The Effect of Communication and EMR Meaningful Use Technologies on Patient Outcomes

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ABSTRACT

We investigate the impact of health information technologies and communication between physicians and nurses on patient outcomes (e.g., mortality, satisfaction, and loyalty). Drawing upon media synchronicity theory, we establish a mediating role of communication between technology enhancement and patient outcomes. We create a unique data set by merging several private and public data sets containing organizational and health IT characteristics in hospitals from 2011 through 2015, and explore the model using several panel regressions with fixed effects. We also calculate indirect and total effects for the communication performance mediation effect. Our findings offer unique contributions to the health IT and communication literature. We show that health information technologies improve communication between physicians and nurses (e.g., medical documentation and health information exchange). Improved communication leads to a reduction in mortality and improves hospital satisfaction and loyalty.

Keywords: health IT, EMR, meaningful use, communication, econometrics

1. Introduction

Sometimes the simplest healthcare improvements lead to the greatest patient benefits. For example, patient infection rates decreased simply from physicians washing their hands before touching patients. Accordingly, infection rates significantly dropped, reducing mortality rates from 22% to 3% (Albert and Condie 1981; Teare 1997).[1] Our work is about another aspect of healthcare that may also seem simple: communication between physicians, nurses, and patients. Communication is a significant factor in a healthcare visit because it lays the foundation for care (Street 1991; Duke et al. 2013). Early studies on physician-patient and nurse-patient communication discovered that these interactions play an integral role in patients' present and future well-being. Specifically, improvement in physician and nurse communication enhanced patient outcomes such as patients' satisfaction with their care, adherence to treatment plans, and quality of life (Crampton et al. 2016).

Besides communication, patient outcomes also improve as healthcare providers are equipped with technology resources and opportunities to build patient rapport and exchange information (Sullivan and Wyatt 2005a; Sullivan and Wyatt 2005b). The transition to electronic medical records (EMR) may assist outcomes and patient-centered communication because of improved access to patient files and comprehensive documentation of medical history (Kossman and Scheidenhelm 2008). EMR use has surged with the introduction of the financial incentive program by the Center for Medicare and Medicaid Services (CMS) by offering payments to hospitals that achieve certain levels of "meaningful use" (Jones et al. 2014). Meaningful use is demonstrated by the extension of EMR capabilities to meet U.S. government standards outlining patient information documentation and exchange between healthcare providers, health insurance agencies, and patients. Accordingly, research concerned with meaningful use technologies have

[1] See Rotter (1997).

found largely positive findings (Buntin et al. 2011; Chaudry et al. 2006). However, many meaningful use studies focus almost exclusively on technology implementation, rather than identifying *how* the technology affects healthcare processes and outcomes (Jones et al. 2014). Understanding the how contributes to maximizing the benefits of implementation such as cost reductions, improved quality of care, and greater patient safety (Lee et al. 2013). In this paper, we argue that one of the ways meaningful use of EMR affects patient outcomes is through improving communication.

The overall impact of EMRs on patient communication remains unclear, as studies have found conflicting results through a diverse range of effects (Alkureishi et al. 2016). Studies have found that EMRs negatively affect patient interaction. A commonly cited negativity is that care providers spend more time entering information and less time interacting with patients (Asan et al. 2014; Park et al. 2012). Nurses report spending 35% of their time on data entry and less than 20% of their time interacting and caring for their patients (Hendrich et al. 2008). Physicians often struggle with dividing their attention between documenting the patient visit and interacting with the patient. Accordingly, patients feel ignored (Swinglehurst et al. 2012), unable to ask questions (Alsos et al. 2012), and afraid to share information (Alsos et al. 2011). As a result, physicians and nurses have experienced diminished rapport with patients and lower levels of patients' reported satisfaction with their care (Duke et al. 2013). Further, it has been shown that EMRs and decision aids have not provided clear evidence regarding the sharing of treatment decisions (Kraner et al. 2007). Conversely, healthcare providers have reported greater efficiency with checking and clarifying information (Shachak and Reis 2009), and patients have expressed relief that physicians and nurses have access to information regarding their personal medical history, particularly with prescription medication because it lowers the burden of recalling medications prescribed (Arar et al. 2005).

Our objective in this paper is to identify the effects of meaningful use technologies on patient outcomes through their impact on physician and nurse communication. We attempt to fill the gaps in the literature by focusing on health information technologies associated with achieving meaningful use of EMR, which we refer to as meaningful use technologies, and analyzing their effects on quantifiable, objective measures from hospitals across the U.S. We establish a research model using media synchronicity theory (MST) and create a unique data set by merging private and public databases that contain hospital-level organizational characteristics over a six-year period. We analyze the data using a series of panel regression models with fixed effects and find that the effects of meaningful use technologies on patient outcomes is partially mediated through their effects on physician and nurse communication. Specifically, our results suggest that enhancing electronic documentation and health information exchange improve patient outcomes in part by also improving communication performance. Further analyzing the effect of meaningful use technologies on communication suggests that nurses are more important in determining quality patient outcomes than physicians and meaningful use technologies assist their communication performance. Lastly, our results demonstrate that the use of decision support systems in hospitals may negatively affect patient outcomes by worsening communication performance.

2. Theoretical Background

We use high-level concepts from MST as the foundation for developing our research model. MST is an extension of media richness theory (Daft and Lengel 1986) and posits that communication and task performance increase as the number of media channels used increases, so long as those channels are able to synchronize (Dennis et al. 2008). Channel synchronization can be defined as the coordination of media working simultaneously toward the same goal; which, according to MST, the goal is to form a shared understanding or agreement. Shared understanding is achieved through iterative communication such that all parties can voice their arguments, arguments are heard and deliberated upon by all parties, and a final argument is collectively agreed upon.

We argue that the purpose of physician-patient and nurse-patient communication is to reach a collective understanding of the health-related issue the patient is experiencing. Healthcare providers require detailed information (i.e., the synchronization of information from multiple media channels) to support an accurate diagnosis and achieve the goal of improved patient well-being. Interpersonal communication remains the most heavily used method for obtaining such information, but meaningful use technologies provide supporting information such as a complete medical history, prescription medications, decision aids, and information regarding their transition in care. Therefore, we argue that the integration of meaningful use with EMR has the potential to enhance communication.

