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 novel sample of U.S. hospitals. We document that a set of previously unidentified determinants drive the updating decision including the way in which hospitals initially adopted their accounting systems, "waves" of updates that are taking place across hospitals, and implementation of price transparency websites at state level that increase hospitals' demand for high quality costing and budgeting 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 prominence of health care in the economy and the current public policy crisis concerning rising costs of medical care.

Keywords: Management Accounting, Accounting System Updating, Health Care Costs

I. Introduction

Our paper uses a novel 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 use our unique data to document determinants that drive the updating decision which have not previously been explored, including evidence on real effects of disclosure regulation in the form of state-level price transparency websites that significantly affected updating of costing and budgeting systems. 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 avenue of research. Expenses related to IT in general and AS in particular represent a significant portion of firm operating expenses: 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). 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. In addition, practitioner advice on if and when firms should update their AS remains fairly vague, which means that firms which do update must use their own heuristics to make the best possible updating decisions.[1] To our knowledge there is no large-scale empirical evidence on which factors drive AS updating or what benefits firms receive from maintaining such AS investments, which signifies that neither academics nor practitioners know what is involved in such updating decisions for a large cross-section.

Over the last several decades, studies have documented the cross-sectional variation in benefits and costs of (in particular management) accounting system *adoption*, identifying characteristics of firms that are more likely to adopt (e.g. Davila and Foster, 2005) and documenting the outcomes adopting firms can expect (e.g. Chenhall and Morris, 1986; Ittner,

[1] For example, circumstances under which updating is recommended by vendors range from the very vague "when your needs outgrow your system" (Zahorsky, 2014) or "when reporting is inadequate" (Dietz, 2014), to the slightly less vague "too many manual processes" (Dietz, 2014; Kennedy, 2014) or "slow response times" (Meyer, 2014).

Lanen, and Larcker, 2002; Maiga and Jacobs, 2008). However, it is unclear that results in the adoption literature will translate to an updating setting. The magnitude of the resources required to implement an AS adoption tend to be much greater than those required in updating. Also, the way in which AS are adopted may affect their subsequent updating. Furthermore, 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. On the determinants side, this leads us to research determinants that are specific to an updating setting, such as the way in which the initial adoption of the AS took place. One determinant of AS updating that we investigate is regulation of price disclosure, which allows us to study how disclosure regulation determines real behavior within the firm, as called for by Leuz and Wysocki (2015). We identify a series of changes to hospital price disclosure that were staggered across 31 U.S. states over the period 2002-2009 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 the requirement to disclose and the accompanying scrutiny increased hospitals' demand for high quality costing and budgeting information, leading to updates of these management accounting systems.

On the outcomes side, estimating the economic benefits of updating or adoption 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. 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 *adoption* on performance and management control system *adoption* on firm growth, respectively. The 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 overall hospital efficiency, measured by operating expenses, and hospital income streams, measured by revenue.

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]

[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.

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. We document that financial accounting systems are already in use by the majority of hospitals in 1987 (97%) and this penetration rate increases to over 99% by the end of our sample period in 2010. On the other hand, the penetration rate of management accounting systems increases more strongly over our sample period; the penetration of costing systems, for example, demonstrated an increase from 40% to 84% (68%) for the constant (full) sample. Inspection of our penetration statistics suggests a logical sequencing of AS adoption, where financial AS clearly precede the adoption of management AS. Most importantly, 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.[3] First, characteristics of the initial adoption affect updating because AS that are self-developed legacy systems have a decreased likelihood of being updated whereas systems developed by outside vendors seem to result in more frequent vendor-pushed updates. Additionally, AS tend to be updated in "waves." For example, hospitals are more likely to update their AS in years when peers in the same multihospital system or county are also updating, or when the hospital is also updating other non-accounting systems. This suggests that factors such as centralized planning, or social and/or spatial proximity play a role in the updating decision.

[3] In contrast, we find that standard *adoption* determinants such as size and competition have relatively little ability to predict updating. Others have pointed this phenomenon out with respect to information systems. See Grabski, Leech, and Schmidt (2011) w.r.t. ERP, Zhu, Kraemer, and Xu (2006) w.r.t. e-business technology, and Khoo and Robey (2007) w.r.t. packaged software.

Furthermore, we find that implementation of the price transparency initiatives described above enticed hospitals to update their costing and budgeting systems, supporting our prediction that they led to a greater demand for costing and budgeting information and that disclosure regulation can have real effects on behavior *within* firms.[4] Finally, more descriptively we find that the extent to which hospitals have a focus on IT affects the propensity to update, where hospitals with very old applications seem to settle on continuing to use those old applications without updating them, and hospitals that have adopted a lot of business applications update more frequently.

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.

Our study is important for several reasons. Notwithstanding several calls for longitudinal work on information systems more generally and AS specifically[5], no research is available on AS *updating*. Additionally, 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. As

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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 indirect 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).

updating by definition has this temporal dimension, prior cross-sectional work is not well-positioned to address this research question. We also believe our results with respect to price transparency are important both in the accounting literature, as they document real effects of disclosure regulation, as well as in the health economics and health policy literatures because they show a real impact on hospitals' decisions to adopt costing and budgeting systems. 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 health care costs are still increasing (WorldHealthOrganization, 2015), making AS of utmost importance in measurement and cost management in this sector. Additionally, this setting is a particularly powerful one for our research question as hospitals operate in a dynamic environment with frequent changes to technology and regulation, potentially necessitating regular updating of AS.

The rest of our paper is organized as follows. In the next section we describe our hypotheses with respect to the determinants and outcomes of AS updating. Section 3 then presents the data used and provides some descriptive statistics, including penetration rates and sequencing of the various AS over time. Section 4 presents our results on the determinants of AS updating. Section 5 uses an instrumental variable analysis to provide evidence on the benefits of updating. The final section concludes and presents avenues for further research.

II. Hypotheses

Because AS updating has not been studied in prior research, some of the results in our study are admittedly descriptive, in particular our evidence on penetration rates and sequencing of AS over time and (some of) the determinants of AS updating. However, we structure our formal analyses around two main hypotheses relating to the determinants and outcomes of AS updating.

