Updating Accounting Systems:
Long-Run Evidence from the Health Care Sector

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Abstract

This paper provides evidence on the determinants of and economic outcomes associated with updates of accounting systems over a 24-year time-span in a large sample of U.S. hospitals. We document that a set of previously unidentified determinants drives the updating decision including “waves” of vendor-pushed updates that are taking place across hospitals, and regulatory impetuses at the state and federal level, such as the implementation of price transparency websites and fair pricing measures and the enactment of Sarbanes-Oxley Section 404, that increase hospitals’ demand for high quality accounting information. Using vendor-pushed updates as an instrumental variable, we document that updating of most types of accounting systems results in immediate and significant reductions in operating expenses. Our findings have implications for settings outside of the health care sector, but they are also important in their own right given the current public policy crisis concerning the rising costs of medical care.

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

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 document that AS have become widespread and the penetration of adoption is high, making the decision to update as a post-adoption decision more and more relevant as most firms now already have AS in place. We provide evidence on determinants that drive the updating decision which have not previously been explored, including evidence on effects of price regulation in the form of state-level price transparency websites and fair pricing measures and on the introduction of Sarbanes-Oxley (hereafter SOX) Section 404. Finally, using vendor-pushed updates as an instrumental variable, we document that the updating of most types of accounting systems leads to immediate and significant reductions in operating expenses.

We define an AS as having an update when a hospital in a given year changes the version/model or vendor of a software 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 their 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 an additional cost accounting system in 2000 when it installed a cost accounting application from Lawson Software in addition to the existing cost accounting system that 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 completely phased out 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.[1] However, many firms continue to use systems 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. While prior research has examined cross-sectional variation in determinants, benefits and costs of (in particular management) 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. This leads us to research determinants that are specific to an updating setting, such as the role of the existing AS vendor in rolling out updates.

One of the determinants of AS updating that we identify is increased demand for internal accounting information as a result of changes in regulation. First, we examine the effects of two different types of state-level price regulation. We exploit the introduction of fair pricing measures across 12 U.S. states over the period 2001-2009 which limits collections hospitals can make from uninsured patients and requires them to provide free care to low to middle income uninsured patients. Hospitals' policies to this effect have to be disclosed prominently in their facilities to make patients aware of this protection. Prior research shows that these measures significantly increased price pressure and substantially reduced payments made by uninsured patients (Bai, 2015; Batty and Ippolito, 2016). We also identify a series of changes to hospital price disclosure that were staggered across 29 U.S. states over the period 2002-2009

[1] CIO's budgets comprised 8.6% of revenue on average for firms across all industries in 2014, and 34% of surveyed firms indicated that the Accounting & Finance Department controls an additional budget for AS (CIOMagazine, 2014).

when states introduced websites on which hospitals publicly disclosed prices of common procedures. These disclosures were intended to inform potential patients and were motivated by concern about the rising costs of health care for patients and the government. Christensen, Floyd, and Maffett (2015) document downward charge price revisions due to these transparency initiatives which they attribute to an increase in public scrutiny. We argue that these price regulations (and the associated disclosures) increased hospitals' demand for high quality management accounting information, leading to updates of these AS (Krishnan, 2005).

We also investigate how the enactment in July 2002 of the Section 404 provision of the SOX Act affected the updating of AS in publicly traded hospitals. This provision required management and external auditors of public companies to produce a report on the adequacy of the company's internal control over financial reporting. In addition to encouraging firms to adopt specialized internal control technology (Masli, Peters, Richardson, and Sanchez, 2010), we argue that mandatory SOX 404 reporting also pervasively affected all other financial systems and the underlying applications that support them (Damianides, 2004; Holmes and Neubecker, 2006), leading to updates of AS.

On the outcomes side, estimating the economic benefits of updating or adopting AS is plagued with issues of endogeneity because the decision to either update or adopt AS within the firm is correlated with other determinants which can also directly affect economic outcomes (for example, broad-based efficiency and cost-saving initiatives, or acquisitions of hospitals). Furthermore, the outcome of interest may in fact also be a motivation for updating or adoption. Up to this point, the prior literature on AS has struggled to address this issue, 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. 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, respectively. Our updating setting provides us with a powerful instrumental variable to examine the economic outcomes of AS updates: vendor-pushed updates, which are relatively exogenous with respect to the hospital. This allows us to answer the call for *longitudinal* evidence on outcomes of AS implementation by Ittner et al. (2002) by examining how updates of these systems affected hospital profitability.

In order to empirically examine our questions, we use the HIMMS (Healthcare Information and Management Systems Society) Analytics Database®, provided to us courtesy of the Dorenfest Institute. This database contains survey data on hospital information technology systems and other hospital characteristics from 1987 to 2010. These yearly surveys cover 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 of the data. The full sample contains 6,995 unique hospitals, and we are able to track 1,916 hospitals throughout every year of the survey. We have data on the presence and updating of six AS: the financial accounting systems of accounts payable and general ledger, and the management accounting systems of costing, budgeting, case mix analysis, and executive information systems (EIS).[2] We begin our study by providing descriptive information on the adoption of AS over time, in particular the penetration rates of the six AS over our sample period and the probable sequencing of adoption of these systems. These descriptive results underscore the importance of studying updating, as virtually all of the hospitals in our sample had at least one system installed even at the beginning of our sample period almost thirty years ago, and most had multiple AS by the end, meaning that the decision to adopt is becoming less relevant than the decision to update.

The results of our analyses identify a series of previously unstudied determinants of AS updating. First, 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 relation. We find that hospitals that share the same vendor for a given AS tend to update at the same time, suggesting vendor-pushed waves of updates when vendors roll out new versions or stop supporting old versions. Next, we find that implementation of both state-level price regulations described above enticed hospitals to update some of their management

[2] A case mix system calculates cost and profitability of various patient categories that are grouped by resource use intensity and is hence similar to a customer profitability system in other industries. An Executive Information System (EIS) integrates information from various parts of the hospital to give executives a high-level perspective on key performance indicators and trends affecting their institution to help them make better decisions.

AS, supporting our prediction that they led to a greater demand for such internal accounting information and allowing us to document the effects of price regulations on AS updating behavior. Furthermore, we document that SOX 404 significantly affected AS updates. Prior research has typically assumed that firms in compliance with Section 404 have a higher quality internal information environment than their non-compliant or unaffected counterparts (e.g. Feng, Li, McVay, and Skaife, 2012; Gallemore and Labro, 2015). We document a mechanism by which this increase in information quality is achieved by showing that the enactment of SOX Section 404 increases the likelihood that firms update their AS.[3]

We further use vendor-pushed updates in an instrumental variables analysis and find that updates of most types of AS lead immediately to significantly lower operating expenses, with some modest increases in revenues. Thus, not just the adoption of AS but their updates after the initial adoption decision can have important economic implications. To our knowledge, ours is the first study that is able to document effects of AS updating; more generally, it is one of very few that is able to convincingly link economic outcomes with investments in AS in any context, either through adoption or through updating.

Our study is important for several reasons. First, our results document several instances in which external regulations led hospitals to make real internal changes by updating their existing AS. These changes have associated costs and benefits that may not have been anticipated. The real effects for AS that we document in this paper are particularly interesting because changes to AS have the potential to affect the quality of information available to firms to use in future decision-making and reporting. Thus while we document benefits of AS updates in the form of lower costs, it is likely that an additional advantage of these updates is to improve future financial reporting quality (Dorantes, Li, Peters, and Richardson, 2013; Feng, Li, and McVay, 2009). There are also interesting implications of our results with respect to each individual regulation. Our price transparency results give us insight on the real effects of

[3] Using firms' disclosures in Lexis-Nexis, Masli et al. (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 and cannot speak to the increased likelihood of adoption or updating given their sample only consists of firms who choose to disclose these adoptions.

disclosure regulation within the firm, as called for by Leuz and Wysocki (2015).[4] Speculatively, our price regulation results may generalize to other settings where price pressure and disclosure is increased, such as the advent of price comparison websites in industries such as travel (Kayak) and consumer products (PriceGrabber). Furthermore, while some evidence suggests that firms generally made improvements to their internal systems in response to SOX, prior research has studied this phenomenon only for the relatively small proportion of firms which choose to publicly report these changes (Masli et al., 2010).

Our results are also important for the health economics and health policy literatures because they show hospital regulation has a real impact on hospitals' decisions to update AS, allowing them to achieve operating expense reductions. In particular, our analysis of both staggered state-level price regulations may foreshadow the impact on AS updating of regulations later introduced at the federal level. Fair pricing provisions were included in the 2010 Affordable Care Act and enacted by the Internal Revenue Service at the end of 2014, and the U.S. Department of Health and Human Services started a yearly release of price information for the 100 most common Medicare stays in May 2013.

Lastly, notwithstanding several calls for longitudinal work on information systems more generally and AS specifically,[5] no research is available on AS *updating*, and the only research with a longitudinal focus on *adoption* has studied start-up firms (Davila and Foster, 2005, 2007; Sandino, 2007) and may not generalize to more mature firms.[6] This lack of research on the determinants of AS updating decisions is most likely caused by data unavailability because it requires the observation of AS across multiple years. Furthermore, our results on the outcomes of AS updating document that significant cost reductions can be achieved through these means. Health care currently makes up 17% of U.S. GDP, and

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[4] While the prior literature on the capital market effects of disclosure regulation is relatively mature, evidence on how regulation affects real behavior *within* the firm is more limited, primarily due to difficulties in anticipating and observing these effects.

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

[6] In the information systems literature, 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. The few available longitudinal studies have looked at Enterprise Resource Planning (ERP) systems, not AS (Cao, Nicolaou, and Bhattacharya, 2013; Gable, Chan, and Tan, 2001; Nicolaou and Bhattacharya, 2006).

health care costs are still increasing (WorldHealthOrganization, 2015) making AS of utmost importance in measurement and cost management in this sector.

II. Hypotheses

We structure our formal analyses around three main hypotheses relating to the determinants and outcomes of AS updating. Our initial two hypotheses relate to the determinants of AS updating. In spite of the sparse empirical work or theory on post-adoption updating or maintenance of existing systems, we make a few predictions on determinants that are likely to affect the probability of updating. A more exploratory set of control variables, several of which are based on the adoption literature, is developed in Section 4.

First, 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 relation. Vendors regularly release new updates or stop supporting older versions (Beatty and Williams (2006), Khoo and Robey (2007)). This may instigate a "wave" of vendor-pushed updating among hospitals that are "vendor peers" (that is, use the same vendor for a particular AS). Those hospitals will hence tend to update their AS at the same point in time. Because vendor peers can come from different geographic regions and hospital systems, the shared variation across peers is limited to the variation caused by the shared vendor and is relatively exogenous. Formally:

> ***H1:*** *Hospitals are more likely to update their AS when other hospitals that share the same vendor are also updating.*

Our next set of hypotheses on the determinants of AS updating relates to the effect of regulation on internal decision-making. Health care is a heavily regulated sector, and it is likely that regulation may affect AS updating decisions. We first study the introduction of fair pricing measures in 12 U.S. states staggered over the period 2001-2009. These measures share two features: (1) limits to collections hospitals can make from uninsured patients below a certain income cap and (2) requirements to provide free care to low to middle income uninsured patients. Hospitals' policies to this effect must be disclosed prominently in their facilities in order to make patients aware of this protection. While there are differences between states in what the income cap is, whether the collection limits are stated with respect to what public or private insurers would pay, and whether insured patients with extremely high deductibles are also covered, Batty and Ippolito (2016) and Bai (2015) calculate that the fair pricing laws have a large impact. Uninsured patients experienced large decreases in payments, and hospitals responded by decreasing the amount of care delivered to these patients and shifting some of this revenue pressure by increasing prices for private insurers (Bai, 2016).

