The Effects of Health IT Innovation on Throughput Efficiency in the Emergency Department

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Abstract

Overcrowding in United States hospitals' emergency departments (EDs) has been identified as a significant barrier to receiving high-quality emergency care, resulting from many EDs struggling to properly triage, diagnose, and treat emergency patients in a timely and effective manner. Priority is now being placed on research that explores the effectiveness of possible solutions, such as heightened adoption of IT to advance operational workflow and care services related to diagnostics and information accessibility, with the goal of improving what is called throughput efficiency. However, high costs of technological process innovation as well as usability challenges still impede wide-spanning and rapid implementation of these disruptive solutions. This paper will contribute to the pursuit of better understanding the value of adopting health IT (HIT) to improve ED throughput efficiency.

Using data from recent years of the National Hospital Ambulatory Medical Care Survey (NHAMCS), I investigate two ways in which ED throughput activity changes due to increased HIT sophistication. First, I use a probit model to estimate any statistically and economically significant decreases in the probability of ED mortality resulting from greater HIT sophistication. Second, my analysis turns to workflow efficiency, using a negative binomial regression model to estimate the impact of HIT sophistication on reducing ED waiting room times. The results show a negative and statistically significant ($p < 0.01$) association between the presence of HIT and the probability of mortality in the ED. However, the marginal impact of an increase in sophistication from basic HIT functionality to advanced HIT functionality was not meaningful. Finally, I do not find a statistically significant impact of HIT sophistication on expected waiting room time. Together, these findings suggest that although technological progress is trending in the right direction to ultimately have a wide-sweeping impact on ED throughput, more progress must be made in order for HIT to directly move the needle on confronting healthcare's greatest challenges.

JEL classification: I10, I18, O33

Keywords: Health Economics; Information Technology; Hospitals; Emergency Department; Efficiency; Innovation

Introduction

Since the founding of modern medicine, recording patient health data, such as vitals, lab results, and health history, has been a hallmark activity of any visit to the doctor. With the recent emergence of the digital age, for the first time the documentation of these personal data points has begun to shift, from the canvas of a manila folder to a tablet or computer in the form of electronic health records (EHRs). The movement to paperless, centralized record-keeping is viewed as a form of process innovation: a technological advancement for an existing production process, intended to improve economic factors, such as costs and productivity. Health information technology (HIT) pioneers' strategic vision has centered itself on technological scalability throughout the entire network of US healthcare practices, including the fundamental idea of interoperability between every practice's record bank, in order to exchange useful patient data and medical insights instantly across the network. The motivation and purpose behind this vision of scalability and wide-spread adoption is multifaceted. Nevertheless, the greatest common denominator between all facets is the hope of implementing IT innovation to address healthcare's biggest efficiency challenges.

For example, as we've seen most recently with the spread of COVID-19, overcrowding in United States hospitals' emergency departments (EDs) has been identified as one of the major barriers to receiving high-quality emergency care. Compounded by the increasing proportion of medical visits classified as 'critical care' or 'emergent,' many EDs struggle to properly triage, diagnose, and treat emergency patients in a timely manner. Priority is now being placed on research that explores the effectiveness of possible solutions, such as heightened adoption of IT to advance operational workflow and care services related to diagnostics and information accessibility. Asplin *et al.* (2003) have labeled this operational segment of the emergency care value-chain as the 'throughput' in their 'input-throughput-output model', developed to better understand the factors of ED crowding.

Although this vision of widespread HIT implementation and interoperability has taken significantly longer than hoped, major progress has been made over the past 15+ years (ONC, 2015). With an influx of government financial and legislative aid directed at the initiative, as well as growing public comfort with opening digital access to personal data records, the United States healthcare system is finally catching up with the times. Medical researchers and health economists have been working to measure the overall *value* of highly sophisticated HIT, hoping to ultimately discover that electronic health information exchange and interoperability (HIEI) has had a positive influence on population health outcomes and overall throughput efficiency. Since it takes time to actually observe the effects of technological disruption in the markets, researchers have only recently become optimistic about the ability to measure the long-run impacts. This paper contributes to a better understanding of how health IT (HIT) improves ED throughput efficiency.

Using data from recent years of the National Hospital Ambulatory Medical Care Survey (NHAMCS), I investigate two ways in which ED throughput activity changes due to increased HIT sophistication. First, I use a probit model to estimate statistically significant decreases in the probability of ED mortality, stemming from greater HIT sophistication. Second, my analysis turns to workflow efficiency, using a negative binomial regression model to estimate the impact that HIT sophistication has on reducing ED waiting room times.

The results show a negative and statistically significant ($p < 0.01$) association between the presence of HIT and the probability of mortality in the ED. However, the marginal impact of an increase in sophistication from basic HIT functionality to advanced functionality is negligible. Additionally, while the results also show a negative association between the presence of HIT and expected waiting room time, the standard error of this relationship is too large to reject the null hypothesis that HIT has no impact.

These findings suggest that although technological progress is trending in the right direction to ultimately have a wide-sweeping impact on ED throughput, more progress must be made in order for HIT to directly move the needle on confronting healthcare's greatest efficiency challenges. Nevertheless, relating these trends and the effects of health IT to mortality rate improvement and overcrowding reduction in emergency departments provides important economic context to recent technology advances that are meant to both save lives and improve efficiency. This empirical analysis leaves room for further discussion, research, and advocacy on the topic of health IT's hand in improving hospital throughput activity, and as a result, the health and wellness of society.

1. Literature Review

The health and economics literature on health IT continues to grow. As previously mentioned, until recently, one of the biggest challenges in conducting a valuation analysis of health IT has been the excessive time it took for the US healthcare system to pick up innovative momentum. Unlike other industries facing similar digital innovation breakthroughs, the United States healthcare system has been incredibly sluggish in its implementation of HIT, such as EHRs, as a means to drive greater efficiency and productivity. The lack of widespread uptake of HIT in hospitals and health practices is typically explained by industry-specific barriers. The fragmentation of the healthcare market, concerns over data privacy and system usability, as well as a lack of technological standards to ensure interoperability between provider networks, have historically contributed to the tardiness of increased efficiency value resulting from HIT implementation (Garber, Gates, Keeler, Vaiana, Mulcahy, Lau, & Kellermann, 2014).

As health IT adoption becomes more feasible for hospitals, the medical and research communities are noticing that emergency care holds a particularly high demand for information technology in its delivery processes, due to the high-stakes, life-or-death nature of an ED (Institute of Medicine, 2007). In urgent medical cases, a doctor's ability to obtain and process high-quality information on the patient is paramount in determining the quality of care provided. Medical experts argue that IT has the ability to show the greatest benefit in the following areas of emergency care: patient management and coordination, communication between the ED and other healthcare providers/networks, clinical decision making, clinical documentation, professional development, and population health monitoring (Institute of Medicine, 2007).

