Information Systems Research

Publication details, including instructions for authors and subscription information:
http://pubsonline.informs.org

Do Electronic Health Records Affect Quality of Care? Evidence from the HITECH Act

Yu-Kai Lin, Mingfeng Lin, Hsinchun Chen

informs
http://pubsonline.informs.org/journal/isre/
INFORMATION SYSTEMS RESEARCH
Articles in Advance, pp. 1–13
ISSN 1047-7047 (print), ISSN 1526-5536 (online)

Do Electronic Health Records Affect Quality of Care? Evidence from the HITECH Act

Yu-Kai Lin,[a] Mingfeng Lin,[b] Hsinchun Chen[c]

[a] Center for Process Innovation, Department of Computer Information Systems, J. Mack Robinson College of Business, Georgia State University, Atlanta, Georgia 30303; [b] Information Technology Management, Scheller College of Business, Georgia Institute of Technology, Atlanta, Georgia 30308; [c] Department of Management Information Systems, Eller College of Management, University of Arizona, Tucson, Arizona 85721

Contact: yklin@gsu.edu, https://orcid.org/0000-0002-3928-9847 (Y-KL); mingfeng.lin@scheller.gatech.edu, https://orcid.org/0000-0003-3239-7412 (ML); hsinchun@email.arizona.edu (HC)

Received: July 11, 2015
Revised: April 19, 2016; January 2, 2017; February 7, 2018; May 22, 2018
Accepted: July 26, 2018
Published Online in Articles in Advance: March 12, 2019

https://doi.org/10.1287/isre.2018.0813

Abstract. The 2009 Health Information Technology for Economic and Clinical Health (HITECH) Act is landmark legislation that places electronic health record (EHR) technologies at the center of health system reform in the United States. However, despite their promises, studies in the EHR evaluation literature have found mixed evidence of EHRs' quality benefits. In contrast to existing research that has focused on EHR investments or adoption, we propose that its actual use should be the focus in evaluating the advantages of EHRs. We leveraged the meaningful use (MU) provisions of the HITECH Act to quantify different degrees of EHR use in a large and heterogeneous set of hospitals. The results provided evidence of EHRs' positive effects on quality of care and reconciled earlier mixed findings by showing that their benefits vary according to different levels of use and hospital characteristics. Specifically, we found that, although adopting EHRs had no significant quality impact, attaining MU of EHRs yielded a significant 0.19–0.43 percentage point increase in process quality of care, which further translates into significant societal benefits. The effect sizes were larger in disadvantaged (i.e., small and rural) hospitals, suggesting the potential of EHRs in mitigating the disparities in the quality of healthcare. This study contributes to this ongoing discussion and the literature on EHR evaluations and use of information systems. Implications for research, policy, and practice are discussed.

History: Anandhi Bharadwaj, Senior Editor; Prasanna Tambe, Associate Editor.
Supplemental Material: The online appendices are available at https://doi.org/10.1287/isre.2018.0813.

Keywords: HITECH • meaningful use • electronic health records • healthcare • information systems adoption • information systems use

1. Introduction

The 2009 Health Information Technology for Economic and Clinical Health (HITECH) Act is landmark legislation designed to modernize the U.S. healthcare system by transitioning from paper-based practice to one that uses information technologies (IT) to facilitate care. Propelled by this legislation, the nation's healthcare industry has seen considerable adoption of electronic health records (EHRs) in the past decade.[1] National surveys have shown that the adoption rate of EHR systems among U.S. hospitals increased from 9.0% in 2008 to 80.5% in 2015 (Adler-Milstein et al. 2017). Similarly, quality-enhancing technologies, such as the clinical decision support system (CDSS), computerized physician order entry (CPOE), and electronic medication reconciliation, are now considered standard components of an EHR system rather than optional additions (Blumenthal and Tavenner 2010).

Although significant progress has been made in digitizing the delivery of care, evidence of the EHR system's effects on care quality remains mixed. Multiple review articles have reported that there is a large gap between the postulated and realized quality benefits of EHRs (e.g., Jones et al. 2014). Among the small set of medical institutions that observed positive effects from EHRs (Devaraj and Kohli 2003), there is little evidence that these effects may be generalized beyond those specific institutions. Considering the nearly $30 billion federal budgets in HITECH and the substantial cost and time involved in implementing an EHR system in clinical practice, many policymakers and healthcare practitioners are concerned about the elusiveness of the quality benefits of their EHR investments.

The lack of robust and generalizable evidence of the quality benefits of EHRs may be attributable, in part, to the distinction between adoption and use in prior EHR evaluations. Most prior studies, which are discussed in detail later, have measured the effects of EHR adoption or investments rather than actual use and often have assumed implicitly that the system will be used properly and effectively after adoption. However, in practice, many factors exist that could inhibit or hinder EHR use after adoption, including healthcare professionals' resistance to technology (Lapointe and Rivard 2005) and inadequate organizational or environmental complementarities (Dranove et al. 2014). Because of these barriers to actual use, EHR technologies may not realize the effects intended despite their presence in a hospital. Many information systems (IS) and operations management studies have found that the degree and effectiveness of postadoption system use have decisive effects on organizations' ability to realize IT business value (Hsieh et al. 2011, Yu et al. 2015, Kim et al. 2016, Burton-Jones and Volkoff 2017). Looking specifically at the healthcare context, Devaraj and Kohli's (2003) pioneering work demonstrated the critical role of IT use in a hospital's quality and profitability in a system of eight hospitals; however, the researchers cautioned that larger and more heterogeneous samples are needed in future research.

Indeed, there are significant variations in hospitals' characteristics, such as size and geographical location. These variations affect not only what types of medical care each hospital provides but also the way in which a hospital appropriates its investments in technologies such as EHRs (Agarwal et al. 2010). Some hospitals, such as Brigham and Women's Hospital in Boston and Vanderbilt University Medical Center in Nashville, possess substantial resources, provide comprehensive care, and have had decades of experience with EHR systems even before HITECH. At the other end of the spectrum, there are small and rural hospitals that face significant fiscal and human capital constraints and were slow to adopt EHR systems (DesRoches et al. 2012). Although hospital characteristics are known to be related, it is of significant interest to uncover the varied quality outcomes of EHR investments in diverse hospital settings to guide future business and regulatory plans for health IT.

In this study, we leverage HITECH's meaningful use (MU) provisions of EHRs to empirically examine the quality effect of EHR use and its heterogeneity in a national sample of hospitals.[2] Because of the challenges in collecting organizational-level IT use data, large-scale inferential tests of the roles of postadoption system use are very rare in the IT business value literature, especially in the healthcare context. The protocols of the MU regulation naturally create a distinction between EHR adoption and different degrees of use. The regulation specifically envisions and implements multiple stages of MU. Each MU stage, defined by a set of specific objectives, is designed so that EHR use at the point of care is more relevant and comprehensive than the previous one. Broadly speaking, the goal of these legislative rules is consistent with the notions of *effective use* (Burton-Jones and Volkoff 2017) and the *feature-centric view of technology use* (Jasperson et al. 2005) in the IS literature. They enable an objective, formal, and context-specific metric of organizational IT use in the healthcare context.

Our study is based on a sample of 2,507 acute-care hospitals and reveals that the degree of EHR use can explain the discrepancy in the quality benefits of EHR technologies. We find that EHR adoption had no significant impact on quality, but the achievement of stages 1 and 2 MU (henceforth, MU1 and MU2) yielded a significant 0.19–0.43 percentage point increase in process quality of care. Our results further suggest that, once the economic barriers to EHR adoption were removed, disadvantaged (i.e., small and rural) hospitals could garner a greater magnitude of quality improvement from meaningful EHR use than their larger and urban counterparts. Overall, our paper contributes by offering potential explanations to reconcile the mixed quality outcomes in the EHR evaluation literature, highlighting the heterogeneity of actual system usage and hospital setting in appropriating EHR investments and demonstrating the policy impacts of HITECH.

