Updating Accounting Systems:
Longitudinal Evidence from the Health Care Sector

Eva Labro*
University of North Carolina

Lorien Stice-Lawrence
University of Southern California

August 2018

* Corresponding author: Kenan-Flagler Business School, CB 3490, McColl Building, Chapel Hill, NC 27599, tel. +1-919 962 5747, e-mail Eva_Labro@unc.edu. We gratefully acknowledge the Dorenfest Institute for providing us with the HIMMS (Healthcare Information and Management Systems Society) Analytics® Database and Ron Borzekowski for making available data manuals for the early part of the time series data. We also thank Ranjani Krishnan (the associate editor) and two anonymous referees, Bill Baber, Ramji Balakrishnan, Amanda Beck, Dirk Black, Mary Ellen Carter, Tony Davila, Leslie Eldenburg (discussant at AAA meeting), Eric Floyd, Fabio Gaertner, Amy Genson Sheneman, Mark Lang, Stijn Masschelein, Andrew Pierce, Jason Schloetzer, Mason Snow, Anne Wyatt, two EAA conference reviewers, workshop participants at Bocconi University, Georgetown University, UCLA and the University of Queensland, and attendees at the AAA meeting, the BYU Accounting Research Symposium, and the EAA conference for their helpful comments. Eva Labro appreciates the financial support of The Arthur Andersen Faculty Fund, the James C. and Ethel M. Crone Fund in Tax Excellence and the M Allen Wilson Endowment for the Center for Tax Excellence. The Internet Appendix can be accessed at https://tinyurl.com/yagt9vgs.

Updating Accounting Systems:
Longitudinal Evidence from the Health Care Sector

Abstract

This paper provides evidence on the determinants and economic outcomes of updates of accounting systems (AS) over a 24-year time-span in a large sample of U.S. hospitals. We provide evidence that hospitals update their AS in response to three types of pressures: *economic pressures*, such as demand side increases in the need for information driven by state-level price regulations and supply side increases in the quality of accounting information driven by vendor rollouts of improved AS; *coercive pressures* imposed by regulators mandating certain practices, such as internal control practices imposed by Sarbanes-Oxley Section 404; and *mimetic pressures* for hospitals to conform their AS to those of their peers, such as local county and prominent "celebrity" peers. We find that only economically driven updates lead to economic benefits in the form of lower operating expenses and higher revenues. In contrast, we find some evidence that AS updates prompted by coercive regulatory and mimetic pressures actually impose economic costs in the form of higher operating expenses.

Keywords: Management Accounting, Accounting System Updating, Health Care Costs, Health Care Price Transparency, Fair Pricing Laws, Sarbanes-Oxley Act Section 404, Economic Determinants, Mimicry, Coercion

I. Introduction

Our paper uses a large dataset of accounting systems (hereafter AS) in hospitals spanning a period of 24 years to examine time series aspects of AS use, in particular determinants and outcomes of updating. We provide evidence that both economic and institutional (coercive and mimetic) determinants drive the updating decision. Using instrumental variables analyses, we find that the updating of AS driven by economic pressures leads to significant reductions in operating expenses and increases in revenues. On the other hand, updates driven by coercive and mimetic forces may actually increase expenses.

We follow the AS definition of Hall (1998) as a system that processes financial transactions as well as non-financial transactions that directly affect the processing of financial transactions.[1] We study eight AS: financial AS supporting basic transactions such as accounts payable and general ledger systems; management AS enhancing analytical capabilities such as costing, budgeting, and executive information systems (EIS); and patient-focused financial AS such as case mix, credit/collection, and patient billing systems.[2] We further define an AS as having an update when a hospital in a given year changes the version/model or vendor of a software

[1] This textbook definition is in line with those used in the academic literature (e.g., Bai, Nunez, and Kalagnanam, 2012), in dictionaries, and by vendors of AS. For example, the Business Dictionary (http://www.businessdictionary.com/definition/accounting-system.html) defines AS as a set of manual and computerized procedures and controls established to gather, classify, analyze, summarize, interpret, and present accurate and timely financial data for management decisions. Debitoor, a vendor, defines an AS as a system used to manage the income, expenses, and other financial activities of a business (Debitoor, 2017). It allows a business to keep track of financial transactions and generates data that aid in the decision-making process.

[2] Borzekowski (2009) also groups systems according to whether they support basic transactions or basic or advanced analytical capabilities. An accounts payable system manages accounts to which the hospital owes money. A general ledger system maintains the overall financial accounts of the hospital (i.e., income statement, balance sheet) and tracks individual transactions. A costing system estimates the cost of treatments and patients. A budgeting system plans and coordinates the acquisition and allocation of resources. An Executive Information System (EIS) provides executives with key performance indicators and trends to help them make better decisions. A case mix system calculates cost and revenue of various patient categories (similar to a customer profitability system). A patient billing system processes current patient charges, while a credit/collection system focuses on patient accounts that are past due. Further detail is available in Internet Appendix A. Some prior research has considered contract management and quality management systems to be AS; for completeness, we report these results in Internet Appendix F.

application or adds an additional software package to an AS for which the hospital already has an existing application. The following three examples illustrate our definition of AS updating. First, St. Dominic Hospital uses the ProClick software developed by MediClick for its general ledger needs and updated to a newer version of the ProClick model in 2006. Second, Bon Secours Community Hospital changed its budgeting system vendor and replaced the previous system from Lawson Software with the Trendstar budgeting module from McKesson in 2003. Third, Grady General Hospital added a costing system in 2000 when it installed a cost accounting application from Lawson Software in addition to the existing costing system it had previously purchased from Siemens Medical Solutions. Grady General used both systems for two years (probably as it migrated data and trained employees on the new system) until the Siemens system was retired in 2002. Importantly, updating in our paper does *not* refer to the initial first-time adoption of AS. In our examples, all three hospitals had adopted the described systems before being included in our sample, and thus the systems were already in place when first observed in the data.

We believe that AS updating constitutes a particularly timely and relevant topic of research. Expenses related to IT in general and AS in particular represent a significant portion of firm operating expenses.[3] Most firms have adopted the various AS we study; however, many firms continue to use AS that were installed decades earlier when technological capabilities and the information demands of the organization were vastly different. To our knowledge there is no large-scale empirical evidence on which factors drive AS updating or what benefits firms receive from updating such AS investments, which signifies that neither academics nor practitioners know what is involved in such updating decisions for a large cross-section. Additionally,

[3] Chief Information Officers' budgets comprised 8.6% of revenue on average for firms across all industries in 2014, and 34% of surveyed firms allocated an additional budget for AS (CIOMagazine, 2014).

financial management support through AS is a particularly pressing issue in the health care setting since this sector currently makes up 17% of U.S. GDP, and health care costs are still increasing (WorldHealthOrganization, 2015). In order to empirically examine AS updating, we use the HIMSS (Healthcare Information and Management Systems Society) Analytics Database®. This database contains survey data on hospital information technology systems and other hospital characteristics from 1987 to 2010 and covers the near-census of hospitals in the U.S. with between 2,900 and 5,243 unique hospitals located in all 50 states and the District of Columbia in each year.

Using a hazard model, we find that economic incentives and coercive and mimetic institutional pressures drive hospitals' updating behavior. In terms of supply-side economic pressures, we find that "waves" of updates occur within hospitals which share vendors as vendor-specific exogenous technological innovations in AS are introduced to the marketplace, such as the launching of a new version or the termination of support of an older version. On the demand-side, staggered state-level price regulations on fair pricing and price transparency measures increase hospitals' need for improved internal accounting information and drive updates of relevant AS. The effect of these state-level regulations are especially interesting because they may foreshadow the effect of similar regulations recently enacted at the federal level. We also find that hospitals respond to coercive regulatory pressures by updating their systems; specifically, hospitals updated their AS in anticipation of Section 404 of the Sarbanes-Oxley Act (SOX 404) that requires high standards for internal control systems. Lastly, hospitals respond to mimetic pressures by updating their AS when their county peers update and in the presence of IT savvy "celebrity" peers.

Although the decision to update AS is often endogenous to potential economic benefits, these determinants analyses present us with several variables that are plausibly exogenous with respect to the individual hospital and capture different motivations behind AS updating. We use these exogenous economic, coercive, and mimetic determinants of AS updating as instruments in instrumental variables analyses and show that the economic benefits of AS updates vary based on the underlying driver of the update. Specifically, we find that when they are driven by economic pressures, updates of AS that support basic financial transactions and enhance managerial analytical capabilities lead to decreases in operating expenses, while patient-focused financial AS updates lead to increases in revenues. On the other hand, AS updates driven by coercive and mimetic pressures appear to lead to *increases* in expenses, supporting the notion that these firms make costly changes to their AS to signal compliance and legitimacy, without making genuine improvements that yield economic benefits.

Our study is important for several reasons. First, notwithstanding several calls for longitudinal work on information systems more generally and AS specifically,[4] limited research is available on AS *updating*. While prior research has examined cross-sectional variation in determinants, benefits, and costs of accounting system *adoption* (e.g., Chenhall and Morris, 1986; Davila and Foster, 2005; Ittner, Lanen, and Larcker, 2002; Maiga and Jacobs, 2008), it is unclear that results in the adoption literature will translate to an updating setting. The decision to update comes at a much later stage in a firm's life cycle than the decision to adopt at which point the objectives and informational needs of the firm may have changed, and the way in which AS are adopted may affect their subsequent updating. The only research with a longitudinal focus on *adoption* has studied start-up firms (Davila and Foster, 2005, 2007; Sandino, 2007) and may not

[4] See, for example Grabski et al., 2011; Hikmet, Bhattacherjee, Menachemi, Kayhan, and Brooks, 2008; Swanson and Dans, 2000; Zhu et al., 2006.

generalize to more mature firms.[5] Furthermore, existing research on operational improvements after updating has focused on remediation of disclosed material weaknesses in internal controls using external data (e.g. Feng, Li, McVay, and Skaife, 2015; Li, Peters, Richardson, and Weidenmier, 2012), while we provide more insights into the determinants and outcomes of a broader set of AS, including those not related to internal controls, using more granular survey data.

Additionally, we are able to answer the call in Ittner et al. (2002) to provide longitudinal evidence on the economic outcomes associated with AS implementation. Up to this point, the prior literature on AS adoption has struggled to estimate economic benefits because the firm's decision to both update and adopt AS is often tied to other firm-level initiatives that may affect the outcome of interest and because firms may respond to current or expected outcomes when making AS-related decisions, leading to endogeneity issues. Prior studies have struggled to address this problem, and most of the management accounting research on outcome effects of adoption simply acknowledges that the research design used may be subject to these concerns.[6] Our data and setting provide us with powerful instrumental variables which allow us to overcome these endogeneity concerns and examine the economic outcomes of AS updates. Furthermore, our results provide novel evidence on heterogeneity in the outcomes associated with AS implementation depending on the driver of the update. This provides further nuance in our understanding of the way that AS can affect economic outcomes and reconciles previous

[5] Furneaux and Wade (2011) point out that their review of more than 1,000 articles published in seven leading information systems journals over the past 20 years resulted in the identification of only 4 articles that gave notable attention to the final stages of the information systems life cycle and that the few available longitudinal studies have looked at Enterprise Resource Planning (ERP) systems, not AS.

[6] Ittner et al. (2002) and Davila and Foster (2007) go furthest in seriously addressing this problem when researching the effect of Activity-Based Costing and management control system adoption on performance and firm growth using a two-stage and simultaneous equations approach, respectively.

conflicting findings on the benefits of AS (Cavalluzzo, Ittner, and Larcker, 1998; Eldenburg and Krishnan, 2008; Geiger and Ittner, 1996; Kaplan and Porter, 2011).