MST proposes that using numerous media channels improve communication performance (Ou et al. 2014). Communication is defined as the combination of conveyance and convergence processes (Dennis et al. 2008). Conveyance processes involve the exchange of new information and the analyzing of that information by other parties. As a result, recipients of the new information require greater cognitive resources for interpretation and analysis, causing lower synchronicity. Convergence processes involve the process of coming to agreement between all parties. Convergence does not require the degree of cognitive resources needed in conveyance because the new information has been evaluated. Therefore, convergence is associated with higher synchronicity. The degree of conveyance and convergence processes needed varies upon each party's knowledge of the task, media, and other parties. Specifically, more conveyance processes will be used when parties have less knowledge and more convergence processes will be used when parties have greater knowledge.

Extending conveyance and convergence processes to patient interactions, conveyance processes occur during physician-patient and nurse-patient interactions in which patients describe their current condition. Physicians and nurses absorb and process the information from the patient. Convergence processes occur when physicians and nurses discuss their diagnosis of the condition and possible treatment options with the patient. Communication with the patient may possess more conveyance processes (i.e., less synchronicity) in the absence of meaningful use technologies because physicians and nurses must gather additional information from the patient to reinforce their mental model of the condition. On the other hand, communication with the patient may possess more convergence processes (i.e., greater synchronicity) in the presence of meaningful use technologies because physicians and nurses have the requisite information at hand when forming their mental model of the condition. Accordingly, the improved synchronicity from meaningful use technologies enhances communication performance and subsequently promotes better patient outcomes. To quantify the effects of communication performance on patient outcomes, we focus on those that are considered among the most important in the communication literature (Ong et al. 1995): patient mortality, patient satisfaction, and patient loyalty. Figure 1 displays our research model.

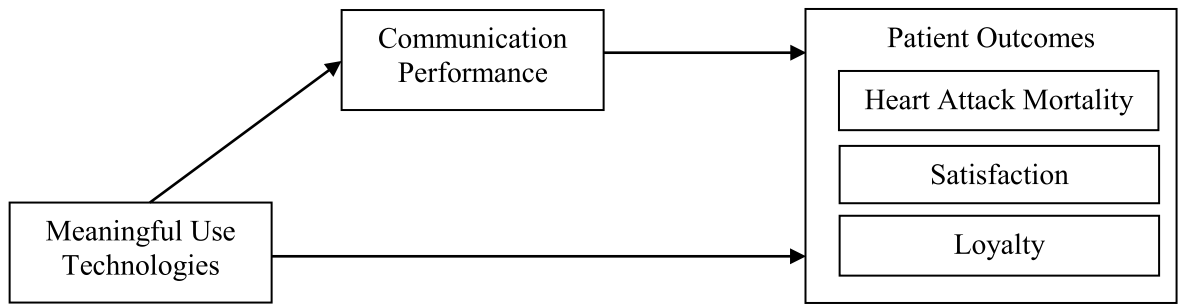

Figure 1. The Mediating Role of Communication between Meaningful Use Technologies and Patient Outcomes

3. Data

We construct our dataset by merging U.S. hospital data for the years 2011 through 2015 from the American Hospital Association's (AHA) Health IT database, the CMS Hospital Compare database, CMS's Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS) survey, and the Healthcare Information and Management Systems Society (HIMSS) Analytics database. AHA and HIMSS obtain data from hospitals using annual surveys while CMS obtains data using a quarterly survey. Hospital responses to AHA and HIMSS surveys are optional but U.S. federal law requires hospitals to report their measures to CMS. AHA and HIMSS surveys are administered during the third quarter each year with responses submitted in the second quarter of the following year. Therefore, we used the third quarter release of data from CMS to account for time, technology, and processing lags, similar to prior literature (Appari et al. 2013). We merged the data from each source according to the Medicare provider number assigned by CMS. The following subsections discuss the specific measures we used from the sources. A list with descriptions of the measures can be found in the Appendix.

Meaningful Use

We obtained our measures for functionalities with meaningful use technologies from the AHA Health IT database. In the survey, respondents mark checkboxes to indicate the capabilities they currently use with EMR documentation, computerized physician order entry (CPOE) systems, clinical decision support (CDS) systems, and health information exchange (HIE). EMR documentation refers to the individual pieces of information an EMR may record. The greater the information an EMR records, the greater the robustness of information available for physicians and nurses. CPOE is a system that allows physicians and nurses to electronically submit requests for a variety of medical tests and prescription medication. CDS is an application system that includes an array of tools designed to analyze large amounts of data to assist physicians and nurses with clinical workflow and decision-making. HIE is a set of system capabilities that allows exchanging patient information with care provider groups across and outside of the hospital. Because responses were checkboxes, we used a binary indicator to represent the usage of a capability, which provided 39 documentation indicators, 5 CPOE indicators, 6 CDS indicators, and 20 HIE indicators. We use the sum of the indicators for each technology to represent its extent of usage.

Communication Performance

Measures for communication performance were retrieved from CMS HCAHPS responses and included the percent of patients reporting poor communication by physicians and nurses as well as poor medication and recovery explanations. Following discharge from a hospital, CMS requests that patients participate in a survey in which they may indicate attitudes and feelings regarding their care. Poor communication is indicated by the response that physicians and nurses "sometimes or never communicated well", administered medication was "sometimes or never explained", and patients "did not receive recovery information".

We create a performance index to capture each of these aspects of hospital communication by first calculating the standard error σ for the ith communication measure in the index. Next, we divide the jth observation within the ith measure by the standard error. Then, we sum the ith measures for the jth observations. Finally, we average the sum for each observation by dividing by *n* number of measures. The equations appear as:

$$\sigma_i = \sqrt{\frac{1}{N_i}\sum_j (x_{ij} - \mu_i)^2}$$

$$\gamma_{ij} = \frac{x_{ij}}{\sigma_i}$$

$$\rho_j = \frac{\sum_i \gamma_{ij}}{n}$$

Patient Outcomes

We investigated three patient outcomes. The first outcome was heart attack mortality from CMS Hospital Compare. We chose to study heart attack mortality because it is an acute condition that requires adequate patient information exchange to determine appropriate treatment and possible lifestyle changes (Liljeroos et al. 2011). Physicians and nurses are often unfamiliar with heart attack patients and rely on formal and informal communication to gather information (Propp et al. 2010). Therefore, advances in healthcare technology may aid physicians and nurses under acute care circumstances in which there is little prior knowledge of the patient.