Most helpful to studying health IT's place in the emergency department's value-chain is the throughput segment of Alspin's Input-Throughput-Output model, developed as a practical framework to understand the process and dynamics of patient flow that leads to varying health outcomes (Alspin et al., 2003). Alspin argues that patient health outcomes are the result of ED throughput, which is affected by various input factors (e.g., patient demographics and care access), output factors (e.g., bed availability and follow-up care access), and organizational/management strategies (e.g., staffing coordination, electronic medical records, and general HIT). Research that has built on Alspin et al. (2003)'s model has focused mainly on the impact of input and output factors on throughput, without directly considering IT and EHR's impacts (Asaro et al., 2007). Asaro, Lewis, & Boxerman (2007) quantify the impact of the input and output factors on ED process outcomes by controlling for patient variables and conducting a multivariate linear regression with dependent variables: length of stay (LOS), wait time, treatment time, and boarding time (Asaro, Lewis, & Boxerman, 2007). The authors use these variables as proxies to measure the quality and efficiency of patient care as a result of throughput activities that can be impacted by input and output factors. While the authors are able to show that certain input and output factors were necessary to improve ED throughput, they do not examine how strategic IT solutions can also contribute to this improvement.

Furukawa (2011) uses Alspin's model to study the effect of electronic health records' (referred to as electronic medical records or EMRs) on throughput activities that increase overall ED efficiency. This study is the first of its kind to use the Input-Output-Throughput model to understand how health IT and EHR adoption contribute to throughput activity and impact patient outcomes through increased ED efficiency. Furukawa (2011) uses the 2006 National Hospital Ambulatory Medical Care Survey (NHAMCS) to analyze ED visit data in a sample of hospitals that was selected and weighted to provide nationally representative information. Distinguishing itself from other research, Furukawa (2011) takes an ordinal approach to categorizing the sophistication of HIT by assigning three different levels: minimal to no EHR, basic functionality, and full functionality. Additionally, this study uses an ED's ability to electronically report public health data as an instrumental variable (I.V.) to account for endogeneity and reverse causality that might result from more proficient hospitals being early embracers of advanced health IT. By looking at health IT's ability to decrease diagnosis time, treatment time, and length-of-stay in the ED, dependent on varying levels of EHR system sophistication, Furukawa (2011) discusses the relative impacts on ED throughput efficiency. The author found that "fully functional EHR" systems had a statistically significant mixed association with efficiency, relative to EDs with "minimal or no EHR" and dependent on various patient condition and acuity levels. However, this analysis also showed that, on average, "basic EHR" had no significant association with greater efficiency, relative to EDs with "minimal or no EHR" (Furukawa, 2011).

Although Furukawa (2011) studied IT solutions implemented through hospital management strategy, rather than just the impact of input and output factors, he chose to stick with the same proxy for patient outcomes as Asaro, Lewis, & Boxerman (2007), meaning he only accounts for throughput improvement by investigating time-related measures. Bickell, Hwang, Anderson, Rojas, & Barsky (2008) were similarly inspired by factors that might help to reduce an emergency patient's time to diagnosis, treatment, and healing with their research on factors for rapid appendicitis care. This study found social and demographic factors, such as disparities in care for uninsured patients and racial bias, that should be considered when redesigning the way an ED prioritizes time-sensitive treatment (Bickell et al., 2008). While this study's conclusion offers fascinating insight into new ways to train, staff, and organize healthcare providers, it does not provide direct implications for adopting innovative strategic solutions that can affect throughput efficiency.

Recognizing health IT as a promising solution to ED crowding and inefficiency, the academic community is now faced with a new task. Researchers are seeking to further examine the positive impact that HIT has on specific operations in the ED and relate its benefit to economics by understanding which factors in ED input-throughput-output are most affected. Recent studies have grabbed a stronger hold on measuring the quality impacts of health IT through cost-effectiveness by engaging data from well-defined specialty areas and focusing on changes in mortality rates. Miller and Tucker (2011) do so with a compelling flow of logic in their measurement of the relative cost-effectiveness associated with HIT implementation in reducing neonatal mortality rates. Although they provide a promising development for health economics, the authors focus mostly on return on investment in monetary values and do not directly relate the impacts of HIT to aspects of throughput efficiency. While time-to-care is an important metric for assessing care of time-sensitive and emergent health conditions, which I do explore in my paper, Miller and Tucker's (2011) focus on mortality inspired me to expand my analysis to this less-traditional indicator of throughput efficiency. More specifically, in addition to considering the impact on wait time, by measuring the likelihood of death in the ED as a proxy for the quality of patient outcomes in time-sensitive scenarios, my paper investigates a new approach to analyzing how varying levels of IT adoption impact throughput activity.

2. Data

2.1 Data Source and Overview of Sample

This paper uses pooled cross-sectional public-use data collected by the National Hospital Ambulatory Medical Care Survey (NHAMCS) between 2007-2009 & 2014-2017.[1] NHAMCS is an annual study conducted by the National Center for Health Statistics. The hospitals used in this study are inducted into the NHAMCS sample by U.S. Census Bureau field representatives. All patient visit records included in these data are part of a clustered probability sample of visits to ED departments of noninstitutional general and short-stay hospitals, excluding Federal, military, and Veterans Administration hospitals, throughout all 50 states and the District of Columbia. IMS Health's (renamed IQVIA following recent merger) Health Care Organization database was used to update the hospital sample frame to more clearly define those with emergency departments. Hospital- and area-specific traits are collected when an ED is introduced into the sample.

Data collection was conducted in 16 four-week periods continuing across each survey year, meaning that the sample of hospitals is variable across each year, differentiating the dataset from panel data. Hospitals with EHR systems provided access to all patient visit data that occurred during a randomly assigned four-week period, while hospitals with no EHR systems reported all patient visit data using paper records. The hospital and area-specific information is automatically paired with each patient visit record reported by the hospital. Participating EDs report relevant data on patient diagnosis, arrival type, disposition outcome, and other visit and demographic characteristics. This paper's investigation focuses only on patients with triage acuity reported as immediate, emergent, urgent, or semi-urgent and excludes patients triaged as non-urgent as well as those who were dead upon arrival at the ED or left without treatment. As reported in *Table 1*, the full sample used in this study consists of 120,420 patient

[1] Data from 2010-2013 do not include information on Health IT capabilities or sophistication and are therefore excluded from the analysis.

records across seven years. A shortcoming of these data is that observations from the first three years represent nearly 59.26% of the entire sample across all seven years. I account for this imbalance with a year fixed effect in my analysis while also considering its limitations in the interpretation of the regression results. *Table 1* also shows that in 2007, only 6.67% of patients received care at hospitals with advanced HIT, compared to 2017, in which 63.36% of patients received care at facilities with the highest level of HIT sophistication. To ensure that this change is consistent for the hospitals themselves, rather than due to a few early adopting hospitals treating a higher percentage of patients in the sample, a similar distribution on the hospital level is provided in *Table 2*. Looking across the years presented in both *Table 1* and *Table 2*, the presence of a clear upward trend towards adoption of advanced HIT suggests this data set's relevance in assisting my primary goal of better understanding the added value of heightened HIT adoption.