II. Hypotheses

We structure our analyses around four main hypotheses relating to the determinants (H1 and H2) and outcomes (H3 and H4) of AS updating. Specifically we predict that both economic and and institutional (coercive and mimetic) pressures will prompt hospitals to update their AS and the economic benefits of these updates will vary depending on which force prompted the update.

Economic pressures refer to events which increase the value of information provided by updated accounting systems. We study both supply-side and demand-side economic pressures that are plausibly exogenous with respect to the hospital. On the supply-side, we examine vendor-“pushed” updates. One of the main differences between adoption and updating for non-self-developed AS is that there is an existing vendor in place with whom the hospital has a relationship. Vendors regularly release new AS updates or stop supporting older versions (Beatty and Williams (2006), Khoo and Robey (2007)), leading to an improvement in the quality of information available to hospitals if they choose to update. This may instigate a “wave” of updating among hospitals that are “vendor peers” (that is, share the same vendor for a particular AS).

On the demand-side, we study two regulatory events that increase hospitals’ need for improved accounting information. First, we study the introduction of fair pricing measures in 12 U.S. states staggered over the period 2001-2009. These measures are meant to curb predatory pricing practices with respect to uninsured patients and impose both limits to collections hospitals can make from uninsured patients and requirements to provide free care for low to middle income uninsured patients. Batty and Ippolito (2016) and Bai (2015) calculate that these fair pricing laws have had a large impact; uninsured patients experienced large decreases in payments, and hospitals responded by shifting services and increasing prices charged to privately insured patients (Bai, 2016). Second, we study price transparency mechanisms adopted by 29 U.S. states staggered over the period 2002-2009 that disclose prices of common procedures by hospitals on state websites. Such disclosure regulation decreases information asymmetry between consumers, payers, and providers, increasing the competitiveness of the market and reducing the likelihood of market failures. Christensen, Floyd, and Maffett (2015) find that the introduction of these price transparency websites significantly decreases the publicly posted charge prices of common procedures in affected hospitals, which they interpret as evidence that price transparency regulations increased public scrutiny of hospital prices.[7] We expect that both fair pricing and price transparency laws will increase hospitals' demand for high quality accounting information as they try to optimize the profitability of their patients (in the case of fair pricing laws) and adjust and justify their prices (in the case of price transparency laws). More generally, we believe that both supply-side and demand-side economic pressures will increase the value of updated AS. Formally:

H1: *Hospitals are more likely to update their relevant AS when economic pressures for high quality accounting information increase.*

While on the supply-side, vendor-pushed updates may affect any type of AS, on the demand-side, we expect only those AS that provide information relevant to the increased economic pressures of the fair pricing regulations and price transparency initiatives to be updated, and therefore predict these effects only for a subset of AS. Specifically, we expect that hospitals will

[7] This interpretation seems reasonable given anecdotal evidence of the reception of these disclosures. For example, a Wall Street Journal article (Beck, 2014) highlighted wide dispersion in the costs for common procedures at hospitals in the Los Angeles area, with the posted charge price for treatment of a brain hemorrhage ranging from $31,688 at Sherman Oaks Hospital to $178,435 at Garfield Medical Center less than 25 miles away.

respond to the downward price pressure of both the fair pricing and the price transparency measures by minimizing operating expenses using information obtained from costing and budgeting systems (Krishnan, 2005). Such costing and budgeting information can help hospitals set and budget for the most appropriate prices and justify these prices in a setting with greater price pressure (Houk and Cleverley, 2014). Additionally, the adoption of fair pricing measures will increase the importance of managing the portfolio of patient types and their conditions as certain patients or conditions may become highly unprofitable. Information relevant to these objectives is gleaned from case mix systems. Lastly, optimizing credit and collections and patient billing becomes more important, as it may become harder to collect on uninsured patients.

Institutional pressures, too, may drive hospitals to update their AS (DiMaggio and Powell, 1983). First, regulators may exert coercive pressure and mandate hospitals to adopt certain practices, regardless of whether they would voluntarily adopt these practices or not. We study Section 404 of the July 2002 SOX Act which required management and external auditors of public companies to produce a report on the adequacy of the company's internal control over financial reporting. Hospitals may succumb to this pressure by investing in the various AS that support such internal control, signaling their compliance and the legitimacy of the generated report, even if the AS changes they make are not substantive and largely only symbolic. For example, Geiger and Ittner (1996) finds that government agencies whose funding rules mandate certain costing practices will indeed install more elaborate costing systems. We expect that the coercive pressure of the enactment of SOX Section 404 leads hospitals to update all AS prior to its effective date.

Second, organizations' choices are also influenced by choices of other referent entities in their social system (DiMaggio and Powell, 1983). Social contagion is an important institutional force that shapes organizational behavior because of mimetic pressures to model an organization after others. This modeling may happen unintentionally or intentionally (DiMaggio and Powell, 1983). Angst, Agarwal, Sambamurthy, and Kelley (2010) find that a hospital's spatial proximity to prior adopters and the celebrity status of prior adopters increases the "infectiousness" of these adopters. Hence, we expect that mimicry-related institutional pressures increase the likelihood of AS updating, and study whether firms update when their local county peers update or when their local peers have been touted as especially technologically savvy. Formally, our hypotheses on the institutional determinants of updating are:

H2a: *Hospitals are more likely to update their AS when coercive pressures to do so increase.*

H2b: *Hospitals are more likely to update their AS when mimetic pressures to do so increase.*

Given these economic and institutional pressures to update, we now consider whether the reason why hospitals updated their AS determines whether they will experience economic benefits. First, we expect that hospitals that update their AS because of economic pressures use the improved accounting information to more efficiently manage their operations and are likely to see benefits on either operating expenses and/or revenues. We predict that updates of AS supporting basic financial transactions or enhancing analytical capabilities (i.e., Accounts Payable, General Ledger, Costing, Budgeting, and EIS AS) in response to such economic incentives can help hospitals to *decrease* their operating expenses. For example, Kaplan and Porter (2011) and Eldenburg and Krishnan (2008) document that hospitals with better cost and budgeting information are able to better manage their costs, for example through: process improvements and redesign, outsourcing, consolidation, and reduction of unused capacity of people, equipment and facilities. Additionally, we expect that General Ledger systems provide the basic backbone to improve capacity utilization and asset management (Eldenburg and Krishnan, 2008), Accounts Payable systems help hospitals manage the expense outlays to vendors, and EIS provide the aggregate level managerial overview required to ensure that cost reducing steps taken in one area are not leading to increased expenses in another area. On the other hand, we expect that updates of patient-focused financial AS (Case Mix, Credit Collections, and Patient Billing AS) in response to economic incentives will *increase* revenues. Eldenburg and Krishnan (2008) find that hospitals can enhance revenues by improving credit and collection techniques, and Tozzi (2017) argues that collecting debt pays better than curing ills for some hospitals. Additionally, hospitals can use the information they gain from case mix systems to identify the types of patients which best generate revenues.

Of course, AS updates may not lead to net benefits even when prompted by economic pressures. Implementation and adjustment costs may outweigh the benefits of the update, or updates may not be substantive enough to deliver appreciable benefits. Additionally, if other hospitals are also updating, benefits to updating may be competed away. Overall, however, for economically driven updates on average to be rational, we predict the following:

***H3a**: Updating of Accounts Payable, General Ledger, Costing, Budgeting and EIS AS driven by economic pressures decreases operating expenses.*

***H3b**: Updating of Case Mix, Credit Collections, and Patient Billing AS driven by economic pressures increases revenues.*

On the other hand, hospitals that update their AS as a reaction to institutional pressures (whether coercive or mimetic) rather than because of a consideration of the economic benefits perform a "label" (Daske, Hail, Leuz, and Verdi, 2013), "ceremonial" (Corbett and Castka,

2015) or “symbolic” (Angst, Block, D'Arcy, and Kelley, 2017) update where they are just going through the motions rather than seeking to make genuine improvements. Such label updates are not accompanied with efforts to integrate the improved accounting information within the organizational decision-making processes, in which case the expense reduction and revenue increasing benefits will not be obtained. Geiger and Ittner (1996) find that while government agencies subject to cost system requirements implement more elaborate costing systems to remain eligible for funding, they do not use these cost systems to improve internal decision-making and control. Cavalluzzo and Ittner (2004) find that performance measurement innovations implemented solely to comply with mandated government requirements are not associated with greater use of the performance data or wider perceived benefits. Daske et al. (2013) find no evidence that voluntary label IFRS adopters obtain any capital market benefits. Furthermore, even label AS updates are not costless and as a result may actually decrease hospital profitability if they do not provide information that hospitals (can) use to optimize their operations. On the other hand, it is possible that updates driven by institutional pressures lead hospitals to experience unanticipated benefits that they had not foreseen.[8] We therefore state our hypotheses about the outcomes of institutionally driven AS updates in the null:

***H4a**: Updating of AS driven by coercive pressures does not affect expenses or revenues.*

***H4b**: Updating of AS driven by mimetic pressures does not affect expenses or revenues.*

III. Data and Descriptive Evidence

The main source of data in our paper is the HIMSS Analytics database which contains survey data on hospital Information Technology systems and other hospital characteristics from 1987 to

[8] Using firms’ disclosures in Lexis-Nexis, Masli, Peters, Richardson, and Sanchez (2010) [Morris (2011)] find that firms announcing an internal control system technology [ERP] adoption subsequent [prior] to SOX enactment are more successful in Section 404 compliance. These papers do not address AS updating specifically or measure economic outcomes and cannot speak to the increased likelihood of adoption or updating given their sample only consists of firms who choose to disclose these adoptions.

2010. Although HIMSS currently owns the rights to all of these data, the earlier surveys were conducted by the Dorenfest Group, which compiled the Dorenfest 3000+ Database using yearly surveys from 1987 to 1995 and the Dorenfest IHDS+ Database with yearly surveys from 1998 to 2004. These databases were sold to information technology vendors to identify potential clients. HIMSS collected the remaining data from 2005 to 2010.[9] The surveys cover an impressive range of hospitals in the U.S., with between 2,900 and 5,243 unique hospitals located in all 50 states and the District of Columbia in each year of the data. The full sample contains 6,995 unique hospitals, with 1,916 tracked in every year. We obtain information on the eight AS from the HIMSS dataset, and define an AS as having an update when the hospital in a given year changes the version/model or vendor of an existing software application or adds an additional software package for an AS where the hospital has an existing application. Hence, in order to be included in the sample, the hospital has to have adopted the AS previously. Internet Appendix A elaborates on the sample, the AS we study, the procedures used to identify AS updates, and the steps taken to validate the data.

Subsets of the HIMSS dataset on *clinical* IT systems (i.e., those used to facilitate and track medical procedures) and electronic medical record systems have been extensively used and vetted in research. To the best of our knowledge, only a handful of papers have used the *business* IT systems data, although typically either cross-sectionally in one year (Angst, Agarwal, Gao, Khuntia, and McCullough, 2014; Setia, Setia, Krishnan, and Sambamurthy, 2011) or over a time series that spans at most about a third of our 24-year time series (Bardhan and Thouin, 2013; Borzekowski, 2009; McCullough and Snir, 2010). Furthermore, they all study business IT systems (or “financial” or “administrative” systems) as a broader category and do not separate

[9] Although data were collected in 1989, we do not have access to this survey.

out the specific AS other than McCullough and Snir (2010) who document that the presence of costing systems and EIS does not affect the hospital's decision to integrate physicians.[10]

Because we did not design the HIMSS survey, not all variables that we would like to include are available to us.[11] However, we supplement HIMSS data with data from the Healthcare Cost Report Information System (HCRIS) database available from the Centers for Medicare and Medicaid Services (CMS), which contains data obtained from the cost reports that hospitals which receive Medicare or Medicaid reimbursements must file each year. These data are available for the years 1996-2010 and allow us to fill in some variables that are not tracked over the full time frame of our sample, for example academic and for-profit status, or that have missing values. HIMSS and HCRIS data are very consistent with each other for hospitals and years where there is overlapping data. For subsets of our data for which financial measures such as operating expenses and revenues are available, the correlation is at least 0.9 across the two datasets, and the indications of for-profit and academic status are very consistent. Internet Appendix B lists all variable definitions and clarifies in which cases we used one or both data sets to construct our variables. Of specific interest is the operating expense variable, which includes all ongoing costs of information system maintenance and updating (Borzekowski, 2009) spread out over expense categories like "Administrative and General," "Central Services and Supply", and "Medical Records and Medical Records Library." Unfortunately, the data do not

[10] Setia et al. (2011) use the 2004 data to study the effect of business and clinical application use on financial performance, while Angst et al. (2014) document that the presence of administrative IT affects the likelihood that hospitals voluntarily disclose quality outcomes in 2007 in California. Bardhan and Thouin (2013) documents that the presence of financial information systems (defined as budgeting, encoding, general ledger, and materials management systems) is associated with lower levels of conformance to best treatment practices, but also with reduced operating expenses. Borzekowski (2009) studies the impact of *adoption* of business IT systems on hospital costs over the early part of our sample (1987 - 1994). To the best of our knowledge, Angst et al. (2010) are the only authors to exploit the full time series in the data but their focus is on electronic medical records systems only.