Our first set of hypotheses relates 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 can make a few predictions on factors that are likely to affect the probability of updating. First, we expect that the manner in which a hospital initially adopted an AS will be related to its subsequent updating decisions, in particular whether the hospital developed their own AS or bought it from an outside vendor. When a hospital has a self-developed legacy AS in place, costs for updating such a system in-house are typically higher as the knowledge about the structure of the AS is concentrated in a limited set of employees, coding languages used may be older, and many legacy AS were not built with ease of updating and maintainability in mind. Legacy updates also typically take longer (Ng, 2001). Resistance to changing to an outside vendor is large, as IT departments feel they have customized these AS with the intricacies of the particular hospital in mind (Gartner, 2008), and the costs to migrate are similar to those of an initial adoption. Hence, H1a is as follows:

H1a: *Hospitals are less likely to update self-developed AS.*

In contrast, updates of non-legacy AS are often vendor-driven when vendors release new updates or stop supporting older versions (Beatty and Williams (2006), Khoo and Robey (2007)). While we cannot directly observe new updates or support termination in our data, other hospitals that share the same vendor for a given AS will also be affected by these events. We can therefore indirectly capture vendor-instigated updating by observing whether other hospitals that use the same vendor ("vendor peers") are updating. 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. Thus, our next hypothesis is:

H1b: *Hospitals are more likely to update their AS when other hospitals that share the same vendor are also updating.*

Several other factors can lead hospitals to update their systems in "waves" where numerous peer hospitals all update at the same time. First, multihospital systems tend to have a standardized schedule of updates that are typically rolled out across all hospitals in the hospital system concurrently, with contractual agreements spanning the entire hospital system. This and the fact that network ties created among hospitals in a hospital system provide access to the experiences of other organizations with AS (Kennedy and Fiss, 2009) leads us to expect that hospitals will be more likely to update when other peers within the same hospital system are also updating. Similar to waves of updates among hospitals within the same hospital system, we expect to find waves of updating among hospitals in spatial proximity to each other (Angst, Agarwal, Sambamurthy, and Kelley, 2010). Hospitals in the same geographic area are subject to the same environmental pressures and may also respond directly to the updates of other hospitals. Thus we expect hospitals in the same county to update at the same time. Formally:

H1c: *Hospitals are more likely to update their AS when peers within the same hospital system are also updating.*

H1d: *Hospitals are more likely to update their AS when peers within the same county are also updating.*

Our final hypothesis on the determinants of AS updating relates to the effect of disclosure regulation on internal decision-making. Health care is a heavily regulated sector, and it is likely that regulation may affect AS updating decisions. We focus on price transparency mechanisms adopted by 31 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 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 cost 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, it is not hard to see why public disclosure of these prices would lead to increased scrutiny of prices. Hospitals can respond to this downward price pressure and still maintain profitability by trying to minimize operating expenses using information obtained from costing and budgeting systems. 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

[7] A substantial literature exists on quality disclosure (see Dranove and Jin (2010) for an overview), including applications in the health care sector. However, it is not clear how disclosure of quality might affect the need for AS.

positive effect on the probability of updating costing and budgeting systems. However, we do not expect there to be an effect on the updating probability of the financial AS because they are not used in determining optimal prices but solely document the outcomes of such decisions made earlier, nor do we expect an effect for case mix systems or EIS. Our final hypothesis relating to determinants of updating is thus:

> ***H1e:*** *The implementation of price transparency websites increases the probability of updating of costing and budgeting systems.*

Our second set of hypotheses relates to the economic benefits of updating. We focus on total operating expenses as the main economic outcome in this paper. 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 accounting systems 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 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.

H2a: *Updating of AS decreases operating expenses.*

Because we would ultimately like to understand the effect of AS updates on overall profitability, for completeness we also examine the effect of AS updates on operating revenues. However, we expect the effect of AS updating on profitability to act mostly through decreases in expenses, and it is difficult to see a clear connection between AS and revenues. While it is possible that management accounting systems such as case mix analysis or executive information systems might benefit firms' revenues through better planning and a focus on more profitable patients, it is unlikely that the updates of any AS would actually decrease revenues. Thus our final hypothesis is simply:

H2b: *The effect of AS updates on operating revenues is nonnegative.*

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.[8]

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 the early years of the survey. [9]

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 actual medical procedures) have been extensively used and vetted in research, although typically either cross-sectionally in one year or over time series that span at most about half of our 24-year time series. Angst et al. (2010) are the only authors to exploit the full time series in the data but their focus is on

[8] 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.

[9] We compared our sample to the list of all Medicare hospitals and all hospitals identified by Oddity Software. A table with the coverage of hospitals in the various states for every year is available from the authors on request.

electronic medical records systems only. To the best of our knowledge, only two papers have used the *business* IT systems data collected by HIMSS. Setia, Setia, Krishnan, and Sambamurthy (2011) use the 2004 data to study the effect of business and clinical application use on financial performance, while Borzekowski (2009) studies the impact of *adoption* of business IT systems on hospital costs over the early part of our sample (1987 - 1994).

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.[10] 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[11] 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

[10] 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.

[11] 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).

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 of our 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 for unique hospitals by state and overall. Median (mean) bed size is 112 (161), and mean Herfindahl-Hirschman Index (HHI) is 5,122 (where 10,000 is no competition and near 0 is perfect competition). 62, 22, 31 and 19 percent of the sample are in a multihospital system, and are academic, for-profit, and rural hospitals, respectively.

Insert Table 1 here.

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[12], 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.

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 accounting systems, Accounts Payable and General Ledger, have a very high and similar penetration rate

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

already at the start of the sample period with both systems being used by 97% of the hospitals in the sample in 1987. By 2010 this penetration rate exceeds 99% for both financial AS. 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% in 2010 for the full sample and 93% for the constant sample which consists of, on average, larger hospitals. 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).[13] 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.

A key takeaway from this figure is that the use of AS in hospitals is widespread, even in the first year of the sample almost thirty years ago. Currently, virtually every hospital in the sample has adopted at least the two financial accounting systems, and most also use several management accounting systems. 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

[13] 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.

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.

Another interesting takeaway from Figure 2 is that there appears to be a fairly clear sequence by which hospitals have adopted their AS over the sample period. In particular, the high penetration of the two financial AS, accounts payable and general ledger, at the beginning of the sample period shows that their adoption clearly precedes that of the management AS. We next see that penetration of case mix systems exceeds that of the other management AS until penetration rates converge in the last few years of the sample. Next follow 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 now have a penetration rate equal to or exceeding all other management AS. 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.

Insert Figure 2 here.

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 much wider spectrum, covering AS updates that range from minor to major. Furthermore, there is likely no reporting bias in favor of successful updates because (1) the data were not made widely available publicly[14] 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

[14] 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 some researchers, but only those whose research is first approved by HIMSS.