2. Research Background and Context

2.1. Measuring Quality Effects of EHRs in Hospitals

Given EHRs' potential to transform healthcare delivery, reduce costs, and minimize errors, there has been a large and growing literature on their effects, including research that has focused on hospital-level quality effects. Table 1 shows a set of representative works designed to measure EHRs' quality impacts on U.S. hospitals. In addition to reaffirming the mixed effects shown in prior reviews of EHR evaluations (e.g., Jones et al. 2014), two empirical issues emerge from Table 1.

First, with the exception of Adler-Milstein et al. (2015), nearly all prior studies are based on data from 2010 or earlier, when the rate and degree of EHR use were low. As U.S. health IT practices have undergone dramatic changes since 2010 because of HITECH, there is now a significant need to consider more recent data in empirical analyses. With this more recent data, Adler-Milstein et al. (2015) found a positive relation between EHR adoption and hospital quality performance. More important, they found that the relationship was stronger in the second half of their panel data (2011 and 2012). One potential explanation for this temporal effect is that beginning in 2011, hospitals began to comply with the federal MU requirements. As such, it is possible that MU, rather than the mere adoption of the technology, is the source of EHRs' effects on quality.

Second, we noticed that very few studies in the literature considered actual EHR use. One reason is that actual IT usage data are considerably more difficult to obtain than adoption data (Zhu and Kraemer 2005, Appari et al. 2013). Defining and measuring EHR use are particularly vexing because the technology serves several types of users (e.g., clinicians, nurses, technicians, administrators, and so on) and offers many different functions, including health information and data repositories,

Table 1. Selected Studies on the Quality Effects of EHRs in U.S. Hospitals

Study	Data period	Sample size	Main dependent variables	Main independent variables	Finding (effect of health IT)
Adler-Milstein et al. (2015)	2009–2012	2,528	Process quality and patient satisfaction	Adoption of EHR	Positive
Agha (2014)	1998–2005	3,880	Outcome quality	Adoption of EMR and CDS	Nonsignificant
Appari et al. (2013)	2006–2010	3,921	Process quality	EHR capability	Positive
Appari et al. (2012)	2009	2,603	Process quality	Adoption of CPOE and eMAR	Nonsignificant
Miller and Tucker (2011)	1995–2006	3,764	Outcome quality	Adoption of EMR	Positive
Himmelstein et al. (2010)	2003–2007	~4,000	Process quality	Degree of computerization	Nonsignificant
Jones et al. (2010)	2004, 2007	2,086	Process quality	EHR capability	Mixed
McCullough et al. (2010)	2004–2007	3,401	Process quality	Adoption of EHR and CPOE	Mixed
Devaraj and Kohli (2003)	Unknown	8	Outcome quality	Use of DSS	Positive

Note. CDS, clinical decision support; CPOE, computerized physician order entry; DSS, decision support system; EHR, electronic health records; eMAR, electronic medication administration record; EMR, electronic medical records.

results management, order management, decision support, electronic communication and connectivity, and so forth. To our knowledge, there is not yet a large, public data source that details actual EHR use in a national sample of U.S. hospitals. Thus, prior research has had to resort to small samples of hospitals and "lean measures" of system use, such as CPU time, that offer limited insights about the way in which use is related to tasks (Devaraj and Kohli 2003, Burton-Jones and Straub 2006).

Taken together, these two issues point to the research gap in measuring the quality effects of EHR use in a large sample of hospitals with usage measures tied closely to the clinical context. The MU provisions of HITECH provide a unique and useful instrument to mitigate this gap as we discuss next.

2.2. Defining Meaningful Use

As its name suggests, the goal of the MU regulation "is not adoption alone, but 'meaningful use' of EHRs—that is, their use by providers to achieve significant improvements in care" (Blumenthal and Tavenner 2010, p. 501). Through inclusive and open processes with extensive public and professional input, the MU regulation implements multiple stages of MU. When hospitals achieve a higher MU stage, it means they (1) use EHR applications more intensively at the point of care and (2) use more advanced applications in their EHR system. MU1 and MU2 began in 2011 and 2014, respectively.[3] Overall, MU1 has 14 core objectives and 10 menu objectives, whereas MU2 has 16 and six, respectively. A hospital must achieve all of the core objectives and half of the menu objectives to comply with the MU regulation.

The hallmark of the MU regulation is that, to quantify MU compliance, each objective is accompanied by a specific, objective, and measurable EHR use requirement. For example, rather than simply requiring hospitals to include CPOE in their EHR systems, the CPOE objective in MU1 specifies the following measure (emphasis added): "*More than 30% of all unique patients* with at least one medication in their medication list admitted to the hospital have at least one medication order entered using CPOE." In MU2, the respective CPOE use requirement becomes more demanding as it not only increases the threshold for all medication orders from 30% to 60% but also expands to cover at least 30% of laboratory and radiology orders. Tables A1 and A2 in Online Appendix A summarize the detailed objectives, measures, and relevant health IT applications in MU1 and MU2.

The regulation also comprises several features that encourage hospitals to archive and maintain MU. Medicare provides incentive payments annually for up to four years, and hospitals may obtain higher payments if they demonstrate MU earlier. After attesting to MU, hospitals must maintain and report their MU status in ensuing years to obtain the recurring payments. Although MU attestations are based on self-reports, recipients of the MU incentive payments are required to maintain supporting documents and screenshots for auditing purposes for six years postattestation. Beginning in 2015, hospitals that do not use EHRs meaningfully have been penalized by a mandated Medicare payment adjustment that increases over time. In summary, these incentive mechanisms encourage hospitals to attain the MU criteria sooner rather than later. As there is no opt-out option and the vast majority of hospitals in the United States are subject to this regulation, it enables large-scale inferences such as ours.

3. Conceptual Model and Hypotheses

The literature on IS use contains substantial discussions of why and how system use is related to organizational outcomes. Many studies have found that the nature of business processes can exert considerable influence on the business value of IT (Mukhopadhyay et al. 1997, Gattiker and Goodhue 2005, Banker et al. 2006, Hsieh et al. 2011). This is particularly true for systems such as enterprise resource planning, electronic data interchange, and EHRs, which promise integrated business processes and data access throughout the value chain. We adapt the IT business value model from Melville et al. (2004) to conceptualize the relationship between EHR use and a hospital's process quality of care (Figure 1).

To summarize, we argue that (1) the quality impact of EHR use is manifested from improved clinical workflow performance; (2) the EHR quality-improving process is mediated by the healthcare setting and physicians' resistance to IT in the focal hospital; and (3) the HITECH Act, as a factor in the macroenvironment, provides resources and guidelines to shape EHR use in the focal hospital. We unpack this conceptual model and develop specific hypotheses as follows.

3.1. Quality Effects of EHR Use in Hospitals

Many healthcare practitioners and researchers argue that any quality improvement interventions, technology-based (e.g., EHR systems) or otherwise (e.g., surgical safety checklists), are advantageous only when they lend adequate support or improvement to clinical workflows. In general, clinical workflow refers to the sequence of care-related mental and physical tasks in the management of a patient visit. These tasks can occur sequentially or simultaneously at several levels: within a clinician's mind, between members of a care team, and across hospital boundaries. Clinical workflows can vary significantly, depending on the nature of the patient visit and the context of the care setting, but five high-level cognitive processes are prevalent: *sensemaking*, *planning*, *monitoring*, *decision making*, and *coordination* (Mickelson et al. 2016). As summarized in Table 2, these cognitive processes are promising venues for clinical quality improvement. Indeed, although achieving effective care entails many different factors, the National Research Council (2009) found that none is more important than the effective use of information and cognitive support for healthcare professionals in clinical workflows.