Hospitals can respond to this pressure and still maintain profitability by trying to minimize operating expenses using information obtained from costing and budgeting systems (Krishnan, 2005). Such costing and budgeting information can help support their pricing decisions and give them insight into cost and revenue forecasts. Additionally, managing the portfolio of patient types and their conditions becomes more crucial as certain patients or conditions may become highly unprofitable, and hospitals may try to attract a greater proportion of patients with more comprehensive insurance plans. Information relevant to these objectives can be gleaned from case mix systems. Our next hypothesis relating to determinants of updating is thus:

> ***H2a:*** *The adoption of fair pricing measures increases the probability of updating costing, budgeting, and case mix systems.*

Our next hypothesis focuses on price disclosure regulation: 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.[7] Christensen et al. (2015) find that the introduction of these price transparency websites significantly decreases the publicly posted charge prices of a set of common procedures in affected hospitals in the year after their introduction, although the amount that patients actually pay is unaffected. They interpret their differential results on charge prices and actual payments as

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[7] A substantial literature exists on quality disclosure (see Dranove and Jin (2010) for an overview), including applications in the health care sector. However, prior research has been silent on how disclosure of prices might affect the need for AS.

evidence that these price transparency regulations increased public scrutiny of hospital prices and hospitals' perceptions of the reputational costs of overcharging. This interpretation seems reasonable given anecdotal evidence of the reception of these disclosures. For example, a recent 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. With such stark differences in price for procedures that on the surface seem identical, it is not hard to see why public disclosure of these prices would lead to increased scrutiny of prices. As with the fair pricing measures, hospitals can respond to this downward price pressure by using information obtained from costing and budgeting systems to maintain profitability (Krishnan, 2005). Alternatively, hospitals may choose to use costing and budgeting information to justify their (existing) prices. Indeed, recent survey evidence finds that justification of prices with good costing information is perceived to be an integral part of price transparency in hospitals and that compiling the data to create meaningful and relevant information is the single greatest challenge to compliance with such disclosure requirements (Houk and Cleverley, 2014). For all of the reasons listed above, we expect that implementation of price transparency initiatives will have a positive effect on the probability of updating costing and budgeting systems. Stated formally:

> ***H2b:*** *The implementation of price transparency websites increases the probability of updating costing and budgeting systems.*

Our last hypothesis on the determinants of updating centers on the Section 404 provision of the SOX Act which was enacted in July 2002 and required management and external auditors of public companies to produce a report on the adequacy of the company's internal control over financial reporting. As a result, investment in information and control systems is needed (Ashbaugh-Skaife, Collins, and Kinney, 2007). While compliance costs such as increased audit fees and internal labor costs are reported to have been high (FinancialExecutivesInternational, 2006; Krishnan, Rama, and Zhang, 2008), these costs may have provided additional impetus for companies to automate their internal control systems in order to decrease these costs going forward (Duffy, 2004). Indeed, Masli et al. (2010) find that 139 firms that announced purchases of internal control monitoring technology between 2003 and 2006 had relatively smaller increases in audit fees, a less delayed audit report, and a lower likelihood of reporting a material weakness the next year. Of course, the installation of such technology is costly in itself (Krishnan et al., 2008), which may stop some firms from doing so.

We argue that the effect of SOX compliance is not solely to encourage firms to adopt specialized internal control technology, but affects all financial systems and the underlying systems and applications that support them (Damianides, 2004; Holmes and Neubecker, 2006). For example, Morris (2011) finds that 108 firms that announced an ERP implementation in the run-up to SOX's effective date (between 1994 and 2003) are less likely to report a material weakness. Masli et al. (2010) finds that those firms that implement internal control monitoring technology in a "transformative" way that embeds it in overall information systems see more benefits. We predict that the SOX Section 404 requirement will touch all AS in the hospital. For example, one of the hospital systems in our sample (IASIS) disclosed in its 2004 Form 10-K that "*A failure of our information systems would adversely affect our ability to properly manage our operations. We rely on our advanced information systems and our ability to successfully use these systems in our operations. These systems are essential to the following areas of our business operations, among others: patient accounting, including billing and collection of net revenue; financial, accounting, reporting and payroll; coding and compliance; laboratory, radiology and pharmacy systems; negotiating, pricing and administering managed care contracts; and monitoring quality of care. If we are unable to use these systems effectively, we may experience delays in collection of net revenue and may not be able to properly manage our operations or oversee the compliance with laws or regulations.*" While anecdotal evidence supports the fact that SOX led to pervasive changes in firms' internal systems, systematic empirical evidence on this is sparse, and the papers we cite above identify only those adoptions or updates which are publicly reported, and their small sample sizes suggest that the vast majority of system updates in response to SOX went undisclosed. As we explain later, our survey data does not rely on such public disclosure.[8] We expect that the enactment of SOX Section 404 leads hospitals to update all AS prior to its effective date. Formally:

H2c: *The enactment of SOX Section 404 increases the probability of updating accounting systems.*

Our last hypothesis relates to the economic benefits of updating. We focus on total operating expenses as the main economic outcome. There are reasons to expect that updates could either increase or decrease expenses. First, it is unlikely that hospitals would update their systems with the *expectation* that the update would increase hospital operating expenses; AS (and in particular management AS such as costing and budgeting systems) are designed to help managers optimize decision-making and increase efficiency. Additionally, outdated systems may not have the capability to meet the growing needs of hospitals, especially in this increasingly digital age. For these reasons, we would expect updates of AS to *decrease* operating expenses.

On the other hand, updated AS may not necessarily lead to net benefits. First, implementation and adjustment costs may outweigh the benefits of the update. Second, updates may not constitute substantive enough changes to deliver beneficial effects of important magnitude; it could be that only those updates that are major or are in hospitals that have not updated their systems for a long time will have an effect. Third, if other hospitals are also updating, benefits to updating may be competed away. Anecdotal evidence suggests that all of these factors can and have led to spectacular failures in the implementation of new systems. The largest press has been given to ERP (Enterprise Resource Planning) mishaps, with companies such as Hershey, Nike, and HP falling victim to implementation problems (Wailgum, 2009), but these types of problems can also occur for AS. Thus, it is also possible that AS updates could lead to *increases* in operating expenses. Overall, for hospitals' updating behavior to be rational, we predict a net

[8] For example, doing a Lexis-Nexis search (searching Business Wire, PR Newswire and "all company information" which includes all EDGAR filings) with the search terms used in Masli et al. (2010) (SOX solution, SOX IT, SOX software) in their search period (2003-2006) does not result in hits for any of the hospital systems in our sample that we know updated their AS.

benefit, as per our hypothesis below. We acknowledge, however, that we will test for average effects and that individual hospitals may have both net costs and net benefits of AS updating.

H3: *Updating of AS decreases operating expenses.*

III. Data and Descriptive Evidence

The main source of data in our paper is the HIMSS (Healthcare Information and Management Systems Society) Analytics database which contains survey data on hospital Information Technology systems and other hospital characteristics from 1987 to 2010. Although HIMSS currently owns the rights to all of these data, the earlier surveys were initially 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]

These 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. Because survey participants were incentivized to continue participating in the survey by being granted access to view summary statistics of their peers, the survey administrators were able to consistently track a large number of hospitals over time, with 1,916 hospitals tracked in every year of the data (the constant sample). Comparison with other lists of hospitals in the U.S. States indicates that the database covers a near-census of hospitals, in particular non-governmental acute care facilities with at least 100 beds, which were the initial criteria for inclusion in the database in

[9] Although data were collected in 1989, we do not have access to this survey. Because the sample starts in 1987, our data is not affected by the regulatory change of the 1983 Medicare prospective payment system which has been shown to have impacted costing system adoption (Hill, 2000). Furthermore, because 2010 is the last year of our sample, our results are not impacted by the Health Care Information Technology for Economic and Clinical Health Act meaningful use criteria (HITECH 2009 act) which could give a regulatory impulse to adopt more IT. Our results are qualitatively similar when we drop 2010, indicating that we also do not capture anticipatory effects of the HITECH act.

the early years of the survey.[10] Figure 1 shows the sample size (in blue) and median bed size, a common metric of hospital size (in red), for both the full and constant samples over time. The graph shows two large increases in sample size in the sample period. First, in 1998 the survey began including hospitals with fewer than 100 beds as long as at least one hospital in their multihospital system had at least 100 beds,[11] and in 2006 and 2007 HIMSS Analytics increased coverage to include additional smaller hospitals. This increase in coverage is apparent from Figure 1 by observing that median bed size for the full sample decreases markedly in the years that the sample coverage increases, whereas the median bed size of the constant sample remains similar over time.

Insert Figure 1 here.

We obtain information on six AS from the HIMMS dataset. 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 collected by HIMSS, although typically either cross-sectionally in one year (Angst, Agarwal, Gao, Khuntia, and McCullough, 2014; Setia, Setia, Krishnan, and Sambamurthy, 2011) or over time series that span 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 don't separate 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.[12]

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[10] We compared our sample to the list of all Medicare hospitals and all hospitals identified by Oddity Software. Texas has the largest representation in our sample (596 hospitals), while Delaware has the lowest (12 hospitals). A table with the coverage of hospitals in the various states for every year is available from the authors on request.

[11] This includes hospitals that are the only hospital in their hospital system (i.e., single hospitals).

[12] 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, Agarwal, Sambamurthy,

Because the survey data were collected over such a long period of time and under multiple formats, there is some variation in which data were collected over time. Our main variables of interest, AS, are consistently tracked. All AS are tracked throughout the entire sample period, other than EIS which are tracked from 1993 onwards, which is around the time they became available. Appendix 1 (first and second section) explains the classification process and event date identification used in constructing comprehensive data on different AS.

Because we did not design the HIMSS survey, not all variables that we would like to include are available to us.[13] 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[14] 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 teaching hospital status are very consistent. Appendix 2 lists all variable definitions and clarifies in which cases we used one or both data sets to construct our variables. 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

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and Kelley (2010) are the only authors to exploit the full time series in the data but their focus is on electronic medical records systems only.

[13] For example, prior literature indicates that the accounting background of the top management team is an important determinant of AS adoption, yet this variable is not collected in the HIMMS survey.

[14] For example, academic (for-profit) status is tracked in the HCRIS data, but is not available in the HIMSS data for hospitals which were not in the 2001-2010 (2004-2010) survey data. Although HCRIS data are restricted to hospitals which receive Medicare and Medicaid reimbursements, this represents a sizeable proportion of the population of hospitals, with 4,813 hospitals currently registered with Medicare (https://data.medicare.gov/browse?tags=hospital+list).

multihospital system, and are for-profit and rural hospitals, respectively. Over the sample period, between 8 (accounts payable, general ledger, case mix) and 15 (executive information systems) percent of applications are updated in any given year. Meanwhile, between 10 (accounts payable) and 16 (executive information systems) percent of systems were developed by hospitals internally, while on average between 10.5 (general ledger) and 18.3 percent (executive information system) of the vendor peers of hospitals' applications have updated their AS in the current year.

Insert Table 1 here.