The second and third patient outcomes we studied were patient's satisfaction and loyalty from the CMS HCAHPS survey. Patient satisfaction is measured on a scale of one through ten.

According to the structure of the survey, patients dissatisfied with their care indicated a score of six or less. In this study, we used the percentage of patients who indicated dissatisfaction with their care as the measure for patient satisfaction. Patient loyalty is measured by asking patients their likelihood of recommending the hospital to a friend or family member. We used the percentage of patients who indicated they would probably or definitely not recommend the hospital as the measure for patient loyalty.

Controls

We consider several control variables to account for various hospital and time characteristics that may also affect communication performance and patient outcomes. Our control variables were gathered from the HIMSS Analytics databases. We control for whether the hospital is for profit or nonprofit using a binary indicator, hospital size by using the number of staffed beds available, patient turnover by taking the natural logarithm of the number of admissions for the given year, and the wealth of the hospital with the natural logarithm of the net operating expenses at the hospital for the given year. Additionally, we control for the location of the hospital, rural hospitals to more urban hospitals, using the rural urban commuting area (RUCA) code according to the hospital's zip code. The health IT characteristics we control for include an indication for if the hospital uses a customized-inhouse IT system and if the hospital's initial EMR implementation occurred in the prior year.

Upon merging the data, we obtain two unbalanced panel data sets, a set for mortality and a set for satisfaction and loyalty. Observations were removed if they were missing from any one of the data sources. The data set for heart attack mortality rates contains 7,871 observations. The data set for percentage of dissatisfied patients and patients unwilling to recommend the hospital contains 11,286 observations. See Table 1 for summary statistics.

Table 1. Summary Statistics

	Mortality Sample					Satisfaction and Loyalty Sample				
Variable:	N	Mean	S.D.	Min	Max	N	Mean	S.D.	Min	Max
Comm. Perf.	7,871	2.631	0.646	0	8.025	11,286	2.484	0.723	0	8.025
Documentation	7,871	33.285	5.822	0	40	11,286	32.737	6.309	0	40
CPOE	7,871	4.179	1.759	0	5	11,286	4.065	1.837	0	5
CDS	7,871	5.079	1.667	0	6	11,286	4.954	1.774	0	6
HIE	7,871	12.528	6.214	0	20	11,286	11.853	6.430	0	20
EMR t-1	7,871	0.095	0.294	0	1	11,286	0.103	0.304	0	1
Customized IT	7,871	0.006	0.079	0	1	11,286	0.006	0.080	0	1
Operating Exp.	7,871	18.160	4.192	0	22.276	11,286	17.615	4.221	0	22.276
Admissions	7,871	8.555	2.414	0	12.623	11,286	7.905	2.545	0	12.623
Staffed Beds	7,871	250.818	191.211	0	1558	11,286	188.88	187.475	0	447
Nonprofit H.	7,871	0.736	0.441	0	1	11,286	0.684	0.465	0	1

4. Analysis and Results

According to our research model, meaningful use technologies as well as physician and nurse communication performance affect patient outcomes. However, it may be possible that other hospital characteristics jointly affect health IT implementation, communication, and patient outcomes. Therefore, we estimate several fixed effects regression models to control for unobserved differences between hospitals. The fixed effects specification enables a separate intercept for each hospital and controls for attributes that have minimal variation over time. For robustness, we estimate models with random effects and establish a natural experiment. All of the robustness tests are consistent with the results presented, increasing confidence in our findings (robustness tests are omitted for sake of brevity; please refer to the Appendix for documentation and discussion of the results).

Table 2. Direct Effect of Communication and Technologies on Patient Outcomes

	Mortality Sample		Satisfaction and Loyalty Sample		
	Model 1	Model 2	Model 3	Model 4	Model 5
Variable:	Mortality	Comm. Performance	Satisfaction	Loyalty	Comm. Performance
Comm.	0.474**		1.140**	0.516**	
Performance	(0.043)		(0.033)	(0.041)	
Documentation	-0.039**	-0.009**	0.008†	0.013**	-0.016**
	(0.004)	(0.001)	(0.005)	(0.004)	(0.002)
CPOE	-0.045**	-0.010**	-0.027†	0.020†	-0.008
	(0.001)	(0.003)	(0.015)	(0.012)	(0.005)
CDS	0.052**	0.007*	-0.012	-0.002	0.035**
	(0.012)	(0.004)	(0.016)	(0.013)	(0.006)
HIE	-0.031**	-0.010**	-0.017**	-0.012**	-0.019**
	(0.003)	(0.001)	(0.004)	(0.003)	(0.001)
Controls					
EMR t-1	0.191**	0.081**	0.119*	0.134**	0.154**
	(0.046)	(0.070)	(0.059)	(0.049)	(0.020)
Customized IT	0.010	-0.258**	-0.276*	-0.186	-0.390**
	(0.287)	(0.089)	(0.374)	(0.299)	(0.129)
Operating	-0.010**	-0.001	0.015**	0.008*	-0.007**
Expense	(0.003)	(0.001)	(0.005)	(0.004)	(0.001)
Admissions	0.017**	0.010**	0.004	-0.010	0.009*
	(0.007)	(0.002)	(0.010)	(0.008)	(0.003)
Staffed Beds	0.001	0.000	-0.001	0.000	0.000
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)
Nonprofit	-0.200	-0.098	0.015	-0.059	-0.119
Hospital	(0.192)	(0.060)	(0.238)	(0.191)	(0.082)
Constant	15.355**	3.059**	3.703**	3.075**	4.282**
	(0.260)	(0.070)	(0.309)	(0.251)	(0.094)
N	7,871	7,871	11,286	11,286	11,286
Hospitals	2,381	2,381	3,479	3,479	3,479
R^2 (overall)	0.023	0.063	0.442	0.428	0.051
χ^2	71.11**	47.04**	126.54**	19.53**	60.33**

Note. Negative coefficients represent decreases in mortality and improved communication, satisfaction, and loyalty.
† $p \leq 0.10$; $*\ p \leq 0.05$; $**\ p \leq 0.01$

We estimate several models using the panel data set and controlling for both hospital and year fixed effects (Table 2). Models 1, 3, and 4 pertain to the direct effects of technologies and communication on our patient outcome measures. Models 2 and 5 are concerned with the effects of technologies on communication performance. Consistent across models 1, 3, and 4, we find that increasing HIE capabilities and greater communication performance are significantly associated with improved patient outcomes. The direct effect for expanding EMR documentation capabilities reduces mortality but also reduces satisfaction and loyalty. The direct effect for increasing CPOE capabilities improves mortality and satisfaction but decreases loyalty. The direct effect for increasing CDS capabilities increases mortality and does not affect satisfaction or loyalty. Across all models, our result for the implementation of EMR in a hospital within the prior year is consistent with Angst et al. (2017). Specifically, we find evidence that the benefits of EMR technologies do not manifest immediately. Hospitals experience short-term detriment to communication performance and patient outcomes.

