Demand for Resource Allocation Technologies:

Adoption of Hospital Surgical Management Software

Eli M. Snir and Jeffrey McCullough[1]

Abstract

Health Information Technology (IT) is an important component of healthcare reform. Health IT holds the promise of improving quality while reducing costs. The broader IT literature frequently recognizes that IT payoffs depend on complementary investments in organization and capital. We build on this literature by evaluating the drivers of hospital surgical management software (HSMS) adoption. HSMS can improve operating room (OR) capacity utilization through both scheduling centralization and scheduling pooling. We draw on both the economics and operations literature to develop a theoretical model that reflects the technological and organizational issues underlying HSMS adoption. We posit that HSMS is complementary to hospitals' organizational and capital investments. First, HSMS' centralization effect is complementary to the scope of specialized surgical services. Second, HSMS' pooling effect is complementary to the number of ORs. We test our hypotheses using a comprehensive dataset of hospitals' characteristics and application-level technology adoptions – data not frequently available in other industries. We estimate proportional hazard models to test our hypotheses. We find that both factors are important HSMS adoption determinants. These results demonstrate the importance of understanding the mechanisms through with different types of IT create value. Our findings further suggest that efficient health IT policies require an understanding of individual technologies within an organizational context.

Keywords: Econometrics; Economics of IS; Analytical modeling; Decision support systems; IT diffusion and adoption; IT and new organizational forms; Longitudinal research.

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1. Introduction

Policy makers and purchasers have advocated increased health information technology (IT) investments to curb health expenditure growth. Hillestad and colleagues (2005) estimate that HIT may yield savings in excess of $80 billion annually. Previous research on IT payoffs show that IT value in general and health IT value in particular depends on complementary organizational and capital investments (*e.g.,* Brynjolfsson and Hitt, 2000). The majority of the IT value literature, however, uses firms as the unit of analysis, measuring IT as a general-purpose technology. We contribute to this literature by exploring the demand for one technology, hospital surgical management software (HSMS) and how it relates to both operating room (OR) capital and specialty service mix. We develop a formal theoretical model that draws on both the operations and economics literatures to reflect the key determinants of HSMS demand and utilization. Finally, we test our theory using a nearly complete census describing hospitals' OR capital, scope of service, and HSMS adoption.

Efficient OR scheduling is critical to hospital efficiency. Operating rooms account for approximately 10% of hospital costs (Viapiano and Ward 2000) and an even larger share of hospital revenues. The scheduling of OR time is complicated as capacity is fixed in the short run and demand is difficult to manage and predict. Operating rooms are used for a wide range of surgical procedures with varying capital and labor inputs. Surgical duration also varies substantially within each procedure (Abouleish *et al*, 2003) and is difficult to predict (Dexter and Traub 2002). Naturally, underutilization carries a substantial opportunity cost. Overutilization incurs a larger, if less tangible, cost. Not only does OR overutilization cause inefficient production, it incurs overtime cost, may reduce clinical quality or delay emergent surgical procedures. Consequently, hospitals are careful to schedule time for procedures with minimal overutilization (Dexter and Traub 2002).

HSMS automates the scheduling and management of surgical procedures. In addition to scheduling it provides information about current and future OR utilization. Furthermore information regarding procedures, staff, surgical equipment inventory, and capital equipment utilization are maintained in the database. Staff interaction with HSMS typically occurs in multiple settings. First, scheduling staff enter appointments either centrally or from physician offices. Second, nurses or technical support staff members provide updated scheduling, utilization, and inventory information on site. Scheduling updates are used to alter the timing and location of other procedures on an ongoing basis. These real-time updates are frequently displayed on large monitors and are crucial to efficiently coordinating OR capacity with labor, equipment, and patients. Finally, administrative personnel generate reports for planning and management purposes.

Surgical scheduling is further complicated by the organization of physician labor. While physicians frequently control hospital resources, they are usually not hospital employees. Rather, most physicians own their own practice with each specialty concentrated in one or few practices. Hospitals usually coordinate OR capacity with physicians by allocating blocks of time to different specialty groups, effectively outsourcing and balkanizing scheduling decisions. Each specialty is allocated a block of time in the weekly OR schedule. Gupta (2007) claims that block-scheduling of OR capacity to specialties is fairly common. While block scheduling may not maximize OR capacity utilization, there are many motivations for this equilibrium. First, block scheduling mitigates physicians' coordination problems between surgical and non-surgical activities. Second, OR utilization requires the coordination of many resources, including; nursing labor, OR technicians, and specialized equipment, not to mention surgeons and anesthesiologists. One of the drawbacks of block scheduling stems from the uncertainty in the number of procedures required by each specialty during the course of a week. Demand for each specialty varies over time, suggesting reallocating OR capacity across specialties. Block-scheduling, however, constrains frequent reallocation, reducing the utilization of scarce OR capacity. We posit that improved intra- and inter-organizational unit coordination is central to the HSMS adoption decision.

HSMS adoption enables a partial transition from block-scheduling to centralized/open scheduling. Such a centralized and flexible scheduling system would have the ability to reallocate OR capacity while managing all complementary resources on an ongoing basis. It would also allow concepts drawn from revenue-management to be applied in OR scheduling (Barut and Sridharan, 2004). This suggests that inefficiency caused by block-scheduling is an important driver of technology adoption. A rigorous theoretical analysis of this issue is discussed in section 3.1.