Figure 2 presents the first descriptive evidence of penetration of the AS, defined as the percent of hospitals that have a specific AS in place in a specific year. Panel A presents graphs for the full sample, while Panel B shows the constant sample. The two financial AS, Accounts Payable and General Ledger, have a very high penetration rate throughout the sample period. In contrast, the management AS start off with lower penetrations and experience greater increases throughout our period. For example, budgeting systems show a penetration rate of almost 50% in 1987 but increase in penetration rate to 81% (93%) in 2010 for the full (constant) sample. Costing systems' use lags budgeting systems. The penetration rate of costing systems is about 40% in 1987 and increases to only 84% for the constant sample by 2010. In an era where cost control is of such major concern, it is worrisome that 16% of the constant sample does not yet have a dedicated costing system in place at the end of the sample period, as they are likely to rely on the flawed costing modules that are built into their financial AS. These modules are typically based on the Ratio-of-Cost-to-Charges allocation method required by the annual Medicare Cost Reports which allocates costs based on revenue generation potential rather than resource consumption (Kaplan and Porter, 2011).[15] Additionally, there is a noticeable drop in penetration of all management AS around 2006 and 2007 for the full sample, again coinciding with the addition of smaller hospitals to the sample; there is no corresponding drop in the constant sample.

[15] Hospitals that have not adopted a costing system yet at the end of our sample period are on average much smaller, have a much lower operating income per bed, are facing less competition, more likely to be in rural areas and not part of a hospital system. This is consistent with the determinants of adoption identified in the prior literature. They also have a lower presence of other business systems (such as budgeting) and clinical systems.

Insert Figure 2 here.

A key takeaway from Figure 2 is that the use of AS in hospitals is widespread, even in the first year of the sample almost thirty years ago. At the end of the sample period, virtually every hospital in the sample has adopted at least the two financial AS, and most also use several management AS. In other words, very few hospitals are facing the decision of whether or not to adopt AS for the first time. Looking forward, the most relevant AS decisions will relate to maintenance of the existing systems, and in particular the decision to update. We view this descriptive evidence as confirmation of the importance of studying AS updating. Figure 2 also uncovers the sequence by which hospitals have adopted their AS over the sample period. The two financial AS, accounts payable and general ledger, typically precede the adoption of the management AS. Within MAS, case mix systems precede costing and budgeting systems, and finally EIS, which were generally not introduced until the mid-90s (as evidenced by their low penetration of 12% when they were first tracked in 1993) but which have a penetration rate equal to or exceeding all other management AS at the end of the sample period. Although sequencing of AS has been examined for small samples of start-up firms in the past (Davila and Foster, 2005, 2007; Sandino, 2007), our paper presents the first evidence on AS sequencing for mature firms over a longer time period.

IV. Updating Accounting Systems over Time

Although we consider our longitudinal evidence on AS adoption to be an interesting contribution to the adoption literature, we consider our most novel and important results to be those relating to the updating of AS, and it is here that we test our hypotheses. Our longitudinal dataset offers three key advantages in examining the process by which hospitals update, the determinants that drive such decisions, and updating outcomes. First, it spans a much larger sample over a much longer time than any prior work for six key AS (Cao et al., 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 as is sometimes the case in other longitudinal survey-based data sets. Third, we believe we capture the cross-section of updates, ranging from minor to major updates and from successful to unsuccessful cases. While there is, to our knowledge, no research on AS updating, the limited existing research on ERP upgrading has relied on (vendor) news releases accessed through Lexis-Nexis. Such news releases arguably only capture the very large and successful updates, and authors have called for alternate ways of identifying the full spectrum of updating firms (Cao et al., 2013). The Dorenfest/HIMSS surveys capture a large cross-section of updates. Furthermore, there is likely no reporting bias in favor of successful updates because (1) the data were not made widely available publicly [16] and (2) the survey uses a standardized questionnaire whereby HIMSS solicits information on specific application types and their associated dates and the respondent fills out the requested fields for every application instead of cherry-picking important or successful systems.

As a reminder, we 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 in which the hospital has an existing application. Two issues complicate this identification. First, because on occasion some models are not covered in every year in the data, we need to ensure that we do not identify an AS as being updated in a year solely because it was not covered in last year's data. Hence, we check whether the current AS model (specific vendor and model version) was used by the hospital in *any* of the preceding four years and only record an update if it was not. It is unlikely that we will misclassify model update years as non-updates using this method because a company would have to use, discontinue, and then readopt a single software model within the space of five years. Second, the vendor name assigned to each vendor by the Dorenfest Institute is sometimes slightly changed in different survey years even though they refer to the same counterparty. For example, Oracle is reported in one year, while Oracle Corp is used in another year. Almost all of these name changes occur in the years when the format of the survey changed (1998 and 2005). So as to not wrongly identify such name changes as an update of an AS, three research assistants reviewed all of the vendors of all applications in the HIMSS

[16] 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.

database to reliably track unique vendors over time, paying particular attention to these transition years.[17, 18] Appendix 1 (section 3) provides further detail about the procedures used to identify updates and the steps we took to validate the data.

Figure 3 depicts the kernel density distributions for durations of the various AS, which describes how long an AS is in place before it is updated. This figure reveals a large amount of cross-sectional variation among hospitals and updates in the time between updates. Some updating happens very quickly, in the first two years after adoption or the prior update. The highest proportion of updates happens 3 or 4 years out. However, there is a long right-hand tail in the distribution, with many hospitals waiting many years between updates.[19] Kremers and Van Dissel (2000) suggest that the older the application becomes, the harder it becomes to update it, which may explain the long tail. There is relatively little variation in duration between updates for the different AS. Only EIS' duration distribution is somewhat dissimilar from the other AS since it peaks much higher around 3-4 years and tails off more quickly. This is likely due in part to the fact that EIS is a relatively new system, as evidenced by its very low penetration when it was first tracked by HIMSS in 1993 (12%). Hence, we cannot observe any hospitals that have had EIS in place without updating it for a very long time.

Insert Figure 3 here.

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[17] Unfortunately, because of the sheer number of specific application *models* throughout our sample period, we were not able to perform a similar procedure for the specific model names. However, the model names in our data are less useful for the purposes of identifying updating as they are missing for almost two thirds of the observations (compared to less than 5% of missing vendor names). Nonetheless, to prevent inconsistent use of model names falsely indicating an update, we only classify the changed model name as an update if the contract or installation date (when present) corroborates evidence of an update by showing a change in the last two years.

[18] Although we tried to identify mergers between application vendors, for the most part our data cannot link vendors who are subsequently purchased by other vendors. Thus while we can comfortably identify vendor peers within a given year, we cannot identify vendor peers across time. We perform screens to our *Vendor_Peer_Update* variable to account for this, as described in Appendix 2. Additionally, changes in vendor names due to acquisitions should not cause us to spuriously identify updates because hospitals with already installed applications generally only change the vendor name that they report when they install a new system; additionally, we take precautions in our analysis to use the application installation date when available to identify updates only in the years that installation dates indicate a change occurred. Any remaining errors in the data caused by our lack of ability to track vendors over time should contribute noise to the analysis, but we do not expect this noise to be correlated with our variables of interest.

[19] We take steps in our data cleaning procedures to ensure that this long tail is not caused by data errors, and anecdotal evidence is consistent with companies using sorely outdated internal systems (Swanson and Dans, 2000).

Next, we move to the determinants of AS updating. In addition to describing how we operationalize the constructs used in Hypotheses H1 and H2, we also more informally posit additional determinants that are unique to an updating context. Furthermore, we include factors that have been shown to be significant predictors of initial adoption. Because of the lack of prior evidence and theory with respect to AS updating, we view evidence on these other determinants as first steps in establishing this literature from a more descriptive standpoint.

To identify changes to vendor peers' systems in order to test H1, we construct *Vendor_Peer_Update* which is calculated as the proportion of other hospitals using the same vendor (i.e., "vendor peers") which updated their AS that year.[20] A large proportion of vendor peers that are updating their systems simultaneously would be a sign that a vendor-specific shock (e.g., a new version of a system) is likely to have occurred. Consistent with H1 we expect this variable to increase the probability of updating. Because some applications are self-developed by hospitals in-house and these systems would have no vendor peers at other hospitals, we also control for whether an application is self-developed or not (*Self_Developed*).[21] In most cases the HIMSS data flag models or vendors which are associated with internally developed systems. In addition, a research assistant manually reviewed all vendor names in our dataset to identify those that are most likely to be self-developed (for example when the name of the hospital or hospital system is given in place of a vendor name, a sign that these systems were generated internally).

Next, in order to identify passing of fair pricing measures needed to test H2a, we use the enactment dates of the fair pricing laws for each state that is reported in Table 1 of Batty and Ippolito (2016). We also find the enactment dates for the 6 states reported in their footnote 6, 2 of which they only use in robustness tests and 4 of which they exclude because the enactment dates are too early or too late

[20] Variable descriptions are included in Appendix 2.
[21] *Vendor_Peer_Update* is hence 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*. We also found similar results if we instead used a measure where all other hospitals which use self-developed applications for the same system were considered vendor peers for self-developed systems.

for their sample.[22] Maine is the first state in our data to enact (in 2001) a fair pricing law. Illinois, Maryland and New Jersey are the last states to enact a fair pricing law (in 2009) that we include in our sample in which 12 states are treated. Consistent with H2a, we expect *Fair_Pricing* (an indicator variable coded 1 if that state enacted a fair pricing measure in the prior year) to have a positive effect on the probability of updating costing, budgeting, and case mix systems.[23]

In order to identify implementation of the price transparency initiatives needed to test H2b, we use the date of the first charge price website disclosure for each state that is reported in Table 1 of Christensen et al. (2015).[24] Pennsylvania was the first state to disclose price charges (in December 2002) and Maine (in April 2009) is the last website adoption we include in our treatment sample of 29 states. Consistent with H2b, we expect *Price_Transparency* (an indicator variable coded 1 if that state adopted a price transparency website in the prior year) to have a positive effect on the probability of updating costing and budgeting systems, since understanding costs is critical to determine optimal prices.

Lastly, to test H2c, 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. Consistent with H2c, we expect these hospitals in publicly traded systems 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 a part of a hospital system subject to SOX 404 implementation in 2004) and *Prep_Years* (an indicator for the two years after SOX 404 was passed during which firms could

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[22] Of these, we include Connecticut (2003), Maryland (2009), Maine (2001), Oklahoma (2007), and Tennessee (2005). Colorado's introduction in 2012 falls outside our sample period. We also add Wisconsin (in 2006), although this state did not technically introduce a fair pricing *law*, yet its major hospital systems revised their policies to limit charges for uninsured patients after the state's attorney general filed complaints about their billing practices.

[23] Because measures that become effective in the second half of the year do not apply to the majority of the decisions made in that year, fair pricing and price transparency measures that became effective in July and later are coded as occurring in the following year.

[24] Because our sample period goes back further and our data constraints are less stringent, we add 4 states to the list of 27 states in Table 1 of Christensen et al. (2015): Arizona, New Hampshire, Maryland and Pennsylvania. We use the dates on which these 4 states introduced price transparency websites as documented in Table 1 in the earlier version of this paper (Christensen, Floyd, and Maffett, 2014). Results in all tables are robust to excluding these 4 states, and if anything are somewhat stronger. The price transparency website implementations in Illinois and Colorado at the end of 2009 fall outside our sample period.

implement changes before mandatory SOX 404 compliance in 2004 — 2002 and 2003). We expect the hazard ratio of this interaction to be greater than one.