Table 1. *IT Sophistication for Each Observation by Year*

	Year							
Level of IT (% of Year)	**2007**	**2008**	**2009**	**2014**	**2015**	**2016**	**2017**	**Total**
Minimal or No HIT	12,464 (56.87%)	9,279 (43.00%)	11,935 (42.83%)	3,478 (24.55%)	1,816 (14.43%)	1,262 (10.80%)	952 (8.96%)	41,186 (34.20%)
Basic HIT	7,992 (36.46%)	9,863 (45.71%)	12,560 (45.07%)	3,814 (26.92%)	3,387 (26.91%)	3,470 (29.69%)	2,939 (27.67%)	44,025 (36.56%)
Advanced HIT	1,461 (6.67%)	2,435 (11.29%)	3,373 (12.10%)	6,874 (48.52%)	7,382 (58.66%)	6,955 (59.51%)	6,729 (63.36%)	35,209 (29.24%)
Total	21,917	21,577	27,868	14,166	12,585	11,687	10,620	**120,420**
% of Full Sample	18.20%	17.92%	23.14%	11.76%	10.45%	9.71%	8.82%	**100%**

Table 2. *Hospital IT Sophistication by Year*

	Year							
Level of IT (% of Year)	**2007**	**2008**	**2009**	**2014**	**2015**	**2016**	**2017**	**Total**
Minimal or No HIT	195 (60%)	146 (45%)	136 (43%)	49 (22%)	31 (16%)	24 (13%)	13 (8%)	594 (34%)
Basic HIT	116 (36%)	145 (45%)	145 (46%)	58 (27%)	52 (26%)	54 (30%)	42 (26%)	612 (35%)
Advanced HIT	15 (5%)	32 (10%)	36 (11%)	111 (51%)	114 (58%)	104 (57%)	107 (66%)	519 (30%)
Total	326	323	317	218	197	182	162	**1725**

From the raw dataset, I created the primary variable of interest, *Level of IT Sophistication*, based on each ED's responses to various questions about its HIT functionalities. The criteria and approach used for each sophistication level were adapted from the standards set forward by a panel of experts in DesRoches, et al.(2008) and by the Office of the National Coordinator for Health Information Technology (ONC) in its definition of "Meaningful Use."[2] Given that multiple papers, including Furukawa (2011), base their measures of HIT adoption on the criteria developed by DesRoches, et al. (2008) and ONC, I use this methodology for my analysis as well. The *Level of IT Sophistication* variable classifies a hospital's HIT system as "minimal to no HIT," "basic HIT," and "advanced HIT" on a discrete scale of 1-3, with 3 representing advanced systems.

With variation in survey design between different years of NHAMCS data since 2006, I have slightly modified the 'advanced functionality' criteria used in Furukawa (2011), in order to apply the same analytical approach to more-recent datasets with fewer time-specific restrictions. The rationale for

[2] "Meaningful use" is a federal definition of EHR standards proposed by the Health Information Technology for Economic and Clinical Health (HITECH) Act of 2009. The Centers for Medicare & Medicaid Services (CMS) and the Office of the National Coordinator for Health IT (ONC) jointly led this initiative in the effort to incentivize HIT adoption that would assist in the improvement in care quality. In April 2018, CMS redesigned the initiative under its Promoting Interoperability Programs. *Source:* https://www.cdc.gov/ehrmeaningfuluse/introduction.html

modifying the ‘advanced’ category is also motivated and informed by expert opinion outlined in DesRoches, et al. (2008). A full table of the IT functions included in each classification can be found in *Table 3*. When adapting the advanced HIT criteria to the information available in my dataset, I followed the argument that advanced functionality is generally defined by the application of HIT in the following four areas: (1) recording patients’ clinical and demographic data, (2) viewing and managing results of laboratory tests and imaging, (3) managing order entry, and (4) clinical decision support (DesRoches, et al., 2008). Additionally, the data suggests near perfect correlation between the dropped advanced IT functions and those nine that remain, which is likely why the NHAMCS terminated the collection of data on those functions in more recent survey years. As a result, the functions used in Furukawa (2011) and excluded from this paper likely have little impact on the classification levels. Hospitals that do not meet the minimum basic HIT functions are classified as “minimal/no HIT.” Those meeting the minimum set of functions are classified as “basic HIT.” Finally, those hospitals that both meet the minimum set of functions and exceed them with four additional advanced IT functions are classified as “advanced HIT.”

Table 3. *Criteria for HIT Sophistication*

Minimal/No HIT	Basic HIT†	Advanced HIT‡
Meets only four or fewer of ‘Basic HIT’ criteria	Patient Demographic Information	Reconciling Lists of Patients’ Medications
	Laboratory Results	Automatic Warnings of Drug Interactions or Contradictions During Treatment
	Computerized Orders for Tests	Reminders for Guideline-Based Interventions and/or Screening Tests
	Imaging Results	Electronic Prescription Sending
	Clinical Notes	

† Must meet all five criteria in category to classify as “Basic HIT”
‡ Must meet all four criteria in category in addition to all four criteria in “Basic HIT” category to classify as “Advanced HIT”

2.2 Summary Statistics

Table 4 provides an overview of the summary statistics for key variables used in my analysis. All binary variables have been coded as indicators for yes/no responses where the result is equal to 1 if “yes” and equal to 0 if “no.” After removing non-urgent cases from the sample, the variable for immediacy consisted of a discrete scale between 2-5 indicating severity in increasing order as semi-urgent, urgent, emergent, or immediate. All other non-binary variables are continuous in the unit measurements listed in *Table 4*. *Table 8* in the appendix, provides an overview of key variable means by the main variable of interest, IT Sophistication Level, showing that patient characteristics do not differ drastically across hospitals at different sophistication levels.

Table 4. *Summary Statistics of Key Variables*

	Mean	Std. Dev.	Min	Max	Obs.
Male	0.4540	0.4979	0	1	120,420
Age (Years)	38.1584	24.0988	0	100	120,420
Race – White	0.7098	0.4538	0	1	104,016
Ethnicity – Not Hispanic/Latinx	0.1499	0.3569	0	1	97,890
Severity	2.8565	0.7503	2	5	120,420
Wait-Time (Minutes)	49.3959	74.4070	0	1,440	118,471
Arrived by Ambulance	0.1815	0.3854	0	1	115,925
Total # of Diagnostic Services	3.3286	3.5592	0	21	119,315
Total # of Procedures	0.6079	0.7034	0	8	117,536
Died in ED	0.0012	0.0352	0	1	120,420
IT Sophistication Level	**1.9504**	**0.7950**	**1**	**3**	**120,420**
ED located in Metropolitan Statistical Area (MSA)	0.8626	0.3443	0	1	120,420
ED Has “Bed Czar” to Manage Bed Availability	0.7671	0.4227	0	1	112,525
ED Has Computer Assisted Triage	0.5954	0.4908	0	1	117,011
ED Has Electronic Dashboard for Pt. Tracking	0.6910	0.4621	0	1	118,454
ED Has Radio Frequency ID (RFID) for Pt. Tracking	0.1681	0.3740	0	1	117,562
ED Practices “Pool Nursing” to Avoid Crowding	0.5131	0.4998	0	1	117,319
ED Went on EMS Diversion at Least Once in Prior Year	0.4723	0.4992	0	1	96,601
ED Follows “Full Capacity Protocol”	0.2444	0.4298	0	1	113,079

The differences in observation count and variable inclusion across the data sample suggest that it is important to construct an analysis that controls for yearly variation and utilizes as many key variables as possible, while also maintaining an adequately large sample size. Regression analysis is conducted, and clustered standard errors are estimated using STATA 15.