On a daily basis HSMS facilitates more efficient operating room work flow. Once the list of daily procedures has been determined, the OR faces considerable uncertainty regarding procedure demand, procedure duration, and the incidence of emergent surgical conditions. Accordingly, there remain a number of important decisions. First, there is substantial leeway in scheduling procedures within the allotted time. Gupta (2007) provides a review of scheduling policies comparing their relative merits. Weiss (1990) suggests scheduling procedures with smaller variance first reduces the overall expected waiting time for all procedures. While the algorithms for scheduling a given set of procedures in a day are well-studied in the academic literature, their implementation frequently requires sophisticated software.

A second set of decisions involves assigning procedures dynamically to operating rooms during the day. When there are multiple ORs in a hospital and multiple patients waiting for procedures, the dynamic allocation decisions become important. In the absence of sophisticated management systems the set of procedures for each OR may be predetermined.

This suggests a second role for OR management systems, coordinating the dynamic scheduling of surgical procedures within a day. There is wide variation in time for each procedure (see e.g., Abouleish *et al*, 2003), complicating the decision regarding the number of procedures to accept each day. As such, the intraday schedule should change with realized procedure times. An adaptive schedule, though, requires coordination among physicians, nurses, and specialized equipment. Moreover, it has to recognize constraints and costs of overtime, specialized equipment, and post-operative capacity. Experimental data indicates that nurses are not well trained to perform these scheduling tasks (Dexter, Willemsen-Dunlap, and Lee, 2007). The benefits from dynamic scheduling stem from the “law of large numbers”. In the extreme, it allows allocating only mean duration for each procedure without buffers, in the initial daily schedule. This seems consistent with the empirical results discussed in Olivares, Terwiesch, and Cassorla (2008) where the allocated time for each procedure is not longer than the median required time while OR overtime is low (Dexter and Traub 2002). These benefits of HSMS are quite important when there are multiple ORs in close vicinity, as the benefits of pooling are increasing in the number of resources (Dexter *et al*, 2004).

The institutional context of HSMS and its relation to the economics and operations literatures are further described in Section 2. In Section 3 we draw on both these literatures to develop a formal model of HSMS adoption and how it interacts with hospitals’ organizational and capital investments. Hypotheses regarding HSMS adoption are then generated. Section 4 describes a novel database that includes a near census of US hospitals. These data describe hospitals’ organizational and capital characteristics as well as application-level IT adoption decisions. These data are particularly useful as application level data for an entire industry are rarely available in the IT literature. In Section 5 proportional hazard models are employed to test our hypotheses. We find that HSMS adoption is increasing in both the number of specialized services and the number of ORs. HSMS adoption is not, however, increasing in individual specialized services nor is it related to OR volume. We discuss these findings and their implications for the broader literature in Section 5.

2. Literature Review

2.1 IT Payoff Literature

Information technology adoption and effectiveness vary by setting and depend on complementary organizational competencies (Cron and Sobol, 1983; Brynjolfsson and Hitt, 2000). Among these are the need for changing workforce composition (Francalanci and Galal, 1998), implementation of business process reengineering (Devaraj and Kohli, 2000), and the ability to outsource IT applications (Prattipati and Mensah, 1997).

While the hospital IT value literature is largely comprised of single-site studies, a few papers have employed panel datasets. Lee and Menon (2000) and Borzekowski (2008) estimate hospital-level cost functions, finding that HIT produces some cost savings. Menon, Lee and Eldenburg (2000) measure the impact of different types of capital and labor on hospital productivity. They find that IT increases performance, on average, but different forms of IT capital have different payoffs. Most pronounced, in their study, are the returns to medical IT capital, including surgical services, as opposed to investments in administrative technologies. Devaraj and Kohli (2003) find that IT investments have a positive lag effect on hospital revenue and quality. This is consistent with a learning-curve for IT implementation. Moreover, they argue that usage by hospital employees drives IT payoffs. Parente and Van Horn (2006) and Hitt and colleagues (2007) identify efficiency gains using hospital production functions. Amarasingham and colleagues (2009) find that health IT substantially reduces mortality and increases quality use cross-sectional data on 41 Texas hospitals. Parente and McCullough (2009) study a national sample of hospitals in a four-year panel and also find that health IT improves quality; although, the magnitude of the quality effect is greatly dampened when panel data are employed. These studies are consistent with the broader research in IT investments that shows a positive impact on firm performance

The majority of recent studies on IT performance emphasize firm-level data and measure IT broadly (Brynjolfsson and Hitt, 1996; Devaraj and Kohli, 2003). Frequently missing in these studies is the granularity of individual applications. Heterogeneity in organizational capabilities drives both the IT adoption decision and has performance implications. Investigation of the individual application is important because different forms of IT may complement or substitute organizational forms (Hubbard, 2000). A notable exception is Banker *et al* (2006) that investigates investments in various manufacturing technologies and their interaction with manufacturing capabilities. Consistent with firm-level studies they find that both capabilities and technologies are important to enhance performance. Similarly, Cooper and Zmud (1990) investigate the use of MRP technologies and find that organizational factors drive the adoption decisions, but not the sophistication of MRP system employed. A few hospital IT studies have examined application level data (e.g., Amarasingham, et al., 2009; Parente and McCullough 2009). Athey and Stern (2002) also conducted a detailed study of Enhanced 911 systems. They found that these information systems improved ambulance response times and decreased mortality. We build on this literature and develop a model that explains surgical software adoption, and find that deployment is consistent with hypotheses generated from the model.