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, vendor names are 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 database to reliably track unique vendors over time, paying particular attention to these transition years.[15] 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.[16] 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

[15] 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.

[16] 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).

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.

Next, we move to the determinants of AS updating. In addition to describing how we operationalize the constructs used in Hypotheses H1a – H1e, 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.

In order to test H1a, the effect of self-developed AS on updating, we use an indicator variable that is coded 1 when a system is self-developed (*Self_Developed*). 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).[17]

Next, to identify changes to vendor peers' systems in order to test H1b, 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. A large proportion of vendor peers that are updating their systems simultaneously would be a sign that a vendor-specific shock

[17] Variable descriptions are included in Appendix 2.

(i.e. a new version of a system) is likely to have occurred. Consistent with H1b we expect this variable to increase the probability of updating.[18]

In order to test H1c and H1d related to "waves" of updates within the same system and county, 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*). In general, we would expect hospitals in multihospital systems to have a higher propensity to update as hospital systems are likely to have a standardized schedule of frequent updates, but we do not make a formal prediction.

Lastly, in order to identify implementation of the price transparency initiatives needed to test H1e, 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).[19] Pennsylvania was the first state to disclose price charges (in December 2002) and Illinois (in November 2009) is the last website adoption we include in our sample. Consistent with H1e, we expect *Price_Transparency* (an indicator variable coded 1

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[18] Because conceptually this variable only applies to hospital systems obtained from an outside vendor, it is unclear how it should be calculated for self-developed systems so that all observations can be included in the same specification. We use two methods. First, we allow all other hospitals that use self-developed systems for the same system type in the current year to be classified as vendor peers of other self-developed systems. This is the version reported in Table 2. This method should have a downward bias on the estimated effect of vendor peer updates because there should be no consistent shared variation between self-developed systems in different hospitals other than through statewide or time-related economic conditions (controlled for with state and year fixed effects). Alternatively, in untabulated analyses we code *Vendor_Peer_Update* as 0 for all self-developed systems, with similar inferences with respect to vendor peers (z-statistics greater than 10 in all specifications.) Neither method is perfect, but both provide similar results. We choose the first because the second method leads to a *Vendor_Peer_Update* variable which is collinear with *Self_Developed* (because it is set to 0 for all self-developed systems), making the resulting hazard ratio for *Self_Developed* difficult to interpret.

[19] 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.

if the prior year was the first year that that state adopted a price transparency website) to have a positive effect on the probability of updating costing and budgeting systems, since understanding costs is critical to determine optimal prices.

We also test for the effect of other potential determinants of AS updating, but we do not have hypotheses for these factors as they are more exploratory. In particular, we 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 standard adoption determinants established in the prior literature (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 et al. (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. [20, 21]

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

[20] We graph penetration of all management AS over time split into subsamples based on standard adoption determinants. The results demonstrate that these determinants also affect adoption 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.

[21] Additional control variables common in the healthcare literature are the hospital's patient mix (in particular Case Mix Index (CMI) and the proportion of patient days from Medicare and Medicaid patients) and whether the hospital is a specialty hospital. We do not include these variables in our main analyses because they limit our sample to Medicare hospitals in the latter half of our sample period (1998-2010). Untabulated tests including them as additional control variables produce inferences that are generally consistent with the specifications reported in the paper. Furthermore, they are included as control variables in Table 5, which focuses on the more recent time period.

will update an AS in the current year as function of time since the last update. The specification of the hazard model is:

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

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 (as is common in settings where this model is used) are right-censored, 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.[22] 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.[23] Our specification includes state and year fixed effects.[24] Inclusion of year fixed effects controls for any contemporaneous changes in

[22] 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.
[23] 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.
[24] 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 a battery of alternative specifications such as omitting all fixed effects, including hospital fixed effects, estimating an OLS specification with year and state or year and hospital fixed effects and an adjustment for heteroskedasticity, or

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

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stratifying the hazard model by hospital as proposed by Allison (1996) and demonstrated in an accounting setting by O'brien, McNichols, and Lin (2005).

Insert Table 2 here.

In support of H1a, we find that AS that are *Self_Developed* have a significantly lower hazard of being updated at any point in time compared to AS provided by outside vendors, with this effect ranging from 49% lower for EIS to 10% lower for case mix systems. Thus the hurdles to overcome when updating a self-developed legacy AS are higher than when the AS was put in place by an external vendor.[25] 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%.[26]

Meanwhile, 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 by about 50% to 75%.[27] The fact that updating is only higher for hospitals in multihospital systems in years when their system peers are also updating suggests that centralized planning rolls updates out across the entire hospital system all at once and supports our notion that hospitals systems update in "waves." Untabled results show that this peer result is even stronger for rural hospitals, which

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[25] Although we cannot observe the specific characteristics of systems that are self-developed, they tend to be used in situations that would suggest they have a higher level of customization, consistent with our priors. For example, financial AS are least likely to be self-developed (under 12%), whereas the percent of self-developed management AS ranges from 13.8% for costing to 16.6% for EIS consistent with hospitals being more likely to invest resources in developing systems that might benefit more from customization. Additionally, hospitals with self-developed systems tend to be larger and more profitable, are more likely to be in a hospital system, and face higher competition than hospitals that buy their systems from outside vendors. This is consistent with hospitals that are more complex and face greater outside pressures having a greater need for customized systems.

[26] 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 the effect of application *Penetration*, the percentage of hospitals that has a particular AS currently installed in a given year, has a hazard ratio of 1.010 and significance at the 1% level (z-statistic = 8.7), possibly as vendors release more routine small updates in an attempt to keep the application in play.

[27] *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* is the product of the hazard ratios of *In_System* and *System_Peer_Update* (e.g. 0.457 x 3.980=1.82 for costing systems, so hospitals in systems are about twice as likely to update costing systems overall). Another specification excluding *System_Peer_Update* confirms that the hazard ratio of *In_System* is significantly greater than one.

most likely depend much more strongly on their hospital system co-members to take advantage of AS. Also, untabled analysis shows that hospitals tend to update AS at the same time that they are updating other systems, supporting the notion of "waves" of updates existing *within* the hospital as well.[28] The positive significance of *County_Peer_Update* for 3 of the 6 systems is suggestive of within-county "waves" where proximity to other updating hospitals in the same county plays a role in the updating of some AS.[29]

Consistent with H1e, 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%. This is consistent with the idea that transparency of prices exerts additional pressure on hospitals to manage their costs better, report them more accurately and increase their ability to justify their prices.[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. Consistent with our prediction, *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 disclosure regulation and suggest that an increase in hospitals' demand for information in response to the additional disclosure led them to make changes to their AS.[31]

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[28] This variable, *Hospital_Update_Count*, is excluded from the complete analysis because of its high degree of collinearity with *Apps_Age*, but it was highly significant, with a z-statistic in excess of 30 in all specifications.