EHR systems, as prescribed under the HITECH Act, comprise several data repositories and applications to support these clinical workflow tasks. For example, the *clinical data repository* allows clinicians to electronically enter and access patient records to establish a timely and accurate understanding of the patient's medical history. Having a central clinical data repository also promotes a shared, consistent view regarding the patient's needs among different members of a care team. *CDSS* is another common EHR component, which is designed to apply a set of clinical rules or models on patient data retrieved from a clinical data repository and propose appropriate clinical plans to manage the patient's current condition better. When confronted with uncertainty, time pressure, and trade-offs, the use of CDSS can improve the decision-making process and enhance the performance of clinical workflows by allowing medical professionals to explore different clinical options effectively. Once a clinician has determined the best course of action, *CPOE* allows the clinician to place orders electronically, and the orders will be transmitted directly to the recipient. CPOE supports clinical workflows in two ways. On the one hand, it verifies and alerts clinicians if there could be potential issues with the orders, such as adverse drug–drug interactions, allergic reactions, and overdosing. On the other hand, it permits efficient information flow and reduces delay and waste during the process of coordination among members of the care team. Along with clinical data repository, CDSS, and CPOE, *specialized applications*, such as laboratory IS, physician documentation, and electronic medication reconciliation, enhance the hospital's capability in integrating information, monitoring events, and detecting anomalies in clinical workflows.

From the lenses of affordance actualization and effective use (Strong et al. 2014, Burton-Jones and Volkoff 2017), meaningful use of these EHR components in

Figure 1. Conceptual Model

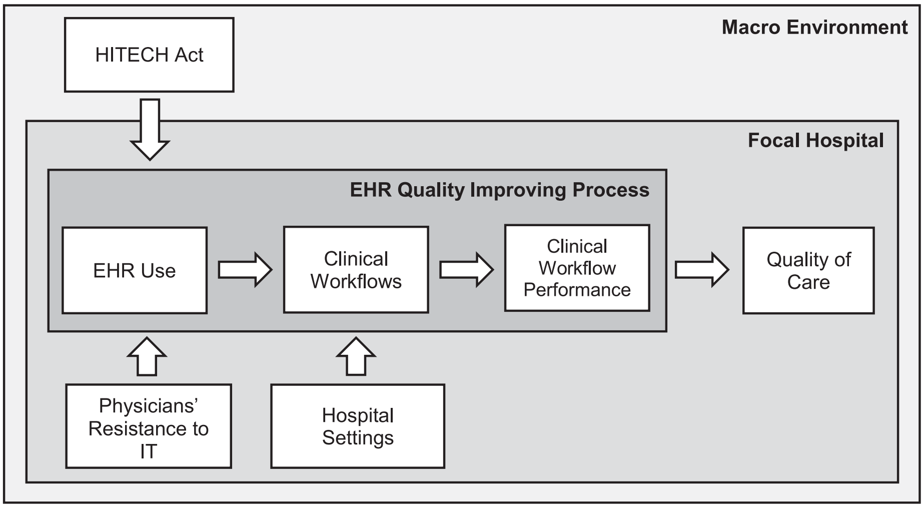

Table 2. Generic Cognitive Processes in Clinical Workflows

Process	Definition	Examples in hospital care	Supporting modules of EHRs
Sensemaking	Deliberate, retrospective efforts to understand and explain events by gathering information, adapting mental models, and story-building	• Clinician interacts with patient to understand why the patient is admitted to the hospital • Clinician reviews medical charts to explain the progression of the patient's condition	CDR, HIE, LIS, PD, RIS
Planning	Generating and adapting methods for action to transform current state into future state desired	• Clinician prescribes surgical patient warfarin or other blood thinners to prevent blood clot formation • Clinician provides diabetic patient with diet and medication instructions at discharge	CDR, CDSS, EMR
Monitoring	Maintaining awareness and control of system state and its progression	• Clinician screens for signs of blood clot (abnormal pain, sweating, etc.) after patient has undergone surgery • Nurse checks patient's vital signs on the bedside monitor	CDR, CDSS
Decision making	Commitment to one or more options or actions after purposeful search and mental simulation	• Clinician determines that patient has stage B heart failure because cardiac dysfunction is present • Clinician prescribes beta blocker to patient with heart attack based on guideline recommendations	CDR, CDSS, CPOE
Coordinating	Managing interdependencies across members of a team with overlapping, common, and interacting activities, roles, and goals	• Laboratory technician follows a laboratory order placed by clinician and collects specimen from patient • Patient receives a prescription from clinician and fills the prescription at pharmacy	CDR, CPOE, LIS, HIE, PD, PP, RIS

Note. CDR, clinical data repository; CDSS, clinical decision support system; CPOE, computerized physician order entry; EHR, electronic health record; EMR, electronic medication reconciliation; HIE, health information exchange; LIS, laboratory information system; MU, meaningful use; PD, physician documentation; PP, patient portal; RIS, radiology information system.

clinical workflows should help hospitals attain improved workflow performance, leading to improved hospital quality outcomes. Meanwhile, an EHR system will not yield the intended benefits unless its quality-enhancing affordances are actualized by the users. Because of the hierarchical nature and professional norms of healthcare, medical professionals' resistance to technology has been pervasive and well documented (see, e.g., Lapointe and Rivard 2005, Kane and Labianca 2011, and Mishra et al. 2012). Studies found that EHR implementation often led to undesirable user reactions; some are passive, such as apathy and circumvention, and others are aggressive, including vandalism and harmful use (Lapointe and Rivard 2005). These resistance behaviors not only render investments in EHRs futile but also affect patient care adversely (Kane and Labianca 2011).

In anticipation of these behavioral challenges in clinical practice, the MU provisions of HITECH impose mandates on the minimum degrees of data collection and application use in an EHR system to ensure that EHR use is sufficiently embedded in clinical workflows. This idea is consistent with Melville et al. (2004, p. 310), who predicted that "the macro environment shapes the degree to which firms can apply IT for organizational improvement." Although, traditionally, clinicians have not responded well to policies that threaten their independence and autonomy (Mishra et al. 2012), studies found that the financial incentives and penalties in HITECH have been very effective in nudging hospitals and healthcare professionals toward the use of EHRs (Adler-Milstein and Jha 2017).

Furthermore, a greater degree of EHR use should lead to better process quality and task performance as shown in many prior studies (Mukhopadhyay et al. 1997, Hsieh et al. 2011, Kim et al. 2016). The measurements of, and the distinction between, MU1 and MU2 provide objective, hospital-level signals for the level and commitment of postadoptive EHR uses in clinical workflows. Although MU1 represents a lower bar, it is still far from an easy undertaking. Jha et al. (2010) point out that, before HITECH, only approximately 2% of U.S. hospitals met all MU1 criteria. In MU2, hospitals are asked to extend the depth and breadth of EHR use further in their daily practice. From the theories of *enhanced use* (Bagayogo et al. 2014) and effective use (Burton-Jones and Volkoff 2017), hospitals can reap more benefits from their EHR investments if the technological features (affordances) are used better in clinical workflows. Thus, greater EHR use, as in MU1 and MU2, should allow healthcare organizations to provide better quality of care because of the EHR-enabled cognitive support in clinical workflows. Considering the MU rules and their effects on clinical workflows, we propose the following hypotheses:

Hypothesis 1a. *Attainment of MU1 has a positive effect on quality in healthcare organizations.*

Hypothesis 1b. *Among the hospitals that have achieved MU1, attainment of MU2 is related to additional quality improvement.*

3.2. Heterogeneity of the Quality Impact of EHR Use

IT business values in general and EHR quality impacts in particular are expected to be heterogeneous across organizations because there are numerous organizational-level mediating factors (Kohli and Grover 2008). In the healthcare context, the size and rurality of a hospital are expected to influence its clinical workflows as well as the effectiveness of the EHR quality-improving process. Although size and rurality are often considered and controlled in prior EHR evaluations, their relationship with the EHR quality effects has received much less attention.