3. Empirical Specification

In using the same data source as Furukawa (2011), I also carry over much of his approach in building my regression, applying it to survey results from selected years following his original 2006-

focused study. My approach expands on prior existing research by measuring health IT's impact on improving hospital throughput through the lens of probability of death in the ED. Since probability of death is unobserved in the data, I chose a probit model specification with the binary variable *DIEDED* for patient death during a visit to the ED as a response indicator as shown in model (1).

(1) $$Pr(DIEDED = 1|X_{it}) = \Phi(\beta_0 + \beta_1 HITLevel_{it} + \beta_2 PtCharacteristics_{it} + \beta_3 VisitCharacteristics_{it} + \beta_4 HospControls_{it} + \delta_t + \varepsilon_{it})$$

Here X_{it} is a vector of the explanatory variables for a given *i* = 1, …, *n* hospital visit during a given *t* = Year {2008, …, 2017}. All explanatory variables included in the above model are vectors that include collections of the key variables described in *Table 4. HITLevel* is a vector of dummy variables which serves to identify the three HIT sophistication classifications: "no or little HIT," "Basic HIT," and "Advanced HIT."

Additionally, it's important to include patient, visit, and hospital attributes when looking at HIT's effect on probability of death in order to control for non-HIT-associated factors that can contribute to probability of death, such as extreme old age or poor administrative management of a crowded ED. *PtCharacteristics* includes demographic information such as sex, race, ethnicity, and age. *VisitCharacteristics* contains variables associated with an individual's visit to the ED such as severity of medical condition determined at triage, mode of arrival, number of diagnostic services performed, number of medical procedures performed, and time spent in ED waiting room. *HospControls* includes characteristics of the hospital at which the patient was seen and help control for hospital quality. The *HospControls* vector includes dummy variables for presence of computer assisted triage, pool nursing, electronic dashboards, "bed czars," RFID, a formal full-capacity boarding protocol, as well as a hospital's metropolitan statistical area (MSA) status, and records of going ambulance diversion in the past year. δ_t is a vector of dummy variable controls for all years of patient visits that account for time variation in the dependent variable not captured by the other explanatory variables. This also allows for an analysis of the data across different samples from separate survey years. Upon running tests for possible correlation, no statistically significant correlation existed between any of the key variables used in the above models. A more detailed explanation of *VisitCharacteristics* and *HospControls* variables used in this study and the rationale for their inclusion can be found in *Table 5.*

The above regression focuses only on deaths occurring in an in-patient hospital setting, across hospitals with varying levels of HIT adoption. For the probit model, I first estimate the coefficients using maximum likelihood estimation (MLE) and then evaluate the average marginal effects of each variable to properly interpret the estimated effect of each variable on the probability of death in the ED.

I then focus on ED throughput by estimating HIT's impacts on patient intake workflow and administrative efficiency. To account for the non-negative count nature of the data, a negative binomial count model is the preferred method. Specifically, I chose to specify a second regression with waiting room time (WAITTIME) as the dependent variable, using a fixed effect negative binomial count model as shown in model (2). For this regression, the coefficients are again estimated using MLE, which returns the estimated impact of each *x* variable on log(*y*). Therefore, a subsequent calculation of the average marginal effects from this regression is also necessary for clearer interpretation of the estimated magnitude of each variable's coefficient on wait time.

(2) $E[WAITTIME_{it}|X_{it}, \varepsilon_{it}], = exp(\alpha + \beta_0 + \beta_1 HITLevel_{it} + \beta_2 PtCharacteristics_{it} + \beta_3 VisitCharacteristics_{it} + \beta_4 HospControls_{it} + \delta_t + \varepsilon_{it})$

Interactions between patient, hospital, and visit characteristic variables are also included in model estimations. These include several interaction terms of patient severity interacted separately with HIT classification level and with ambulance arrival. Estimation for model (2) alone includes additional interaction terms for the interaction between HIT classification level and ambulance arrival. Finally, standard errors in the regressions of both models (1) and (2) were adjusted to account for cluster sampling in the data. After using these regressions to inquire about the presence of an empirical relationship between sophistication of IT-based ED care and ED throughput efficiency, I then seek to interpret the results and discuss their implications for our current understanding of HIT's value and place in the emergency department.

Table 5. *Description and Justification of Key Variables included in VisitCharacteristics and HospControls*

	Variable	Description[3]	Justification
VisitCharacteristics	Severity	Immediacy with which patient should be seen as recorded during time of triage on patient record form. Non-urgent = >2 hours-24 hours, Semi-urgent = >1-2 hours, Urgent = 15-60 minutes, Emergent = 1-14 minutes, and Immediate = Life-threatening conditions that require immediate medical attention.	This controls for variation in the probability of death and expected wait times for differing levels of severity. Non-urgent cases were excluded from the analysis and semi-urgent cases were used as the reference group in regressions.
	Wait-Time (Minutes)	Count variable for amount of time, in minutes, that patient was held in waiting room prior to being seen by a healthcare provider.	In regression (1), this controls for variations in mortality outcomes related to deterioration of patient condition in the time spent prior to receiving treatment. In regression (2), this measures ED throughput efficiency as the dependent variable.
	Arrived by Ambulance	Binary variable to indicate if patient arrived at ED by ambulance.	In regression (1) this controls for cases where medical treatment was provided prior to arrival at the ED. In regression (2) this controls for cases where patients by-pass traditional waiting room procedures as a result of direct Ambulance-to-ED handoffs.
	Total # of Diagnostic Services	Count variable for number of diagnostic services conducted on patient during their visit to the ED.	In regression (1), this measures factors related to the clinical care decision making process for a given patient.
	Total # of Procedures	Count variable for number of medical procedures given throughout the course of a patient's visit to the ED.	In regression (1), this measures factors related to the clinical care treatment process for a given patient.
HospControls	IT Sophistication Level	Categorical variable used to measure an ED's HIT sophistication on an advancing scale of 1-3. See *Table 3* for a more detailed overview.	Key variable of interest. Separated into binary variables in regression analysis with level 1, "minimal to no HIT," used as the reference group.
	ED located in MSA	Binary variable to indicate whether ED is located in a Metropolitan Statistical Area (MSA).	Included in regressions to control for geographic factors that might influence ED mortality or wait times.
	ED Has "Bed Czar" to Manage Bed Availability	Binary variable to indicate whether ED has personnel with the role of "bed czar." A "bed czar" is responsible for coordinating with hospital operations staff to maintain efficient turnaround of inpatient beds.	These control for factors associated with hospitals' efforts to reduce or manage ED overcrowding. Such factors are important to control for because of their expected impact on improving throughput efficiency.
	ED Has Computer Assisted Triage	Binary variable to indicate presence of computer-assisted triage (CAT) in ED. CAT is a tool that aims to provide automated determinations of a patient's severity index to inform patient needs and resource demands, prior to treatment.	
	ED Has Electronic Dashboard	Binary variable to indicate presence of electronic dashboards in the ED. Electronic dashboards are used to track patients in the ED and display live information, integrating various data points such as vital signs, lab results, treatment status, etc.	
	ED Has RFID for Pt. Tracking	Binary variable to indicate presence of radio frequency identification for ED patients and/or resources. Intended to enhance workflow by showing the instantaneous locations of patients, clinicians, and hospital equipment.	
	ED Practices "Pool Nursing"	Binary variable to indicate whether ED practices "Pool Nursing" or "Zone Nursing." This practice is implemented to ensure that nurses are assigned to patients within one collected area, rather than dispersed across different corners of the ED.	
	ED Went on EMS Diversion in Prior Year	Binary variable to indicate whether ED went on EMS diversion at least once in previous calendar year. EMS diversion occurs when ED's become so overcrowded with patients that they must divert inbound ambulances to other regional hospitals in order to ensure patient safety.	
	ED Follows "Full Capacity Protocol"	Binary variable to indicate whether ED follows "Full-Capacity Protocol." Full-Capacity Protocol is an approach that hospitals may take when experiencing overcrowding. When following this protocol, a hospital will redistribute patients from overcrowded units to available beds in other departments.	