Tables 3, 4, and 5 consider the indirect and total effects of meaningful use technologies on patient outcomes. We calculate the indirect effect by multiplying the direct effect for communication performance on patient outcomes (Table 2; Models 1, 3, and 4) with the appropriate technology effect on communication performance (Table 2; Models 2 and 5). The total effect is the sum of the direct and indirect effects and we calculate bootstrapped standard errors for the indirect and total effects. In Table 3, we find that the indirect and total effects for each technology are significantly associated with heart attack mortality and indicate that the mediating effect of communication performance contributes to the technologies effect on mortality. In Tables 4 and 5, the significant indirect effects for documentation, CDS, and HIE provide that communication performance mediates their direct effect on satisfaction and loyalty. The total effects in Table 4 indicate that, after accounting for the mediation of communication performance, enhancing documentation, CPOE, and HIE capabilities increases patient satisfaction but CDS reduces satisfaction. Interestingly, the total effects in Table 5 show that the only technology affecting loyalty after the mediation of communication performance is HIE.

Table 3. Indirect and Total Effects on Mortality

	Documentation	CPOE	Decision	HIE
Direct Effect	-0.039**	-0.045**	0.052**	-0.031**
	(0.004)	(0.001)	(0.012)	(0.003)
Indirect Effect	-0.004**	-0.005**	0.004*	-0.005**
	(0.001)	(0.002)	(0.002)	(0.001)
Total Effect	-0.044**	-0.050**	0.056**	-0.036**
	(0.004)	(0.011)	(0.013)	(0.003)

† $p \leq 0.10$; $* p \leq 0.05$; $** p \leq 0.01$

Table 4. Indirect and Total Effects on Satisfaction

	Documentation	CPOE	Decision	HIE
Direct Effect	0.008†	-0.027†	-0.012	-0.017**
	(0.005)	(0.015)	(0.016)	(0.004)
Indirect Effect	-0.018**	-0.009	0.040**	-0.022**
	(0.002)	(0.006)	(0.007)	(0.001)
Total Effect	-0.010*	-0.036*	0.028†	-0.039**
	(0.005)	(0.015)	(0.016)	(0.004)

† $p \leq 0.10$; $* p \leq 0.05$; $** p \leq 0.01$

Table 5. Indirect and Total Effects on Loyalty

	Documentation	CPOE	Decision	HIE
Direct Effect	0.013**	0.020†	-0.002	-0.012**
	(0.004)	(0.012)	(0.013)	(0.003)
Indirect Effect	-0.008**	-0.004	0.018**	-0.010**
	(0.001)	(0.003)	(0.003)	(0.001)
Total Effect	0.005	0.016	0.016	-0.022**
	(0.004)	(0.012)	(0.013)	(0.003)

† $p \leq 0.10$; $* p \leq 0.05$; $** p \leq 0.01$

Next, we open our communication performance index to explore the effect of meaningful use technologies on the individual communication measures (see Table 6). Model 1 shows that nurse communication improves with increases in documentation, CPOE, and HIE capabilities, while CDS capabilities decrease nurse communication performance. Model 2 demonstrates that physician communication also improves with advances in documentation and HIE. Enhancing documentation, CPOE, and HIE capabilities improves physicians' and nurses' communication regarding medication and post-discharge instructions, as shown by Models 3 and 4. However, increasing CDS functionality leads to worse communication regarding medication and post-discharge instructions.

Table 6. Effect of Technologies on Communication Measures

	Model 1	Model 2	Model 3	Model 4
Variable:	Nurse	Physician	Medication	Post-Discharge
Documentation	-0.017**	-0.008*	-0.068**	-0.102**
	(0.003)	(0.003)	(0.008)	(0.007)
CPOE	-0.017†	0.001	-0.095**	-0.095**
	(0.010)	(0.010)	(0.026)	(0.023)
CDS	0.030**	0.008	0.108**	0.108**
	(0.011)	(0.011)	(0.028)	(0.006)
HIE	-0.024**	-0.012**	-0.075**	-0.107**
	(0.003)	(0.003)	(0.007)	(0.006)
Controls				
EMR t-1	0.207**	0.133**	0.552**	0.808**
	(0.039)	(0.039)	(0.093)	(0.090)
Customized IT	-0.187	-0.386	-2.059**	-0.437
	(0.248)	(0.249)	(0.605)	(0.567)
Operating Expense	0.008**	0.007*	0.017*	-0.011
	(0.003)	(0.003)	(0.008)	(0.007)
Admissions	0.017**	0.015*	0.066**	0.089**
	(0.006)	(0.006)	(0.017)	(0.015)
Staffed Beds	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Nonprofit Hospital	-0.278†	-0.246	-0.648	-0.910*
	(0.158)	(0.158)	(0.411)	(0.361)
Constant	5.089**	4.482**	21.438**	19.637**
	(0.182)	(0.182)	(0.475)	(0.417)
N	11,286	11,286	11,286	11,286
Hospitals	3,479	3,479	3,479	3,479
R^2 (overall)	0.036	0.003	0.015	0.068
F	24.24**	7.33**	44.52**	117.65**

Note. Estimates are for satisfaction and loyalty sample. Similar results found with mortality sample.
Negative coefficients represent improved communication.
$\dagger\ p \leq 0.10; *\ p \leq 0.05; **\ p \leq 0.01$

Finally, we analyze the effects of the individual communication measures on patient outcomes (see Table 7). In Model 1, we find that poor medication and post-discharge instructions increase mortality. Surprisingly, we also find that poor communication from physicians reduces mortality. Model 2 provides that poor communication across our four measures leads to less patient satisfaction. We find in Model 3 that nurse, physician, and medication communication are significantly associated with patient loyalty.