[11] For example, prior literature indicates that the accounting background of the top management team is an important determinant of AS adoption, yet the HIMSS survey does not collect this variable.

separate the cost of AS from other operating expenses and hence we capture the *net* effect on operating expenses in our outcome analyses.

We winsorize all continuous variables at the top and bottom 1%. Table 1 provides descriptive statistics of hospital-level (Panel A) and hospital-application-level (Panels B and C) variables. Median (mean) bed size is 180 (225), and mean Herfindahl-Hirschman Index (HHI) is 4,751 (where 10,000 is no competition and near 0 is perfect competition). 17, 64, 30 and 12 percent of the sample are part of a publicly traded firm, in a multihospital system, and are for-profit and rural hospitals, respectively. Over the sample period, between 6 (Credit/Collections) and 15 (EIS) percent of applications are updated in any given year. Meanwhile, between 10 (Accounts Payable) and 16 (EIS) percent of systems were developed by hospitals internally, while on average between 10 (Patient Billing) and 18 percent (EIS) of the vendor peers of hospitals' applications update their AS in a given year. Internet Appendix C presents descriptive evidence of penetration of AS over time, providing confirmation of widespread adoption of these AS and indicating the importance of researching the decision to update AS. It also presents descriptive evidence on how long an AS is in place before it is updated, with most hospitals updating their AS every 3 or 4 years.

Insert Table 1 here.

Our longitudinal dataset offers three key advantages in examining AS updates. First, it spans a larger sample over a longer period than any prior work for eight key AS (Cao, Nicolaou, and Bhattacharya, 2013; Davila and Foster, 2005). Second, the HIMSS surveys are administered yearly, so participants do not have to rely on long-term recall of information. Third, we capture the cross-section of updates, ranging from minor to major and from successful to unsuccessful. While there is, to our knowledge, no research on *accounting* system updating, the limited research on ERP upgrading has relied on news releases accessed through Lexis-Nexis. Such news releases arguably capture only large and successful updates, and authors have called for alternate ways of identifying the full spectrum of updates (Cao et al., 2013). The surveys are unlikely to suffer from reporting bias in favor of successful updates because (1) the data have not been made widely publicly available[12] and (2) the survey uses a standardized questionnaire where HIMSS solicits information on specific applications and their associated dates and the respondent fills out the requested fields for every application instead of cherry-picking important or successful systems.

IV. Determinants of Updating Accounting Systems over Time

We use a Cox proportional hazards model to estimate the determinants of whether a firm will update a particular AS in a given year. Hazard models are a class of survival models which model the probability that an event will occur at a point in time given that it has not already occurred, where the covariates in the model have a multiplicative effect on the underlying probability known as the hazard rate. In our setting, we estimate the likelihood that a hospital will update an AS in the current year as a function of time since the last update. The hazard model specification is:

$$\lambda(t|\boldsymbol{X}) = \lambda_0(t)\exp(\beta_1 X_1 + \cdots + \beta_p X_p) = \lambda_0(t)\exp(\beta' \boldsymbol{X}) \qquad (1)$$

where the hazard rate $\lambda(t|\boldsymbol{X})$ is the probability that hospital i will update AS_j at time t given that it has not updated the AS_j before time t.[13] t is the time since the last update of AS_j by hospital i. Our data are right-censored, meaning that some hospital AS never experience an update in our

[12] Responding hospitals only received access to highly aggregate data on IT trends in their sector. Only IT vendors were able to purchase the more disaggregate Dorenfest data to support their search for potential customers. In more recent years, data access has been granted to researchers whose research first needs to be approved by HIMSS.

[13] An implicit assumption when using a hazard model in this setting is that hospitals have the option to update in every period. We believe this is reasonable because hospitals always have the option to switch to software provided by a different vendor even if there are no software upgrades available from their current vendor.

sample period. The Cox proportional hazards model represents the hazard rate as a function of a baseline hazard rate, $\lambda_0(t)$, which is the hazard rate for a baseline level of all covariates.[14] The hazard rate is also a function of the levels of the covariates themselves, **X**, which is the vector of independent variables. The updates of different types of AS are analyzed in separate specifications to allow for differences across AS types in the underlying decision-making process that leads hospitals to update their AS. Hospital-application observations are observed yearly, including in years for which there is no update, and each hospital can experience multiple updates of a given AS_j over time, with each of these updating spells (installation and use of an AS until the next update) identified as a separate failure group in the data.[15]

The set of independent variables, **X,** included in our hazard model is comprised of our hypothesized determinants of AS updating as well as a set of control variables. We refer again to Internet Appendix B for precise variable definitions and the sources of the data used. First, to test the supply-driven economic pressures hypothesized in H1, we include *Vendor_Peer_Update* which is calculated as the proportion of other hospitals using the same vendor (i.e., "vendor peers") which updated their AS this year. A large proportion of vendor peers updating their systems simultaneously is a sign that a vendor-specific supply shock (e.g., a new version of an AS that constitutes improved information) is likely to have occurred. Consistent with H1 we expect this variable to increase the probability of updating.[16] To test the demand-driven economic pressures, we use the enactment dates of fair pricing laws to construct *Fair_Pricing,*

[14] One benefit of using a Cox model is that we are able to estimate the hazard ratios without specifying the functional form of this baseline hazard rate, while misspecifying the hazard rate would cause bias in our model.
[15] Cross-correlations between updating spells within the same hospital over time could lead to correlated standard errors. We use heteroscedasticity-robust z-statistics clustered by hospital in our reported results, and inferences are identical when we use bootstrapped z-statistics.
[16] In most cases, the HIMSS data flag internally developed AS. In addition, a research assistant manually reviewed all vendor names to identify those that are most likely to be self-developed (for example when the name of the hospital is given in place of a vendor name). *Vendor_Peer_Update* is always equal to 0 for self-developed systems. As a result, it can be interpreted as the interaction between *Self_Developed* and *Vendor_Peer_Update*.

an indicator variable coded 1 if that state enacted a fair pricing measure in the prior year (Batty and Ippolito, 2016). Maine is the first of 12 states in our sample period to enact a fair pricing law in 2001, and Illinois, Maryland and New Jersey are the last states to enact a fair pricing law in 2009. Consistent with H1, we expect *Fair_Pricing* to have a positive effect on the probability of updating costing, budgeting, case mix, credit/collection, and patient billing systems. Next, we use the date of the first charge price website disclosure for each state to construct *Price_Transparency*, an indicator variable coded 1 if that state adopted a price transparency website in the prior year (Christensen et al., 2015). Pennsylvania was the first state to disclose prices (in 2002) and Maine (in 2009) is the last website adoption in our treatment sample of 29 states. Consistent with H1, we expect *Price_Transparency* to have a positive effect on the probability of updating costing and budgeting systems. Internet Appendix D presents the timeline of the introduction of these regulatory changes.

To test our hypothesis in H2a about coercive regulatory pressures, we identify 10 publicly traded hospital systems with 752 treated hospitals in 45 states and the District of Columbia that were subject to SOX 404. We expect these hospitals to increase updates of their AS in the period just before SOX 404 compliance became mandatory. We identify this using an interaction between *SOX_404* (an indicator variable coded 1 if the hospital was subject to SOX 404 in 2004) and *Prep_Years* (an indicator for 2002 and 2003, the two years after SOX 404 was passed during which firms could implement changes before mandatory SOX 404 compliance in 2004). We expect this interaction to have a positive effect on AS updating.

To test our hypothesis in H2b about mimetic pressures, we construct *County_Peer_Update*, an indicator for whether at least one other hospital in the same county updated the AS of interest that year. Next, similar to Angst et al. (2010), we identify hospitals which are "celebrity" AS users by finding hospitals in our sample which were included in the "100 Most Wired List" published by Hospitals and Health Networks. We then create *Celebrity_Peer,* a binary variable that takes a value of 1 if a hospital is within 15 miles of a "celebrity" hospital that year.[17] We expect both peer variables to have a positive effect on updating if hospitals exhibit mimicking behavior.

We include other potential determinants of AS updating as control variables, which we group into three categories based on whether they relate to the characteristics of the hospital's information systems, other characteristics of the hospital more broadly, or characteristics of the market in which the hospital operates. In terms of characteristics of hospitals' information systems, we control for *System_Peer_Update,* an indicator for whether another hospital within the same hospital system updated the AS of interest in the current period, whether the AS of interest was developed internally (*Self_Developed),* and the age and number of other information systems (*Apps_Age, Business_Depth, Med_Record_Depth, Clinical_Depth).* Other hospital-level characteristics, many of which have been established in the prior literature on adoption (e.g. Davila and Foster, 2005; Hill, 2000; Kim, 1988; Kobelsky, Richardson, Smith, and Zmud, 2008; Krumwiede, 1998; Libby and Waterhouse, 1996), include hospital size (*Bedsize),* whether the hospital is part of a multi-hospital system (*In_System*), and for-profit and academic status (*For_Profit, Academic).* Market controls are the Herfindahl-Hirschmann index (*HHI*) as a measure of competition and rural location (*Rural*).[18] In addition, our hazard model includes state and year fixed effects.[19] Inclusion of year fixed effects controls for contemporaneous changes in

[17] Results are consistent if we use 100 miles.

[18] We do not control for specialty or government status in our main analyses because it limits our sample to Medicare hospitals after 1996. However, untabulated determinants tests including them as control variables produce similar inferences and hospital fixed effects picking up these static characteristics are included in our outcome analyses.

[19] Fixed effects can cause bias in non-linear models when the number of observations per fixed effect group is low (Allison, 2002; Greene, 2004). However, we expect the bias in our models to be low because we have many

the market that may affect all hospitals, such as improvements in medical technology, an increased likelihood of updating in the run-up to Y2K (Anderson, Banker, and Ravindran, 2006), or an elongation of life cycles during the 2008-2009 recession (CreditSuisse, 2012). Year fixed effects also pick up the effect of other regulatory changes at the federal level, such as HIPAA (the Health Insurance Portability and Accountability Act of 1996).[20] Inclusion of state fixed effects controls for static aspects of the state regulatory and economic environment.

Table 2 reports the results of this hazard model of the probability of updating. The effect of a covariate on the hazard rate at any point in time is expressed as a hazard ratio. When a covariate is a 0/1 indicator (e.g., whether or not the hospital is in a rural area), the hazard ratio is the hazard rate of the treatment (e.g., rural) group divided by the hazard rate of the control (e.g., urban) group, or the relative probability that the event will occur at any given point in time for the treatment group, holding all other covariates constant. For example, a hazard ratio of 0.5 would indicate that subjects in the treatment group are half as likely to update as those in the control group. On the other hand, a hazard ratio of 2 would indicate that subjects in the treatment group are twice as likely to update. For continuous variables, the hazard ratio is interpreted as the relative hazard for two groups of subjects that have a one-unit difference in the independent variable of interest. Table 2 reports the hazard ratios associated with each independent variable. Values significantly greater than one indicate the covariate increases the likelihood of an update, while values significantly smaller than one indicate that the covariate decreases the likelihood of an update.