Although the IS literature has suggested that an organization's size and location can mediate IT business values, there are conflicting theoretical arguments about the direction of the effect. With respect to organizational size, some researchers have adopted the resource-based view and suggested that large firms have more slack resources to facilitate IT implementation and use (Damanpour 1996). Other researchers have argued from the perspective of organizational behavior and suggested that large firms' structural inertia may hinder IT use (Zhu and Kraemer 2005). With respect to organizational location, rural hospitals may have fewer resources to promote IT use, but this resource constraint, together with the distance to urban areas, also could be an incentive for them to digitize their businesses (Yaraghi et al. 2015).

When juxtaposing these competing arguments in our research context, those from the resource-based perspective seemed less plausible for three reasons. First, the incentive payments in the MU regulation are designed to subsidize the costs incurred during EHR acquisition, implementation, and use (Washington et al. 2017). These payments are provided annually for up to four years with an initial amount of approximately $2 million. The payments should offset the difference in hospitals' financial ability to promote postadoptive EHR use. Second, several federal agencies have mobilized resources to mitigate challenges related to EHR capital, IT labor, and broadband access in rural areas (Lynch et al. 2014). Specifically, the U.S. Department of Agriculture connects rural healthcare providers with capital loan programs and grants to support the purchase and installation of EHRs. The Departments of Labor and Education offer rural health IT job search and training services, and the Federal Communications Commission facilitates rural healthcare providers' access to broadband services through the Healthcare Connect Fund. All of these policy efforts lead to the intriguing recent phenomenon that rural EHR adoption rates surpass those in urban areas (Whitacre 2015). Finally, the Office of the National Coordinator for Health IT has established many Regional Extension Centers (RECs) across the nation to advise and assist providers in implementing EHRs and MU. Companies in other business settings often need to hire technical and business consultants when implementing large enterprise systems to support best-practice deployment. This gives large, urban firms a significant advantage in their system implementation. In sharp contrast, in our healthcare context, RECs provide such services and expertise at heavily discounted rates—sometimes free of charge—to small and rural hospitals (Blumenthal 2011). These policies provide extra (exogenous) incentives for small and rural area hospitals to adopt EHRs and achieve MU.

In addition to these external resources, there are also reasons *internal* to the hospitals that suggest small and rural area hospitals can benefit more from EHR adoptions and MU. Specifically, *organizational inertia* and *more complicated clinical workflows* in large and urban hospitals pose a greater hurdle to their assimilation of EHRs. It is generally agreed that larger organizations tend to face stronger organizational inertia during postadoption IT use (Zhu and Kraemer 2005). Coupled with the issue of technology resistance discussed earlier, it is even more difficult for large hospitals to overcome this inertia to benefit from EHRs. In contrast, small and rural hospitals are more likely to be agile and respond positively and creatively to challenges and opportunities. Singh et al. (2012) corroborated this, in part, as they found that rural healthcare providers are more likely than are their urban counterparts to use a broader range of EHR capabilities. Because small and rural hospitals provide fewer services, their clinical workflows may be less complicated, which, in turn, reduces the difficulties of integrating EHRs into clinical workflows (Gattiker and Goodhue 2005) when compared with large and urban hospitals.

In summary, small and rural hospitals would be more likely than large and urban hospitals to obtain the expected quality benefits from EHR use in the HITECH era. This led to the following hypotheses.

Hypothesis 2a. *Attainment of MU1 has a greater positive effect on quality in small and rural healthcare organizations than in their counterparts.*

Hypothesis 2b. *Among hospitals that have achieved MU1, attainment of MU2 has a greater positive effect on quality in small and rural healthcare organizations than in their counterparts.*

Table 3. Variable Description

Variable	Description
Quality	A composite score of the process quality of care
Adoption	Whether the hospital has adopted an EHR system
MU1	Whether the hospital has demonstrated MU1
MU2	Whether the hospital has demonstrated MU2
Size	Number of licensed beds (log transformed)
Patientthroughput	Number of inpatient discharges (log transformed)
Medicareratio	Ratio of Medicare inpatients discharged
Medicaidratio	Ratio of Medicaid inpatients discharged
Casemix	Relative severity of the patient base
Competitionintensity	Herfindahl–Hirschman index in a hospital referral region

4. Research Methods

4.1. Data and Variables

We construct a panel data set from 2011 to 2014 with yearly hospital-level observations. Consistent with prior studies (e.g., Furukawa et al. 2010 and Appari et al. 2013), we investigate nonfederal acute-care hospitals in 50 states and the District of Columbia and use the Medicare provider number as a common identifier to integrate hospital-level information from different data sources. Table 3 summarizes the variables in this study, and Table 4 provides the descriptive statistics.

Hospitals' process quality is our dependent variable (*quality*). The process aspect of quality is consistent with evidence-based medicine, and government agencies, accreditation organizations, and prior health IT research have used it widely because it is actionable, targets long-term benefits, influences patient outcomes, and requires less risk adjustment (Rubin et al. 2001). We obtain the quality measure from the Joint Commission (JC). A hospital must be accredited by the JC based on its process quality measures to obtain a service license and qualify as a Medicare-certified provider. We focus on three specific clinical conditions to calculate process quality: acute myocardial infarction (AMI), heart failure, and pneumonia. These are among the most common and expensive conditions treated in U.S. hospitals and were frequently considered in many prior studies (e.g., McCullough et al. 2010 and Appari et al. 2013). Because there are three clinical conditions, each with multiple specific measures, we follow the JC's methodology and measured *quality* as the average of all individual measures weighted by the number of eligible patients in each measurement. Therefore, *quality* is a composite score that represents the degree (in percentage) to which a hospital provides the best-known clinical practice.

Our main independent variables are hospitals' *adoption*, *MU1*, and *MU2* of EHR technology. We use Healthcare Information and Management Systems Society's Analytics Database (HADB) data, which have been used extensively in prior health IT research, to determine *adoption* and the public MU attestation data for *MU1* and *MU2*. Most studies have determined the status of EHR adoption in a hospital by verifying whether the hospital has adopted a set of desired health IT applications (McCullough et al. 2010, Dranove et al. 2014). To maintain a consistent scope of EHR adoption and use, we code *adoption* based on the EHR applications specified in the MU regulation. We use only the core objectives in MU1 because not all hospitals chose the same menu objectives or proceeded to attain MU2. We set *adoption* as one if HADB showed that a hospital adopted all EHR applications relevant to the MU1 core objectives. On the other hand, the MU regulation data indicate when, if ever, a hospital achieved MU1 and MU2. Taken together, Table 5 displays the variations over time in the three key independent variables in our panel data. In the total of 2,507 unique hospitals in our sample, the vast majority achieved MU1 by 2013 and nearly half of these went on to attest to MU2 in 2014.