[29] 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.

[30] Maryland has regulation that limits price increases and hence may have more prevalent costing and budgeting practices among hospitals; our results for *Price_Transparency* continue to hold when Maryland is excluded.

[31] If instead of focusing only on the first year after price transparency websites were implemented we alternatively code an indicator variable set to one in *all* years after the website implementation, untabulated results indicate significant increases in updates of costing systems but not budgeting systems. This implies that in addition to one-

Turning to our more exploratory results, 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*) and clinical applications (*Clinical_Depth)* generally update their AS more frequently, while the effect of *Medical_Record_Depth* is mixed indicating some medical records and AS applications may be substitutes as hospitals face finite budgets. We also find that the age of the stock of the applications (*Apps_Age*) is negatively associated with the likelihood of updating. An increase of the average age of the hospital's applications by one year decreases the hazard of updating by about 30% to 40%. 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.

Finally, we turn to the standard determinants of AS adoption decisions. As a whole, these variables play a much more subdued role in updating than they do in determining adoption. The determinants in the top of Table 2, which are specific to updating, explain much more of the likelihood of updating than the variables that are important determinants of 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, where competition (*HHI*) increases the likelihood of adopting AS, it plays virtually no role in determining updating likelihood for any of the AS. For-profit and academic status impact updating likelihood for 2 and 3 out of 6 AS, respectively, and rural location for only 1 out of 6.

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time adjustments in response to the new websites, hospitals may experience a permanent increase in the frequency of costing system updates in response to the greater need for high quality cost information.

Given the importance of the standard adoption determinants in prior studies on adoption, we find their lack of explanatory power for the updating decision to be descriptively interesting. Table 3 reports a series of likelihood ratio tests on the relative contribution of the standard adoption determinants in explaining updating. The p-values reported in each column indicate the probability that the fit of the model is *not* affected by dropping the variables of interest. In other words, significant p-values indicate that the excluded variables contribute significantly to overall explanatory power. The results in Panel A show that the combined explanatory power of the standard adoption determinants for *updating* is statistically significant for only 4 of the 6 AS. In contrast, Panel B shows that the combined explanatory power of our newly proposed updating determinants (all determinants other than the standard adoption determinants) is highly significant for all application types. Although the Chi-square test statistics cannot be directly compared with those in Panel A because the degrees of freedom are different, their magnitude is at least 100 times greater across the board and the p-values are indistinguishable from 0, suggesting that other determinants play a much larger role in explaining updating than the traditional adoption determinants. For comparison, Panel C reports the change in explanatory power of untabulated logit models of adoption (including control variables analogous to the updating characteristic, where possible) when the standard adoption determinants are excluded to confirm that these factors are important for adoption in our setting. The results are highly significant and the Chi-square test statistics (which have the same degrees of freedom as Panel A) are substantially larger than those in Panel A with values at least 20 times greater, indicating that, as expected and consistent with the prior literature, the standard adoption determinants do play a major role in application adoption.

Insert Table 3 about here.

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. There are several potential explanations for these differences. First, the decision to adopt systems (in particular basic systems such as a general ledger) often comes at an earlier stage in the firm's life cycle (Davila and Foster, 2005, 2007) when the informational needs of the organization first begin to outstrip the ability of management to collect and analyze data through less formal means (such as spreadsheets or "back-of-the-envelope" calculations). The pressures and constraints that an organization faces in this early period in terms of competition, liquidity, and profitability are much more likely to be binding than when the firm is in a more mature stage after the adoption of the initial AS, especially because the magnitude of the resources invested in an initial AS adoption is generally much greater (both absolutely and as a percentage of revenues) than that of a subsequent update. Additionally, adoptions of new AS tend to constitute more substantial changes to the informational capabilities and focus of the organization and could be part of a company's shift in strategic focus. In contrast, updates of existing systems are more likely to be optimizations of processes and strategies that are currently in place.

In summary, the results in this section provide the first evidence on the determinants of updates to existing accounting systems. Our analyses provide support for hypotheses H1a through H1e, and also provide additional descriptive evidence that will be useful to practitioners and researchers alike.

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 and, in particular, 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. Three of these variables are relatively exogenous with respect to the individual hospital: *Vendor_Peer_Update*, *County_Peer_Update*, and *Price_Transparency*. Of the three, *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 three that is predictably associated with all 6 systems, and is the only of the three that varies within state and county in a given year. 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 systems 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.[32] 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 and use *Vendor_Peer_Update* as the instrument in an instrumental variables analysis of the effect of AS updates on operating profit, our outcome of interest, in Table 5.

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 4 provides information on the percent of a hospital's vendor peers that are within the same county, state, 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

[32] 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.

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 4, 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 4 here.

In order to clearly identify whether updates affect profitability via the expense and/or revenue side of profitability, the dependent variables in our regressions in Table 5 are operating expenditures, *Op_Ex,* measured as operating expenditures per bed (i.e. scaled by *Bedsize*), and hospital operating revenues per bed, *Op_Rev*. 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 5. Because the benefits of system updates may appear with a lag, especially those that are the results 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.[33] 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.[34]

In addition to these two main control variables, we control for application- and hospital-level characteristics. The hospital-level controls include the Case Mix Index (*CMI*) issued by the Centers for Medicare and Medicaid Services and the percentage of patient-days in the hospital that are made up of Medicare and Medicaid patient-days (*%Medicare, %Medicaid)*. The relative mix of patients by clinical diagnosis and resource-intensity (*CMI*) and payer type (*%Medicare* and *%Medicaid*) could affect a hospital's expenses and revenues because different types of

[33] Inferences are similar when the specification for *Op_Ex* does not control for *Op_Rev*.

[34] 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.

patients may demand procedures with different associated costs for the hospital and the patient (the hospital's revenues). 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.[35] The use of all of the variables discussed above (in particular *Op_Rev* and the patient mix variables) constrains our sample to the years 1998 to 2010.