Table 7. Effect of Communication Measures on Outcomes

	Model 1	Model 2	Model 3
Variable:	Mortality	Satisfaction	Loyalty
Nurse	0.015 (0.016)	0.656** (0.017)	0.501** (0.013)
Physician	-0.056** (0.016)	0.316** (0.016)	0.242** (0.013)
Medication	0.044** (0.007)	0.071** (0.006)	0.033** (0.005)
Post-Discharge	0.143** (0.007)	0.070** (0.007)	-0.001 (0.005)
Controls			
EMR t-1	0.128** (0.046)	0.020 (0.050)	-0.005 (0.041)
Customized IT	0.295 (0.284)	-0.292 (0.315)	-0.106 (0.250)
Operating Expense	-0.012 (0.003)	-0.002 (0.004)	-0.001 (0.003)
Admissions	0.016* (0.006)	-0.015† (0.008)	-0.026** (0.006)
Staffed Beds	0.001 (0.000)	-0.000 (0.001)	0.000 (0.001)
Nonprofit Hospital	-0.245 (0.192)	0.245 (0.201)	0.104 (0.159)
Constant	12.146** (0.232)	1.273** (0.236)	1.061** (0.187)
N	7,871	11,286	11,286
Hospitals	2,381	3,479	3,479
R^2 (overall)	0.009	0.670	0.670
F	85.67**	513.29**	366.25**

Note. Communication variables represent poor communication. Positive coefficients for Models 2 and 3 represent poor satisfaction and loyalty.
$\dagger\, p \leq 0.10$; $*\, p \leq 0.05$; $**\, p \leq 0.01$

5. Discussion

Overall, our findings demonstrate that advancements in health IT and meaningful use technologies have significant positive effects on patient outcomes through affecting other facets in the healthcare process. Our study offers a significant contribution to the healthcare literature as we provide generalizable empirical findings of communication's mediating effect on the positive impact of meaningful use technologies on patient outcomes. This is a significant finding and contribution to health IT research because it demonstrates the need for continuing study on the complex nature of how IT affects healthcare.

Our analysis offers insight into how meaningful use technologies affect patient outcomes through their effect on communication performance. Specifically, increasing EMR documentation directly reduces patient satisfaction and loyalty but its improvement to communication performance offsets the reduction, which indicates that patients may feel inconvenience with the amount of information requested but ultimately benefit during emergencies. Interpreting the results across our analyses, we find that one of the ways EMR documentation, CPOE, and HIE affects heart attack mortality is through improving communication of medication and post-discharge instructions. Furthermore, patient satisfaction and loyalty may be best served from additional functionality with EMR documentation and HIE because of their positive impact on physician and nurse communication.

We find that nurses benefit the most from meaningful use technologies and have a greater impact on patient outcomes. Nurses are integral in effective information management and flow because they are the primary providers coordinating, delivering, and monitoring patient care (Keenan et al. 2013). Nurses require adequate tools and documentation to better communicate and guide the patient's care toward achieving an optimal outcome (Kossman et al. 2013). Increases in EMR documentation capabilities and HIE functionality facilitate information necessary for nurses to effectively fulfill their role; hence our findings of their effects on nurse communication performance.

The negative effect for physician communication comes from the nature of care for heart attacks. Patients admitted to a hospital for a heart attack may not receive the degree of front-end interaction with physicians because of situational urgency and straightforward diagnosis. Therefore, the physician's primary role is tending to and stabilizing the patient, which may lead to less communication. Patients report that they prefer to receive information from their physician instead of a nurse following a heart attack (Astin et al. 2008), but nurses often care for patients once they are stabilized and perform the frequent interactions to discuss medication and post-discharge instructions (Propp et al. 2010). Therefore, physicians may receive higher responses of poor communication and it is likely nurses who use the increased functionality of CPOE and HIE to their advantage when discussing medication and post-discharge instructions with patients.

Beyond the significant main effects, we believe it is important to address the null and negative effects associated with CDS. As mentioned previously, CDS is an application system designed to analyze large amounts of data to assist physicians and nurses with diagnosis and treatment plans. CDS has been studied extensively in the healthcare literature and has demonstrated increased patient safety and care efficiency (Buntin et al. 2011). However, physicians and nurses exhibit limited critical thinking and reliance on the system in some instances when using advanced EMR capabilities such as CDS (Kossman et al. 2008). Gains in care efficiency resulting from these systems have shifted hospitals toward quicker discharge, requiring healthcare providers to rely on standardized information due to lack of time with patients (Propp et al. 2010). The functionality improvements in CDS center around advising medication prescription and dosage, which according to our expectation with MST should increase medication communication performance. A possible explanation for the observed opposite effect is that physicians and nurses may underestimate the amount of information patients' desire and are able to comprehend (Liljeroos et al. 2011). Thus, our findings contribute to the communication literature by demonstrating that a transition to standardized information may be insufficient and damaging to patient outcomes. Further research should guide the formation and provision of standardized information to foster a positive relationship between efficiency and patient outcomes.

Hospital management may also find our results useful for strategically implementing health IT. Hospitals are federally mandated to achieve specified levels of health IT implementation. In addition, hospitals receive penalties and scrutiny when CMS measures of patient outcomes fail to meet standards. Therefore, hospitals implementing new health IT functionality should focus their efforts on HIE because of its widespread, positive impact on communication and patient outcomes. Management may also consider requiring communication training in conjunction with CDS implementation to improve information sharing when using the system.

We acknowledge that our research is not without limitation. The use of acute heart attack mortality does not always provide an opportunity for extensive communication between physician and patient. Therefore, communication performance for physicians may be negatively skewed in an acute setting. However, it is also possible that physician communication has positive bias in a chronic care setting because patients have extensive interactions with physicians over longer periods. Continuity of care for chronic conditions may reduce the effects of increasing health IT functionality because the physician has extensive knowledge of and history with the patient. Future studies should consider investigating the initial stages of chronic care and health information technology's effects on the development of care.

6. Conclusion

We find that increasing the functionality of health information technologies in hospitals has a positive effect on patient outcomes by improving communication performance of hospital staff. Our results further the health IT literature by being among the first to consider how health IT affects patient outcomes through the mediating role of communication. Using several panel regression models with fixed effects, we find that increasing functionality in EMR documentation and HIE have the greatest overall impact on patient outcomes. The results further suggest that nurses may benefit more from health information technologies than physicians. Our results are consistent and robust across several models that control for individual hospital and health IT characteristics. The implications of our findings offer useful insight for future research in health IT and actionable strategy for hospital management.