Insert Table 2 here.

---

observations in each state and year group. Additionally, our inferences are robust to alternative specifications such as omitting fixed effects or stratifying the model by hospital to control for static hospital characteristic (Allison, 1996).

[20] If we omit year fixed effects and instead include indicators for Y2K and the Recession, we do indeed find that these events have a significant effect on AS updating.

In support of H1, we find that updates rolled out by the vendor at an additional one percent of peer institutions (*Vendor_Peer_Update*) increase the frequency of AS updating about 2% for all AS types.[21] We also find an increased updating hazard for Costing (29%), Case Mix (31%), and Credit/Collections AS (48%) after enactment of fair pricing measures. The effect is positive but insignificant for Budgeting and Patient Billing AS. This is consistent with the regulation requiring hospitals to better understand and manage their costs under price pressure, to create greater insights in the portfolio of patients (e.g., insured vs. uninsured), and to increase collections of those charges that they are permitted to bill.[22] Further, we find a significantly positive effect of the introduction of price transparency regulation on updating for Costing and Budgeting AS, with an increased updating hazard of about 14% and 16%, respectively.[23] Interestingly, we find a significantly negative effect on the updates of Accounts Payable, General Ledger, and Patient Billing AS, potentially because hospitals substituted costing and budgeting updates for some other AS updates in these years. We conclude that hospitals strategically update their AS in order to generate useful accounting information that will help them deal with the impact of price regulations. Our well-identified analyses of staggered state-level price regulations may speak to the likely outcomes of similar initiatives at the federal level, namely fair pricing provisions in the Affordable Care Act effective since 2014 and the U.S. Department of Health and Human Services' price transparency initiative, releasing price information for the 100 most common Medicare stays since 2013.

[21] An untabled analysis suggests that the effect of vendor upgrades is stronger when applications are mature and maintenance and upgrade fees are a more important part of the vendor revenue mix (Gable, Chan, and Tan, 2001).

[22] To further support the notion that our results are driven by economic incentives to improve accounting information after fair pricing laws, in untabulated analyses we find that hospitals are especially prone to update their AS after fair pricing laws when they serve a higher proportion of uninsured patients and when they previously were more likely to charge higher prices to uninsured patients (they faced low competition from other hospitals—HHI above the median).

[23] In untabulated results we find that the effect of price transparency initiatives on costing and budgeting updates is strongest in settings where downward price pressure and public scrutiny are likely to be strongest, in particular when competition is high (HHI is below the median), and for large and academic hospitals, respectively.

Moving to institutional drivers of AS updating, consistent with H2a we find that hospitals subject to SOX 404 are more likely to update their AS (with the exception of Accounts Payable and Credit/Collections AS which show insignificant results) in the two years between the enactment of the regulation and its implementation, indicative of coercive institutional pressures. The increased likelihood ranges from 36% for General Ledger to 79% for Case Mix AS and is highly significant. Next, consistent with H2b, we find that institutional mimetic pressures lead to social contagion. *County_Peer_Update* is significantly positive for 6 of the 8 AS, suggesting within-county contagion through the proximity of updating hospitals. The effect of having a *Celebrity_Peer* in proximity to the focal hospital is significantly positive for 4 of the 8 AS, while 3 other coefficients are positive yet insignificant, suggesting that hospitals update in response to their peers being recognized for their high-quality information systems.[24] We note briefly that our control variables are well behaved. For example hospitals tend to update at the same time as other hospitals within their hospital system (*System_Peer_*Update) and hospitals with many business applications (*Business_Depth*) update their AS more frequently. Internet Appendix G provides details on a variety of untabulated tests ensuring that our inferences are robust.[25]

Next, we explore the extent to which there are complementarities among AS. Although each of the 8 AS that we study has distinct functions, it is likely that they address overlapping needs and generate synergies with eachother. For example, Grabner and Moers (2013) discuss how a set of management control practices can be described as either a "package" of independent elements or a "system" of interdependent elements, where practices within a system are

[24] Interestingly, we find consistent and significant evidence that hospitals are less sensitive to all of our hypothesized determinants in H1 and H2 (with the exception of *County_Peer_Update*) when their existing systems are very old (in the top decile), consistent with some hospitals exhibiting technological "inertia" where limited resources allocated to information systems make them much less responsive to external drivers of updating.

[25] Some prior research has also considered quality and contract management systems as AS. For completeness, we report results on these systems in Internet Appendix F. While *Vendor_Peer_Update* and *County_Peer_Update* are strongly significant determinants, we find weak results on all other determinants of interest. It is indeed not clear how the different regulatory shocks that provide price pressure or SOX 404 would affect both systems.

complementary in the sense that use of one element increases the benefit of other elements. To the extent that all AS are intended to address the financial needs of an organization, we expect all AS to be complements to a degree, with greater complementarity between AS which address more similar needs.

In Table 3 we use the empirical approach from Indjejikian and Matějka (2012) to test for complementarities between updates of AS by estimating the conditional correlations among all 8 AS after controlling for the determinants of updating in Table 2. If managers expect updates of two AS to create synergies for hospital outcomes, or if certain pairs of systems are less costly to update jointly than separately (for example because they are offered jointly by vendors, or because updating them involves changes to similar interrelated information systems) then we would expect the correlation of their update residuals to be positive (i.e., they are complements). Our results indicate that there is significant complementarity between all 8 AS, with particularly strong complementarity between Accounts Payable and General Ledger (AS supporting basic financial transactions), Costing and Budgeting (AS enhancing analytical capabilities), and Credit/Collections and Patient Billing (patient-focused financial AS). The complementarities in Table 3 are consistent with the categories that we use to group our systems, with AS within each of the three categories generally exhibiting greater complementarities with other AS within the same category than with AS in other categories. Further, in untabulated results we find that the conditional correlations of AS updates with updates of clinical and medical records systems are much lower than complementarities among AS (generally less than 0.2 [0.1] for medical record [clinical] systems). This indicates that we are not just documenting positive complementarities between IT upgrades in general but complementarities driven by the similar functions of AS.[26]

[26] Although our evidence on the co-occurrence of AS updates suggests the presence of complementarities, untabulated tests of complementarities in the expense and revenue outcomes of AS updates fail to find significant

Insert Table 3 here.

V. Outcomes of Accounting System Updating over Time

In this section, we delve into the outcomes of AS updates in order to provide evidence on the implications of AS updating for hospital profitability and in particular how the effects of AS updating vary depending on the driver of the update. Before estimating the effects of AS updating, it is important to recognize that both the outcome variables of interest and the AS update itself are driven by hospital decisions, and hence AS updating is endogenous. In order to address this endogeneity, our tests of economic outcomes use several different instrumental variables analyses.

In H1 and H2 we explored both economic and institutional (coercive and mimetic) factors that prompt hospitals to update their AS. On the economic determinants side, we have *Vendor_Peer_Update*, *Fair_Pricing,* and *Price_Transparency*. As a coercive determinant, we have *SOX_404*, and as mimicry determinants, we have *County_Peer_Update* and *Celebrity_Peer*. All of these determinants are reasonably exogenous with respect to the individual hospital and are therefore potential candidates to be used as instruments in an instrumental variables analysis. For example, *Vendor_Peer_Update* reflects vendor-specific technological innovations such as the release of a new version of the application or the termination of support for older versions. A vendor's scheduled update of a particular AS is based on vendor-specific factors such as technical expertise and workload of other development projects, or on demand for a specific system update by hospitals throughout the country, and is unlikely to directly affect economic outcomes at the hospital level other than AS updates.

---

interactive effects. This could be because our determinants analysis is lacking key control variables and thus overstating potential complementarities, because of a lack of power in our outcomes tests, because vendors require hospitals to update certain AS together even in the absence of complementarities, or because managers consistently overestimate synergies. We find this last possibility to be the least plausible, but cannot rule out any of these explanations.

Similarly, *Fair_Pricing, Price_Transparency,* and *SOX_404* reflect exogenous regulatory events, while *County_Peer_Update* and *Celebrity_Peer* reflect decisions made by other hospitals, exogenous to the focal hospital.

One benefit of having many potential instruments is that the use of different instrumental variables can help us identify heterogeneity in AS updating. As discussed in Angrist, Imbens, and Rubin (1996), the IV coefficient provides the estimated effect of the treatment (in this case, AS updating) on the outcome (expenses and revenues) only for the set of subject who are induced to take the treatment by the instrument (in this case, one of our exogenous determinants). For example, if the instrument is SOX 404, then the IV coefficient estimates the effect of AS updating only for hospitals which update their AS because of SOX 404 and otherwise would not have. This is referred to the local average treatment effect (LATE). Only when there is no heterogeneity in the effect of the treatment (AS updating) will the LATE be the same for all (valid) instruments. In our setting, however, we anticipate that there may be heterogeneity in the outcomes of AS updating. While we predict in H3 that AS updates driven by economic pressures will lead to decreased expenses and increased revenues, our hypothesis in H4 is that AS updates driven by coercive or mimetic pressures may either increase or decrease economic benefits. Thus by using instruments from our three different types of exogenous determinants (economic, coercive, and mimetic) we can compare the estimated IV coefficients to see whether there is heterogeneity in the effect of AS updates across updates driven by different pressures.[27]

[27] One other caveat with interpreting IV coefficients is that they cannot provide evidence on the effect of the treatment for observations which do not respond to the instrument, either because they would have received the treatment either way (alwaystakers) or because they do not receive the treatment regardless of the instrument (nevertakers) (Imbens and Wooldridge, 2009). For example, our results cannot speak to the effect of economically driven updates for hospitals who do not update when their vendor peers do, nor to the effect of mimicry updates for hospitals who would have updated regardless of their peers' actions.

Practically, although all of our exogenous determinants are candidate instruments, not all of them are empirically appropriate. Specifically, an IV analysis requires a strong instrument because a weak instrument can introduce more bias into the IV analysis than was initially in the OLS analysis. Therefore, to test H3 and H4, we select the strongest instrument in each of our three groups. For each set of analyses, we consider only instruments that were significant determinants of AS updating in Table 2 and run separate IV analyses using each potential instrument. We choose the instrument that leads to the highest F-statistic of excluded instruments in the first stage in each group.[28] For H3 on the outcomes of updates driven by economic incentives, this procedure results in the selection of *Vendor_Peer_Update* for all analyses. Because H3 is the only outcome hypothesis stated in the alternative, we present additional information and validation supporting *Vendor_Peer_Update* as an instrument for this analysis in Internet Appendix E. For H4a, *SOX_404* is the only possible instrument for updates driven by coercive forces. It is only a significant driver for 6 of the 8 AS, so we cannot present results for the outcomes of Accounts Payable and Credit/Collections updates driven by coercion. Lastly, using this approach, we select *Celebrity_Peer* as the instrument for Costing and General Ledger AS updates driven by mimetic forces, and *County_Peer_Update* for the remaining AS. While *Vendor_Peer_Update* is a strong instrument, with all first-stage F-statistics of excluded instruments far above the critical value outlined in Table 1, column 4, of Stock, Wright, and Yogo (2002) (8.96) for each analysis, on occasion the coercive and mimicry IVs drop below this critical value. In order to base inferences only on coefficients unlikely to be biased, we do not report coefficients in analyses where the F-statistics drop below the critical value.