We also test for the effect of other potential determinants of AS updating, but we do not have formal hypotheses for these factors as they are more exploratory. Additionally, as many of these factors are endogenous, they are important to control for but must be interpreted with caution. In particular, we research whether hospitals update their systems in "waves" where numerous peer hospitals all update at the same time. We construct *System_Peer_Update* and *County_Peer_Update,* which are indicators for whether at least one other hospital updated the AS of interest in the current period that is within the same hospital system or county, respectively. Because only hospitals that are within a multihospital system can have system peers, we also control for whether a hospital is part of a multihospital system (*In_System*). We would expect hospitals in multihospital systems to have a higher overall propensity to update as hospital systems are likely to have a standardized schedule of updates. Furthermore, network ties created among hospitals in a hospital system provide access to the experiences of other organizations with AS (Kennedy and Fiss, 2009) as does spatial proximity to each other (Angst et al., 2010).

We also test how the extent to which the hospital has a focus on IT affects its likelihood of updating. We study how the previous adoption of other applications in the business domain or in other domains (medical records and clinical) affects the updating decision. We expect firms with many business IT applications to also have a relatively stronger IT focus so it is likely that a hospital that is high on *Business_Depth* (the number of unique business software applications that the hospital has installed) will be more inclined to update AS. The presence of clinical and medical records systems, however, is more ambiguous; it might indicate synergies between these types of systems, leading to a positive effect on AS updating, or they might vie for the same IT budget, leading to a negative effect of *Med_Record_Depth* and *Clinical_Depth* (again defined as the number of unique software applications in the respective category) on AS updating. Therefore, we have no signed prediction. We also include the age of all other applications that the hospital has in place, *Apps_Age* and *Apps_Age^2*. Age of the general application stock could be negatively associated with AS updating if hospitals are simply settled in a routine where they use old AS, do not feel the need to update, or encounter a lot of resistance to updating. Swanson and Dans (2000) describe case studies where applications simply age in place until "they have screamingly reached the end of life." On the other hand, age of the general application stock could have a positive effect if the need for updating is greater because other applications are aging.

Lastly, we include determinants 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) to research if the determinants that led a hospital to make an initial adoption of an AS still play a role when the hospital decides whether or not to update its AS. Consistent with measures in the health care literature, we include hospital *Bedsize* as a measure of size, Herfindahl-Hirschmann index (*HHI*) as a measure of competition, for-profit (*For_Profit*) and academic status (*Academic*), and rural location (*Rural*). Size has been shown to have a positive effect on adoption because of both greater needs for coordination because of complexity and greater resource availability; for the same reasons, we would expect size to have a positive effect on updating. However, it is possible that large firms embed a structural inertia, which Zhu, Kraemer, and Xu (2006) show to negatively impact innovation routinization and adapting of existing information systems. If the determinants of updating are the same as those of adoption, we would further expect that for-profit, academic, and high-competition (low HHI), and urban (non-rural) hospitals would be more likely to update their systems.[25, 26]

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

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[25] We graph penetration of all management AS over time split into subsamples based on these adoption determinants. The results demonstrate that these determinants also affect penetration rates longitudinally and not just in a single cross-section (although they appear to matter most in the beginning of our sample period). We omit this figure from the paper for parsimony, but it is available from the authors on request.

[26] Another control variable common in the healthcare literature is whether the hospital is a specialty hospital; specialty hospitals might have significantly different clinical and cost structures leading to different investments in information technology. We do not include this variable in our main analyses because it limits our sample to Medicare hospitals. However, untabulated tests including it as a control variable produce inferences that are consistent with the specifications reported in the paper for all parts of hypotheses 1 and 2. Furthermore, we also control for whether a hospital is a specialty hospital, as well as all other static hospital-level variables, in Table 4 by including hospital fixed effects.

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 this 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 specification of the hazard model is:

$$\lambda(t|\boldsymbol{X}) = \lambda_0(t)\exp(\beta_1 X_1 + \cdots + \beta_p X_p) = \lambda_0(t)\exp(\beta^{\prime}\boldsymbol{X})$$

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. t is the time since the last update of AS_j for hospital *i*. Our data are right-censored (as is common in settings where this model is used), meaning that some hospital AS never experience an update in our 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.[27] 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 application types in the underlying decision-making process that leads hospitals to update their AS. Hospital-application observations are observed yearly, including 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.[28] Our specification includes state and year fixed effects.[29] Inclusion of year fixed effects controls for any contemporaneous changes in the market that may affect all hospitals, such as improvements in medical technology, an increased likelihood of updating in the run-up to Y2K

[27] One benefit of using a Cox model is that we are able to estimate the hazard ratios without specifying the functional form of the baseline hazard rate, while misspecifying the hazard rate would cause bias in our model. However, our model would be more efficient if we could specify the true underlying baseline hazard form, which is unobservable.

[28] Cross-correlations between updating spells within the same hospital over time could lead to correlated standard errors. We use bootstrapped standard errors in our reported results, but inferences are identical when we use heteroscedasticity-robust standard errors clustered by hospital.

[29] 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 theoretical bias in our models to be low because we have many hospital-AS-year observations in each state and year group. Additionally, our inferences are robust to alternative specifications such as omitting all fixed effects or stratifying the hazard model by hospital (to control for characteristics fixed at the hospital level) as proposed by Allison (1996) and demonstrated in an accounting setting by O'brien, McNichols, and Lin (2005).

(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 which applied to all hospitals, such as HIPAA (the Health Insurance Portability and Accountability Act of 1996), and which may affect the demand for AS updates but which are implemented across all states at the same time, meaning that we cannot separately examine their effects. Inclusion of state fixed effects controls for aspects of the state regulatory environment that are constant over time.

Table 2 reports the results of this hazard model on the probability of updating. The effect that a covariate has 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 located 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 group (e.g., urban), 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. The values reported in Table 2 are the hazard ratios associated with each independent variable. Thus, 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.

In support of H1, we find that updates rolled out by the vendor at an additional one percent of peer institutions (*Vendor_Peer_Update*) increases the frequency of AS updating about 2% for all AS types. An additional untabled analysis suggests that the effect of vendor upgrades on propensity to update is stronger when applications are mature and maintenance and upgrade fees become a much more important part of the vendor revenue mix (Gable et al., 2001). Results of a pooled hazard model stratified by application type show that systems that are more widely used are updated more frequently; the effect of application *Penetration*, the percentage of hospitals that have a particular AS currently installed in a given year, has a hazard ratio of 1.011 and significance at the 1% level (z-statistic = 9.26), possibly as vendors release more routine small updates in an attempt to keep the application in play.

Consistent with H2a, we find an increased updating hazard for costing systems (32%) and case mix systems (35%) after enactment of fair pricing measures. The effect is positive but insignificant for budgeting systems. This is consistent with the regulation requiring hospitals to better understand and manage their costs under price pressure and to create greater insights in the portfolio of patients (e.g., insured vs. uninsured) and their conditions. We also observe an increased hazard of updates of the FAS and EIS and conclude that an overall better accounting environment helps hospitals deal with the impact of fair pricing measures. These results are particularly important because our well-identified analysis of staggered state-level fair pricing measures may also inform the likely outcome to be expected from fair pricing provisions included in the 2010 Affordable Care Act at the *federal* level and enacted by the Internal Revenue Service at the end of 2014. However, these later rules are more limited than those of the treated states in that they only apply to tax-exempt hospitals and give hospitals discretion in determining eligibility for financial assistance.

Consistent with H2b, we find a significantly positive effect of the introduction of price transparency regulation on updating for costing and budgeting systems in the following year, with an increased updating hazard of about 15% and 17%, respectively.[30] Interestingly, we find a significantly negative effect on the updates of the two financial AS, accounts payable and general ledger, potentially because hospitals substituted costing and budgeting updates for financial AS updates in these years. *Price_Transparency* has no effect on the updating of case mix systems and EIS. Overall, our results with respect to price transparency regulation provide important evidence on the real effects of price disclosure regulation. Like with the fair pricing measures, the results of our staggered state-level price transparency

[30] Maryland has regulation that limits price increases and hence may have more prevalent budgeting practices among hospitals; our result continues to hold when Maryland is excluded.

analysis may foreshadow the impact on AS updating of the yearly release of price information at the federal level by the U.S. Department of Health and Human Services which started in May 2013. These data show the charge prices for the 100 most common Medicare inpatient stays at approximately 3,000 different hospitals in all 50 states and Washington D.C., as well as their average corresponding Medicare payments.

Consistent with H2c, we find that hospitals subject to SOX 404 are more likely to update their AS (other than accounts payable which shows insignificant results) in the two years between the enactment of the regulation and its implementation (2002 and 2003).[31] The increased likelihood ranges from 34% for general ledger systems to 83% for case mix systems and is highly significant.[32]

Turning to our more exploratory results, we observe that updating "waves" take place within hospital systems and within counties. Hospitals in multihospital systems in which their system peers are updating (*System_Peer_Update)* are about four times more likely to update as hospitals in systems where peers aren't updating, with that likelihood even increasing to six times for EIS. On the other hand, the main effect of *In_System* actually decreases the hazard of updating.[33] It is important to note that, since all public hospitals required to meet SOX 404 stipulations are also in hospital systems, the earlier mentioned effect of SOX 404 implementation on AS updating is over and above the "regular" effect of hospital system waves. The positive significance of *County_Peer_Update* for 4 of the 6 systems is also suggestive of within-county "waves" where proximity to other updating hospitals in the same county plays a role in

[31] A few hospitals in our sample period are part of hospital systems that have been public at one time but which were not subject to SOX 404 in 2004, for example firms below the $75 million public float cut-off or firms which became public and thus subject to SOX 404 later in our sample period. Our results are robust to excluding hospitals in these other systems.

[32] Only one hospital system reported a material weakness in the years following SOX 404 implementation, so we are not able to test for the role of AS updating in remediations.

[33] *System_Peer_Update* can be written alternatively as *In_System x System_Peer_Update* as hospitals only have system peers when they are in a multihospital system. This means that the total effect of *In_System* for hospitals whose system peers are updating is the product of the hazard ratios of *In_System* and *System_Peer_Update* (e.g., 0.441 x 3.940=1.74 for costing systems), so hospitals in systems whose peers are also updating are about twice as likely to update costing systems relative to hospitals not in systems. However, hospitals in multihospital systems whose peers are not updating are less likely than independent hospitals to update, supporting the notion that hospital systems update in "waves".

the updating of some AS.[34] Next, we document a role for the IT focus of a hospital in updating decisions. We find that hospitals that have adopted a lot of business applications (*Business_Depth*) generally update their AS more frequently, while the effects of *Medical_Record_Depth* and *Clinical_Depth* are mixed or insignificant. We also find that the age of the stock of the applications (*Apps_Age*) is negatively associated with the likelihood of updating; hospitals with very old applications seem to just settle on continuing to use those old applications (termed the "bystander" strategy in Grenadier and Weiss (1997)), although the effect of *Apps_Age^2* is positive, suggesting that this negative result gets weaker at more extreme application ages. Overall, these results suggest that hospitals with a stronger emphasis on IT, indicated by whether they have a reasonably wide and up-to-date selection of applications, are also more likely to update their AS. Next, *Self_Developed* has a significantly positive effect on the likelihood of updating for four of the six AS. Because *Vendor_Peer_Update* can be interpreted as the interaction of *Self_Developed* and *Vendor_Peer_Update* as it is only non-zero when an application has an outside vendor, *Self_Developed* needs to be interpreted as a main effect. Thus, on average, self-developed systems tend to be updated more frequently than outsourced AS *when outsourced AS do not have any vendor peer updates*.[35]

Finally, we turn to determinants identified in the AS adoption literature. As a whole, these variables play a much more subdued role in updating than they do in determining adoption. For example, *Bedsize* has a hazard ratio equal to one across the board in every updating hazard model, which means size has no discernible effect on the likelihood of updating. Similarly, for-profit status is insignificant throughout. Academic status impacts updating likelihood positively for 2 out of 6 AS, and rural location negatively for only 1 out of 6. Of these attributes, the only one that seems to play an important role both in adoption and in updating is competition (*HHI*) which increases the likelihood of adopting AS and also the probability of updating for 3 of the 6 AS. A series of untabled likelihood ratio tests on the relative

[34] The presence of county-specific effects could raise concerns about correlated error terms among hospitals within the same county; thus in robustness we also cluster standard errors by county in both the hazard and instrumental variables analyses and find similar results.