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The Effect of Communication and EMR Meaningful Use Technologies on Patient Outcomes

Appendix

Overview

Contained within the Appendix are a descriptive list of the variables used in the study and a series of discussions and tables offering robustness to the results we describe in the paper. Table A1 describes each of the main and control variables we use throughout our analysis. The following section briefly explains the difference between a model with fixed effects and a model with random effects as well as reasoning for why consistency between them strengthens the identification of our findings. The section includes Tables A2 through A7, which provide the results from estimating our panel regression models with random effects. We conclude with a description of forming a natural experiment with our data set and its usage as a robustness check. Tables A8, A9, A10, and A11 present the results of the natural experiment.

Table A1. Variable Descriptions

Variables	Description
Dependent Variables	
Heart Attack Mortality	CMS Hospital Compare measure MORT-30-AMI. The death rate for heart attack patients.
Patient Satisfaction	CMS HCAHPS measure H-HSP-RATING-0-6. Percent of patients for: "Patients who gave their hospital a rating of 6 or lower on a scale from 0 (lowest) to 10 (highest)."
Patient Recommendation	CMS HCAHPS measure H-RECMND-DN. Percent of patients for: "Patients who reported NO, they would probably not or definitely not recommend the hospital."
Independent Variables	
Doctor Communication	CMS HCAHPS measure H-COMP-2-SN-P. Percent of patients for: "Patients who reported that their doctors 'Sometimes' or 'Never' communicated well."
Nurse Communication	CMS HCAHPS measure H-COMP-1-SN-P. Percent of patients for: "Patients who reported that their nurses 'Sometimes' or 'Never' communicated well."
Medication Communication	CMS HCAHPS measure H-COMP-5-SN-P. Percent of patients for: "Patients who reported that staff 'Sometimes' or 'Never' explained about medicines before giving it to them."
Post-Discharge Communication	CMS HCAHPS measure H-COMP-6-N-P. Percent of patients for: "Patients who reported that NO, they were not given information about what to do

	during their recovery at home."
Documentation	The sum of the functionalities for clinical documentation in the health IT system.
CPOE	The sum of the functionalities for a computerized physician order entry system implemented in the health IT system.
CDS	The sum of the functionalities for a clinical decision support system implemented in the health IT system.
HIE	The sum of the functionalities for health information exchange in the health IT system.
Control Variables	
EMR t-1	An indication that the hospital implemented their initial EMR system in the prior year.
Customized IT	An indication that the hospital has implemented a customized health IT system.
RUCA (Appendix only)	A measure for the setting of a hospital with measures closer to 1 being a rural setting and measures closer to 10 being an urban setting.
Nonprofit Hospital	An indicator for nonprofit hospitals.
Operating Expense	The operating expenses for a hospital in a given year.
Admissions	The number of patients admitted to the hospital for any condition in the given year.
Staffed Beds	The number of beds available to patients in the hospital in the given year.

Panel Regression Models with Random Effects

The main analysis for our paper uses a fixed effect to capture unobserved heterogeneity between our hospital observations that is time-invariant. Examples of time-invariant characteristics within hospitals include the hospital's physical attributes, employee culture, and management guidance. The underlying assumptions for fixed effects are that the time-invariant characteristics may bias our outcome variable and they are unique to the hospital. We argue that such characteristics are likely present in hospitals. For instance, a hospital's physical location may bias heart attack mortality based on the socio-economic status of the surrounding population the hospital serves. Therefore, a hospital located in a low-income area may treat more patients at higher risk of heart attack mortality, due to the relationship between poverty and health.

An alternative approach to the fixed effects model is a random effects model. Random effects models assume that the variation across entities occurs at random and is uncorrelated with the predictor variables. One advantage of using random effects is that we may include the time invariant variables in the estimation that would otherwise be absorbed in a fixed effects model. For example, the assumption becomes a hospital's physical location is a random occurrence and treated as part of the error term. We argue that the random effects model is inappropriate for our estimation because of biased estimates caused from omitted variables.

We also conduct a Hausman test to determine the most appropriate model. The null hypothesis in the test is that the error terms are not correlated (i.e., rejecting the null hypothesis indicates fixed effects is appropriate and failing to reject the null hypothesis indicates random effects is appropriate) (Allison 2009). We find that $p < 0.01$ for each model in our study, indicating fixed effects as the preferred model.

Although the fixed effects model is the recommended approach, we check the random effects models for consistency in results. Consistency between the models indicates that the unobservable variables do not significantly bias our findings. For instance, when include the estimate for the physical location of the hospital in the random effects model, although it is significant, we retain similar estimates to the fixed effects model. Thus, we are confident that our findings represent true changes in patient outcomes and communication rather than the product of unobservable attributes within and between hospitals. Tables A2 through A7 present the results of our panel regression models with random effects.

Table A2. Direct Effect of Communication and Technologies on Patient Outcomes - Random Effects

	Mortality Sample		Satisfaction and Loyalty Sample		
	Model 1	Model 2	Model 3	Model 4	Model 5
Variable:	Mortality	Comm. Performance	Satisfaction	Loyalty	Comm. Performance
Comm. Performance	0.242**		1.608**	1.591**	
	(0.031)		(0.029)	(0.034)	
Documentation	-0.038**	-0.010**	0.010*	0.014**	-0.015**
	(0.003)	(0.001)	(0.005)	(0.004)	(0.002)
CPOE	-0.057**	-0.005	-0.008	0.034**	-0.004
	(0.010)	(0.003)	(0.015)	(0.012)	(0.005)
CDS	0.063**	0.006	-0.040*	-0.018	0.032**
	(0.011)	(0.004)	(0.016)	(0.013)	(0.005)
HIE	-0.026**	-0.011**	-0.013**	-0.007*	-0.020**
	(0.003)	(0.001)	(0.004)	(0.003)	(0.001)
Controls					
EMR t-1	0.204	0.084**	0.056	0.055	0.153**
	(0.044)	(0.014)	(0.059)	(0.050)	(0.019)
Customized IT	-0.296	-0.236**	-0.145	-0.031	-0.421**
	(0.231)	(0.080)	(0.336)	(0.266)	(0.109)
RUCA	0.107**	-0.074**	-0.026	-0.110**	-0.119**
	(0.014)	(0.006)	(0.020)	(0.014)	(0.006)
Operating Expense	-0.011**	-0.001	0.017**	0.013**	-0.007**
	(0.003)	(0.001)	(0.005)	(0.004)	(0.002)
Admissions	0.026**	0.009**	0.002	-0.011	0.017**
	(0.006)	(0.002)	(0.009)	(0.008)	(0.003)
Staffed Beds	-0.001**	0.001**	0.000	-0.001**	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Nonprofit Hospital	-0.235**	-0.237**	-0.533**	-0.718**	-0.102**
	(0.055)	(0.025)	(0.095)	(0.068)	(0.029)
Constant	15.966**	3.334**	2.344**	1.348**	4.448**
	(0.169)	(0.049)	(0.238)	(0.184)	(0.063)
N	7,871	7,871	11,286	11,286	11,286
Hospitals	2,381	2,381	3,479	3,479	3,479
R^2 (overall)	0.093	0.131	0.437	0.450	0.201
χ^2	960.27**	859.37**	3633.42**	2834.86**	1633.10**