[28] Inferences are similar when we use other instruments from the same determinants type when these other instruments had F-statistics surpassing critical values; in cases where the F-statistics were below the critical values, we tended to observe coefficients with distorted magnitudes and inconsistent signs, consistent with the IV coefficients being biased in the case of weak instruments.

To test H3 and H4 on the effect of AS updates on hospital outcomes we estimate the following specifications:

$$\boldsymbol{Op\_Ex_{i,t+n}} = \boldsymbol{\beta_1 TYPE\widehat{\_Update}_{ikt}} + \beta_2 Op\_Rev_{i,t+n} + \beta_3 Growth\_Bedize_{i,t+n} + \beta_4 CMI_{i,t+n} + \beta_5 \%Medicare_{i,t+n} + \beta_6 \%Medicaid_{i,t+n} + \beta_7 \%Clinical\_Updates_{it} + \beta_8 \%MR\_Updates_{it} + \beta_9 Application\_Level_{ikt} + \beta_{10} Hospital\_Level_{i,t+n} + \delta_{t+n} + \gamma_i \qquad (2)$$

$$\boldsymbol{Op\_Rev_{t+n}} = \boldsymbol{\beta_1 TYPE\widehat{\_Update}_{ikt}} + \beta_2 Growth\_Bedize_{i,t+n} + \beta_3 CMI_{i,t+n} + \beta_4 \%Medicare_{i,t+n} + \beta_5 \%Medicaid_{i,t+n} + \beta_6 \%Clinical\_Updates_{it} + \beta_7 \%MR\_Updates_{it} + \beta_8 Application\_Level_{ikt} + \beta_9 Hospital\_Level_{i,t+n} + \delta_{t+n} + \gamma_i \qquad (3)$$

where *i* refers to the hospital, *t* refers to the year, *n* refers to the years since the update of interest, and *k* refers to each of our eight AS.

Our main dependent variable of interest in Equation 2 is operating expenditures. *Op_Ex* is measured as operating expenditures per bed (i.e., scaled by *Bedsize*) and includes the expense incurred for the AS update. The dependent variable in Equation 3 is hospital operating revenues per bed, *Op_Rev*. The independent variable of interest, and the only coefficient we report in Table 4, is the predicted value of *Update* ($TYPE\widehat{\_Update}$) from the first stage instrumental variables analysis where a determinant of AS updating from the group "TYPE" (economic, coercive, or mimetic) is used as the instrument and *Update* indicates the presence of an AS update. Because the benefits of AS updates may appear with a lag and because costs of implementation may offset benefits in the first year of the update, we report results where *Update* is measured concurrently with *Op_Ex* and *Op_*Rev and at a one- and two-year lag.

The determinants of operating expenses and revenues are very similar as both are tied to the economic fundamentals of the hospital such as patient volume and number of procedures; thus both sets of outcome regressions contain the same control variables. The only exception is that the *Op_Ex* specifications also control for *Op_*Rev to alleviate concerns that our two outcome measures capture the same effect. Another key control variable is the change in hospital bed size (*Growth_Bedsize*) to ensure that a denominator effect or changes in economies of scale are not driving either set of results. Further, we control for the types of conditions being treated in the hospital using the Case Mix Index (*CMI*) and the types of payers using the percentage of Medicare and Medicaid patient-days (*%Medicare, %Medicaid)* because patient medical conditions and reimbursement rates of different payers can affect hospital expenses and revenues.

We also include all of the hospital-year-level and application-year-level variables from Table 2. The application-level variables are included to ensure that factors that drove the original decision to update did not also directly affect expenses or revenues. All hospital-level variables (such as bedsize or for-profit status) are measured in the same period as the dependent variable (*Op_Ex* or *Op_Rev*), and all application-level variables are measured in the same period as *Update*. We further add controls for concurrent updates of clinical and medical records systems (*%Clinical_*Updates, *%MR_*Updates) to control for general investments in information technology. Lastly, we include hospital and year fixed effects to ensure that no other static hospital-level or yearly economy-wide factors are driving our results. The use of all of the variables discussed above (in particular *Op_Rev* and the patient mix variables) constrains our sample to the years 1999 to 2010.

Consistent with our prediction in H3a, the results in Table 4 show that AS updates driven by economic pressures have a significant negative effect on operating expenses. In particular, Accounts Payable, General Ledger, Costing, Budgeting, and EIS updates have a negative effect on operating expenses over the three years beginning the year of the update. The most significant operating expense benefits are reaped relatively quickly, in the year of and the year after the update, although Budgeting and EIS AS show marginally significant effects two years out. This is consistent with the evidence in Figure 3 of the Internet Appendix that hospitals update their AS every 3 to 4 years. Further, consistent with H3b, we find that revenues significantly increase 2 years after an update for Case Mix, Credit/Collections and Patient Billing AS, with earlier benefits for patient billing and credit/collections. Overall, the results in Table 4 provide evidence consistent with economically driven AS updates leading to economic benefits.

In contrast, we find no evidence of economic benefits associated with AS updates driven by coercive and mimetic pressures. Neither coercive- nor mimicry-driven updates have a consistent relation with operating revenues, but both appear to have a significantly positive effect on operating expenses, with coercive-driven updates being most problematic. This is consistent with updates driven by coercive and mimetic pressures failing to lead to the benefits associated with economic updates while still being costly to implement.[29]

Insert Table 4 here.

Although we do not report the coefficients of control variables in Table 4 for parsimony, we note briefly that they behave reasonably. In Columns 1-3, *Op_Rev* has a coefficient ranging between 0.588 and 0.643 meaning that for every dollar of revenues the hospital has about 60 cents in expenses after controlling for other determinants. *Growth_Bedsize* is negative and significant in all specifications. In Columns 1-3, this finding supports the notion that hospitals experience economies of scale where total operating expenses per bed decrease as the number of beds increases. In Columns 4-6, this is consistent with growth in the capacity of a hospital leading to some excess capacity and thus lower revenues per bed.

[29] We also examined outcomes up to five years after the update and found no consistent significant result for AS updates driven by any of our three drivers after two years, again consistent with Figure 3 in Internet Appendix C that hospitals update their AS every 3 or 4 years.

We believe that the results in Table 4 provide interesting and compelling evidence that there are differences in the benefits of AS updates driven by economic, coercive, and mimetic pressures. So far, we have focused only on the sign and significance of our results without discussing their economic magnitude. As a first pass, we note that because both *Op_Ex* and *Op_Rev* are scaled by *Bedsize*, the coefficients on $TYPE\_Update_t$ can be loosely interpreted as the dollar change in year *t+n* operating expenditures (revenues) per hospital bed as a result of an update in year *t* driven by pressure TYPE (either economic, coercive, or mimetic). Our data's *Op_Ex* measure cannot disentangle expense and depreciation costs of AS from regular operating expenses, so we capture the expense benefit of an AS update net of any updating costs.[30] For example, the results with respect to economically driven Costing AS updates in Panel C have a coefficient of -34,716 in Column 2. This implies that Costing updates driven by economic pressures lead to an average decrease in operating expenses of $34,716 per bed in the year after the update (*t+1*). The magnitudes of the significant operating expense decreases due to economic pressures range from 12,074 in Column 3 of Panel E (benefits of EIS updates in year *t+2*) to 47,212 in Column 1 of Panel C (benefits of Costing updates in year *t*). The magnitude of revenue increases due to economically driven updates ranges from $29,404 per bed for Patient Billing AS in year *t* to $79,040 for Case Mix AS in year *t+2*. The size of these coefficients is reasonable in comparison with the mean total operating expenditures of hospitals in our sample of $94 million and mean operating expenditures and revenues per bed of $487,508 and $502,824, respectively.

In contrast, the absolute coefficient sizes for the effect of coercive and mimicry driven AS updates on operating expenses per bed tend to be larger, with significant increases in operating expenses ranging from 69,962 for coercive Budgeting AS updates in year *t+1* to 279,626 for

[30] To the extent that AS update costs are depreciated over time, the expense reductions may be overstated in the first year, but the entire depreciation cost will be covered over the 3 year period studied, as this is the depreciation duration prescribed by the American Hospital Association (AmericanHospitalAssociation, 2013).

mimicry driven Costing AS updates in year *t+2*. These larger coefficients are likely due to two factors. First, there appears to be little to no expense benefit to net against the cost of the new system. Second, these coefficients report the local average treatment effects (LATE) for hospitals treated by our coercive and mimetic forces, which tend to be twice as large on average as the broader set of hospitals affected by the *Vendor_Peer_Update* instrument, leading to greater variance in expenses per bed and larger potential coefficients.

One concern with the coefficients reported in Table 4 is that the effect of AS updates on operating expenses and revenues is estimated separately for every period, without controlling for the effect of AS updates in prior periods.[31] This can lead to inaccurate coefficient sizes. Therefore, in Table 5 we re-estimate the effects of AS updates on operating expenses and revenues in a pooled analysis where AS updates in the current and prior two periods are all included as independent variables in the same specification. This specification is more demanding on the strength of our instruments because it (1) requires data for all three periods be available, decreasing our sample size, and (2) includes three endogenous regressors in the same equation. As the number of endogenous regressors and instruments increases, so do the requirements on the strength of the instruments and the critical value for the F-statistic from the test of excluded instruments (Stock et al., 2002). In our setting, the inclusion of multiple lags exacerbates the weak instrument problem because not all of the instruments are good predictors of the endogenous regressors; for example, vendor peer updates in time *t* do not predict AS updates in time *t-2*. As a result, none of the specifications using coercive or mimicry driven instruments have F-statistics from the test of excluded instruments which exceed the Stock et al.

[31] In fact, the inclusion of hospital fixed effects means that the average effect of AS updates in other periods is incorporated into the hospital fixed effect and removed from the estimated effect in the current period, further distorting the interpretation of the coefficient.

(2002) critical values. Hence, we can only estimate the effect of economically driven AS updates using this pooled analysis.

Insert Table 5 here.

The expense results in Table 5 provide very similar results to those of economically driven updates in Table 4 in terms of sign and significance, and often produce coefficients that are slightly larger. The expense decreases due to economically driven AS updates range from \$23,635 per bed for EIS updates two years ago to \$67,157 per bed for Budgeting AS updates two years ago. In the pooled specification, the revenue benefits of economically driven updates are less prevalent, with only updates of Patient Billing AS leading to significant increases in revenues of \$49,463 and \$77,635 per bed in the year of and following the update. Overall, the results in Table 5 provide further evidence in support of H3 that economically driven AS updates provide economic benefits to hospitals and suggest that the magnitude of these benefits ranges from about 5% to 14% in terms of net expense reductions, and 10% to 15% in terms of revenue increases.

In untabulated cross-sectional analyses, we also explore which hospitals benefit most from economically driven AS updates. We find evidence that suggests the benefits of AS updates are largest for hospitals facing higher competition, those serving a more complex patient base (proxied for by CMI), and those which had the poorest quality AS prior to the update (proxied for by prior AS age).[32] Future studies can expand on these results. For example, do institutional buy-in (i.e., how willing clinical staff are to adjust procedures based on input from financial systems) or financial constraints affect the impact of AS updates? In Internet Appendix H, we

[32] This last finding is particularly interesting because in untabulated determinants analyses we found that hospitals with very old systems are much less likely to respond to economic pressures to update, consistent with them potentially suffering from resource constraints which prevent updating. Combined, these results indicate that firms subject to resource constraints may be forced to put off investments in information technology, even though this may lead to aging AS where the benefits of updating are likely to be greatest.

perform robustness tests to ensure that our results are not driven by the specific empirical design used in the reported tables. Overall, our results appear robust and economically significant.[33]

VI. Conclusion and Future Research

This paper uses a large dataset of accounting systems (AS) spanning a period of 24 years with between 2,900 and 5,243 unique U.S. hospitals in each year of the data to examine the updating of eight different AS over time. We find that hospitals update their AS in response to economic, coercive, and mimetic pressures. First, hospitals update their AS in response to supply-side economic pressures as vendors push out new AS upgrades, while staggered state-level price regulations such as fair pricing and price transparency measures increase demand-side economic pressures for improved internal accounting information. Second, hospitals update their AS when regulators exert coercive institutional pressure by mandating that hospitals adopt certain practices, for example increased internal control requirements under Section 404 of the Sarbanes-Oxley Act. Lastly, mimetic institutional pressures from county and celebrity peers shape hospitals' AS updating behavior as well.