[35] However, outsourced AS have at least one vendor peer update more than 90% of the time, so this main effect is not very meaningful.

contribution of these determinants in explaining updating confirms these findings. Given the importance of these determinants in prior studies on adoption, we find their lack of explanatory power for the updating decision to be descriptively interesting. Together, these results suggest that, although adoption and updating decisions are related, they are not the same decision and are not necessarily motivated by the same factors.

In short, the results of our hazard analysis provide evidence in support of H1 and H2a-H2c, and offer more descriptive insights on other determinants of AS updating which will be of interest in future updating research. In the next section we further support the importance of these results by estimating the economic outcomes associated with AS updates.

V. Outcomes of AS Updating

In this section we delve into the outcomes of AS updates in order to provide evidence on the importance of AS updating for hospital profitability. Because the decision to update is endogenous, it is difficult to directly attribute changes in hospital outcomes to the update itself rather than to other hospital-level decisions. In order to address this issue, our final analysis uses an instrumental variables approach to estimate the effect of AS updates on economic outcomes. In Table 2 we explored a variety of factors that can prompt hospitals to update their AS. Four of these variables are relatively exogenous with respect to the individual hospital: *Vendor_Peer_Update*, *Fair_Pricing, Price_Transparency*, and *SOX_404*. Of the four, *Vendor_Peer_Update* has by far the strongest ability to predict updates (with z-statistics above 10 for all six systems), is the only of the four that is predictably associated with all 6 systems, and varies within state and county in a given year while also being applicable to the vast majority of firms. For these reasons, we choose *Vendor_Peer_Update* as our instrumental variable.

Vendor_Peer_Update is an appropriate instrument in this context because the shared drivers of a hospital's AS updates with those of its vendor peers are changes made by the application vendor (e.g., the release of a new version of the existing application, or the termination of support for older applications) that are vendor-pushed and hence exogenous with respect to the hospital. A vendor's scheduled update of a particular accounting application (e.g., Meditech's update of Trendstar to version 2007.1) 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. While hospitals are not forced to update their systems when their vendors push an update out, these exogenous events are associated with increases in the ex ante probability that a given hospital will update. As discussed in Angrist, Imbens, and Rubin (1996), random assignment to treatment in an instrumental variables design (in our setting, the development of new applications or termination of support of existing systems that is exogenous with respect to individual hospitals) can lead to a valid research design even when subjects' compliance with the treatment is nonrandom (e.g., hospitals may choose not to update, even when their vendor has discontinued technical support for their current system), as long as there are no subjects whose probability of treatment always increases when they are assigned to the non-treatment group and vice versa (Angrist et al. (1996) label these individuals "defiers"). We believe this assumption is reasonable in our setting because it is unlikely that individual hospitals would be *less* likely to update their own systems as a result of vendor-pushed updates.[36] Lastly, although *Vendor_Peer_Update* is not a perfect measure of vendor-pushed updates, variation in this variable that is not attributable to vendor events or statewide or yearly economic conditions (controlled for by our fixed effects) is likely only to contribute noise to the measure. However, as shown in Table 2 and our (untabulated) first stage regressions, *Vendor_Peer_Update* has a strong effect on the probability of AS updating, with first stage F-statistics from the test of excluded instruments above Stock and Yogo (2005)'s critical values in all specifications. Thus we can rule out the possibility that it is a weak instrument.

To give additional detail on the *Vendor_Peer_Update* variable, we provide some descriptive statistics on how hospitals' vendor peers are spread across counties, states, and hospital systems. Table 3 provides information on the percent of a hospital's vendor peers that are within the same county, state,

[36] For a helpful and intuitive review of the validity of instrumental variables when compliance with treatment is nonrandom, see Angrist and Pischke (2014), Section 3.2.

and hospital system for each of the six AS. For example, on average 0.92%, 7.13%, and 6.87% of hospitals' vendor peers for their budgeting system are within the same county, state, and hospital system in a given year. One concern would be if virtually all of a hospital's vendor peers for a given AS were within the same hospital system. Because hospital systems have centralized decision-making and tend to roll out updates of a given accounting application at the same time, this could mean that our *Vendor_Peer_Update* variable would actually be capturing hospital-system-wide decisions to update, which are not exogenous. As can be seen from Table 3, vendor peers for all six AS are spread across multiple counties, states, and hospital systems, with an average of less than 6.85% of a hospital's vendor peers located in the same county, state, or hospital system across all systems. This wide distribution of vendor peers and the low percentages of local peers support our use of *Vendor_Peer_Update* as an instrument because these peers are subject to a variety of economic environments, and thus their shared impetus for updating is restricted to their common vendor, as opposed to region-, system-, or hospital-system-specific reasons for updating. Thus we believe that our *Vendor_Peer_Update* variable is reasonably and convincingly exogenous with respect to individual hospitals. Furthermore, we will report on robustness checks that exclude vendor peers in the same hospital system later.

Insert Table 3 here.

The results of our instrumental variable analysis are reported in Table 4. The main dependent variable of interest in our regressions is operating expenditures, *Op_Ex,* measured as operating expenditures per bed (i.e., scaled by *Bedsize*). For completeness, and to understand if AS updates may have any impact on the revenue side, we also include hospital operating revenues per bed, *Op_Rev*, as a dependent variable. The independent variable of interest is *Update,* which identifies the presence of an AS update. We choose to run our outcomes analysis separately for each of our six different AS because each system type could potentially have a different effect on hospital operating outcomes. Because of this, *Update* refers to updates of a different system in each of the six panels of Table 4. Because the benefits of AS updates may appear with a lag, especially those that are the result of more long-term decisions, 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 different outcome measures are capturing the same effect.[37] In other words, we are testing whether AS updates affect revenues, and also whether these updates lead to efficiency gains such that total expenses decrease even when revenues are held constant. Another key control variable for both outcomes is the change in hospital bed size (*Growth_Bedsize*) to ensure that a denominator effect is not driving either of the sets of results. Firms which are updating their AS might also be expanding; returns to scale could decrease operating expenses per bed as the number of beds increases without any real efficiency gains due to the system updates.[38]

We also control for three hospital-level characteristics that are key in an outcomes setting. First, because the mix of patients that a hospital serves can have a large effect on a hospitals costs and revenues, we control for the Case Mix Index (*CMI*) issued by the Centers for Medicare and Medicaid Services; certain conditions are much more cost-intensive to treat, and this variable allows us to control for the relative mix of patients by clinical diagnosis and resource-intensity. Additionally, different types of payers tend to provide different reimbursement rates and may tend to cover different procedures so we control for the percentage of patient-days in the hospital that are made up of Medicare and Medicaid patient-days (*%Medicare, %Medicaid)*. While both of these control variables are only available for the

[37] Inferences are similar when the specification for *Op_Ex* does not control for *Op_Rev*.
[38] As discussed previously, there are some years for which operating expenses or revenues are missing from the HIMSS data (i.e., 1987/1998-2003 and pre-2005, respectively). For these years, and any other individual missing observations, we replace the missing values with the operating revenue and expense data from the Medicare cost reports (HCRIS) data which is available starting in 1996; the correlation of the HCRIS data with our measures is high where both are available (>0.9). However, in untabulated analyses we perform the main analysis using only the value of these variables from the HCRIS data, which spans the entire post-1996 period, and find similar results.

post-1998 sample period, this coincides with the time period during which operating expenses and revenues are available, meaning that this restriction is not binding for this test.

Lastly, we also include all of the hospital-year-level and application-year-level variables from Table 2. All hospital-level control variables are measured in the same period as the dependent variable (either *Op_Ex* or *Op_Rev*), and all application-level control variables are measured in the same period as *Update*. 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. Lastly, we include hospital and year fixed effects to ensure that unobserved static hospital-level or yearly economy-wide factors are not driving our results.[39] 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 H3, the results in Table 4 show that AS updates have a significant negative effect on operating expenses. In particular, costing, budgeting, accounts payable, general ledger system, and to a lesser extent EIS updates have a significantly negative effect on operating expenses in the year of and the year following the update, with most of the decrease concentrated in the year of the update. The most important operating expense benefits of the updates are reaped immediately, although there are still significant reductions one year out and the signs remain negative (yet insignificant) two years out for all but case mix systems. This suggests that AS updates identify low-hanging fruit in terms of savings which can immediately be acted on, with further cost management possible over the next couple years. While we cannot observe which changes exactly are made to manage these expenses down based on the improved accounting information, Kaplan and Porter (2011) identify several courses of action based on their extensive case study evidence that hospitals typically take to manage costs after obtaining better information: process improvements and redesign that eliminate steps and variations that do not contribute to improved patient outcomes, reducing waste and idle time,

[39] Note that the presence of hospital fixed effects causes static hospital-level control variables, such as *Rural* or *Academic*, to be excluded from the final model. Results are similar if instead of hospital fixed effects we include state fixed effects and static hospital-level control variables.

optimizing processes over the complete care cycle, utilizing all clinicians at the “top-of-their license,” and reduction of unused capacity of people, equipment and facilities. While the results for *Op_Rev* show that most of the revenue changes are insignificant, they indicate some benefits of updating with increases in operating revenues after updates of accounts payable, general ledger, case mix systems, and EIS occurring with delay. Speculatively, it is possible that the freed up monies due to the significant and immediate operating expense decreases are subsequently used in revenue generating investments such as quality improvements in staff and facilities. Also, the negative (yet usually insignificant) signs on revenues in the year of the update may indicate that hospitals are immediately cutting out some unprofitable revenue streams. Kaplan and Porter (2011) find that revisiting prices is common in the hospital setting after obtaining better accounting information. Our survey data do not allow us to observe such detailed actions taken, but we would welcome further research that could obtain deeper insights into hospital cost and revenue management.

Insert Table 4 here.

Because both dependent variables are scaled by *Bedsize*, the coefficients on $Update_t$ 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. For example, the results with respect to budgeting system updates in Panel B have a coefficient of -48,735 in Column 1. This implies that budgeting system updates lead to an average decrease in operating expenses of $48,735 per bed in the year of the update ($t+0$). The absolute values of the significant coefficients on operating expense decreases in Table 4 range between 49,845 in Column 1 of Panel A (benefits of costing system updates in the current year), and 14,670 in Column 2 of Panel E (benefits of EIS updates one year after). 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 $486,898 and $502,337, respectively.

Although we do not report the coefficients of control variables in Table 4 for parsimony, we note briefly that they seem to behave reasonably. In Columns 1-3, *Op_Rev* has a coefficient ranging between

0.599 and 0.636 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 the 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. Note too that we include several controls for patient mix (*CMI, %Medicare, %Medicaid*), so the coefficient on *Update* does not capture changes in this mix.