3 Institute of Medicine (2007).

4. Results & Discussion

4.1 Results from Regression (1)

Table 6 reports the average marginal effects of the coefficients from the probit regression for death in the emergency department. All indicator (dummy) variables are relative to the base (reference) group, which has been excluded from the estimation. The three categorical variables in this regression that have been transformed to multiple category binary indicators are HIT level, age, and severity. For these variables, all binary indicators are estimated against the base case of a female minority patient over the age of 60, presenting with a semi-urgent medical condition to an ED with no or very little HIT. Additional base group characteristics are defined by the “0” responses to any other dummy variable included in the regression.

In total, I ran three separate specifications of the probit regression model, in order to better interpret the explanatory power of including certain interaction effects. Column (1) reports the average marginal effects for each variable relative the base group. In column (2), I add interaction effects between HIT and severity levels to account for the possibility that more-severe patients with life-threatening conditions disproportionally visit technologically sophisticated hospitals. Controlling for this interaction allows for an easier interpretation of the standalone association between HIT and probability of death. Additionally, to account for the different impact that rapid transport to the hospital has on patient outcomes between varying severity levels, interactions between ambulance arrival and patient severity are included in the third regression results shown in column (3). As expected, the marginal effects of Basic and Advanced HIT in all three regressions are negative, aligning with the theory that adopting HIT is impactful in reducing probability of death in the ED. However, the marginal effects for these variables hold statistical significance in the second and third regression, though not in the first. This outcome indicates the explanatory power of including the interaction terms in the regression.

Table 6. *ED Death and IT Sophistication. Average Marginal Effects from Probit Regression (1).*

Variable DIEDED	**(1)**		**(2)**		**(3)**	
Basic HIT	-0.000519	(0.000343)	-0.00971**	(0.00121)	-0.0110**	(0.00171)
Advanced HIT	-0.000157	(0.000410)	-0.0102**	(0.00129)	-0.0115**	(0.00195)
Pt. Severity- Urgent	-0.0000310	(0.000583)	-0.00121	(0.000877)	-0.00118	(0.000667)
Pt. Severity- Emergent	0.00169**	(0.000576)	0.000846	(0.000661)	0.00938**	(0.00156)
Pt. Severity- Immediate	0.00452**	(0.000641)	0.00335**	(0.000681)	0.0107**	(0.00174)
Wait Time	-0.00000336	(0.00000512)	-0.00000346	(0.00000492)	-0.00000339	(0.00000485)
Male	0.000594*	(0.000279)	0.000585*	(0.000276)	0.000581*	(0.000281)
White	-0.000376	(0.000324)	-0.000405	(0.000323)	-0.000404	(0.000323)
Not Hispanic/Latinx	-0.000420	(0.000437)	-0.000478	(0.000437)	-0.000478	(0.000443)
AGE 0-20	-0.00273**	(0.000728)	-0.00276**	(0.000715)	-0.00274**	(0.000763)
AGE 20-40	-0.00191**	(0.000426)	-0.00192**	(0.000426)	-0.00188**	(0.000459)
AGE 40-60	-0.00196**	(0.000416)	-0.00195**	(0.000408)	-0.00193**	(0.000454)
Hospital is in MSA	-0.000738*	(0.000309)	-0.000715*	(0.000313)	-0.000737*	(0.000322)
Pt. Arrived by Ambulance	0.00287**	(0.000527)	0.00283**	(0.000516)	0.0107**	(0.00176)
Total # of Procedures Given	0.00101**	(0.000141)	0.00102**	(0.000141)	0.00102**	(0.000178)
Total # of Diagnostic Services	-0.000339**	(0.0000513)	-0.000346**	(0.0000507)	-0.000345**	(0.0000620)
Computer Assisted Triage	0.000531	(0.000283)	0.000551*	(0.000275)	0.000552*	(0.000281)
Pool Nursing	0.000376	(0.000260)	0.000420	(0.000259)	0.000402	(0.000260)
Electronic Dashboard	0.0000218	(0.000404)	0.00000531	(0.000389)	0.00000980	(0.000389)
Bed Czar	-0.000158	(0.000327)	-0.000147	(0.000320)	-0.000161	(0.000320)
RFID	-0.000352	(0.000355)	-0.000380	(0.000361)	-0.000370	(0.000363)
Went on Diversion Last Year	0.000157	(0.000275)	0.000167	(0.000272)	0.000175	(0.000273)
Full Capacity Boarding Protocol	-0.0000237	(0.000309)	-0.0000177	(0.000308)	0.00000480	(0.000302)
HITlevel2 X Urgent			0.00899**	(0.00150)	0.000413	(0.000441)
HITlevel2_X Emergent			0.00935**	(0.00136)	0.00106*	(0.000461)
HITlevel2 X Immediate			0.00949**	(0.00126)	0.00106*	(0.000509)
HITlevel3_X Urgent			0.0107**	(0.00159)	0.000953	(0.000555)
HITlevel3 X Emergent			0.00965**	(0.00141)	0.00167**	(0.000623)
HITlevel3 X Immediate			0.0104**	(0.00135)	0.00185**	(0.000573)
Amb. Arrival X Urgent					0.0103**	(0.00186)
Amb. Arrival X Emergent					0.0106**	(0.00176)
Amb. Arrival X Immediate					0.0108**	(0.00175)
N	58,886		58,886		58,886	
pseudo R-sq.	0.548		0.556		0.559	

Note: Standard errors are reported in parentheses. *, ** indicates significance at the 5% and 1% level, respectively. Full regression results including year fixed effect can be found in appendix.