We use an instrumental variables framework to show that only economically driven updates lead to economic benefits. Using vendor-pushed updates to capture effects of economically driven updates, we document immediate and significant reductions in operating expenses following some AS updates and delayed revenue benefits following other AS updates. In contrast, we find AS updates driven by coercive forces (SOX 404) or mimetic pressures (county and celebrity peers) appear to lead to *increased* expenses. These results are important because to our knowledge we are the first study to show both economic benefits of AS updating and that the driver behind the update can affect the economic benefits of the update itself.

[33] We also report results on the outcomes of economically driven updates of quality and contract management systems in Internet Appendix F. Evidence of financial outcomes for these systems is limited to nonexistent.

We believe our results on AS updating provide several key contributions to both academia and practice. First, we document a link between external regulation and real changes *within* firms that update their AS. This finding is important more generally in understanding the full costs and benefits of regulation changes and has important implications for each regulation individually. Importantly, regulation that increases demand-side economic incentives for firms to improve their AS, such as fair pricing and price transparency measures, may offer economic benefits for those hospitals that decide to update their AS. On the other hand, regulation that coercively mandates changes to internal systems where there is no clear economic need may lead to expense increases.

Second, we document a strong link between the motivation behind the decision to update AS and whether or not economic benefits are obtained. Only updates driven by economic incentives generate profitability improvements, while updates driven by coercive and mimetic institutional forces do not because updates in these cases are focused on the external perception that information has improved ("label" updates) without actually targeting increases in specific information quality. Additionally, while research on the benefits of AS typically struggles with endogeneity concerns, our data and setting allow us to use instrumental variables analyses to convincingly estimate the economic outcomes associated with hospitals' updating behavior.

Lastly, despite various academic calls for studying updating, its practical importance, and the vague advice on the topic available to practitioners, our understanding of what impacts firms' decisions to update their AS has remained minimal. Our setting to examine this topic is particularly interesting because hospitals operate in a dynamic environment, meaning that timely and appropriate AS updates are especially important.

We welcome further research on AS updating. While the health care sector is a very important sector that accounts for 17% of U.S. GDP (WorldHealthOrganization, 2015), further research can study if our results generalize to other sectors of the economy. It is possible that our results on price disclosure and price pressure may generalize to the advent of price comparison websites in other sectors such as Kayak in the travel industry and PriceGrabber, which captures prices of consumer products. It would also be interesting to examine the effect of AS updates on additional outcomes, gain deeper insights on exactly how operating expense reductions and revenue increases are achieved based on improved accounting information, and to explore how updates to AS affect the quality of external financial reporting. Furthermore, future studies can provide normative guidance on the best AS updating strategy. We look forward to research that provides answers to these important questions.

References

Allison, P. (2002). *Bias in Fixed-Effects Cox Regression with Dummy Variables*. Working Paper. University of Pennsylvania.

Allison, P. D. (1996). Fixed-Effects Partial Likelihood for Repeated Events. *Sociological Methods Research, 25*(2), 207-222.

AmericanHospitalAssociation. (2013). *Estimated Useful Lives of Depreciable Hospital Assets*.

Anderson, M. C., Banker, R. D., and Ravindran, S. (2006). Value Implications of Investments in Information Technology. *Management Science, 52*(9), 1359-1376.

Angrist, J. D., Imbens, G. W., and Rubin, D. B. (1996). Identification of Causal Effects Using Instrumental Variables. *Journal of the American Statistical Association, 91*(434), 444-455.

Angst, C. M., Agarwal, R., Gao, G., Khuntia, J., and McCullough, J. S. (2014). Information Technology and Voluntary Quality Disclosure by Hospitals. *Decision Support Systems*, 367-375.

Angst, C. M., Agarwal, R., Sambamurthy, V., and Kelley, K. (2010). Social Contagion and Information Technology Diffusion: The Adoption of Electronic Medical Records in U.S. Hospitals. *Management Science, 56*(8), 1219-1241.

Angst, C. M., Block, E. S., D'Arcy, J., and Kelley, K. (2017). When Do IT Security Investments Matter? Accounting for the Influence of Institutional Factors in the Context of Healthcare Data Breaches. *MIS Quarterly, 41*(3), 893-916.

Bai, G. (2015). California's Hospital Fair Pricing Act Reduced the Prices Acutally Paid by Uninsured Patients. *Health Affairs, 34*(1), 64-70.

Bai, G. (2016). Applying Variance Analysis to Understand California Hospitals' Expense Recovery Status by Patient Groups. *Accounting Horizons, 30*(2), 211-223.

Bai, X., Nunez, M., and Kalagnanam, J. R. (2012). Managing Data Quality Risk in Accounting Information Systems. *Information Systems Research, 23*(2), 453-473. doi: 10.1287/isre.1110.0371

Bardhan, I. R., and Thouin, M. F. (2013). Health Information Technology and its Imact on the Quality and Cost of Healthcare Delivery. *Decision Support Systems*, 438-449.

Batty, M. M., and Ippolito, B. N. (2016). *Financial Incentives, Hospital Care, and Health Outcomes: Evidence from Fair Pricing Laws*. AEI Economics Working Paper Series. American Enterprise Institute.

Beatty, R. C., and Williams, C. D. (2006). ERP II: Best Practices for Successfully Implementing an ERP Upgrade. *Communications of the ACM, 49*(3), 105-109.

Beck, M. (2014, Feb 23). How to Bring the Price of Health Care into the Open, *Wall Street Journal*.

Borzekowski, R. (2009). Measuring the cost impact of hospital information systems: 1987–1994. *Journal of Health Economics, 28*, 938-949.

Cao, J., Nicolaou, A. I., and Bhattacharya, S. (2013). A Longitudinal Examination of Enterprise Resource Planning System Post-Implementation Enhancements. *Journal of Information Systems, 27*(1), 13-39.

Cavalluzzo, K. S., and Ittner, C. D. (2004). Implementing Performance Measurement Innovations: Evidence from Government. *Accounting, Organizations and Society, 29*(3-4), 243-267.

Cavalluzzo, K. S., Ittner, C. D., and Larcker, D. F. (1998). Competition, Efficiency, and Cost Allocation in Government Agencies: Evidence on the Federal Reserve System *Journal of Accounting Research, 36*(1), 1-32.

Chenhall, R. H., and Morris, D. (1986). The Impact of Structure, Environment, and Interdependence on the Perceived Usefulness of Management Accounting Systems. *The Accounting Review, 61*(1), 16-35.

Christensen, H. B., Floyd, E., and Maffett, M. (2015, May). *The Effects of Price Transparency Regulation on Prices in the Healthcare Industry*. Booth Working Paper, (14-33). Chicago Booth.

CIOMagazine. (2014). 2014 State of the CIO Survey (pp. 4).

Corbett, C. J., and Castka, P. (2015). Management Systems Standards: Diffusion, Impact and Governance of ISO 9000, ISO 14000, and Other Management Standards. *Foundations and Trends in Technology, Information and Operations Management, 7*(3-4), 161-379.

CreditSuisse. (2012). The Apps Revolution Manifesto —Volume 1: The Technologies *Equity Research* (pp. 99). U.S.A.

Daske, H., Hail, L., Leuz, C., and Verdi, R. S. (2013). Adopting a Label: Heterogeneity in the Economic Consequences Around IAS/IFRS Adoptions. *Journal of Accounting Research, 51*(3), 495-547.

Davila, A., and Foster, G. (2005). Management Accounting Systems Adoption: Evidence and Performance Implications from Early Stage / Startup Companies. *The Accounting Review, 80*(4), 1039-1068.

Davila, A., and Foster, G. (2007). Management Control Systems in Early-Stage Startup Companies. *The Accounting Review, 82*(4), 907–937.

Debitoor. (Ed.) (2017) Debitoor Dictionary.

DiMaggio, P. J., and Powell, W. W. (1983). The Iron Cage Revisited: Institutional Isomorphism and Collective Rationality in Organizational Fields. *American Sociological Review, 48*(2), 147-160.

Eldenburg, L., and Krishnan, R. (2008). The Influence of Ownership on Accounting Information Expenditures. *Contemporary Accounting Research, 25*(3), 739-772.

Feng, M., Li, C., McVay, S. E., and Skaife, H. (2015). Does Ineffective Internal Control Over Financial Reporting Affect a Firm's Operations? Evidence from Firms' Inventory Management. *The Accounting Review, 90*(2), 529-557.

Furneaux, B., and Wade, M. (2011). An Exploration of Organizational Level Information Systems Discontinuance Intentions. *MIS Quarterly, 35*(3).

Gable, G. G., Chan, T., and Tan, W.-G. (2001). Large Packaged Application Software Maintenance: a Research Framework. *Journal of Software Maintenance and Evolution: Research and Practice, 13*, 351-371.

Geiger, D. R., and Ittner, C. D. (1996). The Influence of Funding Source and Legislative Requirements on Government Cost Accounting Practices. *Accounting, Organizations and Society, 21*(6), 549-567.

Grabner, I., and Moers, F. (2013). Management control as a system or a package? Conceptual and empirical issues. *Accounting, Organizations and Society, 38*(6-7), 407-419.

Greene, W. (2004). The Behaviour of the Maximum Likelihood Estimator of Limited Dependent Variable Models in the Presence of Fixed Effects. *The Econometrics Journal, 7*(1), 98-119.

Hall, J. A. (1998). *Accounting Information Systems* (2nd ed.). Boston: South Western College Publishing.

Hill, N. T. (2000). Adoption of Costing Systems in US Hospitals: An Event History Analysis 1980-1990. *Journal of Accounting and Public Policy, 19*, 41-71.

Houk, S., and Cleverley, J. O. (2014). How Hospitals Approach Price Transparency. *Healthcare Financial Management*(Sep), 8 pp.

Imbens, G. W., and Wooldridge, J. M. (2009). Recent Developments in the Econometrics of Program Evaluation. *Journal of Economic Literature, 47*(1), 5-86. doi: 10.1257/jel.47.1.5

Indjejikian, R. J., and Matějka, M. (2012). Accounting Decentralization and Performance Evaluation of Business Unit Managers. *The Accounting Review, 87*(1), 261-290. doi: 10.2308/accr-10168

Ittner, C. D., Lanen, W. N., and Larcker, D. F. (2002). The Association Between Activity-Based Costing and Manufacturing Performance. *Journal of Accounting Research, 40*(3), 711-726.

Kaplan, R. S., and Porter, M. (2011). How to Solve the Cost Crisis in Health Care. *Harvard Business Review, 89*(9), 46-64.

Khoo, H. M., and Robey, D. (2007). Deciding to Upgrade Packaged Software: a Comparative Case Study of Motives, Contingencies and Dependencies. *European Journal of Information Systems, 16*, 555-567.

Kim, K. K. (1988). Organizational Coordination and Performance in Hospital Accounting Information Systems: An Empirical Investigation. *The Accounting Review, 63*(3).

Kobelsky, K. W., Richardson, V. J., Smith, R. E., and Zmud, R. W. (2008). Determinants and Consequences of Firm Information Technology Budgets. *The Accounting Review, 83*(4), 957–995.

Krishnan, R. (2005). The Effect of Changes in Regulation and Competition on Firms' Demand for Accounting Information. *The Accounting Review, 80*(1), 269-287.

Krumwiede, K. R. (1998). The Implementation Stages of Activity-Based Costing and the Impact of Contextual and Organizational Factors. *Journal of Management Accounting Research, 10*, 239-277.