Note. Negative coefficients represent decreases in mortality and improved communication, satisfaction, and loyalty.

† $p \leq 0.10$; $* p \leq 0.05$; $** p \leq 0.01$

Table A3. Indirect and Total Effects on Mortality

	Documentation	CPOE	Decision	HIE
Direct Effect	-0.038**	-0.057**	0.063**	-0.026**
	(0.003)	(0.010)	(0.011)	(0.003)
Indirect Effect	-0.002**	-0.001	0.001	-0.003**
	(0.000)	(0.001)	(0.001)	(0.000)
Total Effect	-0.040**	-0.058**	0.064**	-0.029**
	(0.003)	(0.010)	(0.011)	(0.003)

† $p \leq 0.10$; $* \, p \leq 0.05$; $** \, p \leq 0.01$

Table A4. Indirect and Total Effects on Satisfaction

	Documentation	CPOE	Decision	HIE
Direct Effect	0.010*	-0.008	-0.040*	-0.013**
	(0.005)	(0.015)	(0.016)	(0.004)
Indirect Effect	-0.024**	-0.007	0.051**	-0.032**
	(0.002)	(0.008)	(0.008)	(0.002)
Total Effect	-0.014**	-0.014	0.011	-0.045**
	(0.005)	(0.015)	(0.016)	(0.004)

† $p \leq 0.10$; $* \, p \leq 0.05$; $** \, p \leq 0.01$

Table A5. Indirect and Total Effects on Loyalty

	Documentation	CPOE	Decision	HIE
Direct Effect	0.014**	0.034**	-0.018	-0.007*
	(0.004)	(0.012)	(0.013)	(0.003)
Indirect Effect	-0.024**	-0.007	0.050**	-0.031**
	(0.002)	(0.008)	(0.008)	(0.002)
Total Effect	-0.010**	0.027*	0.033*	-0.038**
	(0.004)	(0.012)	(0.013)	(0.003)

† $p \leq 0.10$; $* \, p \leq 0.05$; $** \, p \leq 0.01$

Table A6. Effect of Technologies on Communication Measures with Random Effects

	Model 1	Model 2	Model 3	Model 4
Variable:	Nurse	Physician	Medication	Post-Discharge
Documentation	-0.017**	-0.008**	-0.063**	-0.102**
	(0.003)	(0.003)	(0.008)	(0.007)
CPOE	-0.009	0.014	-0.067**	-0.059**
	(0.010)	(0.010)	(0.025)	(0.022)
CDS	0.024*	0.000	0.090**	0.084**
	(0.010)	(0.010)	(0.026)	(0.023)
HIE	-0.027**	-0.013**	-0.078**	-0.107**
	(0.003)	(0.003)	(0.007)	(0.006)
Controls				
EMR t-1	0.248**	0.138**	0.598**	0.979**
	(0.040)	(0.039)	(0.102)	(0.090)
Customized IT	-0.316	-0.590**	-2.274**	-1.183*
	(0.225)	(0.218)	(0.553)	(0.489)
RUCA	-0.244**	-0.228**	-0.614**	-0.099**
	(0.015)	(0.013)	(0.031)	(0.029)
Operating Expense	0.009**	0.007*	0.017*	-0.016*
	(0.003)	(0.003)	(0.008)	(0.007)
Admissions	0.023**	0.020**	0.099**	0.098**
	(0.006)	(0.006)	(0.015)	(0.014)
Staffed Beds	0.002**	0.002**	0.005**	0.003**
	(0.000)	(0.000)	(0.000)	(0.000)
Nonprofit Hospital	-0.841**	-0.179**	-0.629**	-0.738**
	(0.071)	(0.062)	(0.149)	(0.135)
Constant	5.984**	4.887**	22.222**	19.414**
	(0.140)	(0.130)	(0.323)	(0.288)
N	11,286	11,286	11,286	11,286
Hospitals	3,479	3,479	3,479	3,479
R^2 (overall)	0.161	0.147	0.198	0.105
χ^2	990.55**	762.32**	1428.94**	1535.21**

Note. Estimates are for satisfaction and loyalty sample. Similar results found with mortality sample. Negative coefficients represent improved communication.
$\dagger\ p \leq 0.10$; $*\ p \leq 0.05$; $**\ p \leq 0.01$

Table A7. Effect of Communication Measures on Outcomes with Random Effects

	Mortality Sample	Satisfaction and Loyalty Sample	
	Model 1	Model 2	Model 3
Variable:	Mortality	Satisfaction	Loyalty
Nurse	-0.030**	0.732**	0.628**
	(0.013)	(0.014)	(0.011)
Physician	-0.053**	0.364**	0.287**
	(0.013)	(0.014)	(0.011)
Medication	0.031**	0.083**	0.048**
	(0.006)	(0.006)	(0.004)
Post-Discharge	0.102**	0.085**	0.017**
	(0.006)	(0.006)	(0.004)
Controls			
EMR t-1	0.178**	-0.015	-0.068†
	(0.044)	(0.048)	(0.040)
Customized IT	-0.019	-0.026	0.088
	(0.232)	(0.268)	(0.204)
RUCA	0.117**	0.100**	0.021*
	(0.014)	(0.015)	(0.010)
Operating Expense	-0.011**	-0.004	-0.003
	(0.003)	(0.004)	(0.003)
Admissions	0.027**	-0.016*	-0.030**
	(0.006)	(0.008)	(0.006)
Staffed Beds	-0.001**	-0.001**	-0.002**
	(0.000)	(0.000)	(0.000)
Nonprofit Hospital	-0.262**	0.125†	-0.237**
	(0.057)	(0.073)	(0.050)
Constant	13.335**	0.209	0.335**
	(0.144)	(0.160)	(0.117)
N	7,871	11,286	11,286
Hospitals	2,381	3,479	3,479
R^2 (overall)	0.072	0.685	0.704
χ^2	846.85**	12592.98**	13610.70**