2.2 OR scheduling Literature

Given the importance of surgical capacity in the hospital, both as a critical resource and as a driver of hospital services, there is a large literature dedicated to analyzing the optimal utilization of fixed capacity by different specialties. Gupta (2007) reviews the issues studied in the literature. One unique aspect of the surgical scheduling is “block scheduling” of capacity. The long-term allocation of capacity to blocks can be viewed as a multi-item newsvendor problem with a single capacity constraint (Hadley and Whitin, 1963), where the items are specialties, each facing stochastic demand for their time. Solutions for this general problem are discussed in Erlebacher (2000) with the hospital allocating capacity based on the utility from different specialties. A similar question arises when surgical capacity is increased. Dexter, Ledolter, and Wachtel (2005) propose a solution procedure that emphasizes the information requirements of measuring demand for various subspecialties. They argue that effective allocations can be realized even with partial information, primarily from specialties for whom capacity is constrained and have a high contribution margin. Gupta (2007) expands on their model and identifies future research direction.

We adapt this literature to identify the value of moving away from a block scheduling system to centralized scheduling. Dexter *et al* (2004) argues that dynamic allocation of OR capacity within a day is essential for reducing overtime costs. For example, the model in Barut and Sridharan (2004) offers a revenue management application for dynamic constrained capacity utilization. Such an approach could be applied once OR scheduling software is installed.

2.3 OR-IT Literature

There is a broad scope of OR scheduling and decision support software implemented currently. Dexter, Willemsen-Dunlap, and Lee (2007) investigate experimentally the use of different intra-day notification systems and find that both passive displays, such as computer monitors, and active displays, which send text-messages regarding status changes, do not significantly improve intra-day OR scheduling to minimize overtime costs or increasing efficiency. However, coupled with decision support systems that provide clear scheduling guidance, decisions improved by approximately 16%. The authors suggest that decision support technology is important to improving OR scheduling. Furthermore, they argue that hospital personnel are insufficiently trained in surgical scheduling. Perhaps more importantly decisions were made using incorrect heuristics, at time, such as current utilization of available capacity instead of overall utilization of multiple units.

De Deyne and Heylen (2004) describe how one surgical information system was utilized in the context of elective surgery to dynamically assign procedures to ORs. Their analysis of one hospital attributes an increase in the number of procedures to more effective OR capacity use with a decrease in overtime cost and a reduction in OR idle time.

3. Theory and Hypotheses

3.1 Transitioning from Block Scheduling to Centralized Scheduling

OR scheduling is a complex task due to interactions with multiple physicians, capacity constraints, physical equipment and nurses required for different procedures, and availability of downstream resources. We concentrate on the complexities related to scheduling physicians' patients into fixed capacity. A number of alternatives are commonly used in practice. At the extremes are block-scheduling and open scheduling, although frequently hybrid methods are used in practice. We describe each of these in detail to motivate the adoption of HSMS.

Block scheduling: Physicians have dedicated blocks of OR time for their patients. The advantages of block scheduling are that they reduce the need for coordination across physicians. It also facilitates scheduling specialized equipment and staff required for by each specialty. When block scheduling is implemented, there are three planning horizons for a given day of interest:

Long-term schedule: The hospital has a long term schedule, usually weekly or monthly, where specialties or subspecialties are given access to blocks of time. These block may be a full day of OR once a week, or 4 hours every other week, for example. Within a specialty time blocks may be further allocated to individual physicians or physician practices. Blocks are changed infrequently.

Short-term schedule: At some cut-off point before the day of interest, excess capacity is freed by specialties. The cut-off is usually set at 1 to 3 days. This allows for limited reallocation of capacity across specialties.

Day-of-surgery: Based on the scheduled procedures for a given day, specialized equipment and nurses are assigned to operating rooms. There is still some flexibility in implementing the schedule based on updated estimates and realized surgical durations.

Open scheduling removes the restrictions of allocating time to specialties, by centralizing scheduling of all procedures. The advantages are in better utilization of fixed capacity by removing the constraints of assigned blocks of time. The disadvantage of open scheduling is the coordination requirement for assigning individual procedures. These coordination costs increase when there are multiple ORs or multiple specialties served.

In practice hybrids of these approaches are possible. We model the adoption of scheduling software as moving from the extreme of block scheduling to open scheduling. In practice, there is a continuum between these extremes and HSMS facilitates moving towards open scheduling. Reducing coordination costs facilitates reallocating capacity across subspecialties more frequently than in traditional systems.

We begin by analyzing allocation under block-scheduling. Consider a hospital with fixed surgical capacity K. Capacity is measured in time available within a specified calendar period, for example one week. The hospital serves n specialties, each of whom has surgical capacity demand. Denote by T_i the continuous random variable[2] representing the weekly time demand for use of the capacity by specialty i = 1 .. n, with pdf and cdf of d_i and D_i respectively. For example, a physician who performs open-heart surgery has a random number of patients each time period and the duration of each surgery is random. The total periodic time required is T_i.

Surgical capacity varies by specialty with value v_i per unit capacity per unit time. This value may incorporate non-pecuniary aspects of serving a specialty, as well as the average revenue generated. Value is net of OR variable costs.