Li, C., Peters, G. F., Richardson, V. J., and Weidenmier, M. W. (2012). The Consequences of Information Technology Control Weaknesses on Management Information Systems: The Case of Sarbanes-Oxley Internal Control Reports. *MIS Quarterly, 36*(1), 179-203.

Libby, T., and Waterhouse, J. H. (1996). Predicting Change in Management Accounting Systems. *Journal of Management Accounting Research, 8*, 137-150.

Maiga, A. S., and Jacobs, F. A. (2008). Extent of ABC Use and Its Consequences. *Contemporary Accounting Research, 25*(2), 533-566.

Masli, A., Peters, G. F., Richardson, V. J., and Sanchez, J. M. (2010). Examining the Potential Benefits of Internal Control Monitoring Technology. *The Accounting Review, 85*(3), 1001-1034.

McCullough, J. S., and Snir, E. M. (2010). Monitoring Technology and Firm Boundaries: Physician-Hospital Integration and Technology Utilization. *Journal of Health Economics, 29*, 457-467.

Morris, J. J. (2011). The Impact of Enterprise Resource Planning (ERP) Systems on the Effectiveness of Internal Controls over Financial Reporting. *Journal of Information Systems, 25*(1), 129-157.

Sandino, T. (2007). Introducing the First Management Control Systems: Evidence from the Retail Sector. *The Accounting Review, 82*(1), 265–293.

Setia, P., Setia, M., Krishnan, R., and Sambamurthy, V. (2011). The Effects of the Assimilation and Use of IT Applications on Financial Performance in Healthcare Organizations. *Journal of the Association for Information Systems, 12*(3), 274-298.

Stock, J. H., Wright, J. H., and Yogo, M. (2002). A Survey of Weak Instruments and Weak Identification in Generalized Method of Moments. *Journal of Business & Economic Statistics, 20*(4), 518-529.

Tozzi, J. (2017, Dec 18). A Hospital Giant Discovers that Collecting Debt Pays Better than Curing Ills, *Bloomberg*.

WorldHealthOrganization. (2015). World Health Statistics.

Table 1. Descriptive Statistics

Panel A. Hospital-Level Variables

	N	Mean	Median	Std	P25	P75
Celebrity_Peer	51,748	0.14	0.00	0.35	0.00	0.00
Apps_Age	51,748	6.23	5.90	2.69	4.26	7.86
Business_Depth	51,748	7.28	6.00	5.27	3.00	10.00
Med_Record_Depth	51,748	3.48	3.00	1.84	2.00	5.00
Clinical_Depth	51,748	5.52	5.00	3.57	3.00	7.00
Bedsize	51,748	224.71	180.00	180.22	98.00	310.00
In_System	51,748	0.64	1.00	0.48	0.00	1.00
SOX_404	51,748	0.17	0.00	0.37	0.00	0.00
For_Profit	51,748	0.30	0.00	0.46	0.00	1.00
Academic	51,748	0.40	0.00	0.49	0.00	1.00
HHI	51,748	4,751	3,779	3,649	1,379	10,000
Rural	51,748	0.12	0.00	0.33	0.00	0.00
Op_Ex	30,663	487,508	431,069	272,018	306,165	600,457
Op_Rev	30,663	502,824	443,749	291,522	308,103	625,314
Growth_Bedsize	30,663	0.01	0.00	0.12	0.00	0.00
CMI	30,663	1.38	1.33	0.25	1.20	1.54
%Medicare	30,663	46.31	47.61	14.35	36.60	56.22
%Medicaid	30,663	13.80	11.58	10.24	6.35	18.48

Hospital-level variables used in the hazard analysis are available for the full sample period (1987-2010). Variables used only in Tables 4 & 5 are available for the years 1999-2010. Descriptive statistics are provided for the largest sample for which data are available to estimate models relating to General Ledger systems.

Panel B. Accounting System Updates

System	N	Mean	Median	Std
Accounts Payable	51,518	0.08	0	0.28
General Ledger	51,748	0.08	0	0.28
Costing	36,576	0.09	0	0.28
Budgeting	40,661	0.10	0	0.30
EIS	26,829	0.15	0	0.36
Case Mix	45,829	0.08	0	0.28
Credit/Collections	37,653	0.06	0	0.24
Patient Billing	52,635	0.08	0	0.27

Accounting system updates, by system type. The mean represents the proportion of hospital-application-year observations in which an update is recorded.

Panel C. Application-Level Variables

	Accounts Payable	General Ledger	Costing	Budgeting	EIS	Case Mix	Credit/ Collections	Patient Billing
Vendor_Peer_Update	10.654	10.399	12.866	13.635	18.346	11.090	10.784	10.256
County_Peer_Update	0.009	0.002	0.016	0.010	0.017	0.017	0.281	0.101
System_Peer_Update	0.251	0.246	0.298	0.312	0.352	0.269	0.289	0.249
Self_Developed	0.099	0.106	0.126	0.144	0.159	0.126	0.094	0.109

Mean values of application-level variables by AS type.

Table 2. Determinants of Application Updating

	Predicted Effect	(1) Accounts Payable	(2) General Ledger	(3) Costing	(4) Budgeting	(5) EIS	(6) Case Mix	(7) Credit/ Collections	(8) Patient Billing
Economic Forces									
Vendor_Peer_Update	+	1.017***	1.020***	1.023***	1.018***	1.012***	1.020***	1.022***	1.021***
		(12.11)	(13.68)	(16.46)	(16.44)	(11.71)	(17.04)	(11.54)	(14.21)
Fair_Pricing	+†	1.421***	1.285**	1.293***	1.075	1.136	1.307***	1.479***	1.041
		(3.166)	(2.020)	(2.113)	(0.841)	(1.321)	(2.282)	(2.824)	(0.333)
Price_Transparency	+*	0.735***	0.751***	1.140*	1.157***	0.941	0.899	0.904	0.810**
		(-3.288)	(-2.916)	(1.366)	(2.052)	(-0.832)	(-0.897)	(-0.930)	(-2.352)
Coercive Forces									
SOX_404 x Prep_Years	+	0.937	1.356***	1.400***	1.452***	1.367****	1.789***	1.145	1.376****
		(-0.487)	(3.088)	(3.050)	(3.571)	(2.800)	(5.419)	(1.032)	(2.674)
Mimetic Forces									
County_Peer_Update	+	1.893***	0.936	1.157	1.273*	1.241**	1.561***	1.468***	1.162***
		(5.542)	(-0.165)	(1.281)	(1.647)	(2.023)	(4.456)	(6.650)	(2.625)
Celebrity_Peer	+	1.178***	1.107*	1.214***	1.064	1.065	1.142**	0.985	1.075
		(2.588)	(1.648)	(3.343)	(1.189)	(1.360)	(2.301)	(-0.225)	(1.176)
		Hospital Information System Characteristics							
System_Peer_Update		3.887***	3.553***	3.961***	4.335***	6.565***	3.190***	4.165***	3.191***
		(25.44)	(23.64)	(21.65)	(26.00)	(26.60)	(21.30)	(18.55)	(22.06)
Self_Developed		1.012	1.264***	1.414***	1.259***	0.952	1.259***	1.732***	1.239***
		(0.195)	(3.964)	(5.324)	(4.099)	(-0.868)	(3.882)	(6.343)	(3.453)
Apps_Age		0.638***	0.656***	0.648***	0.679***	0.690***	0.604***	0.608***	0.628***
		(-14.97)	(-13.69)	(-14.14)	(-14.04)	(-13.58)	(-17.06)	(-12.89)	(-16.38)
Apps_Age^2		1.010***	1.006**	1.010***	1.011***	1.012***	1.013***	1.008**	1.010***
		(3.350)	(1.993)	(3.961)	(4.981)	(5.652)	(4.739)	(2.218)	(3.824)
Business_Depth		1.038***	1.033***	1.031***	1.048***	1.060***	1.030***	1.009	1.014**
		(6.586)	(5.614)	(5.410)	(10.08)	(12.32)	(5.607)	(1.351)	(2.511)

Med_Record_Depth	1.020	1.020	0.948***	0.977*	0.980	0.978	1.011	1.002
	(1.403)	(1.376)	(-3.460)	(-1.853)	(-1.489)	(-1.561)	(0.643)	(0.149)
Clinical_Depth	0.984**	1.001	1.016**	1.013*	1.008	1.027***	1.032***	1.022***
	(-2.024)	(0.100)	(1.968)	(1.862)	(1.205)	(3.516)	(3.283)	(2.588)
			Hospital Characterisitcs					
Bedsize	1.000	1.000***	1.000	1.000	1.000	1.000	1.000	1.000
	(-1.169)	(-2.643)	(0.493)	(-1.048)	(-0.311)	(-0.618)	(1.057)	(-1.058)
In_System	0.449***	0.459***	0.437***	0.366***	0.251***	0.518***	0.374***	0.504***
	(-14.58)	(-13.76)	(-11.52)	(-16.08)	(-17.97)	(-11.04)	(-11.75)	(-12.13)
SOX_404	0.856**	0.984	1.062	0.821***	0.678***	0.864**	0.816**	0.811***
	(-2.375)	(-0.246)	(0.792)	(-3.129)	(-5.566)	(-2.098)	(-2.288)	(-2.975)
For_Profit	0.992	1.025	0.958	1.047	1.041	0.964	1.152**	1.193***
	(-0.160)	(0.436)	(-0.622)	(0.813)	(0.658)	(-0.601)	(1.995)	(3.222)
Academic	1.025	1.077*	1.125**	1.059	1.014	1.034	1.141**	1.100**
	(0.604)	(1.752)	(2.369)	(1.298)	(0.308)	(0.757)	(2.138)	(2.145)
			Market Characteristics					
HHI	1.000*	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	(-1.709)	(-1.271)	(0.0990)	(-1.157)	(1.432)	(-1.039)	(0.740)	(-0.284)
Rural	0.917	0.841***	1.021	0.998	0.931	0.983	1.038	0.903
	(-1.402)	(-2.681)	(0.273)	(-0.0347)	(-1.102)	(-0.260)	(0.471)	(-1.550)
State and Year Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	51,518	51,748	36,576	40,661	26,832	45,829	37,653	52,635
Wald χ^2, Entire Model	4313	4095	3135	3267	3499	3712	3036	3655
Prob. > χ^2, Entire Model	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001

Estimates of the hazard ratios in a Cox proportional hazards model, where the dependent variable in each column is the hazard of updating a given application at time t, and t is measured in years since the last update. We use the Efron method to deal with tied failure times. The predicted signs refer to the sign of the z-statistics (i.e. the effect is relative to a baseline hazard ratio of 1). †Prediction for costing, budgeting, case mix, credit/collections, and patient billing systems. *Prediction for costing and budgeting systems.

Robust z-statistics clustered by hospital in parentheses

*** p<0.01, ** p<0.05, * p<0.1 (One-tailed p-values where there is a signed prediction)

Table 3. Complementarity of AS Updates

Conditional Correlation of AS Updates After Controlling for Determinants of Updating

Pearson (above) / Spearman (below) Correlations

	Accounts Payable	*General Ledger*	*Costing*	*Budgeting*	*EIS*	*Case Mix*	*Credit/ Collections*	*Patient Billing*
Accounts Payable		**0.87765**	0.46722	0.45733	0.29587	0.43094	0.46923	**0.50794**
General Ledger	**0.88303**		0.47525	0.46342	0.2958	0.44887	0.48011	**0.52614**
Costing	0.43566	0.45023		**0.66005**	0.38147	**0.50961**	0.40089	0.38453
Budgeting	0.43342	0.44277	**0.6743**		0.39188	0.4834	0.36177	0.35701
EIS	0.29482	0.28862	0.39448	0.4236		0.38215	0.30115	0.29847
Case Mix	0.48217	0.48563	**0.54344**	**0.50104**	0.38463		0.48451	**0.5055**
Credit/Collections	0.4981	0.49575	0.47005	0.41557	0.32957	**0.51354**		**0.73244**
Patient Billing	**0.53534**	**0.54162**	0.41564	0.3843	0.29908	**0.53958**	**0.70871**	

Correlations of residuals from OLS regressions where AS updates are regressed on all determinants of updating from Table 2 (including time since last update). All correlations significant at the 1% level. Correlations larger than 0.5 bolded.