To capture the heterogeneity among hospitals, we control for several internal and external factors. We use the number of licensed beds to represent *size* and the number of annual discharges to represent *patientthroughput*. We take the logarithm of these two variables because their values are highly variable and skewed. Because the MU regulation's financial incentives are made through Medicare and Medicaid, we also control for the proportions of Medicare and Medicaid patients discharged among the total discharged (*Medicareratio* and *Medicaidratio*). We consider the complexity of a

Table 4. Descriptive Statistics

		Mean	Standard deviation	1	2	3	4	5	6	7	8	9
1	*Quality*	97.927	2.837									
2	*Adoption*	0.718	0.45	0.113								
3	*MU1*	0.677	0.468	0.105	0.323							
4	*MU2*	0.113	0.317	0.123	0.171	0.246						
5	*Size*	5.172	0.767	0.216	0.173	−0.018	0.024					
6	*Patientthroughput*	8.995	0.901	0.248	0.201	−0.022	0.018	0.936				
7	*Medicareratio*	0.355	0.115	−0.089	−0.084	−0.009	−0.033	−0.359	−0.403			
8	*Medicaidratio*	0.135	0.098	−0.101	−0.085	−0.059	−0.049	0.005	−0.01	−0.165		
9	*Casemix*	1.494	0.258	0.254	0.153	0.007	0.039	0.652	0.655	−0.28	−0.111	
10	*Competitionintensity*	0.163	0.147	0.007	0.009	0.014	0.02	−0.046	−0.045	0.155	0.039	−0.005

Table 5. Temporal Variation of Key Independent Variables in the Sample

	Year			
EHR	2011	2012	2013	2014
Adoption = 1	1,427	1,968	2,398	2,451
MU1 = 1	502	1,491	2,292	2,376
MU2 = 1	0	0	0	1,094

hospital's patient population using the transfer-adjusted case mix index (*casemix*). Finally, we account for the intensity of local competition (*competitionintensity*) in our empirical models using the Herfindahl–Hirschman index based on the number of inpatient discharges from each hospital in a hospital-referral region (HRR).

4.2. Empirical Strategy

To distinguish the effects of EHR adoption and MU, we make a mild assumption that there is no delayed MU attestation, in that we assume hospitals would proceed to MU1/MU2 attestation and obtain the incentive payments from the Centers for Medicare & Medicaid Services once they met the regulatory criteria. This assumption is consistent with a basic premise in accounting and finance: present earnings generally are preferable to future earnings, especially given the low cost of the attestation procedure. It is also realistic given the financial burden on hospitals of acquiring and implementing an EHR system and the financial subsidies available for MU achievement. Under that assumption, we estimate the following model:

$$\begin{aligned} Quality_{it} = \alpha_0 + \alpha_1 Adoption_{it} + \alpha_2 MU1_{it} + \alpha_3 MU2_{it} \\ + X'_{it}\delta + c_i + \alpha_4 Trend_t + \epsilon_{it}. \end{aligned} \tag{1}$$

Subscripts i and t index individual hospitals and time periods, respectively. $Quality_{it}$ is the process quality score of hospital i at time t. $Adoption_{it}$, $MU1_{it}$, and $MU2_{it}$ are indicators of the respective EHR adoption and use status. To address hospital-related confounders, X_{it} is a vector of the control variables discussed earlier, and c_i is the fixed effects (FEs) that account for time-invariant, hospital-level unobserved effects. $Trend_t$ is a linear trend variable. We use the time trend rather than yearly FEs because of a data limitation: MU2 begins in 2014, which also is the last period of our panel data.[4] This prevents us from using yearly FEs to estimate the effect of MU2 because it would be absorbed in the 2014 FE. To alleviate concerns related to this specification, we report the results from another empirical model that excludes $MU2_{it}$ but includes yearly FEs:

$$\begin{aligned} Quality_{it} = \beta_0 + \beta_1 Adoption_{it} + \beta_2 MU1_{it} \\ + X'_{it}\xi + c_i + \nu_t + \mu_{it}, \end{aligned} \tag{2}$$

where v_t is the yearly FEs.

Although we can address many identification issues through FEs and multiple specifications, some sources of endogeneity may still remain, and the results should be interpreted accordingly. Here, we acknowledge three potential issues in our estimation. First, there could be unobservable variables that simultaneously influence quality of care and whether/when hospitals choose to adopt EHRs or achieve MU. Our estimates of *adoption*, *MU1*, and *MU2* would be biased upward (downward) if these unobserved variables are positively (negatively) related to quality of care. As an example, hospitals might have internal quality-improvement initiatives that would affect MU attainment and quality of care simultaneously. To mitigate the concerns about omitted variable bias, we control for an array of hospital attributes and examine only the quality variations within each hospital at the point it achieves adoption/MU1/MU2. We also test our model using an instrumental variable approach, which we report in Section 5.2, and it generates qualitatively similar conclusions. Second, hospitals could provide a fraudulent MU status to obtain the Medicare incentive payments. However, these are, at best, isolated cases because the MU regulation has auditing mechanisms to ensure the veracity of MU attainment. Furthermore, such measurement errors would, in fact, work *against* the relations that we study and result in an attenuation bias in the estimated coefficients of *MU1* and *MU2*. Finally, multicollinearity could be a threat to our estimation. *Adoption*, *MU1*, and *MU2* are highly correlated because they are a sequence of dependent behaviors. We evaluate whether multicollinearity is a concern through a variance inflation factor (VIF) analysis. We find that all variables have a VIF less than 10 (max = 7.63 from the collinearity between *size* and *patientthroughput*), suggesting that multicollinearity may not be a significant issue in our analyses (Mason and Perreault 1991).

5. Results

5.1. Main Results

Columns (A)–(E) of Table 6 show the main results of our empirical analysis. Columns (A)–(C) show the estimates from model (1) with hospital FEs and the trend variable, and columns (D) and (E) are the results from model (2) with hospital and yearly FEs. Because adoption, MU1, and MU2 are sequentially dependent, the estimate for *MU1* (and *MU2*) should be interpreted as an additional performance gain on top of what had been realized from *adoption* (and *MU1*). We find that *adoption* has an insignificant coefficient, and the coefficients for *MU1* and *MU2* are positive and significant. The effect size and direction of *adoption* and *MU1* are consistent across different specifications regardless of how we incorporate the time effect, which gives us some confidence in the estimate of *MU2* shown in column (C). Interestingly, the estimate of *MU2* (0.186) is considerably smaller than that

Table 6. Regression Results (Dependent Variable Is *Quality*)

	Main analysis					Robustness check		
	(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)
Adoption	0.138 (0.132)	0.134 (0.131)	0.163 (0.135)	0.151 (0.131)	0.147 (0.131)	0.016 (0.114)		
MU1		0.405*** (0.081)	0.428*** (0.082)		0.347*** (0.079)		0.236*** (0.075)	
MU2			0.186** (0.088)					0.178* (0.095)
Size	−0.290 (0.314)	−0.278 (0.316)	−0.289 (0.320)	−0.319 (0.322)	−0.310 (0.324)	−0.297 (0.317)	−0.010 (0.472)	−0.110 (0.472)
Patientthroughput	0.141 (0.388)	0.166 (0.389)	0.192 (0.390)	0.435 (0.402)	0.459 (0.403)	0.130 (0.390)	−0.332 (0.457)	−0.238 (0.630)
Medicareratio	−1.520 (1.729)	−1.436 (1.726)	−1.256 (1.728)	−0.129 (1.778)	−0.026 (1.775)	−1.550 (1.732)	−2.865** (1.278)	−1.792 (1.608)
Medicaidratio	0.908 (0.990)	0.869 (0.983)	0.845 (0.984)	1.315 (0.984)	1.294 (0.979)	0.906 (0.996)	0.448 (1.005)	0.785 (1.243)
Casemix	1.205** (0.598)	1.202** (0.597)	1.196** (0.597)	0.813 (0.587)	0.827 (0.587)	1.207** (0.598)	1.207** (0.557)	0.752 (0.805)
Competitionintensity	−0.111 (3.546)	−0.134 (3.533)	−0.754 (3.448)	−6.527* (3.600)	−6.560* (3.584)	−0.143 (3.532)	3.294 (3.585)	2.562 (4.753)
Trend	0.367*** (0.028)	0.239*** (0.037)	0.205*** (0.045)			0.379*** (0.027)	0.300*** (0.041)	0.385*** (0.043)
Hospital fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	No	No	No	Yes	Yes	No	No	No
Instrumental variable	No	No	No	No	No	Yes	Yes	Yes
Cragg–Donald statistic	—	—	—	—	—	74.93	1,444.42	2,215.68
Adjusted R^2	0.585	0.587	0.587	0.592	0.594	0.584	0.631	0.683
Number of hospitals	2,507	2,507	2,507	2,507	2,507	2,507	2,121	2,021

Notes. Robust standard errors are shown in parentheses (clustered on hospital). Across different specifications, the results show that achievement of MU1 and MU2 were associated with significant positive quality effects, and adoption had a positive but insignificant effect. This indicates the role and importance of use.