We assume that in the absence of scheduling software, fixed blocks of capacity are allocated to each specialty *ex ante*. This is consistent both with recent studies (e.g., Dexter *et al*, 2005; Gupta, 2007) and our qualitative interviews with health system administrators. Allocated time for specialty i is denoted by K_i. For simplicity, we further assume that K_i is fixed for long periods of time, e.g., a year. HSMS enables scheduling that is more similar to open scheduling.

When allocating blocks of time, we assume that each specialty's total OR time demand per period (e.g., a week), T_i, is Normally distributed: $T_i \sim N\left(\mu_i, \sigma_i^2\right)$. Thus total time demand: $T \sim N\left(\mu, \sigma^2\right)$, with $\mu = \sum_{i=1}^{n} \mu_i$ and $\sigma^2 = \sum_{i=1}^{n} \sigma_i^2$ when demand across specialties is uncorrelated.[3] This arrangement of capacity demand and allocation conforms to a classic "newsvendor problem" for the single specialty. Balancing the cost of insufficient capacity with the opportunity cost of OR capacity drives each specialties' optimal capacity, denoted by K_i^e.

Capacity is fixed in the short run for most settings, thus optimization cannot be achieved by altering capacity. Hospitals may, however, allocate capacity across specialties and may also invest in

2 We ignore issues relating to discrete assignment.

3 When demand across specialties is correlated $\sigma^2 = e^t \Sigma e$, with Σ the variance-covariance matrix.

HSMS. For any allocation, in some time intervals capacity will exceed demand for all specialties. We assume here that unused capacity has no value[4]. Given the random nature of demand, there may also be insufficient capacity to meet demand for all specialties. Moreover, in a block-scheduling system, demand may exceed allocated capacity for some specialty while another cannot utilize its designated capacity.

We focus on the case when there is sufficient capacity to meet expected demand, $K > \mu$, but it would not cover allocating the efficient amount to each specialty $K < \sum_{i=1}^{n} K_i^e$. Our focus here on the case of $K > \mu$ reflects the underlying reality that hospitals are careful to reserve some excess OR capacity. This is because of the tremendous costs (in terms of human life) that occur if an ongoing procedure were prematurely terminated or an emergent surgical case went untreated. This modified problem is analogous to a constrained multi-item newsvendor problem, which has been studied in the literature (Hadley and Whitin, 1963; Silver, Pyke, and Peterson 1998; Erlebacher, 2000). The binding constraint here is total available capacity.

The probability that demand exceeds capacity is denoted by (1-D_i). Excess demand is not filled when realized capacity requirement exceeds *ex ante* allocation (i.e., when realized $T_i > K_i$). Assuming that providers do not intentionally overbook capacity, specialty i's expected value of capacity i is:

$$\pi_i\left(K_i\right) = v_i\left(E\left[T_i \mid T_i < K_i\right]D_i\left(K_i\right) + K_i\left[1 - D_i\left(K_i\right)\right]\right) - cK_i\,. \tag{1}$$

where c denotes the opportunity cost of OR capacity per unit time. It can be shown that π_i is concave in its argument – a standard result for the newsvendor problem. The overall expected payoff from OR capacity is simply: $\pi\left(K\right) = \sum_{i=1}^{n} \pi_i\left(K_i\right)$.

4 It is straightforward to add additional cost factors in the model, including the value of excess capacity and penalties for unmet demand. These only impact x^e, and do not alter our model substantially.

We begin with the unconstrained capacity case for an individual specialty. We identify the fractile of demand served for each specialty, denoted by $x_i \equiv D_i(K_i)$. When capacity is unconstrained, the efficient solution is:

$$D_i\left(K_i^e\right) = x_i^e = \frac{v_i - c}{v_i} \tag{2}$$

Turning to the hospital's optimization problem of allocating fixed capacity across multiple specialties, we have:

$$\underset{K_i}{Max}\left\{\pi(K)\right\} = \underset{K_i}{Max}\left\{\sum_{i=1}^{n}\pi_i\left(K_i\right)\right\}. \tag{3}$$

$$\text{S.T.:} \sum_{i=1}^{n} K_i = K$$

In this context cost c is implicitly defined as the opportunity cost of OR capacity. The optimal solution for a constrained multi-item newsvendor in this context is found by finding λ^b such that:

$$D_i\left(K_i^b\right) = x_i^b = \frac{v_i - \lambda^b}{v_i} \quad and \quad \sum_{i=1}^{n} K_i^b = K \tag{4}$$

Superscript b indicates the solution for a block-scheduling allocation. If (4) can be satisfied with $\lambda = c$ then we have $K_i^b = K_i^e$ and the capacity constraint is not biding. When the capacity constraint is binding we have $\lambda^b > c$. The optimal solution is found by choosing the smallest value of λ^b satisfying (4). This minimizes inefficiency associated with the capacity constraint, with the constrained fractile of demand served closest to the efficient fractile.

From the solution in (4) a number of conclusions can be reached. First more valuable specialties attain higher service levels, as measured by the fractile of OR time demand that is served. Second, when the value of all specialties is the same, they each receive the same service level. Formally, if $\forall i\ v_i = v$ then $x_i^b = x^b$. These results are useful for evaluating HSMS value.