Table 4. Heterogeneity in the Effect of Accounting System Updates

	(1)	(2)	(3)	(4)	(5)	(6)
	Op_Ex ***t+0***	**Op_Ex** ***t+1***	**Op_Ex** ***t+2***	**Op_Rev** ***t+0***	**Op_Rev** ***t+1***	**Op_Rev** ***t+2***
ECON_Update $_t$ Predicted Effect	- †	- †	- †			
Panel A. Accounts Payable Systems						
ECON_Update $_t$	-29,267***	-30,450***	-9,466	8,585	35,499**	-10,554
	(-3.561)	(-3.847)	(-0.972)	(0.529)	(2.529)	(-0.733)
COERC_Update $_t$	*No Valid Instrument*					
MIMIC_Update $_t$	-30,608	-24,258	-44,575	99,306	134,104	-17,298
	(-0.542)	(-0.219)	(-0.492)	(0.906)	(1.034)	(-0.115)
Observations	30,655	27,242	23,920	30,655	27,242	23,920
Panel B. General Ledger Systems						
ECON_Update $_t$	-16,327**	-36,835***	-11,177	22,756	53,404***	35,716**
	(-2.012)	(-3.904)	(-1.113)	(1.411)	(3.248)	(2.394)
COERC_Update $_t$	74,126*	108,596***	154,346**	-274,118***	53,917	-127,799
	(1.776)	(2.592)	(2.477)	(-3.311)	(0.784)	(-1.532)
MIMIC_Update $_t$	*F < CV*	90,956**	168,838**	*F < CV*	174,701**	-268,624***
		(2.230)	(2.491)		(2.567)	(-2.688)
Observations	30,663	27,274	23,970	30,663	27,274	23,970
Panel C. Costing Systems						
ECON_Update $_t$	-47,212***	-34,716**	-16,105	-40,700	-6,688	23,108
	(-2.902)	(-2.191)	(-0.966)	(-1.196)	(-0.237)	(0.867)
COERC_Update $_t$	14,822	86,794**	182,221***	-58,352	230,583***	-253,682***
	(0.410)	(2.419)	(3.120)	(-0.895)	(3.531)	(-2.913)
MIMIC_Update $_t$	*F < CV*	79,155**	279,626***	*F < CV*	220,244***	-396,026***
		(1.982)	(3.076)		(3.218)	(-2.920)
Observations	24,589	21,952	19,438	24,589	21,952	19,438
Panel D. Budgeting Systems						
ECON_Update $_t$	-46,963***	-44,068***	-23,240*	-11,684	-13,463	14,329
	(-2.598)	(-2.929)	(-1.379)	(-0.342)	(-0.511)	(0.541)
COERC_Update $_t$	19,720	69,962**	142,350***	-164,117***	391,477***	-76,719
	(0.608)	(2.174)	(3.085)	(-2.796)	(5.757)	(-1.195)
MIMIC_Update $_t$	-25,544	48,794	165,494*	-73,527	-97,977	-32,885
	(-0.525)	(0.733)	(1.807)	(-0.690)	(-0.866)	(-0.239)
Observations	26,294	23,276	20,434	26,294	23,276	20,434
Panel E. Executive Information Systems						
ECON_Update $_t$	-6,556	-14,307**	-12,074*	-13,545	32,653**	16,219
	(-0.783)	(-1.695)	(-1.401)	(-0.918)	(2.369)	(1.176)
COERC_Update $_t$	-21,503	*F < CV*	*F < CV*	-26,596	*F < CV*	*F < CV*
	(-0.334)			(-0.216)		
MIMIC_Update $_t$	96,398	*F < CV*	*F < CV*	12,089	*F < CV*	*F < CV*
	(1.347)			(0.0851)		
Observations	21,611	18,868	16,151	21,611	18,868	16,151

	(1) Op_Ex *t+0*	(2) Op_Ex *t+1*	(3) Op_Ex *t+2*	(4) Op_Rev *t+0*	(5) Op_Rev *t+1*	(6) Op_Rev *t+2*
ECON_Update $_t$ Predicted Effect				+*	+*	+*
Panel F. Case Mix Systems						
ECON_Update $_t$	23,928	12,246	2,651	-51,201	-2,615	79,040***
	(1.244)	(0.721)	(0.145)	(-1.716)	(-0.0913)	(2.758)
COERC_Update $_t$	-73,029	-15,624	260,579***	-58,278	135,043	-430,159***
	(-1.077)	(-0.272)	(2.922)	(-0.470)	(1.262)	(-3.022)
MIMIC_Update $_t$	-80,586	*F < CV*	*F < CV*	42,820	*F < CV*	*F < CV*
	(-0.824)			(0.246)		
Observations	27,868	24,938	22,100	27,868	24,938	22,100
Panel G. Credit/Collections Systems						
ECON_Update $_t$	18,997	-9,205	12,238	-6,065	33,276*	42,675**
	(1.440)	(-0.656)	(0.776)	(-0.263)	(1.424)	(1.955)
COERC_Update $_t$			*No Valid Instrument*			
MIMIC_Update $_t$	11,790	23,178	27,766	-78,695	-133,158**	-41,365
	(0.286)	(0.540)	(0.550)	(-1.135)	(-1.989)	(-0.537)
Observations	28,418	25,297	22,278	28,418	25,297	22,278
Panel H. Patient Billing Systems						
ECON_Update $_t$	2,740	-18,633*	-5,161	29,404*	56,656***	33,713**
	(0.263)	(-1.766)	(-0.405)	(1.542)	(3.224)	(2.002)
COERC_Update $_t$	77,063*	108,763**	112,648*	-251,165***	123,672	-81,962
	(1.681)	(2.273)	(1.714)	(-2.741)	(1.510)	(-0.923)
MIMIC_Update $_t$	186,027	*F < CV*	*F < CV*	138,655	*F < CV*	*F < CV*
	(1.429)			(0.686)		
Observations	30,628	27,280	24,054	30,628	27,280	24,054
Controls	Y	Y	Y	Y	Y	Y
Hospital & Year FE	Y	Y	Y	Y	Y	Y

Instrumental variables analysis (IV-GMM) of the effect of accounting system updates on expenses and revenues (*Op_Ex, Op_Rev)* using significant exogenous Economic, Coercive, and Mimetic determinants from Table 2 as instruments. Each cell reports the estimated effect of *Update* $_t$ on the outcome in period $t+n$ using either an economic, coercive, or mimetic IV. When multiple potential instruments exist, the one yielding the highest F-statistic from the test of excluded instruments is used. Results reported only when the F-statistic from test of excluded instruments is greater than the critical value outlined in Table 1, Column 4 of Stock, Wright, Yogo (2002) (8.96). Hospital-Level Controls$_{t+n}$ comprise all hospital-level variables from Table 2 plus: *Growth_Bedsize*, *CMI*, *%Medicare*, *%Medicaid*, *%Clinical_Updates*, *%MR_Updates*, and (for Column 1) *Op_Rev* The remaining variables from Table 2, calculated for each AS, comprise Application-Level Controls$_{tk}$. †Panels A - E. *Panels F - H.

Heteroskedasticity robust z-statistics clustered by hospital in parentheses

*** p<0.01, ** p<0.05, * p<0.1 (One-tailed p-values where there is a signed prediction)

Table 5. The Effect of Accounting System Updates Driven by Economic Incentives: Pooled Analysis

	(1) Op_Ex_t	(2) Op_Rev_t		(1) Op_Ex_t	(2) Op_Rev_t
Predicted Effect	- †	+ *		- †	+ *
Panel A. Accounts Payable Systems			*Panel B. General Ledger Systems*		
ECON_Update $_t$	-35,319***	-9,852	*ECON_Update* $_t$	-13,456	-50,729*
	(-2.752)	(-0.405)		(-0.990)	(-1.916)
ECON_Update $_{t-1}$	-65,488***	53,217*	*ECON_Update* $_{t-1}$	-46,204***	52,282**
	(-4.154)	(1.909)		(-2.924)	(2.064)
ECON_Update $_{t-2}$	-25,529*	13,069	*ECON_Update* $_{t-2}$	-5,550	50,112**
	(-1.618)	(0.524)		(-0.404)	(2.518)
Observations	23,092	23,092	Observations	23,105	23,105
Panel C. Costing Systems			*Panel D. Budgeting Systems*		
ECON_Update $_t$	-43,964**	-29,594	*ECON_Update* $_t$	-57,141***	-23,370
	(-1.793)	(-0.604)		(-2.584)	(-0.645)
ECON_Update $_{t-1}$	-38,247	3,431	*ECON_Update* $_{t-1}$	-55,126***	-24,126
	(-1.127)	(0.0589)		(-2.366)	(-0.663)
ECON_Update $_{t-2}$	-40,190*	17,352	*ECON_Update* $_{t-2}$	-67,157***	29,506
	(-1.465)	(0.402)		(-2.625)	(0.703)
Observations	17,739	17,739	Observations	19,085	19,085
Panel E. Executive Information Systems			*Panel F. Case Mix Systems*		
ECON_Update $_t$	417.7	8,927	*ECON_Update* $_t$	46,853*	-110081
	(0.0389)	(0.459)		(1.655)	(-2.419)
ECON_Update $_{t-1}$	-17,073	72,143**	*ECON_Update* $_{t-1}$	35,137	-6,038
	(-0.903)	(2.281)		(1.246)	(-0.125)
ECON_Update $_{t-2}$	-23,635*	31,896	*ECON_Update* $_{t-2}$	9,282	45,351
	(-1.447)	(1.216)		(0.366)	(1.124)
Observations	14,013	14,013	Observations	20,603	20,603
Panel G. Credit/Collections Systems			*Panel H. Patient Billing Systems*		
ECON_Update $_t$	26,625	11,811	*ECON_Update* $_t$	12,140	49,463**
	(1.572)	(0.363)		(0.777)	(1.681)
ECON_Update $_{t-1}$	1,922	49,281	*ECON_Update* $_{t-1}$	-23,468	77,635***
	(0.0856)	(1.279)		(-1.355)	(2.642)
ECON_Update $_{t-2}$	16,881	25,687	*ECON_Update* $_{t-2}$	-6,898	28,992
	(0.803)	(0.797)		(-0.440)	(1.208)
Observations	21,276	21,276	Observations	23,156	23,156
Controls	Y	Y		Y	Y
Hospital & Year FE	Y	Y		Y	Y

Instrumental variables analysis (IV-GMM) of the effect of accounting system updates in periods *t*, *t-1*, and *t-2* on expenses and revenues (*Op_Ex, Op_Rev)* in *t* using *Vendor_Peer_Update* in *t, t-1,* and *t-2* as instruments. Hospital-Level Controls comprise all hospital-level variables from Table 2 plus: *Growth_Bedsize*, *CMI*, *%Medicare*, *%Medicaid, %Clinical_Updates, %MR_Updates,* and (for Column 1) *Op_Rev*. The remaining variables from Table 2, calculated for each AS in *t*, *t-1*, and *t-2*, comprise Application-Level Controls. All F-statistics from the test of excluded instruments exceed Stock, Wright, Yogo (2002) critical values. †Panels A - E. *Panels F - H.

Heteroskedasticity robust z-statistics clustered by hospital in parentheses
*** p<0.01, ** p<0.05, * p<0.1 (One-tailed p-values where there is a signed prediction)