Primarily focusing on the estimates in the third regression, I find that the presence of either basic or advanced HIT is associated with a 1.1% reduction in the marginal probability of death in the ED. This result, while small economically, is statistically significant at the 1% level. Perhaps most interesting is that although exclusive criteria were imposed to classify hospitals between basic and advanced HIT, when tested against the base group with minimal/no HIT, the marginal effects of basic and advanced show little differences in comparison to one another. This is surprising given the clear systematic trend of upward investment toward advanced HIT adoption in recent years, as reported in *Table 2* by a spike from 5% to 66% of hospitals having advanced HIT systems in place between 2007 and 2017.

With such a sharp growth in advanced HIT adoption over recent years, the results of this regression call into question the value of investing in more-advanced HIT, beyond the level of basic functionality. One possible explanation is that the chief improvements for reducing probability of death during an ED visit are already realized once basic HIT is adopted. Perhaps, advanced HIT contributes more to throughput efficiency within other dimensions that are not related to acute-care patient outcomes, such as electronic prescription ordering, which is useful after the person leaves the hospital. Additionally, while the sophistication classification criteria remain constant over the years included in this sample, it is likely that the usability of advanced HIT has improved over time. With a larger proportion of observations in the sample coming from earlier years, it is conceivable that these results might provide a skewed snapshot of advanced HIT that is overly representative of its usability in the earlier sample years.

Even if the problem stems from changes in practical usability of advanced HIT over time, rather than just adoption of it, one might still wonder what it takes for the diagnostic and clinical support services included in advanced HIT to have as significant of an influence in yielding better patient outcomes as technological trailblazers have always hoped. Sahni, Huckman, Chigurupati, and Cutler

(2017) call this discrepancy a “common story” in today’s healthcare system, citing the struggle many healthcare systems are facing to create return on investment when integrating new IT systems. These authors note that healthcare practitioners are quick to criticize these technologies as being overly time-consuming and difficult to use in such a way that the IT systems often cause disruptions in proper patient interactions. In the subsequent discussion, Sahni et al. (2017) suggest the central reason this story is so common is that the hospitals implementing new HIT systems are overwhelmingly prioritizing the electronic functions for revenue management, causing care quality improvement functions to fall under the radar. As a result, following HIT adoption, “relatively few organizations have taken the important next step of analyzing the wealth of data in their IT systems to understand the effectiveness of the care they deliver.”[4]

To address this call to action and line of inquiry, we can observe existing trends in other variables within the above regression. Looking at the visit characteristic variables, we see that the effect of increases in the total number of diagnostic services performed on a patient is statistically significant and *negatively* associated with the probability of ED death. This relationship between diagnostic services and better health outcomes, falls in line with the increasing role of specialized and precise diagnostic services within our healthcare system’s transition toward personalized medicine. Healthcare’s wide-sweeping transition towards personalized medicine is pushing clinicians to focus more on healing through therapies tailored to a patient’s condition. Not surprisingly, then, we also see that the total number of treatments has a *positive* and statistically significant association with probability of ED death. With this in mind, it is encouraging to see that the days of misdiagnoses and unnecessary treatments are possibly, and justifiably as we see in this regression, becoming artifacts of the past. Even if advanced HIT doesn’t presently show substantial added value beyond that of basic systems, it is nevertheless

[4] *Sahni et al. (2017), p. 130.*

important to consider the future impact of advanced HIT in the ED. As advanced diagnostic services focused on precision medicine continue to gain prominence and demand in high-quality patient care, more technology specializing in that area will be necessary to support the system.

Additionally, the marginal effects of arrival by ambulance in this regression point to further areas of future improvement. Even after controlling for the interaction of patient severity and ambulance arrival, the results show a statistically significant positive association between ambulance transport and the probability of death. A possible explanation for this can be attributed to the increasing utilization of ambulance transport by patients with non-urgent conditions, paired with the effects of overcrowded EDs. 911-response ambulances do not have the ability to prioritize certain cases over others based on patient acuity levels. Therefore, if local ambulances are backlogged with non-urgent cases, more severe medical emergencies requiring immediate attention are often faced with longer times to receive treatment. Additionally, if the nearest ED is overcrowded, that hospital will go on ambulance diversion and will stop accepting patients from ambulances, causing further delays in the time patients must wait to receive treatment. Though ambulances are traditionally and publicly viewed as tools for safe and quick transportation to the ED when you need it most, misuse of emergency medical services (EMS) and the effects of overcrowding have potential for dire consequences (Olshaker & Rathlev, 2006). In order to address this problem, developments are already underway to adopt interoperable technologies that allow for remote patient triage and improved communication between EMS providers and ED clinicians (Institute of Medicine, 2007). Adopting and implementing such technologies will enable ambulances to remain available for the most urgent patients and allow ED personnel to obtain greater amounts and sophistications of information about incoming patients in order to allocate the proper resources and curb the pitfalls of an overcrowded ED. This is of primary importance when preparing for public health crises, like what we're experiencing now with COVID-19, when a sudden surge of demand for expanded hospital capacity appears.

4.2 Results from Regression (2)

Table 7. *ED Wait Time and IT Sophistication. Average Marginal Effects from Negative Binomial Regression (2).*

Variable WAITTIME	**(1)**		**(2)**	
Basic HIT	-0.254	(2.331)	-3.216	(2.496)
Advanced HIT	2.886	(3.264)	-3.886	(3.353)
Pt. Severity- Urgent	0.0864	(1.012)	-4.581**	(1.643)
Pt. Severity- Emergent	-9.015**	(1.949)	-14.04**	(3.736)
Pt. Severity- Immediate	-33.06**	(3.652)	-34.67**	(5.836)
Male	-2.093**	(0.659)	-2.070**	(0.660)
White	-7.651**	(1.406)	-7.592**	(1.395)
Not Hispanic/Latinx	-4.816*	(2.061)	-4.840*	(2.044)
AGE 0-20	-5.280**	(1.461)	-5.094**	(1.440)
AGE 20-40	0.328	(1.072)	0.390	(1.065)
AGE 40-60	1.649	(0.995)	1.710	(0.992)
Hospital is in MSA	15.60**	(2.507)	15.65**	(2.504)
Pt. Arrived by Ambulance	-13.39**	(1.367)	-13.36**	(1.365)
Hospital Uses Computer Assisted Triage	-0.429	(2.038)	-0.506	(2.022)
Hospital Uses Pool Nursing	1.787	(2.001)	1.814	(1.996)
Hospital Has Electronic Dashboard	4.323	(2.288)	4.274	(2.283)
Hospital Has Bed Czar	5.618*	(2.213)	5.448*	(2.210)
Hospital Uses RFID	-5.006	(2.912)	-5.022	(2.891)
Hospital Went on Diversion Last Year	2.489	(2.069)	2.492	(2.057)
Full Capacity Boarding Protocol	2.185	(2.433)	2.231	(2.429)
HITlevel2 X Urgent			4.667*	(2.245)
HITlevel2_X Emergent			4.832	(4.633)
HITlevel2 X Immediate			1.986	(8.156)
HITlevel3_X Urgent			10.47**	(2.665)
HITlevel3 X Emergent			11.09*	(5.326)
HITlevel3 X Immediate			-0.676	(9.114)
N	60,441		60,441	
pseudo R-sq.	0.008		0.008	

Note: Standard errors are reported in parentheses. *, ** indicates significance at the 5% and 1% level, respectively. Full regression results including year fixed effect can be found in appendix.