Consistent with our predictions in H2a, the results in Table 5 show that AS updates have a significant negative effect on operating expenses. In particular, costing, budgeting, accounts payable, and general ledger system updates have a significantly negative effect on operating expenses in the year of and the two years 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 and two years out. 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. Consistent with H2b, the results for *Op_Rev* show that most of the revenue changes are insignificant, but that the signs tend to be positive. Although these results are much weaker, they show some benefits of updating with increases in operating revenues after updates of accounts payable, general ledger, and case mix systems, typically only occurring in the two periods

[35] 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.

following the update.[36] Our results do not provide any evidence that updates of executive information systems provide benefits to hospitals in our sample period.[37]

Insert Table 5 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 general ledger system updates in Panel D have a coefficient of -16,560 in Column 1 and 21,537 in Column 6. This implies that general ledger system updates lead to an average decrease in operating expenses of $16,560 per bed in the year of the update (*t+0*) and an average increase in operating revenues of $21,537 per bed two years after the update (*t+2*). The absolute values of the significant coefficients on operating expense decreases in Table 5 range between 44,331 in Column 1 of Panel A (benefits of costing system updates in the current year), and 11,055 in Column 3 of Panel D (benefits of general ledger system updates two years 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 $419,033 and $487,108, respectively. The magnitude of the benefits we document with respect to expenses is similar to that of Borzekowski (2009) who looks at adoption of clinical and accounting systems over the early years of our sample period (although he is not able to address issues of endogeneity), providing assurance that our IV estimates are probable in magnitude.

[36] 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. Our data does not include measurements of such investments, so we cannot test this indirect channel.

[37] This could be due to a lack of power (the sample size is somewhat smaller because fewer hospitals have adopted these systems), or because these systems are newer and the potential benefits of an update are smaller (hospitals only started adopting them in the mid-90s), or because the types of hospitals that have these systems in place tend to be more efficient in general so system updates may have a smaller marginal effect.

Although we do not report the coefficients of control variables in Table 5 for parsimony, we note briefly that they seem to behave reasonably. In Columns 1-3, *Op_Rev* has a coefficient ranging between 0.606 and 0.644, 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.

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.* [38]

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

[38] 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.

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 4 demonstrates, the vast majority of hospitals' vendor peers are in different states and counties, making this effect unlikely 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 4, 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 4 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.[39]

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 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 novel 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 accounting systems. 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 the manner in which systems were initially adopted (e.g. vendor-pushed updates versus self-developed legacy systems), “waves” of updates that occur within and across hospitals within a given year, state-level disclosure regulation that affects hospitals’ demand for information, and a hospital’s focus on IT are important determinants in the updating decision. They appear to play a much larger role than standard adoption determinants, suggesting that the updating decision has a very different

[39] 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 replace *Vendor_Peer_Update* with 0 for all self-developed systems.

character than the adoption decision. Lastly, using vendor-pushed updates as an instrumental variable, we document immediate and significant reductions in operating expenses following an AS update. On the other hand, revenues experience only modest increases. 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, 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. The setting also allows us to answer the call in Leuz and Wysocki (2015) for more research on indirect "real" effects of disclosure regulation by demonstrating a link between implementation of price transparency websites and AS updates *within* the firm. 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.

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 would also be interesting to examine the effect of AS updates on additional outcomes and to further explore the interplay between firms' decisions to adopt and update their systems. 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 important 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).[40] 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), indicating 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

[40] The list is available on request.

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 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. [41] 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

[41] 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.

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.

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).
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.
Long_Dur	An indicator variable coded 1 if the average time since the last update of the hospital’s costing and budgeting systems in the current year is >= 13 years (one standard deviation above the mean).
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.
Price_Transparency	Indicator variable coded 1 if the *prior* year was the first year that that state adopted a price transparency website. 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).
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.
Sum_Updates	The sum of two indicator variables, Cost_Update and Budget_Update, where Cost_Update (Budget_Update) is set to 1 if the hospital updated its costing (budgeting) system in the current year, and 0 otherwise.
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.]

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

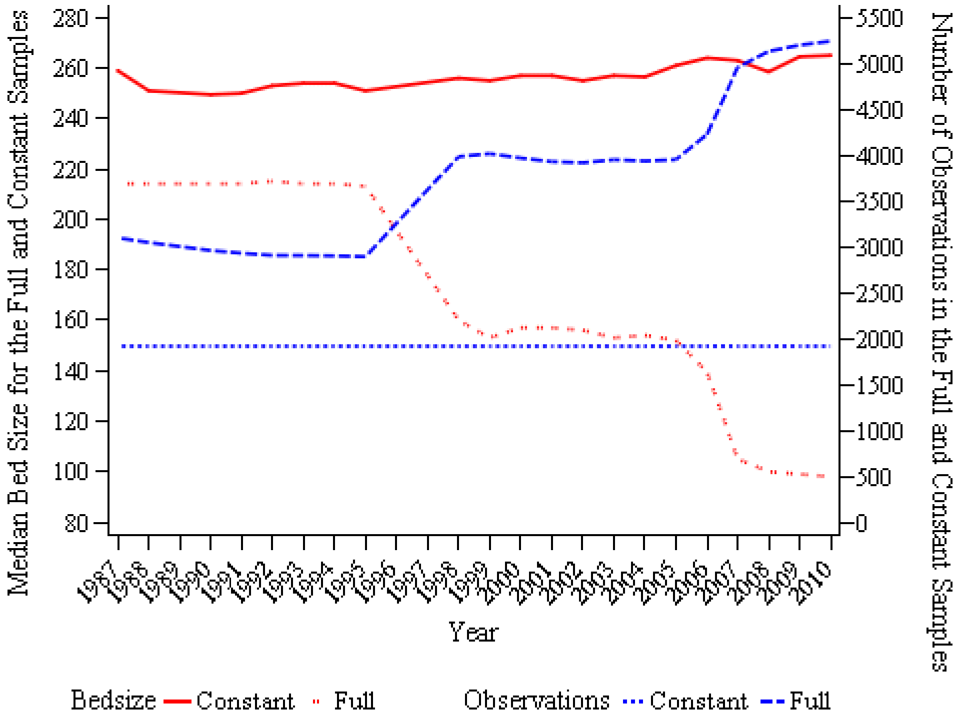
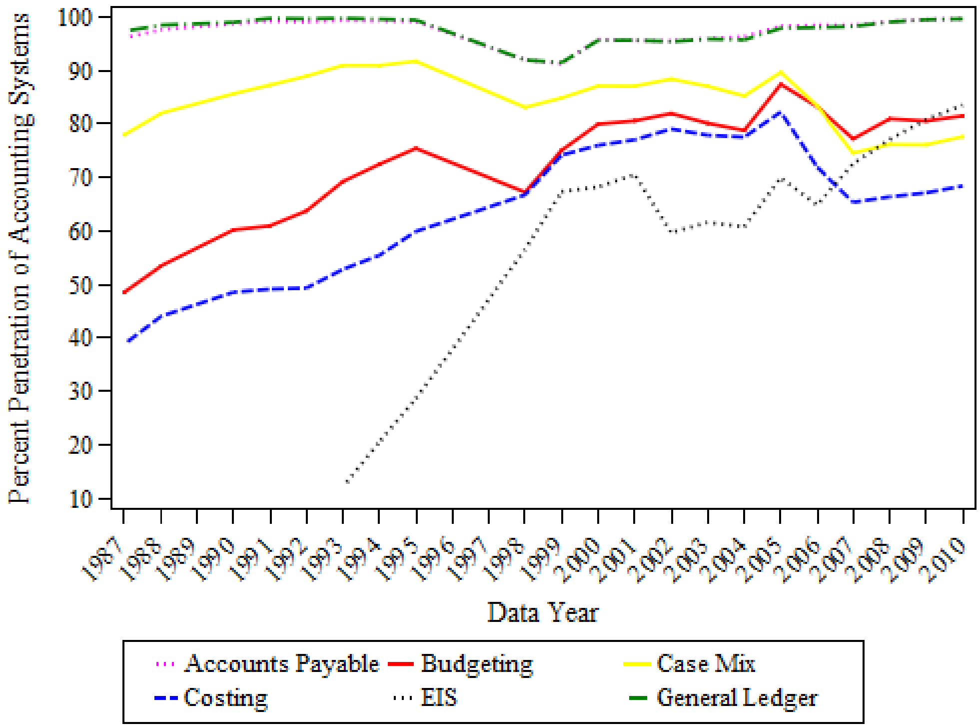