For some AS, our results show delayed revenue increases. The fact that our results demonstrate opposite effects on expenses and revenues (decreases versus increases) suggests that these results are not necessarily two sides of the same coin. Because expenses and revenues are usually closely linked, a decrease in revenues could directly translate into a decrease in expenses because a decrease in the economic activity that drives revenues would decrease the amount of associated costs. However, our results show that the results go in opposite directions for the two outcomes, and we obtain them when controlling for revenues in the expense specifications. Our results are also unlikely to be due to a denominator effect or because of economies of scale because we control for both *Bedsize* and *Growth_Bedsize* [40]

As in every study that uses an instrumental variables analysis, one potential concern is the appropriateness of the instrument, in particular whether or not the exclusion restriction holds. In our case, if *Vendor_Peer_Update* has a direct effect on *Op_Ex* or *Op_*Rev it could bias our estimate of the effect of *Update* in favor of us finding significant results. If regional economic conditions at the state- or county-level drive hospitals' decisions to update their AS and also impact their operating outcomes, and if *Vendor_Peer_Update* is capturing these forces because some vendor peers are in the same county or state, then our IV estimates could be overstating the true effect of updating. However, as Table 3 demonstrates, the vast majority of hospitals' vendor peers are in different states and counties, making this effect unlikely

[40] In untabulated tests we also used the number of patient days instead of *Bedsize* as a scalar for *Op_Ex.* Inferences for operating expenses are similar, although results for revenues are weak and mixed.

to be driving our overall results. In addition, our tests control for all of the determinants in Table 2, including *County_Peer_Update* which would capture updates of other hospitals in close proximity which experience almost identical economic conditions, and year fixed effects which capture economic conditions for all hospitals in the same time period. To further alleviate this concern, we run untabulated robustness tests that include state-year fixed effects which control for the current economic conditions of the state in which a hospital resides, and also specifications where standard errors are clustered by county or by state. Inferences are unchanged.

One further concern about the *Vendor_Peer_Update* measure is that it could be capturing updates that are rolled out at the hospital system level. Such system-wide updating decisions might accompany other policy changes that could directly affect operating expenses and revenues. As demonstrated in Table 3, most of a hospital's vendor peers reside in different hospital systems, and we also control for *System_Peer_Update*, meaning that hospital system peers are unlikely to be driving our results. However, comparison of the mean and median percent of vendor peers within the same system as shown in Table 3 shows that the means tend to be much larger than the median percentages (which are all less than 1%); thus it appears that a few hospitals have a large proportion of vendor peers which are in the same hospital system. In order to ensure that these outlier hospitals, and vendor peers within the same hospital system in general, do not drive our results, in untabulated robustness tests we construct a new version of *Vendor_Peer_Update* that excludes vendor peers that reside in the same hospital system. Results using this restricted measure are qualitatively unchanged.[41]

In general, the inferences from our final table are robust to a variety of specifications. Overall, we view our results on the economic outcomes of updates to be an important first step in this previously unexplored area. Although it is always difficult to establish causality, we believe that vendor peer updates

[41] Because the causal mechanism for our instrument works only through hospitals that have purchased their systems from outside vendors, it does not affect self-developed systems. In line with this, our inferences are unchanged when we exclude self-developed systems from the analysis or, as we also did to show robustness of our determinants results in Table 2, if we use all other self-developed systems as the vendor peers for self-developed applications instead of coding *Vendor_Peer_Update* as 0 for self-developed systems, which we do in our main specifications.

are relatively exogenous shocks, and our analyses provide suggestive evidence that the updating decision is an important one. Our results demonstrate that AS updates lead to efficiencies that are manifested in reductions in operating expenses within hospitals.

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 time series aspects of the adoption and updating of six management and financial AS. Our results allow us to provide descriptive information on the relative sequencing of AS adoption over time and show that AS are relatively mature and have been adopted by the majority of hospitals in our sample, indicating that post-adoption decisions such as updating have become more and more relevant. We find that factors such as "waves" of updates that occur within vendors, state-level price regulation that affects hospitals' demand for internal accounting information, and Section 404 of the Sarbanes-Oxley Act that requires high standards for internal control systems are important determinants in the updating decision. Lastly, using vendor-pushed updates as an instrumental variable, we document immediate and significant reductions in operating expenses following an AS update. These results are especially important because to our knowledge we are the first study to show economic benefits of AS updating.

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. It allows us to answer the call in Leuz and Wysocki (2015) for more research on indirect real effects of disclosure regulation in particular by demonstrating a link between implementation of price transparency websites and AS updates within the firm. Our well-identified results on how staggered state-level price transparency and fair pricing measures affect AS updating may foreshadow the effect of similar regulations recently enacted at the federal level. Additionally, we document that public hospitals are highly likely to update the full range of their AS to comply with the provisions of Section 404 of SOX. We speculate that this result generalizes to firms in other industries that were subject to SOX 404.

Second, although companies invest significant resources in AS and rely on the information they provide for decision-making, clear evidence on the benefits of these systems has been difficult to obtain because of concerns about endogeneity. Using an instrumental variable analysis, we document that AS updates lead to hospital cost reductions. We believe that this finding is particularly relevant in an era when health care providers and governments are struggling to keep health care costs under control. 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 system updates are especially important.

Given that our research suggests that we cannot generalize our knowledge of what determines AS adoption to updating, we would welcome further research on 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 result that price disclosure and price pressure leads firms to update their MAS 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 insights on exactly how operating expense reductions are achieved based on improved accounting information, and to explore how updates to AS affect the quality of external financial reporting which relies on this internally generated information. 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.

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Appendix 1: Data Procedures

1. Accounting Systems Categories

Although each application tracked in the database is identified by hospital, application type, vendor, year the application was contracted, and other identifying information, there is some variation over time in how different applications are labeled, in particular when the survey changed in 1998 and 2005. To allow us to consistently identify specific applications over time, we examined all of the application types identified in the survey over the entire sample period and classified each application as being either a clinical application, medical records application, or business application. Business applications are related to the business aspect of hospital operations; for example, all accounting and financial applications are business applications. Clinical applications are used to assist hospitals in their mission to treat patients, and medical records applications are related to the information storage and organization task that hospitals face of keeping track of patient medical information. Each business application was further assigned one of 27 specific business application labels, based on a set of categories very similar to that used in Setia et al. (2011).[42] Of these 27, we consider 6 to be AS and hence the subject of this paper. Where multiple applications are classified in the same category, we record an update when any of the applications are updated; however, the data only contains one observation per hospital-application type-year.

2. Dates Related to AS

Three dates in the data provide information about the current version of an AS and are used in our updating analysis. First, the contract date is the date on which a hospital contracted to purchase a particular AS model. We also observe the first year for which each AS was listed in the database as "fully operational", which we refer to as the implementation date. Lastly, the install date is the date on which a particular AS model was installed. We observe an average lag of 4 to 8 months between the install date and implementation date, even controlling for systematic differences driven by when the survey can actually observe implementation (i.e., at what point during the year the survey was administered). This indicates that the install and implementation dates mark the beginning and end of application installation, respectively, even though none of the data manuals have a specific definition of the install date. While we would ideally like to study all of these dates separately, the install date is only tracked during the first part of the sample, and the implementation date is subject to measurement error because it is extrapolated from our data. Only the contract date is available and precisely measured for the entire sample period (with the exception of the first year, 1987), so we opt to focus on this date. However, because the contract date has a relatively high amount of missing values (approximately 40% of application-year

[42] The list is available on request.

observations), we replace the missing contract date with the install date (when available) in order to calculate the time since the last model update. In cases where both the contract and install dates are available, the median difference between them is 0 years (and less than a year on average), so this substitution seems reasonable. We further replace any remaining missing contract dates with the implementation year, adjusted for the median difference between contract and implementation year, by application type. Replacing missing contract dates undoubtedly adds some noise to our analysis, with approximately a fifth of the dates in our sample affected by one of these two methods, but this makes it less likely for us to find meaningful results.

In addition to the procedures described above, we take steps to alleviate various small errors in our data, such as contract dates going very far back in time or many years beyond the survey dates. A list of these steps is available from the authors on request. All of these procedures are essential in identifying the length of time between application updates and allow us to calculate the model duration used in our hazard models. Updates for which we cannot determine the time since the last update (left censored) are excluded from the sample.

3. AS Updates and their Timing

We use the information provided about AS model names and dates (described above) to identify model updates. As already outlined in the text, if the model name is available, we identify model updates by checking whether the current AS model was used by the hospital for that AS category in *any* of the preceding four years. We check all four prior years to ensure that we do not record updates for models that simply were not covered in some years of the data. Where contract dates are available, we identify model updates by identifying if the contract date has occurred within the last two years. [43] To prevent double counting a single model change, we only identify model updates using this method if the AS was not also updated in the previous year. If both the contract date and model name are available, we recognize model updates as above if the model has not been used in the previous four years and the AS contract year is at most three years before the current year.

[43] The surveys were not collected in 1996 and 1997, and we do not have access to the 1989 data. In an effort to capture AS updates during these gaps, we extend this period to three years for the 1998 and 1990 observations.

Appendix 2: Variable Definitions

Variable Name	**Variable Description**
%Medicaid	The percent of the hospital's total patient days that are for Medicaid patients.
%Medicare	The percent of the hospital's total patient days that are for Medicare patients.
Academic	Indicator variable coded 1 if the hospital is classified as an academic hospital in the HIMSS data, or if the HCRIS data has positive intern salary or is classified as a teaching hospital.
Apps_Age	The average age (years since last update) of all applications in the current hospital-year (excluding the current application observation).
Bedsize	Number of licensed beds in the hospital
Business_Depth	The number of unique software applications that are categorized as "Business Office" for a given hospital-year.
Clinical_Depth	The number of unique software applications that are categorized as "Clinical" for a given hospital-year.
CMI	Case Mix Index obtained from CMS (Centers for Medicare and Medicaid Services). The CMI represents the average diagnosis-related group (DRG) relative weight for that hospital, where the value assigned to each DRG indicates the amount of resources required to treat patients in that group.
County_Peer_Update	An indicator variable coded 1 if a hospital in the same county-year updated the AS of interest.
Duration	The number of years since the last update of the given AS (measured since the prior update if the AS was updated in the current year).
Fair_Pricing	Indicator variable coded 1 if fair pricing measures were implemented in the state in the prior year.
For_Profit	Indicator variable coded 1 if the hospital is ever classified as a for-profit entity in either the HIMSS or HCRIS data.
Growth_Bedsize	$(Bedsize_t - Bedsize_{t-1})/Bedsize_{t-1}$
HHI	Yearly Herfindahl-Hirschman Index of hospital concentration measured at the county-year level using all hospital-year observations available.
Hospital_Update_Count	The number of applications (excluding the current AS) that a hospital updated in the current year.
In_System	An indicator variable coded 1 if the hospital is within a multi-hospital system and 0 otherwise.
Med_Record_Depth	The number of unique software applications that are categorized as "Medical Records" for a given hospital-year.
Op_Ex	Operating expenses per bed (i.e., total operating expenditures/bedsize), obtained from the HIMSS data. Operating expenditures are not available from the HIMSS data for the years 1987, and 1998-2003; missing values of operating expenditures after 1996 are filled in from the HCRIS cost reports data where available.
Op_Rev	Net operating revenue of the hospital per bed, obtained from the HIMSS data. Operative revenues are not available from the HIMSS data prior to 2005; missing values of net operating revenues after 1996 are filled from the HCRIS cost reports data where available.
Penetration	The percent of hospitals in the sample that have a particular AS (e.g., costing) currently installed in a given year.
Prep_Year	An indicator variable coded 1 if the data year is 2002 or 2003 (the two years after the passage of Sarbanes-Oxley during which firms could prepare to be SOX-compliant before 2004).