***$p < 0.01$; **$p < 0.05$; *$p < 0.10$.

for *MU1* (0.428). We note that the literature has also documented the diminishing marginal returns between the scale and benefits of IT (Hitt et al. 2002) and between the time elapsed since implementation and IT benefits (Gattiker and Goodhue 2005). In summary, our main results show that MU1 and MU2 attainments are significantly related to positive quality effects, which support Hypotheses 1a and 1b.

Although these results provide evidence that MU has a statistically significant effect on care quality, a natural question is whether the effect is economically meaningful. We draw from the medical literature and recent inpatient death statistics to provide suggestive evidence of the practical importance of this effect. The medical literature shows a strong association between process quality and in-hospital mortality. According to Peterson et al. (2006), every 10-percentage-point increase in process quality is associated with a 10-percentage-point decrease in the likelihood of in-hospital mortality (adjusted odds ratio = 0.90). In model (1), the effects of *MU1* and *MU2* were 0.428 and 0.186, respectively. With 715,000 in-hospital deaths annually in the United States (Hall et al. 2013), a 0.428 (0.186) increase in process quality from EHR use translates roughly to 3,060 (1,330) lives saved annually.

5.2. Robustness Checks

To examine the robustness of these results, we consider two alternative empirical specifications. First, we consider an alternative measure of EHR use. Our main analysis characterized hospitals' use of EHRs based on two dichotomous variables, that is, *MU1* and *MU2*. However, in practice, hospitals can (and often do) go beyond the minimum degrees of data collection and application use specified in the MU1/MU2 rules. As such, it would be useful to construct a continuous variable to represent the degree of EHR use and estimate its effect on quality. Details of this analysis and its results are in Online Appendix B. Consistent with our main analysis, we find a positive and significant estimate for this alternative measure of EHR use.

In our second robustness check, we conduct an instrumental variable estimation to address concerns of endogeneity in our main analysis. In this analysis, we construct an instrumental variable, HRR-level MU saturation, which represents the percentage of *other* hospitals in an HRR that have attained MU1.[5] A valid instrument needs to satisfy two criteria: it should be correlated with the endogenous variable but uncorrelated with the error term conditional on other explanatory variables. In this regard, the HRR-level MU saturation should be a valid instrument because social contagion theory and existing empirical evidence on the diffusion and spillover of EHRs suggest that EHR use is contagious (Miller and Tucker 2009, Angst et al. 2010). In the meantime, it is unlikely that a focal hospital would change its process quality of care (e.g., providing AMI patients with aspirin within 24 hours after hospital arrival) because other hospitals in the local market have attained MU1. One concern is that hospitals in more (or less) advanced regions may find it easier to change process and technology, leading to a potential link between process quality of care and HRR-level MU saturation. Because the exclusion restriction cannot be directly tested, we alleviate this concern by noting that our empirical model includes hospital-level FEs and hospital size to at least partially address the impacts from such regional heterogeneity.

Notice that we have three endogenous variables (*adoption*, *MU1*, and *MU1*) but only one instrument. As a methodological limitation, we are only able to instrument these endogenous variables separately. Specifically, we construct three panel data sets with increasingly smaller sets of hospitals. The first data set is the same as the one used in our main analysis, and we use it to evaluate the effect of *adoption* by instrumenting *adoption* with HRR-level MU saturation. The second data set is limited to observations from hospitals that have adopted an EHR system, and we use it to evaluate the impact of *MU1* conditional on *adoption* by instrumenting *MU1* with HRR-level MU saturation. The third data set is limited to the hospitals that have achieved *MU1*, which we use to evaluate the impact of *MU2* conditional on *MU1* by instrumenting *MU2* with HRR-level MU saturation. As such, the estimates of our instrumental variable analysis should be interpreted as the effect of one status conditional on achieving the previous one.

Columns (F)–(H) in Table 1 present the results from this instrumental variable estimation. The Cragg–Donald *F* statistics for these three models are all well above the critical values suggested by Stock and Yogo (2005), indicating that the instrumentation is reasonably strong. These estimates are qualitatively similar to the main results and show that *adoption* has a positive but insignificant coefficient, whereas the coefficient estimates for *MU1* and *MU2* are positive and significant.

5.3. Effect Heterogeneity

Next, we examine the way in which the effects varied, depending upon hospital size and rurality. We stratify the original sample into groups and then reestimated model (1) in each. We define three groups of hospital sizes by the number of beds: *small* (<100 beds), *medium* (100–300 beds), and *large* (>300 beds). For hospital location, we map each hospital's zip code to a rural–urban commuting area (RUCA) code and then classify hospitals as *urban* or *rural*.[6]

Table 7 displays the results from this stratification analysis. Across the size and location groups, *adoption* has statistically insignificant coefficients, and the coefficients for *MU1* are positive and significant. This finding is consistent with the premise that EHRs' quality benefits stem from appropriate use rather than adoption. By comparing the coefficients of *MU1* across the columns, we also see that disadvantaged (i.e., small and rural) hospitals achieved a greater quality gain from *MU1* than the larger and urban ones did. The Chow test confirms that the coefficients differed significantly across hospital sizes ($F = 4.11$, $p < 0.01$) and locations

Table 7. Stratification Analysis (Dependent Variable Is *Quality*)

	Hospital size			Hospital location	
	Small	Medium	Large	Rural	Urban
Adoption	0.467	0.045	0.093	0.280	0.100
	(0.460)	(0.156)	(0.126)	(0.341)	(0.134)
MU1	0.751***	0.371***	0.223***	0.716***	0.327***
	(0.250)	(0.108)	(0.086)	(0.207)	(0.085)
MU2	0.465	0.135	0.089	0.547**	0.080
	(0.312)	(0.106)	(0.084)	(0.276)	(0.079)
Hospital fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	No	No	No	No	No
Adjusted R^2	0.570	0.539	0.605	0.586	0.551
Number of hospitals	662	1,237	608	693	1,814

Notes. Robust standard errors are shown in parentheses (clustered on hospital). Control variables are included in the estimations, but the results are not shown here because of space limitations. The results show significant quality benefits from MU1 achievement across all strata, but small and rural hospitals exceed their counterparts in the degree of effect realized. On the other hand, only rural hospitals see a significant effect of MU2 achievement. This suggests substantial heterogeneity in the MU1/MU2 effects.
***$p < 0.01$; **$p < 0.05$.

(F = 1,091.84, $p < 0.01$), which, in turn, support Hypothesis 2a. With respect to MU2, we find that the estimated coefficients of *MU2* are significant only in rural hospitals and not in urban hospitals nor any size stratum. Thus, Hypothesis 2b is only partially supported. We suspect that the insignificant *MU2* in the other settings might be attributable to the loss of power in the reduced sample size. Nevertheless, with respect to health IT policy, it is intriguing to see that rural hospitals can benefit significantly from MU2. Because health information exchange is an integral part of MU2, these results indicate that rural hospitals could mitigate the limitations of their rurality and improve quality of care through the coordination with distant clinicians and hospitals that technology allows.