Figure 2. Penetration of Accounting Systems Over Time

Panel A. Full Sample



Panel B. Constant Sample

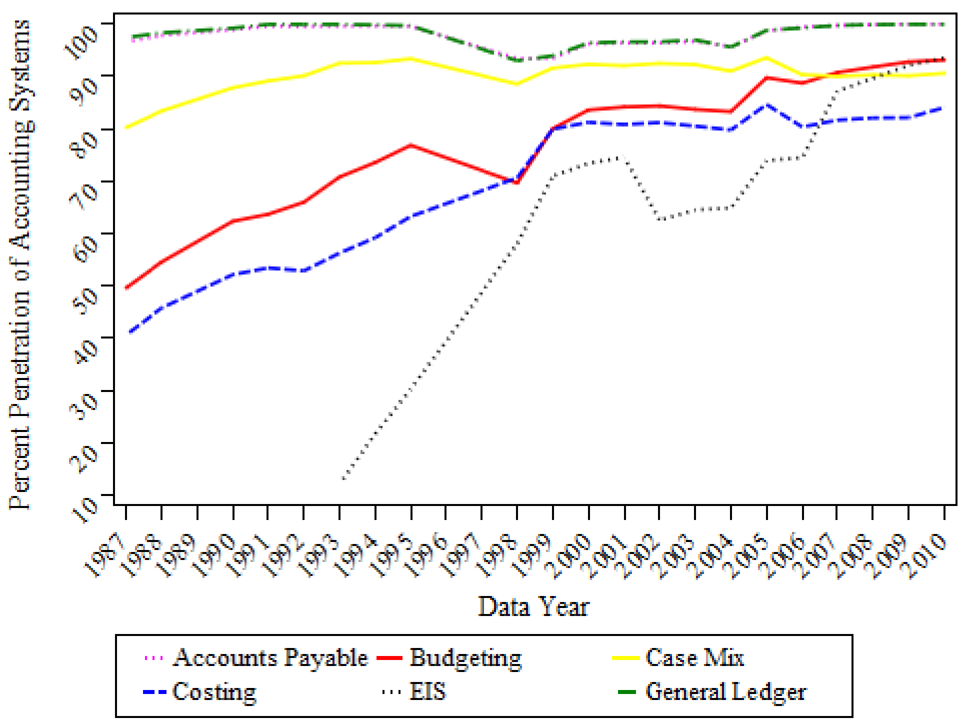


Figure 3. Kernel Density Distribution of System Durations at Time of Update

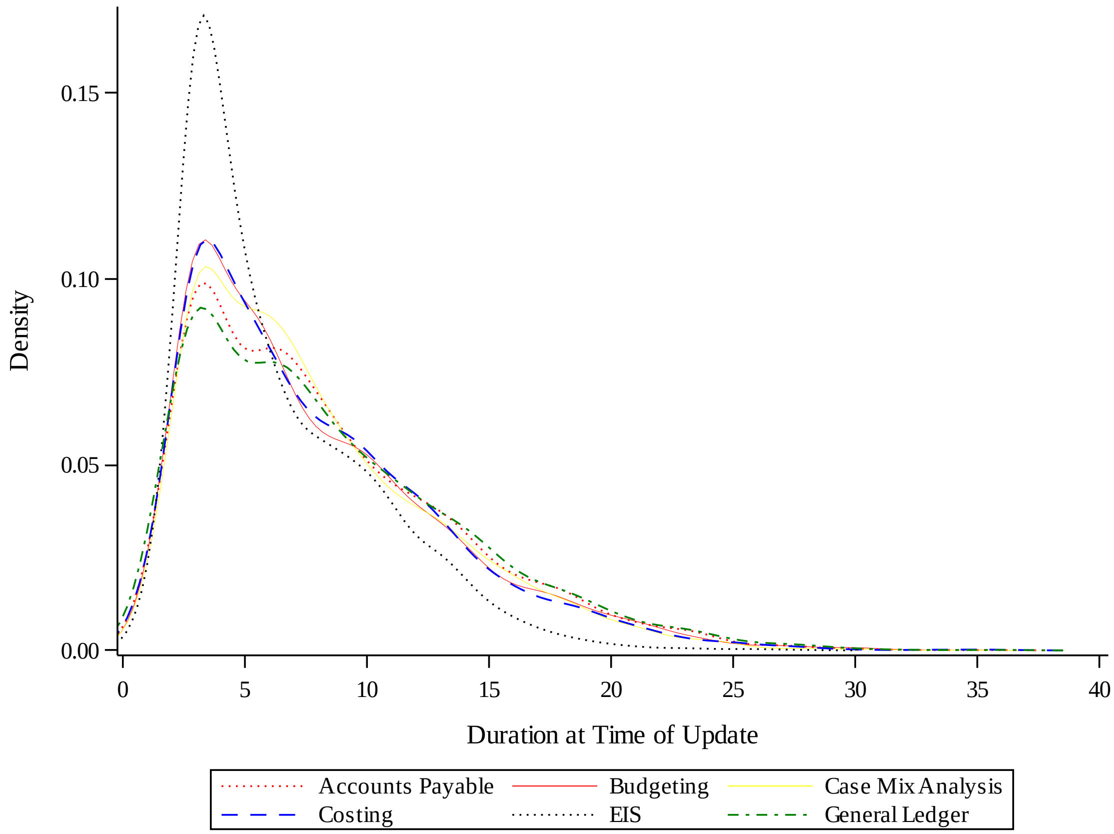


Table 1. Descriptive Statistics by State

STATE	# Unique Hospitals	Mean Bedsize	Median Bedsize	Mean HHI	Proportion of Hospitals in System	Proportion of Academic Hospitals	Proportion of For-Profit Hospitals	Proportion of Rural Hospitals
AK	17	76.35	36	8632	0.53	0.12	0.35	0.53
AL	137	161.03	115	6361	0.66	0.2	0.4	0.46
AR	104	121.58	75	7143	0.62	0.17	0.43	0.3
AZ	104	145.67	106.5	2403	0.71	0.21	0.51	0.07
CA	535	182.51	148	1804	0.72	0.3	0.33	0.02
CO	118	141.04	88	5525	0.66	0.19	0.33	0.15
CT	44	241.88	177	3305	0.33	0.41	0.03	0.05
DC	16	333.22	309.5	1243	0.63	0.63	0.38	0
DE	12	291.67	174	4405	0.5	0.25	0.11	0
FL	306	213.41	154	2981	0.81	0.22	0.54	0.06
GA	203	146.32	90	7058	0.62	0.13	0.4	0.29
HI	31	134.06	105.5	3028	0.81	0.26	0.19	0.19
IA	139	101.23	28	7715	0.49	0.15	0.08	0.2
ID	48	71.71	25	8495	0.46	0.08	0.22	0.29
IL	275	196.94	149	4170	0.55	0.27	0.19	0.05
IN	183	157.91	107	6305	0.61	0.14	0.33	0.12
KS	160	84.3	34.25	7757	0.48	0.11	0.21	0.36
KY	126	153.65	100	7418	0.72	0.2	0.38	0.45
LA	199	125.61	90	4664	0.65	0.18	0.53	0.17
MA	144	180.41	155.5	1913	0.63	0.33	0.21	0.01
MD	62	234.39	212.5	4492	0.6	0.37	0.08	0.06
ME	47	101.46	64	5251	0.63	0.13	0.28	0.38
MI	223	177.5	119	4936	0.58	0.27	0.22	0.22