Given the demand fractile served and the distribution of demand, the allocated capacity is:

$$K_i^b = \mu_i + \sigma_i \Phi^{-1}\left(x_i^b\right). \tag{5}$$

where $\Phi(\cdot)$ is the CDF of the Standard Normal distribution. Aggregating capacity across n specialties gives capacity allocation without scheduling software:

$$K^b(n) = K = \sum_{i=1}^{n} K_i^b = \sum_{i=1}^{n} \mu_i + \sigma_i \Phi^{-1}\left(x_i^b\right) = \mu + \sum_{i=1}^{n} \Phi^{-1}\left(x_i^b\right)\sigma_i \tag{6}$$

In effect, HSMS shifts scheduling towards centralization. With multiple surgical specialties, the weighted-average value per unit time is approximately:

$$v = \sum_{i=1}^{n} \mu_i v_i \Big/ \mu$$

Hence, the problem facing the OR, after installing scheduling software, parallels (3), with only a single specialty. From the solution in (4), we have:

$$D\left(K^s\right) = x^s = \frac{v - \lambda^s}{v} \tag{7}$$

Superscript s indicates the solution using scheduling software. From the properties of the Normal distribution capacity allocation is described by:

$$K^s(n) = K = \mu + \Phi^{-1}\left(x^s\right)\sigma \tag{8}$$

Available capacity is independent of chosen scheduling technology. $K^b = K^s$. For scheduling software to be valuable the OR would prefer a higher service level under centralized scheduling. This occurs when $x^s > x^b$. Comparing (6) with (8) we have that:

$$\sum_{i=1}^{n} \Phi^{-1}\left(x_i^b\right)\sigma_i \quad = \quad \Phi^{-1}\left(x^s\right)\sigma \tag{9}$$

Since $\sigma < \sum_{i=1}^{n} \sigma_i$ when demand is not perfectly correlated, and $\Phi^{-1}\left(\cdot\right)$ is monotonically increasing, centralized scheduling usually increases the fractile served. Another perspective on this result is that the capacity constraint is less severe under centralized scheduling $\lambda^s < \lambda^b$, from the same reasoning.[5]

In the case of binding capacity constraints ($K < \sum K_i^e$) where $\pi_i\left(x_i\right)$ is concave, we can compare expected OR value with and without HSMS, based on equation (9). The following difference identifies HSMS value.

$$V^s = \pi^s\left(x^s\right) - \sum_{i=1}^{n} \pi^b\left(x_i^b\right). \tag{10}$$

This value is usually positive as the capacity constraint is less severe with centralized scheduling. When the value of all specialties is equal, V^s is strictly positive, as $x_i^b = x^b < x^s$. Central to our analysis is that the value of HSMS increases in the number of specialties. This is due to pooling of demand across specialties, with the difference $\sum_{i=1}^{n} \sigma_i - \sigma$ increasing in n. This generates our first key Hypothesis:

***Hypothesis 1*:** HSMS adoption is increasing in the number of specialties served.

3.2 Dynamic Allocation of Procedures to ORs

As discussed earlier, HSMS is used to dynamically assign procedures to ORs, effectively pooling demand for OR capacity. To model the generated value we make the following simplifying assumptions

[5] This result does not always hold when aggregating across specialties. If the difference in values across specialties is very large, the capacity constraint may become more severe under centralized scheduling. However, this occurs only under extreme cases.

about OR capacity and utilization. Assume there are l OR units, each with identical capacity A, measured in units of time. In total the unit has $A(l) = lA$ capacity. For the sake of exposition we assume that the service time for each procedure is i.i.d. with a Normal distribution[6], denoted by $S_j \sim N\left(m, s^2\right)$. In managing the OR one important decision is to decide how many procedures to schedule in a day. If p procedures are scheduled, the time required for completing them is $S(p) \sim N\left(pm, ps^2\right)$.

The random time required to complete procedures each day implies that there will be cases where required OR time exceeds capacity. In these cases overtime costs are incurred. In other cases the OR will have excess capacity, when all scheduled procedures complete early. OR managers face an optimization problem in choosing the number of procedures to schedule, p (Gerchak, Gupta, and Henig, 1996). Optimization involves balancing the cost of overtime with the opportunity cost of idle OR capacity. This tradeoff creates a novel newsvendor problem, optimizing over the number of procedures, rather than available capacity. The nature of this solution is quite complex, providing little applicability for managers.

Instead of analyzing the optimal solution, we assume that OR managers employ a heuristic in deciding how many procedures to schedule. Using this heuristic they choose the probability of requiring overtime (1-z). With capacity $A(l)$ and p procedures the probability that overtime is not necessary becomes, $z \equiv \Pr\{S(p) < A(l)\} = \Phi\left(\frac{mp - A(l)}{s\sqrt{p}}\right)$, where $\Phi(\bullet)$is the CDF of the Standard Normal distribution. The number of procedures set, p, is then chosen to adhere to the policy of the predetermined z. Given the policy z, the capacity required, as a function of p, can be rewritten as:

$$A(l, p) = pm + zs\sqrt{p}$$

Given a capacity for l ORs, $A(l)$, the number of procedures $p(l)$ is chosen to satisfy

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6 The assumption of identical distributions is not required but is chosen to simplify the exposition.

$$z = \Phi\left(\frac{mp(l) - A(l)}{s\sqrt{p(l)}}\right). \tag{11}$$

Inspecting $p(l)$ provides another source of benefit for scheduling systems. If, in the absence of such systems each OR is scheduled independently, only $p(1)$ procedures are scheduled for each OR. For the entire OR, $lp(1)$ procedures are scheduled. By utilizing scheduling software $p(l)$ procedures are scheduled daily. Since $A(l,p)$ is sub-linear in p it can be shown that $p(l) > lp(1)$. Formally this is the result of: $\frac{\partial A(l,p)}{\partial p} < m + zs$. Intuition for this result is based on pooling across ORs. As the number of units increases the impact of variation in procedure time is reduced. This allows maintaining a high service level, z, with less "safety capacity". As a result, more procedures can be scheduled, without reducing service.