6. Discussion

The goal of this study was to explore the effect of EHR use spurred by HITECH on hospitals' quality of care. We leveraged the federal MU regulation to quantify EHR use and conducted large-scale inferential tests on the quality impact of EHR use. Results from our analyses show positive quality effects associated with MU1 and MU2 achievement. In contrast, we detected no significant quality effect from EHR adoption alone. The MU regulation mandates embedding EHR-enabled cognitive support in clinical workflows, which explains why MU could improve the quality of care in practice. On closer examination, we found the quality effect of MU1/MU2 attainment varied significantly by hospital size and rurality. Compared with their counterparts, the MU1 effect was significantly greater in small, rural hospitals, and the MU2 effect was significant only in rural hospitals.

This study makes two contributions to the literature. First, we complement and extend prior EHR evaluation research. Existing research in this area has focused largely on EHR adoption and paints a mixed picture of EHRs' effects on hospital care quality (Jones et al. 2014). Understanding why some EHR implementations are successful and others are not has been a pressing topic among health IT researchers, policymakers, and practitioners (Agarwal et al. 2010). Given healthcare professionals' prevalent resistance to IT, we proposed that actual EHR use should be the focus when evaluating EHRs' quality benefits. We reconciled earlier mixed findings by showing that the quality benefits of EHRs vary according to different levels of use (i.e., adoption, MU1, and MU2) and hospital settings (i.e., size and rurality). Second, this study also contributes to the IT business value literature. When investigating the link between IT use and business outcomes, most prior research has relied on lean measures of IT use, such as CPU processing time, machine hours, or the number of reports generated (e.g., Mukhopadhyay et al. 1997 and Devaraj and Kohli 2003). Burton-Jones and Straub (2006, p. 232) remind us that "Although such lean measures can be convenient, they are unfortunately inexact because they do not refer to the aspect of usage that may be most relevant in a specific context. . . . In contrast to lean measures, rich measures incorporate the nature of the usage activity." This study responds to the call for richer measures of system usage at the organizational level and provides new evidence on the link between an organization's IT use and performance.

Our findings have important policy implications. When Congress passed the HITECH Act in 2009, the primary policy goal was to digitize the healthcare delivery system to provide safer and more effective care. Today, despite the fact that almost all U.S. hospitals use EHR technologies, the ambitious specifications and short timelines for implementation have raised doubts about the actual clinical effects of the MU regulation. Our results provide evidence for the law's benefits to clinical quality as well as its potential to mitigate quality disparities in disadvantaged hospitals. As HITECH begins to phase out, new legislation and regulations will continue to address many of the unsolved issues associated with health IT, such as interoperability, privacy, and security (Washington et al. 2017). Although it will take many years to realize the full effects of HITECH, our findings demonstrate, at least in part, that HITECH can be a useful reference model in implementing future health IT policies.

This study offers practical implications for managers in healthcare and other industries. First, our findings should help dispel hospital managers' doubts about the quality values of EHR technologies. In addition, our results highlight that the degree of postadoption EHR usage could explain the discrepancy in EHR payoff in hospitals. This has two implications for hospital managers. On the one hand, hospital managers should consider strategies to engage and motivate clinicians to use the technologies effectively. On the other hand, hospital managers should assess and redesign clinical workflows to promote EHR use. Finally, an indirect implication of our results is that, regardless of the industry, managers should allocate resources to create an environment that is conducive to effective IS use when they make their IT investment decisions. This is particularly important for organizations that anticipate a high level of user resistance during or after IT implementation.

There are limitations to this study that provide opportunities for future research. The first set of limitations is related to the empirical methods used. As we acknowledged earlier, despite our best efforts, we cannot eliminate potential endogeneity and alternative explanations of the effects observed. This is an issue in most empirical studies, especially when studying the effects of organizational IT adoption and use. Another set of limitations stems from the scope of this study. For example, we examined only the process quality of care. Although this is a common metric in the healthcare literature, we do not know whether the effect of EHR use could be extended to other metrics, such as patient outcomes and satisfaction or length of hospitalization. Further, we examined only the main effects of adoption and MU when a hospital reached the respective status. Because IT can have lagged effects after adoption and use, it would be interesting for future research to enrich our results by modeling these delayed effects when more years of data become available. Finally, there may be other theoretically important moderators in the causal path between MU and quality of care. The recent work on theories of effective use and affordance actualization is a promising approach to extend our study and reveal deeper causal structures involved in creating business values from system usage (Strong et al. 2014, Burton-Jones and Volkoff 2017).

7. Conclusion

EHR technologies play a vital role in advancing the quality of the U.S. healthcare system. However, the literature provided mixed evidence on the link between EHRs and hospital quality. We believe the link was obscured by physicians' resistance to IT and the lack of large-scale, contextualized data on EHR usage. The unique protocols and data from the MU provisions of the HITECH Act alleviate these issues and allow us to reconcile the mixed findings in the literature. Results from our analysis indicate that the levels of system use in clinical workflows can explain the discrepancy in EHRs' quality benefits to hospitals. Meanwhile, we show that the quality effects of EHR use were heterogeneous and larger in disadvantaged hospitals.

Acknowledgments

The authors thank the senior editor, the associate editor, and the anonymous reviewers for insightful and constructive comments throughout the review process. The authors are also grateful for helpful comments from Corey Angst, Randall Brown, Sue Brown, Nirup Menon, and Eric Zheng. All errors remain the authors' own.

Endnotes

[1] This paper does not distinguish between EHRs and electronic medical records. Although there were early attempts to delineate their differences, the terms often are used interchangeably in the literature, and we use EHRs here because it is the standard terminology in our policy context.

[2] There are many ways to measure quality of care. In this study, we considered whether the hospitals' inpatient care processes follow the best practices suggested by clinical guidelines and evidence. See Section 4.1 for details.

[3] The stage 3 MU is scheduled to be implemented in 2018.

[4] This data range is constrained by the availability of the JC quality measures.

[5] Our data contain hospitals from 302 HRRs, and on average, each HRR has 28.4 hospitals (standard deviation = 28.8).

[6] We did not include rurality in our models directly because it is time-invariant and will be absorbed into the hospital FEs. For details about the RUCA classification scheme, see http://depts.washington.edu/uwruca/ruca-approx.php (accessed July 11, 2015).

References

Adler-Milstein J, Jha AK (2017) HITECH act drove large gains in hospital electronic health record adoption. *Health Affairs* 36(8): 1416–1422.

Adler-Milstein J, Everson J, Lee SYD (2015) EHR adoption and hospital performance: Time-related effects. *Health Services Res.* 50(6):1751–1771.

Adler-Milstein J, Holmgren AJ, Kralovec P, Worzala C, Searcy T, Patel V (2017) Electronic health record adoption in U.S. hospitals: The emergence of a digital "advanced use" divide. *J. Amer. Medical Informatics Assoc.* 24(6):1142–1148.

Agarwal R, Gao G, DesRoches C, Jha AK (2010) The digital transformation of healthcare: Current status and the road ahead. *Inform. Systems Res.* 21(4):796–809.

Agha L (2014) The effects of health information technology on the costs and quality of medical care. *J. Health Econom.* 34:19–30.

Angst CM, Agarwal R, Sambamurthy V, Kelley K (2010) Social contagion and information technology diffusion: The adoption of electronic medical records in U.S. hospitals. *Management Sci.* 56(8):1219–1241.

Appari A, Johnson ME, Anthony DL (2013) Meaningful use of electronic health record systems and process quality of care: Evidence from a panel data analysis of U.S. acute-care hospitals. *Health Services Res.* 48(2 part 1):354–375.

Appari A, Carian EK, Johnson ME, Anthony DL (2012) Medication administration quality and health information technology: A national study of US hospitals. *J. Amer. Medical Informatics Assoc.* 19(3):360–367.

Bagayogo F, Lapointe L, Bassellier G (2014) Enhanced use of IT: A new perspective on post-adoption. *J. Assoc. Inform. Systems* 15(7): 361–387.