Table 7 reports the estimated average marginal effects of the variables from the negative binomial model on ED wait room time. The explanatory variables in this estimation are almost identical to those in the prior regression, with minor changes. Aside from a change in the model specification and dependent variable, the second regression in *Table 7* only adds interactions between HIT level and patient severity. If an ED has capacity for additional patients, it will admit all patients arriving from ambulances at the time of their arrival. Therefore, additional interactions between ambulance arrival and patient severity were not justified in this model since wait time would not differ between patients arriving by ambulance with varying levels of severity.

Looking at both regression models for wait time, there is no statistically significant association between HIT sophistication and wait time. Although the direction of the marginal effects for both basic and advanced HIT point toward a negative relationship between HIT adoption and overall wait time, this relationship remains speculative since the effect is not statistically significant at conventional levels. The imprecise estimates are likely due to the limitations of the data set used in this analysis. After testing several different model types and constructions, it was clear that much of this limitation comes from the construction of the data set. However, these results in addition to Furukawa (2011)'s findings suggest that certain strategies, such as focusing on wait times for specific years or using balanced panel data, might allow for more-precise estimates that describe the effect of HIT on lowering patient ED wait times.

Nevertheless, similar to the findings of Bickell, et al. (2008), the results of these models indicate the possibility of discrimination or bias against patients in the waiting room based on age, sex, race, and ethnicity. While this is not surprising given the social landscape in the United States, it highlights that aspects of bias and inequity are present for patients from the moment they walk through the hospital doors, prior to even receiving treatment. By summing the marginal effects of patient characteristics, we see that all else constant, a white male in his teens is likely to wait nearly 20-minutes less on average for treatment than is his counterpart in the base group. Due to data limitations, it is not clear whether this disparity comes from within-hospital differences in care or differences across hospitals that disproportionately treat under-represented groups. Future research could shed light on such distinctions.

Finally, the effects of overcrowding in the ED seem to be ever present in the results of this regression. For example, the average marginal effect of hospitals located in metropolitan statistical areas (MSAs) is associated with a higher wait times than in hospitals not located in MSAs. Intuitively, this makes sense, since the population density is greater in MSAs and could result in more-crowded EDs. As reported in *Table 8*, hospitals at higher HIT sophistication levels, on average, are more likely to be located in MSAs and treat more patients with severe life-threatening conditions than do those at lower sophistication levels. This systematic trend is also reflected by the positive signs of the coefficients for interactions between severity and HIT level in the results below. Additionally, those same hospitals with greater HIT sophistication are more likely have recently put their EDs on ambulance diversion due to overcrowding and lack of available beds. This is problematic because the patients with more-severe conditions are the ones that most need fast treatment but are obstructed in getting that treatment due to overcrowding. In fact, research suggests that ambulance diversion, which at one point was extremely rare, has become commonplace at hospitals in various large cities, often occurring on a daily basis (Institute of Medicine, 2007).

Certain measures have been put in place to try to alleviate overcrowding and avoid the risk of boarding admitted patients in ED treatment areas while they wait for an open inpatient bed. One noticeable example in the data is a staff member titled “bed czar,” who is responsible for keeping track of hospital bed availability and ensuring more-efficient bed turnarounds in the ED. As the results show, the inclusion of this role in the ED is actually associated with longer wait times, having the opposite of the intended effect. Although it is likely that the effect of a bed czar is estimated as such because they are only present in hospitals that already have overcrowding problems affecting wait time (i.e., reverse causality), this result still reflects that some proposed solutions to overcoming ED overcrowding may not be effective. With longitudinal data that allowed for identification and observation of the same hospitals across years of study, it is possible we would see through a difference-in-differences analysis that after the creation of a bed czar position, wait times decreased on average. Unfortunately, other hospital interventions to address this problem, such as the use of pooled nursing, electronic dashboards for patient tracking, and radio frequency ID (RFID) systems are not precisely estimated in the regressions, making it difficult to interpret their effects. However, there is a large existing literature suggesting significant associations between these techniques and reduced wait times. Looking into the relationship between IT sophistication and the effectiveness of the above techniques to reduce wait time and increase throughput efficiency is an important area of further research.

5. Conclusion

The COVID-19 outbreak in recent months has resulted in unprecedented challenges on the healthcare system, particularly targeting emergency departments and hospital ICUs. Factors such as the high degree of virus contagion, the limited availability of diagnostic tests, and the intensity of the symptoms for those who fall ill, have caused the quantity of patients requiring immediate care to skyrocket over the past few weeks, far beyond full-capacity. With no proven treatments or preventative vaccinations currently available, the CDC has tasked health care providers to make concerted efforts to "mobilize all aspects of healthcare to reduce transmission of disease, direct people to the right level of care, and decrease the burden on the healthcare system" (CDC, 2020). In order to do so, hospitals across the world are looking to health IT as the vehicle to help shift modes of care delivery and "flatten the curve."

Between 2007 and 2017, adoption of highly sophisticated HIT grew by over 600% among the sample of hospitals represented in this study. The preceding analysis shows that adoption of HIT has a statistically significant association with reduced probability of death in an ED and not with reduced waiting time. The negligible difference between the impacts of basic and advanced HIT on mortality in the ED suggests that either hospitals are not taking full advantage of advanced HIT's diagnostic and clinical decision support functionalities, or hospitals selectively adopt the level of HIT commensurate with their needs. However, these needs are rapidly changing with each day. In recent memory, never before has the importance of advanced HIT functionality's role in reducing likelihood of death and avoiding overcapacity in the ED been so pertinent. By taking careful steps in order to more fully leverage HIT's functionality on efforts to reduce overcrowding and to achieve quality precision and personalized medicine, EDs can expect to see significant improvement in throughput efficiency.

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Appendix

***Table 8**. Means of Key Variables by IT Sophistication*

	Mean			
	No or Minimal HIT	Basic HIT	Advanced HIT	Collective
Male	0.4545	0.4556	0.4513	0.4540
Age	37.76	38.53	37.65	38.1584
Race – White	1.281	1.431	1.437	0.7098
Ethnicity – Not Hispanic/Latinx	0.0884	0.115	0.148	0.1499
Immediacy	2.907	2.919	3.034	2.8565
Wait-Time	47.70	54.24	53.12	49.3959
Arrived by Ambulance	0.172	0.185	0.234	0.1815
Total # of Diagnostic Services Conducted	3.138	3.375	4.602	3.3286
Total # of Procedures Given	0.624	0.628	0.619	0.6079
Died in ED	0.00133	0.00117	0.000931	0.0012
MSA	0.722	0.883	1	0.8626
ED Has “Bed Czar”	0.667	0.753	0.924	0.7671
ED Has Computer Assisted Triage	0.382	0.695	0.881	0.5954
ED Has Electronic Dashboard for Pt Tracking	0.368	0.676	0.886	0.6910
ED Has RFID for Pt Tracking	0.0936	0.102	0.253	0.1681
ED Practices “Pool Nursing”	0.403	0.477	0.721	0.5131
ED Went on Ambulance Diversion >1 Time in Year Prior	0.365	0.555	0.544	0.4723
ED Follows “Full Capacity Protocol”	0.169	0.266	0.162	0.2444