This generates our second key hypothesis.

***Hypothesis 2*:** HSMS are adopted more frequently by hospital systems that have more ORs.

3.3 Other motivations for OR management technology adoption – secondary hypotheses

Hospitals' HSMS adoption decisions will, of course, be influenced by factors other the number of ORs and mix of surgical specialties. Although such factors are incidental to our motivating theoretical model they will play a role in our empirical estimates and merit consideration. Consequently, base our discussion and hypothesis of other factors on the hospital IT adoption literature (Borzekowski, 2002; Cutler, et al., 2006; and Furukawa, et al., 2008; and McCullough, 2008) rather than incorporating them in our theoretical model. Several factors emerge as potential health IT adoption drivers. Hospital scale is a common determinant of adoption while service scope (i.e., the variety of clinical service) has not been found to affect health IT adoption (e.g., McCullough 2008). It is also important to note that hospitals differ in their objectives and organization. Ownership (i.e., for-profit, non-profit, and government), system membership, and academic status might will change hospitals' health IT demand.[7]

The role of scope and scale roughly correspond to Hypotheses One and Two respectively. Our hypotheses specifically pertain to the number of surgical specialties and OR capacity. Our theoretical predictions are not relevant to other measures of scale such as surgical volume. *Ceteris paribus*, we would also expect adoption to increase in surgical volume but this would less clearly reflect our underlying theory. While we have fewer relevant alternative measures of scope, we might expect that academic hospitals will have a greater mix of surgical services than non-academic hospitals; thus we build on Hypotheses One and Two with Hypotheses Three and Four:

Hypothesis 3: HSMS adoption is increasing in surgical volume or scale independent of OR capacity.

Hypothesis 4: HSMS adoption is more prevalent among academic hospitals.

Hospital ownership may also play a role in health IT adoption behavior. While the literature is mixed on the topic, some studies have found that for-profit hospitals are more likely to invest in cost-reducing health IT applications (e.g., Parente and Van Horn 2006). While we will control for government ownership, we have no *a priori* expectations on their behavioral differences. Multihospital system members have also been found to have higher health IT adoption rates (McCullough 2008). There are many potential theoretical motivations for this finding such as learning across facilities, bargaining power

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[7] We note that market characteristics (e.g., competition) and hospital financial characteristic have not been found to influence adoption (Borzekowski 2002; Cutler, et al., 2006; and McCullough 2008). This is somewhat reassuring as hospital financial variables would likely be endogenous to technology adoption decisions. Capps and Cuellar (2008) provide an interesting counter-example in that they find a relationship between competition and technology adoption. Their finding is less relevant to our situation as they examine quality-enhancing rather than cost-reducing process innovations.

in purchasing, lower costs of capital for large purchases, etc. Consequently, we posit the following hypotheses:

Hypothesis 5: HSMS adoption is more prevalent among for-profit hospitals.

Hypothesis 6: HSMS adoption is more prevalent among multihospital system members.

4. Data

We test our hypotheses using data containing both hospital characteristics and HSMS adoption with hospital characteristics. In particular, we use the American Hospital Association’s (AHA’s) annual survey as a source of hospital characteristics. The Healthcare Information and Management Systems Society (HIMSS) Analytics Database provides detailed hospital IT adoption data for a variety of applications including HSMS. The HIMSS data have been validated by a variety of previous studies (e.g., Borzekowski 2002 and 2008; Fonkych and Taylor, 2005; Parente and Van Horn, 2006; Furukawa, *et al.*, 2008; McCullough 2008). This combination of detailed firm characteristic and IT application data are rarely available in other industries.

Our sample consists of a panel of 1776 hospitals observed yearly during 1998-2004. These hospitals are acute care, non-federal, urban institutions. Key AHA variables include surgical capacity, surgical volume, surgical service scope, and general hospital characteristics. Surgical capacity is measured as the count of operating rooms while surgical volume is the number of surgical procedures. The scope of surgical services is measured by a set of indicators reflecting the mix of physician services offered by individual hospitals. These indicators are, of course, imperfect measures of surgical service mix but they do capture some portion of the relevant variation. Specific indicators include: open heart surgery, transplant surgery, surgical oncology, sports medicine, obstetrics, sports medicine, obstetrics, the presence of a cardiac intensive care unit (ICU), and the presence of a neonatal ICU. We also construct a count of these services as it is the number of different services, rather than the presence of any given service, that relates to Hypothesis 1.[8] General hospital characteristics include academic status measured by Council of Teaching Hospital (COTH) membership, multihospital system membership, and hospital ownership. Hospital ownership is characterized by indicators for government ownership and for-profit ownership, nonprofit ownership is the (excluded) reference category.

Operating room management IT is, of course, our technology of interest from the HIMSS data. This is defined as application that automates operating room functions, including; surgical case scheduling and charge processing. OR management applications may also provide inventory control and maintain databases of staff members, rooms, procedures and capital equipment. Finally, these applications generate periodic reports regarding OR utilization (Sheldon I Dorenfest, 2001).

4.1 Methods & Results

We study hospitals' HSMS adoption behavior to test our hypotheses. We begin by examining univariate correlations and then present results from multivariate hazard models. Table 1 describes HSMS prevalence across time. About 73% of hospitals used HSMS in 1998 and this figure grew to more than 94% of hospitals by 2004.

