adopted health IT applications. Finally, we also show the efficiency improvement brought by ED telemedicine program does not compromise care quality and in fact decreases costs for patients.

This paper contributes to the literature on the relationship between technology adoption and healthcare efficiency. Given that ED telemedicine adoption rate remains low and grows at a very slow rate, our research provides ground for policymakers to incentivize hospitals to adopt telemedicine in ED. Our empirically identified heterogeneous effects of ED telemedicine adoption also provide direct guidance to healthcare providers considering telemedicine. In particular, hospital with highly congested ED or subject to a large fluctuation in occupancy rate can benefit the most from ED telemedicine adoption. We believe that our research will help facilitate the "meaningful use" of this promising technology to reduce ED congestion and to improve ED care delivery quality.

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Table 1: Telemedicine Adoption Status

U.S.

year	Freq.	telemedicine (%)	tele_ed (%)
2010	5,283	21.11	4.32
2011	5,301	25.49	5.34
2012	5,372	28.85	6.66
2013	5,373	33.95	9.25
2014	5,344	38.96	10.70
mean		29.70	7.27

NY

year	Freq.	tele_ed	tele_ed (%)
2010	176	10	5.68
2011	188	11	5.85
2012	179	10	5.59
2013	177	17	9.60
2014	184	23	12.5
mean			7.85

Table 2: Variable Definition

Outcome Measure	**Definition**
los	Length of stay in days.
duration	Length of stay in hours.
totchg	Total charges for the visit in U.S. dollars.
read_7	7-day ED readmission indicator.
read_30	30-day ED readmission indicator.
mort_7	7-day ED death indicator.
mort_30	30-day ED death indicator.
Treatment Variable	**Definition**
tele_ed	Dummy variable indicating whether a hospital adopts telemedicine in ED.
Patient Control	**Definition**
num_dx	Total number of ICD-9-CM diagnoses for a visit.
num_proc	Total number of procedures performed on a patient during a visit.
L1dccs1	Patient's major diagnosis code based on HCUP Clinical Classifications Software.
age	Age in years at admission.
female	Indicator of sex.
race	Patient's race and ethnicity.
pl cbsa	Patient location: Core Based Statistical Area
zipinc qrtl	Median household income national quartile for patient ZIP Code.
ahour	Admission hour.
dhour	Discharge hour.
pay1	Expected primary payer type (Medicare, Medicaid, private insurance, etc.)
dispuniform	Disposition of patient.
dqtr	Patient discharge quarter.
Hospital Control	**Definition**
ptrafc	Average number of ED patients received by a hospital each day for a given month.
NofBeds	Number of Licensed Beds.
NofFTE	Number of full-time equivalents.
Other Health IT	**Definition**
ehr	Indicator for EHR adoption.
edis	Indicator for EDIS adoption.
IEInitiative	Indicator for HIE adoption.

Table 3: Effect of ED Telemedicine on Care Quality

	(1) read_7	(2) read_30	(3) mort_7	(4) mort_30	(5) totchg
tele_ed	-0.027	-0.010	0.009	-0.018	-144.3**
	(-0.78)	(-0.29)	(0.10)	(-0.19)	(-2.14)
Patient Control	Y	Y	Y	Y	Y
Hospital Control	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y
Other HIT	Y	Y	Y	Y	Y
N	23546169	23546210	22945349	23297511	18010016
R^2	0.025	0.035	0.390	0.373	0.226

Note. Columns 1-4 correspond to Logistic regression.
Column 5 corresponds to OLS regression.
Columns 5 further incorporates los as control variable.
t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Effect of ED Telemedicine on ED Waiting Time

	(1) OP-20	(2) OP-20	(3) OP-20
tele_ed	-2.349**	-2.956**	-2.849**
	(-2.24)	(-2.41)	(-2.30)
Hospital Control	N	Y	Y
Time FE	Y	Y	Y
Hospital FE	Y	Y	Y
Other HIT	N	N	Y
N	8921	7561	7561
R^2	0.0701	0.0831	0.0841

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Propensity Score Matching Result

	(1) los	(2) duration	(3) los	(4) duration
treated	-0.028	-0.769		
	(-1.31)	(-1.43)		
tele_ed			-0.037***	-0.779**
			(-2.77)	(-2.34)
Patient Control	Y	Y	Y	Y
Hospital Control	Y	Y	Y	Y
Time FE	Y	Y	Y	Y
Hospital FE	N	N	Y	Y
Other HIT	Y	Y	Y	Y
N	2387361	2377164	2670404	2660637
R^2	0.609	0.236	0.597	0.232

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Note. $treated = 1$ for *adopter*, $treated = 0$ for *never adopter*.

Table 6: Effect of ED Telemedicine on Patients' Length of Stay

	(1) los	(2) los	(3) los	(4) los	(5) duration	(6) duration	(7) duration	(8) duration
tele_ed	-0.025***	-0.037***	-0.025***	-0.025***	-0.634***	-0.811***	-0.635***	-0.643***
	(-3.35)	(-3.86)	(-3.38)	(-3.33)	(-3.32)	(-3.73)	(-3.32)	(-3.30)
IEInitiative		0.009				0.318		
		(0.79)				(1.14)		
ehr			-0.003				-0.004	
			(-0.33)				(-0.01)	
edis				-0.0009				-0.086
				(-0.12)				(-0.45)
Patient&Hospital Control	Y	Y	Y	Y	Y	Y	Y	Y
Time&Hospital FE	Y	Y	Y	Y	Y	Y	Y	Y
N	18061128	11793350	18061128	18061128	17487787	11375528	17487787	17487787
R^2	0.510	0.498	0.510	0.510	0.146	0.157	0.146	0.146

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Heterogeneous Effect by Patient Severity & ED Occupancy Level

	(1) los	(2) duration	(3) los	(4) duration	(5) los	(6) duration
tele_ed	-0.103***	-2.828***	-0.120***	-3.165***	-0.020***	-0.491***
	(-3.19)	(-3.01)	(-4.12)	(-3.63)	(-2.90)	(-2.83)
num_dx	0.029***	0.793***				
	(10.44)	(11.35)				
tele_ed × num_dx	0.025***	0.710**				
	(2.78)	(2.53)				
num_proc			0.016***	0.455***		
			(10.00)	(14.34)		
tele_ed × num_proc			0.014***	0.380***		
			(3.94)	(3.33)		
EDCong					0.004**	0.138***
					(1.99)	(2.71)
tele_ed × EDCong					-0.011***	-0.251***
					(-2.92)	(-3.04)
EffectAtMean	-0.045***	-1.207***	-0.036***	-0.934***	-0.027***	-0.644***
	(-3.35)	(-3.43)	(-3.21)	(-3.04)	(-3.82)	(-3.72)
Patient&Hospital Control	Y	Y	Y	Y	Y	Y
Time&Hospital FE	Y	Y	Y	Y	Y	Y
Other HIT	Y	Y	Y	Y	Y	Y
N	18061128	17487787	17289522	16728330	18061128	17487787
R^2	0.511	0.149	0.554	0.268	0.510	0.146

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$