***Table 9.** Full Regression Results from Probit (1)*

Variable DIEDED	**Probit Coefficients**	**Average Marginal Effects**
Basic HIT	-4.613**	-0.0110**
	(0.342)	(0.00171)
Advanced HIT	-4.830**	-0.0115**
	(0.379)	(0.00195)
Severity- Urgent	-0.493	-0.00118
	(0.280)	(0.000667)
Severity- Emergent	3.932**	0.00938**
	(0.187)	(0.00156)
Severity- Immediate	4.487**	0.0107**
	(0.312)	(0.00174)
HITlevel2 X Urgent	4.302**	0.0103**
	(0.577)	(0.00186)
HITlevel2_X Emergent	4.456**	0.0106**
	(0.407)	(0.00176)
HITlevel2 X Immediate	4.515**	0.0108**
	(0.404)	(0.00175)
HITlevel3_X Urgent	5.031**	0.0120**
	(0.570)	(0.00233)
HITlevel3 X Emergent	4.594**	0.0110**
	(0.447)	(0.00213)
HITlevel3 X Immediate	4.914**	0.0117**
	(0.400)	(0.00208)

Wait Time	-0.00142	-0.00000339
	(0.00205)	(0.00000485)
Male	0.244*	0.000581*
	(0.111)	(0.000281)
White	-0.170	-0.000404
	(0.134)	(0.000323)
Not Hispanic/Latinx	-0.201	-0.000478
	(0.187)	(0.000443)
AGE 0-20	-1.149**	-0.00274**
	(0.291)	(0.000763)
AGE 20-40	-0.789**	-0.00188**
	(0.155)	(0.000459)
AGE 40-60	-0.810**	-0.00193**
	(0.163)	(0.000454)
MSA	-0.309*	-0.000737*
	(0.130)	(0.000322)
Arrived by Ambulance	4.498**	0.0107**
	(0.185)	(0.00176)
Amb. Arrival X Urgent	-0.0667	-0.000159
	(0.288)	(0.000705)
Amb. Arrival X Emergent	-3.722**	-0.00887**
	(0.308)	(0.00181)
Amb. Arrival X Immediate	-3.155**	-0.00752**
	(0.317)	(0.00148)
Total # Procedures Given	0.427**	0.00102**
	(0.0546)	(0.000178)
Total # of Diagnostic Services	-0.145**	-0.000345**
	(0.0222)	(0.0000620)
Computer Assisted Triage	0.232*	0.000552*
	(0.110)	(0.000281)
Pool Nursing	0.169	0.000402
	(0.104)	(0.000260)
Dashboard	0.00411	0.00000980
	(0.163)	(0.000389)
Bed Czar	-0.0673	-0.000161
	(0.135)	(0.000320)
RFID	-0.155	-0.000370
	(0.151)	(0.000363)
Hosp. on Amb. Diversion Last Year	0.0736	0.000175
	(0.114)	(0.000273)
Full Capacity Boarding Protocol	0.00201	0.00000480
	(0.127)	(0.000302)
Year- 2008	0.173	0.000413
	(0.181)	(0.000441)
Year- 2009	0.444*	0.00106*
	(0.183)	(0.000461)
Year- 2014	0.443*	0.00106*
	(0.209)	(0.000509)
Year- 2015	0.400	0.000953
	(0.232)	(0.000555)
Year- 2016	0.699**	0.00167**
	(0.241)	(0.000623)
Year- 2017	0.776**	0.00185**
	(0.223)	(0.000573)
_cons	-6.807**	
	(0.305)	

N	58,886	58,886
pseudo R-squared	0.559	0.559

Note: Standard errors are reported in parentheses. *, ** indicates significance at the 5% and 1% level, respectively.

Table 10. *Full Regression Results from Negative Binomial Regression (2)*

Variable WAITTIME	**Negative Binomial Regression Coefficients**	**Average Marginal Effects of Neg. Binomial Reg.**
Basic HIT	-0.0694	-3.216
	(0.0537)	(2.496)
Advanced HIT	-0.0839	-3.886
	(0.0724)	(3.353)
Severity- Urgent	-0.0989**	-4.581**
	(0.0354)	(1.643)
Severity- Emergent	-0.303**	-14.04**
	(0.0815)	(3.736)
Severity- Immediate	-0.748**	-34.67**
	(0.127)	(5.836)
HITlevel2 X Urgent	0.101*	4.667*
	(0.0482)	(2.245)
HITlevel2_X Emergent	0.104	4.832
	(0.100)	(4.633)
HITlevel2 X Immediate	0.0429	1.986
	(0.176)	(8.156)
HITlevel3_X Urgent	0.226**	10.47**
	(0.0569)	(2.665)
HITlevel3 X Emergent	0.239*	11.09*
	(0.115)	(5.326)
HITlevel3 X Immediate	-0.0146	-0.676
	(0.197)	(9.114)
Male	-0.0447**	-2.070**
	(0.0143)	(0.660)
White	-0.164**	-7.592**
	(0.0292)	(1.395)
Not Hispanic/Latinx	-0.104*	-4.840*
	(0.0436)	(2.044)
AGE 0-20	-0.110**	-5.094**
	(0.0309)	(1.440)
AGE 20-40	0.00843	0.390
	(0.0230)	(1.065)
AGE 40-60	0.0369	1.710
	(0.0213)	(0.992)
MSA	0.338**	15.65**
	(0.0529)	(2.504)
Arrived by Ambulance	-0.288**	-13.36**
	(0.0289)	(1.365)
Computer Assisted Triage	-0.0109	-0.506
	(0.0436)	(2.022)
Pool Nurse	0.0392	1.814
	(0.0430)	(1.996)
Dashboard	0.0922	4.274
	(0.0492)	(2.283)

Variable WAITTIME	**Negative Binomial Regression Coefficients**	**Average Marginal Effects of Neg. Binomial Reg.**
Bed Czar	0.118*	5.448*
	(0.0475)	(2.210)
RFID	-0.108	-5.022
	(0.0623)	(2.891)
Went on Diversion Last Year	0.0538	2.492
	(0.0443)	(2.057)
Full Capacity Boarding Protocol	0.0482	2.231
	(0.0524)	(2.429)
Year- 2008	-0.0424	-1.967
	(0.0623)	(2.894)
Year- 2009	0.0705	3.267
	(0.0661)	(3.063)
Year- 2014	-0.288**	-13.34**
	(0.0877)	(4.079)
Year- 2015	-0.387**	-17.95**
	(0.0902)	(4.234)
Year- 2016	-0.310**	-14.37**
	(0.104)	(4.849)
Year- 2017	-0.407**	-18.86**
	(0.108)	(5.007)
_cons	3.852**	
	(0.0925)	
lnalpha	0.201**	
	(0.0267)	
N	60,441	60,441
pseudo R-squared	0.008	0.008

Note: Standard errors are reported in parentheses. *, ** indicates significance at the 5% and 1% level, respectively.