Table 1. OR management System adoption rates

Year	Install	Adopt
1998	73%	7%
1999	88%	9%
2000	91%	2%
2001	92%	1%
2002	93%	2%
2003	93%	1%
2004	94%	1%

8 We tested our results (below) to sensitivity to the set of services included in our scope measures. The general conclusion was quite robust to alternative specifications of service scope.

Cross-hospital adoption differences, presented in Table 2, suggest that many hospital characteristics are correlated with adoption behavior. The first column of Table 2 describes the average value of each characteristic for our sample during 1998.[9] Subsequent columns describe the characteristics of three subsamples. The first subsample includes the 1298 early adopting hospitals, those that had HSMS prior to 1998. Late adopters comprise the second subsample, these 359 hospitals adopted during 1998-2004. The final subsample of 119 hospitals never adopted. We find that early adopters had, on average, more operating rooms, performed more surgeries, and had a wider service scope than the average hospital. They were also more likely to offer open heart surgery, neonatal ICU, and surgical oncology. Late adopters had lower capacity, performed fewer surgeries and served fewer surgical specialties than early adopters. Similarly, Late adopters had less capacity, lower volume, and a narrower scope than late adopters.[10]

A similar pattern emerges for some specific services. In particular, early adopters are more likely to offer open heart surgery, surgical oncology, and neonatal ICUs. As above, late adopters are less likely to offer these services and their prevalence is even lower among non-adopters. Hospital characteristics may also play a role in adoption. We find that academic hospitals and multihospital system members are more likely to be early adopters. Additionally, government-owned hospitals are less likely to adopt HSMS.

9 We focus on 1998 statistics because it is conceivable, if unlikely, that changes in hospital characteristics could be caused by HSMS adoption. Focusing on the distribution of initial year characteristics minimizes this problem. Ultimately, the distributions of these characteristics are relatively stable with time and results are qualitatively similar when focusing on cross-group differences in other years.

10 Significance levels reported in Table 2 describe differences between a sub-group and the group mean. It is worth noting that statistics that are significantly different from the group average are largely significant across sub-groups.

Table 2. 1998 hospital characteristics by adoption timing

Characteristic	Average	Early	Late	Never
OR count	7.41	11.15***	9.32**	5.49***
Surgical volume	8625	9219***	7892***	4356***
Scope	3.27	3.42***	3.02***	2.34***
Obstetrics	0.86	0.86	0.86	0.76***
Ortho/sports medicine	0.46	0.46	0.45	0.41
Cardiac surgery (ICU)	0.55	0.57*	0.51	0.43***
Open Heart surgery	0.33	0.38***	0.26***	0.08***
Neonatal ICU	0.35	0.38***	0.28***	0.17***
Surgical Oncology	0.64	0.68***	0.58***	0.41***
Transplant surgery	0.08	0.09	0.07	0.08
Academic (COTH)	0.12	0.14*	0.09**	0.04***
For-profit	0.19	0.20	0.17	0.14
Government-owned	0.12	0.10**	0.16**	0.21**
System member	0.71	0.73**	0.66*	0.58***
Number of hospitals	1776	1298	359	119

* denotes significance at p=0.10, ** at p=0.05, and *** at p=0.001

While these correlations are interesting, they do not directly test our hypotheses. Since our covariates are likely correlated, it is not clear whether we're observing a capacity effect, a volume-based scale effect, or both. Similarly, HSMS might be more useful for specific surgical services, the presence of those services would, by construction, be correlated with scope. Consequently, multivariate models will provide better tests for our hypotheses.

We wish to simultaneously measure the effect of capacity, service scope, and other factors on adoption. Furthermore, we want to take into account the durable and dynamic nature of technology adoption decisions. Consequently, we employ hazard models to infer IT demand from hospitals' revealed preferences. Hazards measure the rate at which events occur conditional upon a hospital being "at risk" of having an event. Thus, we measure the adoption rate for those hospitals that have not previously adopted

– this effectively reduces our sample size to 478 hospitals. Formally, we measure the hazard of adoption at time t, $h(t)$.

$$h(t) = h_0(t)\exp\{\alpha + K'\beta + V'\gamma + S'\delta + X'\theta + \varepsilon\}$$

Where $h_0(t)$ is a non-parametric function of time also called a base line hazard, in this case a set of year dummies. Operating room capacity (K), OR volume (V), and service scope (S) measures are also included. We also incorporate hospital controls (X), including; COTH membership, ownership, and multihospital system membership. Parameters $\{\alpha,\beta,\gamma,\delta,\theta\}$ are interpreted as proportional shifts in the baseline hazard. Finally, ε is an error term (also known as frailty). Since we're estimating a continuous time process measured in discrete time we use a complementary-log-log specification estimated by maximum likelihood.

We report two specifications, one in which scope is a series of service line indicators and the other in which scope is the count of service lines. The first column of Table 3 describes a model with service line indicators, Model 1. These coefficients should be interpreted as proportional shifts in an underlying baseline hazard. We find that an increase of one operating room increases the hazard of HSMS adoption by 9%. This is consistent with hypothesis 2; specifically, that HSMS systems may coordinate procedures of uncertain duration across multiple operating rooms. As the number of procedures increases the risk that total utilization time exceeds capacity decreases. This allows for "overbooking" an OR when management software is available. This capacity effect is also consistent with a traditional scale effect where adoption is a fixed cost that can be spread over high volume. We attempt to address this possibility by also including a surgical volume and its interaction with OR capacity. Neither has a significant effect on technology adoption and we reject Hypothesis 3. Capacity and scale effects are nearly identical in Models 1 and 2.