Price_Transparency	Indicator variable coded 1 if the state adopted a price transparency website in the prior year. Dates obtained from Table 1 of Christensen et al. (2014) and Christensen et al. (2015).
Rural	Indicator variable coded 1 if the hospital is located within a zipcode for which at least 50% of the population lives in a rural area, according to the 2000 U.S. Census, or if the hospital reported it was in a rural area in at least one HCRIS cost report.
Self_Developed	Indicator variable coded 1 if the AS was self-developed by the hospital. Many self-developed AS are identified in the HIMSS database itself; additionally, three research assistants manually reviewed all of the application vendors in the database and identified those that are actually a hospital or hospital system itself instead of an outside vendor (i.e., the hospital listed itself as the vendor when it had self-developed the AS).
SOX_404	An indicator variable coded 1for hospitals that were part of hospitals systems that were subject to SOX 404 in 2004.
Specialty_Hosp	Indicator variable coded 1 if the hospital is a specialty hospital, according to data provided in the HCRIS dataset. Non-specialty hospitals: general short- and long-term hospitals. Specialty hospitals: cancer, psychiatric, rehabilitation, religious non-medical, pediatric, alcohol & drug, other.
System_Peer_Update	Indicator variable coded 1 if another hospital in the hospital's multihospital system or purchasing group updated the AS of interest in the current year.
Vendor_Peer_Update	The percent of other hospitals which share the same vendor for a particular AS type that updated the AS in the current year. When a hospital has changed vendor in the current year, this measure is the percent of hospitals which shared its *prior* year vendor that updated this year. [Excludes hospital-AS-years where fewer than 2 other hospitals use the same vendor for the same AS. Also excludes observations where all hospitals that used a given vendor changed vendor in that year. This variable is set to 0 for all self-developed systems.]

Dollar amounts are deflated by CPI to be in constant year 2000 dollars.

Figure 1. Median Bedsize and Sample Size Over Time for the Full and Constant Samples

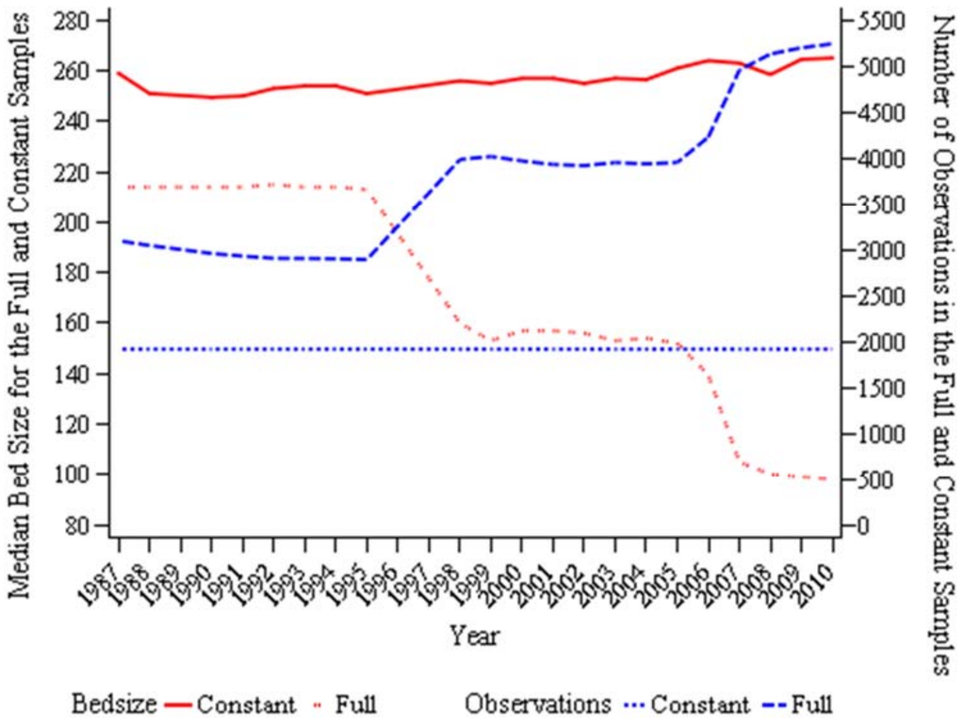
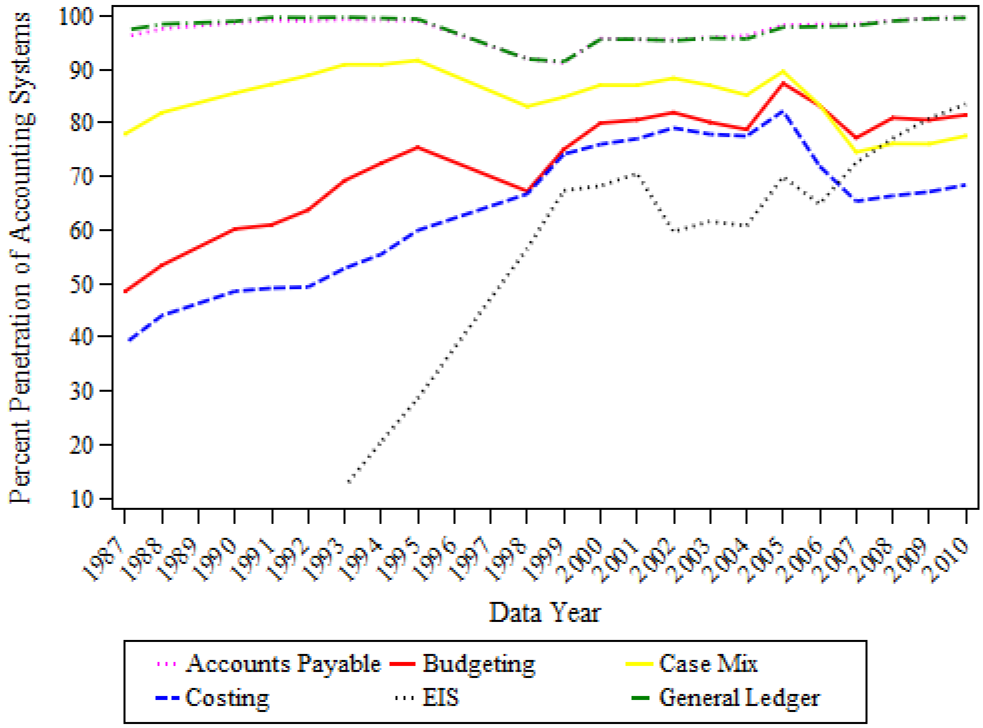