MN	172	139.71	56	6415	0.52	0.19	0.06	0.34
MO	168	172.64	109.5	5672	0.57	0.24	0.28	0.17
MS	123	120.53	76	7520	0.56	0.04	0.48	0.45
MT	66	58.28	25	8695	0.41	0.05	0.18	0.53
NC	160	167.94	120	7381	0.63	0.14	0.34	0.33
ND	57	77.37	25	8308	0.46	0.14	0.09	0.68
NE	99	88.43	25	7531	0.32	0.18	0.08	0.39
NH	32	117.13	86	5434	0.31	0.09	0.11	0.31
NJ	139	249.97	228	2684	0.6	0.38	0.16	0.03
NM	45	109.94	69	7040	0.77	0.2	0.63	0.02
NV	42	141.14	75.5	4377	0.74	0.19	0.58	0.1
NY	294	267.85	209	3146	0.48	0.43	0.09	0.09
OH	281	194.84	142	4901	0.63	0.26	0.23	0.09
OK	158	97.59	52	6361	0.66	0.13	0.49	0.29
OR	77	122.55	77	6214	0.69	0.18	0.11	0.09

PA	309	194.4	161	3617	0.57	0.31	0.27	0.08
RI	15	229.73	204	3310	0.47	0.47	0.08	0
SC	91	155.91	105	6631	0.73	0.16	0.44	0.26
SD	61	61.39	25	8281	0.74	0.1	0.13	0.48
TN	201	160.71	109	5827	0.78	0.18	0.45	0.3
TX	596	139.4	96	4901	0.67	0.14	0.47	0.12
UT	52	109.56	49	5281	0.85	0.15	0.43	0.1
VA	106	203.67	155	7544	0.66	0.33	0.35	0.25
VT	16	97.88	55	8763	0.13	0.13	0.2	0.31
WA	119	138.4	110	4580	0.47	0.22	0.15	0.19
WI	185	132.87	99	5465	0.63	0.22	0.17	0.24
WV	65	148.87	101	7912	0.49	0.25	0.36	0.29
WY	33	65.79	43	8348	0.39	0.06	0.26	0.18
Overall	6995	160.89	112	5122	0.62	0.22	0.31	0.19

Each unique hospital in the database is represented once in these statistics; for hospitals for which multiple years of data were available, we use the median value for each hospital to calculate the aggregated statistics.