Banker R, Bardhan I, Chang H, Lin S (2006) Plant information systems, manufacturing capabilities and plant performance. *MIS Quart.* 30(2):315–337.

Blumenthal D (2011) Implementation of the federal health information technology initiative. *New England J. Medicine* 365(25): 2426–2431.

Blumenthal D, Tavenner M (2010) The "meaningful use" regulation for electronic health records. *New England J. Medicine* 363(6):501–504.

Burton-Jones A, Straub DW (2006) Reconceptualizing system usage: An approach and empirical test. *Inform. Systems Res.* 17(3):228–246.

Burton-Jones A, Volkoff O (2017) How can we develop contextualized theories of effective use? A demonstration in the context of community-care electronic health records. *Inform. Systems Res.* 28(3):468–489.

Damanpour F (1996) Organizational complexity and innovation: Developing and testing multiple contingency models. *Management Sci.* 42(5):693–716.

DesRoches CM, Worzala C, Joshi MS, Kralovec PD, Jha AK (2012) Small, nonteaching, and rural hospitals continue to be slow in adopting electronic health record systems. *Health Affairs* 31(5):1092–1099.

Devaraj S, Kohli R (2003) Performance impacts of information technology: Is actual usage the missing link? *Management Sci.* 49(3):273–289.

Dranove D, Forman C, Goldfarb A, Greenstein S (2014) The trillion dollar conundrum: Complementarities and health information technology. *Amer. Econom. J.: Econom. Policy* 6(4):239–270.

Furukawa MF, Raghu TS, Shao BBM (2010) Electronic medical records, nurse staffing, and nurse-sensitive patient outcomes: Evidence from California hospitals, 1998–2007. *Health Services Res.* 45(4): 941–962.

Gattiker T, Goodhue D (2005) What happens after ERP implementation: Understanding the impact of interdependence and differentiation on plant-level outcomes. *MIS Quart.* 29(3):559–585.

Hall MJ, Levant S, DeFrances CJ (2013) Trends in inpatient hospital deaths: National hospital discharge survey, 2000–2010. *NCHS Data Brief* 118:1–8.

Himmelstein DU, Wright A, Woolhandler S (2010) Hospital computing and the costs and quality of care: A national study. *Amer. J. Medicine* 123(1):40–46.

Hitt LM, Wu DJ, Zhou X (2002) Investment in enterprise resource planning: Business impact and productivity measures. *J. Management Inform. Systems* 19(1):71–98.

Hsieh JJPA, Rai A, Xu SX (2011) Extracting business value from IT: A sensemaking perspective of post-adoptive use. *Management Sci.* 57(11):2018–2039.

Jasperson J, Carter PE, Zmud RW (2005) A comprehensive conceptualization of post-adoptive behaviors associated with information technology enabled work systems. *MIS Quart.* 29(3):525–557.

Jha AK, DesRoches CM, Kralovec PD, Joshi MS (2010) A progress report on electronic health records in U.S. hospitals. *Health Affairs* 29(10):1951–1957.

Jones SS, Rudin RS, Perry T, Shekelle PG (2014) Health information technology: An updated systematic review with a focus on meaningful use. *Ann. Internal Medicine* 160(1):48–54.

Jones SS, Adams JL, Schneider EC, Ringel JS, McGlynn EA (2010) Electronic health record adoption and quality improvement in US hospitals. *Amer. J. Managed Care* 16(12 suppl. HIT):SP64–SP71.

Kane GC, Labianca G (2011) IS avoidance in health-care groups: A multilevel investigation. *Inform. Systems Res.* 22(3):504–522.

Kim SH, Mukhopadhyay T, Kraut R (2016) When does repository KMS use lift performance? The role of alternative knowledge sources and task environments. *MIS Quart.* 40(1):133–156.

Kohli R, Grover V (2008) Business value of IT: An essay on expanding research directions to keep up with the times. *J. Assoc. Inform. Systems* 9(1):23–39.

Lapointe L, Rivard S (2005) A multilevel model of resistance to information technology implementation. *MIS Quart.* 29(3):461–492.

Lynch K, Kendall M, Shanks K, Haque A, Jones E, Wanis MG, Furukawa M, Mostashari F (2014) The health IT regional extension center program: Evolution and lessons for healthcare transformation. *Health Services Res.* 49(1 part 2):421–437.

Mason CH, Perreault WD (1991) Collinearity, power, and interpretation of multiple regression analysis. *J. Marketing Res.* 28(3):268–280.

McCullough JS, Casey M, Moscovice I, Prasad S (2010) The effect of health information technology on quality in U.S. hospitals. *Health Affairs* 29(4):647–654.

Melville N, Kraemer K, Gurbaxani V (2004) Review: Information technology and organizational performance: An integrative model of IT business value. *MIS Quart.* 28(2):283–322.

Mickelson RS, Unertl KM, Holden RJ (2016) Medication management: The macrocognitive workflow of older adults with heart failure. *JMIR Human Factors* 3(2):e27.

Miller AR, Tucker C (2009) Privacy protection and technology diffusion: The case of electronic medical records. *Management Sci.* 55(7):1077–1093.

Miller AR, Tucker CE (2011) Can healthcare information technology save babies? *J. Political Econom.* 119(2):289–324.

Mishra AN, Anderson C, Angst CM, Agarwal R (2012) Electronic health records assimilation and physician identity evolution: An identity theory perspective. *Inform. Systems Res*. 23(3 part 1): 738–760.

Mukhopadhyay T, Rajiv S, Srinivasan K (1997) Information technology impact on process output and quality. *Management Sci.* 43(12):1645–1659.

National Research Council (2009) *Computational Technology for Effective Healthcare: Immediate Steps and Strategic Directions* (National Academies Press, Washington, DC).

Peterson ED, Roe MT, Mulgund J, DeLong ER, Lytle BL, Brindis RG, Smith SC, et al. (2006) Association between hospital process performance and outcomes among patients with acute coronary syndromes. *J. Amer. Medical Assoc.* 295(16):1912–1920.

Rubin HR, Pronovost P, Diette GB (2001) The advantages and disadvantages of process-based measures of healthcare quality. *Internat. J. Quality Healthcare* 13(6):469–474.

Singh R, Lichter MI, Danzo A, Taylor J, Rosenthal T (2012) The adoption and use of health information technology in rural areas: Results of a national survey. *J. Rural Health* 28(1):16–27.

Stock JH, Yogo M (2005) Testing for weak instruments in linear IV regression. Andrews DWK, ed. *Identification and Inference for Econometric Models* (Cambridge University Press, New York), 80–108.

Strong D, Volkoff O, Johnson S, Pelletier L, Tulu B, Bar-On I, Trudel J, Garber L (2014) A theory of organization-EHR affordance actualization. *J. Assoc. Inform. Systems* 15(2):53–85.

Washington V, DeSalvo K, Mostashari F, Blumenthal D (2017) The HITECH era and the path forward. *New England J. Medicine* 377(10):904–906.

Whitacre BE (2015) Rural EMR adoption rates overtake those in urban areas. *J. Amer. Medical Informatics Assoc.* 22(2):399–408.

Yaraghi N, Du AY, Sharman R, Gopal RD, Ramesh R (2015) Health information exchange as a multisided platform: Adoption, usage and practice involvement in service co-production. *Inform. Systems Res.* 26(1):1–18.

Yu S, Mishra AN, Gopal A, Slaughter S, Mukhopadhyay T (2015) E-procurement infusion and operational process impacts in MRO procurement: Complementary or substitutive effects? *Production Oper. Management* 24(7):1054–1070.

Zhu K, Kraemer KL (2005) Post-adoption variations in usage and value of e-business by organizations: Cross-country evidence from the retail industry. *Inform. Systems Res.* 16(1):61–84.