Figure 2. Penetration of Accounting Systems Over Time

Panel A. Full Sample



Panel B. Constant Sample

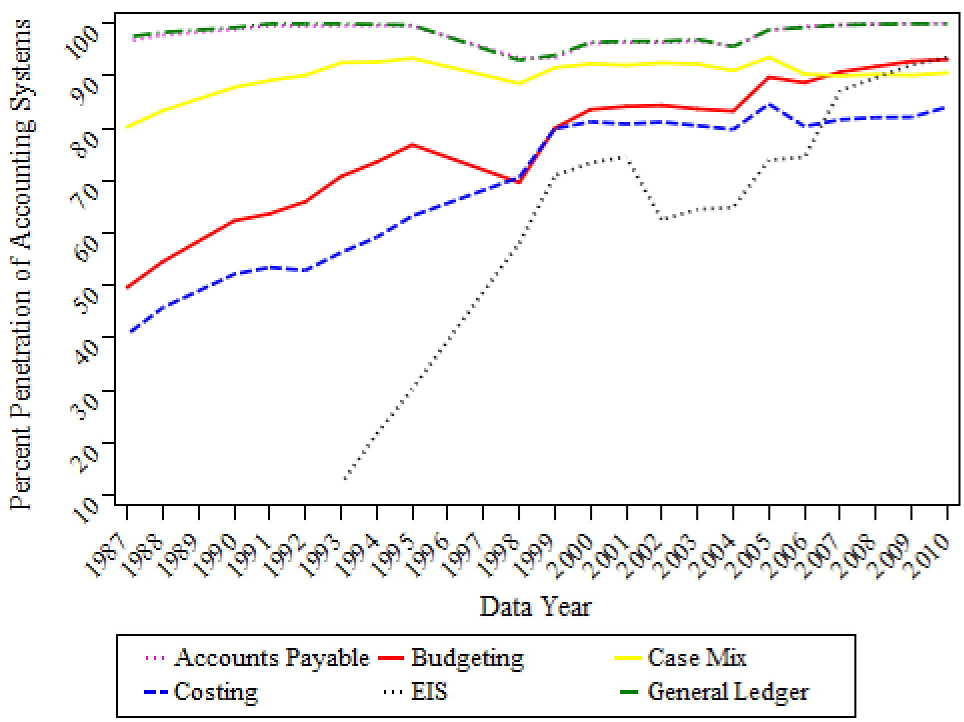


Figure 3. Kernel Density Distribution of System Durations at Time of Update

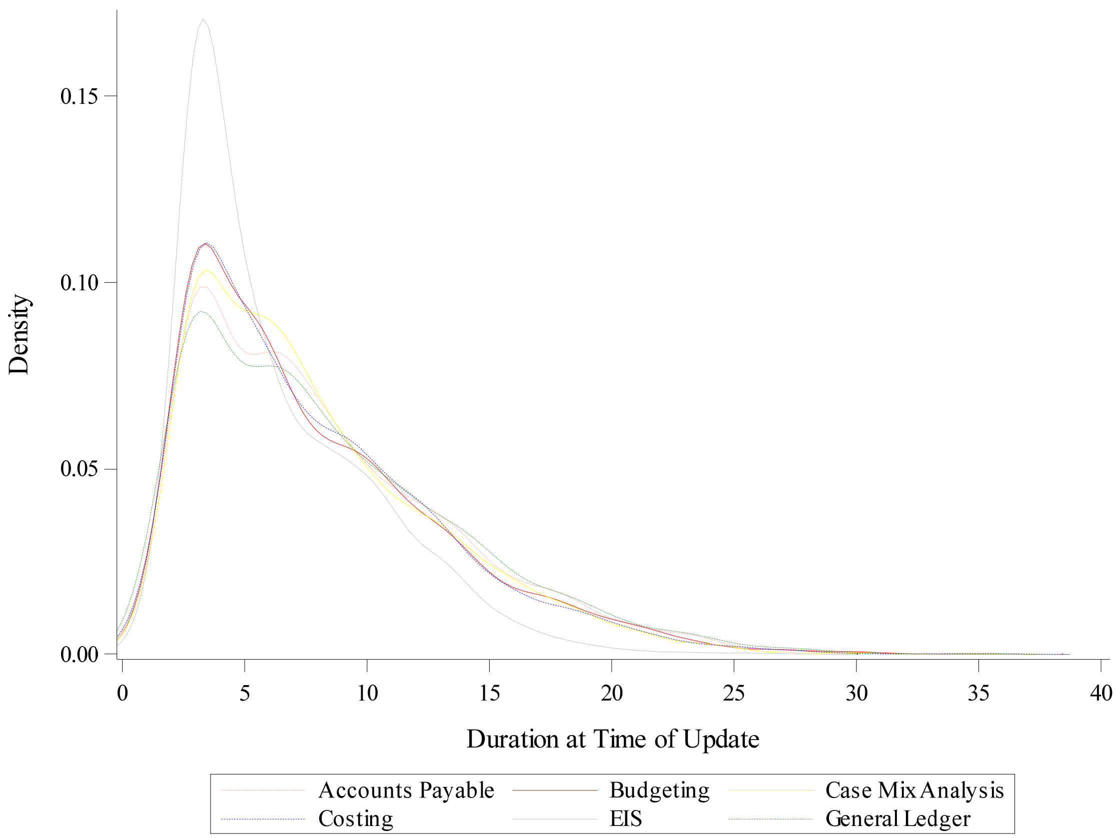


Table 1. Descriptive Statistics

Panel A. Hospital-Level Variables

	N	Mean	Median	Std	P25	P75
SOX_Firm	51,744	0.17	0.00	0.37	0.00	0.00
In_System	51,744	0.64	1.00	0.48	0.00	1.00
Apps_Age	51,744	6.23	5.90	2.70	4.25	7.85
Business_Depth	51,744	7.29	6.00	5.29	3.00	10.00
Med_Record_Depth	51,744	3.48	3.00	1.84	2.00	5.00
Clinical_Depth	51,744	5.52	5.00	3.57	3.00	7.00
Bedsize	51,744	224.83	180.00	180.61	98.00	310.00
For_Profit	51,744	0.30	0.00	0.46	0.00	1.00
HHI	51,744	4,751	3,779	3,649	1,379	10,000
Rural	51,744	0.12	0.00	0.33	0.00	0.00
Academic	51,744	0.40	0.00	0.49	0.00	1.00
Op_Ex	30,536	486,898	431,117	269,787	306,575	599,681
Op_Rev	30,536	502,337	443,984	289,045	308,619	624,706
Growth_Bedsize	30,536	0.01	0.00	0.12	0.00	0.00
CMI	30,536	1.38	1.33	0.25	1.20	1.54
%Medicare	30,536	46.30	47.60	14.31	36.62	56.19
%Medicaid	30,536	13.83	11.61	10.24	6.38	18.50

Hospital-level variables used in the hazard analysis are available for the full sample period (1987-2010). Variables used only in Table 4 are available for the years 1999-2010. Descriptive statistics are provided for firms for which data are available to estimate models relating to General Ledger systems as these systems are the most prevalent.

Panel B. Accounting System Updates

System	N	Mean	Median	Std
Costing	36,576	0.09	0	0.28
Budgeting	40,667	0.10	0	0.3
Accounts Payable	51,514	0.08	0	0.28
General Ledger	51,744	0.08	0	0.28
Case Mix	45,828	0.08	0	0.28
EIS	26,820	0.15	0	0.36

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

	Costing	Budgeting	Accounts Payable	General Ledger	Case Mix	EIS
Vendor_Peer_Update	12.951	13.717	10.728	10.477	11.187	18.28
System_Peer_Update	0.298	0.312	0.251	0.246	0.269	0.352
County_Peer_Update	0.016	0.01	0.009	0.002	0.017	0.017
Self_Developed	0.126	0.144	0.099	0.106	0.126	0.159

Mean values of application-level variables by AS type.

Table 2. Determinants of Application Updating

	Predicted Effect	(1) Costing	(2) Budgeting	(3) Accounts Payable	(4) General Ledger	(5) Case Mix	(6) EIS
Vendor_Peer_Update	+	1.022***	1.018***	1.018***	1.021***	1.020***	1.012***
		(16.34)	(15.46)	(12.91)	(14.07)	(13.74)	(12.62)
Fair_Pricing	+†	1.316**	1.078	1.434***	1.277**	1.350***	1.166*
		(1.858)	(1.092)	(3.348)	(2.063)	(2.552)	(1.752)
Price_Transparency	+*	1.152*	1.172**	0.757***	0.766***	0.926	0.948
		(1.587)	(2.170)	(-2.790)	(-2.787)	(-0.705)	(-0.718)
SOX_404 x Prep_Years	+	1.398***	1.441***	0.987	1.340***	1.829***	1.380***
		(2.612)	(3.124)	(-0.0982)	(3.202)	(4.324)	(2.413)
			Control Variables				
SOX_404		1.073	0.829***	0.867**	0.993	0.850**	0.698***
		(1.067)	(-2.956)	(-1.965)	(-0.115)	(-2.166)	(-5.572)
System_Peer_Update		3.940***	4.305***	3.830***	3.512***	3.166***	6.545***
		(20.82)	(31.79)	(30.92)	(26.97)	(20.16)	(27.14)
In_System		0.441***	0.367***	0.454***	0.462***	0.520***	0.251***
		(-14.18)	(-18.18)	(-16.21)	(-14.08)	(-11.11)	(-17.03)
County_Peer_Update		1.147	1.259*	1.863***	0.936	1.551***	1.241***
		(1.131)	(1.880)	(6.193)	(-0.0102)	(4.313)	(2.629)
Apps_Age		0.656***	0.680***	0.643***	0.654***	0.616***	0.695***
		(-13.09)	(-13.84)	(-16.90)	(-14.59)	(-18.87)	(-10.63)
Apps_Age^2		1.009***	1.011***	1.009***	1.006**	1.011***	1.011***
		(3.496)	(5.328)	(4.021)	(2.320)	(4.815)	(4.491)
Business_Depth		1.030***	1.046***	1.038***	1.032***	1.029***	1.059***
		(5.030)	(8.761)	(7.630)	(5.371)	(6.550)	(10.28)
Med_Record_Depth		0.947***	0.980	1.022*	1.020	0.980	0.978
		(-3.848)	(-1.511)	(1.651)	(1.107)	(-1.563)	(-1.441)
Clinical_Depth		1.020**	1.015**	0.984**	1.002	1.028***	1.010*
		(2.560)	(2.218)	(-2.040)	(0.233)	(3.558)	(1.769)
Self_Developed		1.390***	1.266***	1.034	1.300***	1.283***	0.956
		(4.738)	(3.694)	(0.548)	(4.492)	(3.641)	(-0.822)
Bedsize		1.000	1.000	1.000	1.000***	1.000	1.000
		(0.449)	(-0.988)	(-1.061)	(-2.625)	(-0.748)	(-0.458)
For_Profit		0.954	1.040	0.984	1.021	0.982	1.022
		(-0.761)	(0.706)	(-0.335)	(0.371)	(-0.371)	(0.464)
HHI		1.000	1.000*	1.000**	1.000**	1.000	1.000
		(-1.002)	(-1.860)	(-2.517)	(-1.979)	(-1.589)	(0.993)
Rural		1.013	1.008	0.913	0.845***	0.975	0.919
		(0.182)	(0.167)	(-1.494)	(-2.895)	(-0.381)	(-1.206)
Academic		1.129**	1.054	1.026	1.082**	1.038	1.008
		(2.481)	(1.386)	(0.759)	(2.062)	(1.043)	(0.185)

State and Year Fixed Effects	Y	Y	Y	Y	Y	Y
Observations	36,576	40,667	51,514	51,744	45,828	26,820
Wald χ^2, Entire Model	3157	3235	4152	4116	3601	3435
Prob. > χ^2, Entire Model	< 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 only for costing, budgeting, and case mix systems. *Prediction only for costing and budgeting systems.

Bootstrapped z-statistics in parentheses

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

Table 3. Distribution of Vendor Peers

	Same County *Mean*	Same County *Median*	Same State *Mean*	Same State *Median*	Same System *Mean*	Same System *Median*
Costing Systems	0.98%	0%	6.84%	3.91%	6.84%	0.45%
Budgeting Systems	0.92%	0%	7.13%	3.99%	6.87%	0.51%
Accounts Payable Systems	0.76%	0%	6.85%	3.81%	6.86%	0.22%
General Ledger Systems	0.72%	0%	6.76%	3.77%	6.31%	0.23%
Case Mix Systems	0.83%	0%	6.66%	3.85%	5.16%	0.23%
Executive Information Systems	1.12%	0%	7.04%	3.68%	8.85%	0.82%
Overall	0.86%	0%	6.85%	3.85%	6.64%	0.35%

Descriptive information about the distribution of other hospitals in the current year who share the same vendor for a given system (i.e. vendor peers). For each system type, the table provides the mean and median percentage of vendor peers who are in the same county, state, and hospital system.

Table 4. The Effect of Accounting System Updates

	(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*
Predicted Effect	-	-	-			
Panel A. Costing Systems						
$Update_t$	-49,845***	-34,420**	-17,671	-38,648	-5,907	25,036
	(-3.031)	(-2.183)	(-1.057)	(-1.124)	(-0.210)	(0.941)
Observations	24,509	21,908	19,406	24,509	21,908	19,406
R^2	0.634	0.614	0.604	0.276	0.258	0.235
Panel B. Budgeting Systems						
$Update_t$	-48,735***	-45,186***	-23,239	-12,203	-10,829	20,967
	(-2.698)	(-3.020)	(-1.382)	(-0.356)	(-0.417)	(0.796)
Observations	26,201	23,226	20,399	26,201	23,226	20,399
R^2	0.644	0.620	0.601	0.296	0.272	0.248
Panel C. Accounts Payable Systems						
$Update_t$	-30,092***	-30,558***	-8,702	11,699	36,236***	-10,265
	(-3.624)	(-3.867)	(-0.900)	(0.717)	(2.593)	(-0.719)
Observations	30,544	27,183	23,887	30,544	27,183	23,887
R^2	0.653	0.633	0.618	0.296	0.276	0.258
Panel D. General Ledger Systems						
$Update_t$	-16,708**	-35,405***	-10,668	21,884	52,943***	36,382**
	(-2.043)	(-3.783)	(-1.071)	(1.346)	(3.246)	(2.445)
Observations	30,547	27,208	23,928	30,547	27,208	23,928
R^2	0.657	0.632	0.617	0.293	0.270	0.254
Panel E. Case Mix Systems						
$Update_t$	20,832	13,349	3,715	-57,476*	-1,509	78,980***
	(1.095)	(0.819)	(0.209)	(-1.957)	(-0.0538)	(2.815)
Observations	27,765	24,874	22,055	27,765	24,874	22,055
R^2	0.649	0.629	0.604	0.290	0.275	0.236
Panel F. Executive Information Systems						
$Update_t$	-6,298	-14,670*	-10,805	-17,913	31,440**	16,972
	(-0.754)	(-1.745)	(-1.263)	(-1.208)	(2.309)	(1.242)
Observations	21,532	18,825	16,124	21,532	18,825	16,124
R^2	0.658	0.637	0.624	0.283	0.262	0.241

Application-Level Controls $_{tk}$	Y	Y	Y	Y	Y	Y
Hospital-Level Controls $_{t+n}$	Y	Y	Y	Y	Y	Y
Hospital and Year Fixed Effects	Y	Y	Y	Y	Y	Y

The results of an instrumental variables analysis of the effect of accounting system updates on hospital expenses and revenues (*Op_Ex, Op_Rev)* using *Vendor_Peer_Update* as an instrument. The Hospital-Level Controls$_{t+n}$ comprise all time-varying hospital-level control variables from Table 2 as well as: *Growth_Bedsize*, *CMI*, *%Medicare* , *%Medicaid,* and (for Columns 1-3) *Op_Rev*. The Application-Level Controls$_{tk}$ are comprised of the remaining determinants from Table 2 and correspond to each of the six systems, *k*. F-statistics from the test of excluded instruments well exceed Stock and Yogo (2005) critical values in all specifications.

Heteroskedasticity robust z-statistics clustered by hospital in parentheses

*** p<0.01, ** p<0.05, * p<0.1