Table 3. Hazard of adopting OR management IT

Variable	Model 1	Model 2
	e^{β}	
OR count	1.09***	1.16***
	(0.03)	(0.05)
Surgical volume	1.000	1.000
	(0.00)	(0.00)
OR count x Surgical volume	1.000	1.000
	(0.00)	(0.00)
Scope		1.27**
		(0.13)
Scope x Surgical volume		1.000
		(0.00)
Scope x OR count		0.98**
		(0.01)
Obstetrics	0.886	
	(0.16)	
Ortho/sports medicine	0.990	
	(0.13)	
Cardiac surgery (ICU)	1.013	
	(0.14)	
Open Heart surgery	1.017	
	(0.21)	
Neonatal ICU	1.245	
	(0.23)	
Surgical Oncology	1.53*	
	(0.35)	
Transplant surgery	1.031	
	(0.27)	
Academic (COTH)	0.575	0.973
	(0.21)	(0.36)
For-profit	1.53**	1.63***
	(0.27)	(0.29)
Government-owned	1.162	1.200
	(0.20)	(0.20)
System member	1.40**	1.39**
	(0.19)	(0.19)

* denotes significance at p=0.10, ** at p=0.05, and *** at p=0.001.

We find one important difference between our two models. In Model 1, we reject correlations between any service indicator and HSMS adoption. This implies that *ceteris paribus*, HSMS adoption is independent of hospital's specific clinical services. Conversely, the count of services is a strong predictor of HSMS adoption in Model 2. This implies that the number of services being coordinated, rather than the type of specific services, drives HSMS adoption. In fact, adding one service causes a nearly 30% increase in the hazard of adoption. These results are consistent with our motivating theory in general and Hypothesis 1 in particular. We also find that the scope effect is diminishing in capacity. This suggests that HSMS value is realized when capacity constraints are binding. Efficient OR scheduling appears to hold less value when surgical capacity is high relative to capacity demand.

We also measure the effect of hospital characteristics on adoption. We find no evidence that academic hospitals differ in their HSMS adoption behavior; thus, we reject Hypothesis 4. We do find that for-profit hospital adoption rates are more than 50% higher than non-profit adoption rates. Government-owned institutions' adoption appears similar to that of other non-profit hospitals. These results are consistent with Hypothesis 5. Finally, we find that multihospital system members are about 40% more likely to adopt than freestanding hospitals.

4.2 Robustness tests

We take a series of steps to test the robustness of our work. While our empirical approach allows for completely non-parametric duration dependence as well as parametric unobserved heterogeneity, it does make one strong assumption – proportionality. Consequently, we test for non-proportionality in the effect of each covariate. We cannot reject proportionality, strongly suggesting that the model is correctly specified.

We also tested alternative specifications with different sets of control variables. We first tested models with more flexible scale and scope effects. We then explored alternative service scope measured based on inpatient and outpatient services. In each case, the results were consistent with those presented above. We then tested the relevance of payer mix (e.g., Medicare and Medicaid versus private insurance) as it might be correlated with unobserved patient severity. We finally tested the effect of vertical integration between hospitals and physicians as it might alter the equilibrium distribution of OR resources. In all cases results were consistent with those presented in Table 3.

5. Discussion

We build on the IT value literature by focusing on the capabilities and role of HSMS in US hospitals. We draw on both the economic and operations literature to develop theoretical models of scheduling software demand. The first model measures the value of transitioning OR scheduling from block scheduling to open/centralized scheduling, enabled by HSMS adoption. The model indicates that the number of specialties served by the OR drives technology demand due to the inefficiency of block scheduling. A second model evaluates the benefits of adoption using within-day scheduling as the unit of analysis. Comparable to revenue management models, technology adoption is driven by the number of ORs. HSMS facilitates pooling across operating rooms, reducing variation in utilization.

We test our model empirically using a large dataset of hospital HSMS adoption decisions. We estimate models of HSMS adoption to infer complementarities between health IT, capital investments, and organizational investments. We find that HSMS is complementary to OR capital but that adoption is not otherwise increasing in the scale of production. We further find that HSMS is complementary to the number of specialty services but is uncorrelated with individual services. Thus, complementarities appear to reflect our underlying model rather than generic scale and scope measures. This is in contrast with other health IT adoption studies. We also find that HSMS adoption is higher for both for-profit hospitals and multihospital system members.

Ultimately, a detailed understanding of IT and complementarity is crucial to the realization and understanding of IT value. Furthermore, an application-level understanding is critical to ongoing developments in health policy. The American Recovery and Reinvestment Act of 2009 provides approximately $19 billion in subsidies to increase health IT adoption, along with requirements that providers implement “meaningful use” of electronic health records by 2015. Federal health IT subsidies will likely exceed $50 billion over the next four years and funding rules will specify functional capabilities of IT investments. These policies reflect the importance of understanding IT value at a granular level and understanding its functional interactions within an organization. While the importance of these issues is clear, the evidence base to support such policies is incomplete. A 2008 CBO report (Orszag, 2008) discusses the practical difficulties of effectively targeting health IT adoption subsidies.

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