Note. Communication variables represent poor communication. Positive coefficients for Models 2 and 3 represent satisfaction and loyalty.
† $p \leq 0.10$; $* p \leq 0.05$; $** p \leq 0.01$

Natural Experiment

The next robustness check was establishing a natural experiment. The objective for establishing a natural experiment is to again ensure identification of our effects on patient outcomes and communication. Hospitals and patient care are complex environments in which many confounding factors exist. For instance, heart attack mortality may be influenced by extraneous factors such as a person's lifestyle and family history. Therefore, we believe it is important to ensure we have strong identification for the effects in this study.

Our data lends itself to the formation of a natural experiment because we capture significant changes in the implementation of meaningful use technologies. Specifically, we establish a treatment effect indicating when a hospital increased their capabilities with meaningful use technologies. We determined an increase in capabilities by taking the average increase across all hospitals between 2011 and 2015. The calculated average increase was 6.53, which we rounded to 7.

The period prior to treatment was indicated by a 0 until the hospital increased their capabilities by 8 or more (i.e., a greater than average increase). The treatment was indicated by a 1 for each yearly observation following the greater than average increase. For example, suppose a hospital has 40 meaningful use capabilities in 2011, 42 in 2012, 42 in 2013, 55 in 2014, and 57 in 2015. We place the years 2011, 2012, and 2013 in the pre-treatment period. Years 2014 and 2015 are in the treated period. Hospitals that did not increase their meaningful use capabilities more than the average were used as a control with an indication of 0 across all yearly observations.

We analyze the treatment effect using a panel regression with fixed effects. We estimate the effect of the treatment on communication performance in Table A8, heart attack mortality in

Table A9, patient satisfaction in Table A10, and patient loyalty in Table A11. The results of our estimations provide that, with the exception of patient loyalty, increases in meaningful use capabilities significantly affect communication performance and patient outcomes. Table A11 provides that the treatment effect increases the percentage of patients who will not recommend the hospital. Although this effect is contrary to our primary analysis, we argue that the effect is consistent with our findings. The creation of our treatment effect does not account for the specific technologies experiencing increases in functionality. Therefore, hospitals may increase any of the four meaningful use technologies in our study and so long as the increase is greater than average it falls in the treatment category. Many hospitals in our data set follow a similar trajectory of increasing meaningful use capabilities such that they expand EMR documentation, CPOE, CDS, and HIE in that respective order. We also find that a significant proportion of our hospitals join the treatment group following implementation of CPOE and CDS functionalities. According to our initial analysis in the paper, our results provide that increases EMR documentation, CPOE, and CDS functionalities lead to less patient loyalty. Thus, the treatment effect heavily reflects the transition with these technologies. Taken together, the results from our natural experiment lend further support to the identification of the effect of meaningful use technologies on patient outcomes and communication performance.

Table A8. Natural Experiment Communication Performance

Variable:	Comm. Performance
Treatment	-0.104**
	(0.070)
Controls	
EMR t-1	0.088**
	(0.014)
Customized IT	-0.179*
	(0.092)
Operating Expense	-0.006**
	(0.001)
Admissions	0.011**
	(0.002)
Staffed Beds	0.000
	(0.000)
Nonprofit Hospital	0.024
	(0.050)
Constant	2.751**
	(0.070)
N	11,485
Hospitals	3,549
R^2 (overall)	0.011
χ^2	31.17**

$\dagger\ p \leq 0.10$; $*\ p \leq 0.05$; $**\ p \leq 0.01$

Table A9. Natural Experiment Heart Attack Mortality

Variable:	Mortality
Treatment	-0.273**
	(0.054)
Comm. Performance	0.073†
	(0.040)
Controls	
EMR t-1	0.311**
	(0.048)
Customized IT	0.024
	(0.038)
Operating Expense	-0.022**
	(0.004)
Admissions	0.030**
	(0.007)
Staffed Beds	-0.000
	(0.001)
Nonprofit Hospital	0.383*
	(0.178)
Constant	14.267**
	(0.280)
N	7,721
Hospitals	2,324
R^2 (overall)	0.006

χ^2	16.85**

$\dagger\ p \leq 0.10; *\ p \leq 0.05; **\ p \leq 0.01$

Table A10. Natural Experiment Patient Satisfaction

Variable:	Satisfaction
Treatment	-0.233** (0.046)
Comm. Performance	1.126** (0.033)
Controls	
EMR t-1	0.121* (0.059)
Customized IT	-0.256 (0.374)
Operating Expense	0.014** (0.005)
Admissions	-0.000 (0.010)
Staffed Beds	-0.001 (0.001)
Nonprofit Hospital	0.013 (0.238)
Constant	3.836** (0.278)
N	11,485
Hospitals	3,549
R^2 (overall)	0.432
χ^2	174.03**

$\dagger\ p \leq 0.10; *\ p \leq 0.05; **\ p \leq 0.01$

Table A11. Natural Experiment Patient Loyalty

Variable:	Loyalty
Treatment	0.106* (0.028)
Comm. Performance	0.732** (0.027)
Controls	
EMR t-1	0.061 (0.048)
Customized IT	-0.080 (0.310)
Operating Expense	0.013** (0.004)
Admissions	-0.013 (0.008)
Staffed Beds	-0.000 (0.000)
Nonprofit Hospital	-0.015

	(0.171)
Constant	2.028**
	(0.255)
N	10,494
Hospitals	3,413
R^2 (overall)	0.415
χ^2	97.89**

† $p \leq 0.10$; $* p \leq 0.05$; $** p \leq 0.01$

References

Allison, P. D. 2009. *Fixed Effects Regression Models*, Volume 160, SAGE Publications.