Table 2. Determinants of Application Updating

	Predicted Effect	(1) Costing	(2) Budgeting	(3) Accounts Payable	(4) General Ledger	(5) Case Mix	(6) EIS
Self_Developed	-	0.600***	0.799***	0.796***	1.002	0.896*	0.512***
		(-8.828)	(-5.667)	(-4.128)	(0.0354)	(-1.648)	(-9.487)
Vendor_Peer_Update	+	1.021***	1.019***	1.020***	1.024***	1.021***	1.013***
		(16.13)	(18.19)	(13.21)	(15.80)	(21.18)	(11.35)
In_System		0.457***	0.376***	0.456***	0.467***	0.527***	0.256***
		(-10.80)	(-16.94)	(-14.39)	(-12.72)	(-12.59)	(-19.09)
System_Peer_Update	+	3.980***	4.148***	3.748***	3.481***	3.182***	6.156***
		(21.10)	(29.47)	(26.49)	(23.48)	(22.39)	(30.84)
County_Peer_Update	+	1.094	1.038	1.844***	0.911	1.584***	1.292***
		(0.716)	(0.231)	(4.679)	(-0.225)	(4.699)	(2.748)
Price_Transparency	+*	1.172*	1.157***	0.781***	0.738***	0.979	0.979
		(1.725)	(2.741)	(-3.434)	(-2.842)	(-0.194)	(-0.262)
Apps_Age		0.670***	0.683***	0.646***	0.656***	0.625***	0.704***
		(-13.65)	(-14.77)	(-12.32)	(-14.56)	(-16.96)	(-12.04)
Apps_Age^2		1.008***	1.011***	1.008**	1.005*	1.009***	1.011***
		(3.413)	(5.274)	(2.515)	(1.835)	(3.937)	(5.551)
Business_Depth		1.022***	1.043***	1.035***	1.030***	1.027***	1.045***
		(3.922)	(9.006)	(5.136)	(4.902)	(5.212)	(9.671)
Med_Record_Depth		0.956***	0.980*	1.030*	1.024	0.979*	0.992
		(-3.110)	(-1.647)	(1.902)	(1.432)	(-1.689)	(-0.657)
Clinical_Depth		1.025***	1.022**	0.990	1.006	1.033***	1.026***
		(3.211)	(2.498)	(-1.078)	(0.899)	(4.970)	(3.769)
		Standard Adoption Determinants					
Bedsize		1.000	1.000	1.000	1.000*	1.000	1.000
		(0.739)	(-0.630)	(-0.533)	(-1.914)	(-0.537)	(-0.267)
For_Profit		1.049	0.986	0.920**	1.040	0.987	0.821***
		(1.154)	(-0.417)	(-2.134)	(0.894)	(-0.302)	(-4.893)
HHI		1.000	1.000	1.000**	1.000	1.000	1.000
		(-0.640)	(-1.265)	(-2.237)	(-1.206)	(-1.623)	(0.747)
Rural		0.982	1.007	0.919	0.844***	0.957	0.986
		(-0.263)	(0.144)	(-1.392)	(-3.135)	(-0.785)	(-0.232)
Academic		1.116**	1.049	1.038	1.101**	1.043	1.072*
		(2.431)	(1.192)	(0.966)	(2.059)	(1.206)	(1.764)
State and Year Fixed Effects		Y	Y	Y	Y	Y	Y
Observations		38,048	42,310	54,239	54,564	47,918	27,668
Wald χ^2, Entire Model		21919	37096	71339	65516	57753	8815
Prob. > χ^2, Entire Model		0	0	0	0	0	0

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 and budgeting systems.

Bootstrapped z-statistics in parentheses

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

Table 3. The Importance of Standard Adoption Determinants in Updating

	(1) Costing	(2) Budgeting	(3) Accounts Payable	(4) General Ledger	(5) Case Mix	(6) EIS
Panel A. L.R. Test of Updating Models With and Without Standard Adoption Determinants						
L.R. Test χ^2 (5)	15.50	3.847	16.21	21.43	5.537	31.58
Prob. > χ^2	0.00841	0.572	0.00626	0.000673	0.354	0.0000072
Panel B. L.R. Test of Updating Models With and Without Non-Adoption Determinants						
L.R. Test χ^2 (11)	3193	3610	5005	5340	4365	3305
Prob. > χ^2	< 0.000001	< 0.000001	< 0.000001	< 0.000001	< 0.000001	< 0.000001
Panel C. L.R. Test of Adoption Models With and Without Standard Adoption Determinants						
L.R. Test χ^2 (5)	1477	973.4	N/A	N/A	1189	615.1
Prob. > χ^2	< 0.000001	< 0.000001	N/A	N/A	< 0.000001	< 0.000001

Panel A reports the results of Likelihood Ratio tests to examine the contribution of the standard adoption determinants to the explanatory power of the updating models. For comparison, in Panel B we provide L.R. test results when we instead exclude the remaining (non-adoption) determinants from the updating models. Panel C reports L.R. test results when excluding standard adoption determinants from untabulated logit models of AS *adoption* (there is not sufficient variation to calculate adoption models for Accounts Payable and General Ledger as essentially all firms had adopted these systems by the beginning of the sample period). A significant p-value indicates that the excluded variables contribute significant explanatory power to the overall model. Degrees of freedom indicated in parentheses.

Table 4. 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 5. 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	-	-	-	>=0	>=0	>=0
Panel A. Costing Systems						
$Update_t$	-44,331***	-8,094	-16,143	10,430	-13,531	-3,409
	(-3.330)	(-0.722)	(-1.417)	(0.392)	(-0.647)	(-0.188)
Observations	26,344	24,056	21,509	26,344	24,056	21,509
R^2	0.648	0.635	0.616	0.287	0.274	0.251
Panel B. Budgeting Systems						
$Update_t$	-44,003***	-18,031*	-2,595	3,286	-10,503	4,147
	(-3.482)	(-1.886)	(-0.275)	(0.139)	(-0.598)	(0.263)
Observations	28,066	25,388	22,528	28,066	25,388	22,528
R^2	0.654	0.644	0.617	0.302	0.288	0.265
Panel C. Accounts Payable Systems						
$Update_t$	-29,961***	-16,396***	-5,336	6,749	17,451*	-6,522
	(-4.870)	(-3.070)	(-0.869)	(0.546)	(1.739)	(-0.678)
Observations	32,583	29,739	26,470	32,583	29,739	26,470
R^2	0.668	0.653	0.636	0.308	0.294	0.279
Panel D. General Ledger Systems						
$Update_t$	-16,560***	-19,312***	-11,055*	-5,642	13,478	21,537**
	(-3.082)	(-3.606)	(-1.940)	(-0.516)	(1.399)	(2.439)
Observations	32,612	29,818	26,563	32,612	29,818	26,563
R^2	0.672	0.654	0.635	0.308	0.293	0.276
Panel E. Case Mix Systems						
$Update_t$	15,652	11,059	7,522	-15,523	2,601	39,933***
	(1.483)	(1.301)	(0.825)	(-0.858)	(0.167)	(2.611)
Observations	29,962	27,451	24,601	29,962	27,451	24,601
R^2	0.664	0.650	0.623	0.305	0.290	0.266

Panel F. Executive Information Systems

Update $_t$	-8,958	-12,190	-8,515	-17,656	20,228	3,967
	(-1.089)	(-1.579)	(-1.109)	(-1.227)	(1.561)	(0.356)
Observations	22,888	20,359	17,656	22,888	20,359	17,656
R^2	0.655	0.649	0.626	0.287	0.270	0.253
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

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