# Implementing electronic lab order entry management in hospitals: Incremental strategies lead to better productivity outcomes

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**Abstract:**

This paper evaluates the impact of varying implementation of electronic lab order entry management (eLAB) system strategies on hospitals' productivity in the short run. Using the American Hospital Association's Annual Surveys for 2005–2008, we developed hospital productivity measures to assess facilities' relative performances upon implementing eLAB systems. The results indicate that different eLAB system implementation strategies were systematically related to changes in hospitals' relative productivity levels over the years studied. Hospitals that partially implemented an eLAB system without completing the roll-out experienced negative impacts on productivity. The greatest loss in short-term productivity was experienced by facilities that moved from having no eLAB system to a complete implantation in one year—a strategy called the "Big Bang". The hybrid approach of a limited introduction in one period followed by complete roll-out in the next year was the only eLAB system implementation strategy associated with significant productivity gains. Our findings support a very specific strategy for eLAB system implementation where facilities began with a one-year pilot program immediately followed by an organization-wide implementation effort in the next period.

**Keywords:** HIT implementation | Data envelopment analysis | Hospitals | Malmquist index | Hospital Management

**Article:**

1. Introduction

Among the factors that contribute to waste and inefficiency in the U.S. healthcare system, the duplication and unnecessary ordering of laboratory and diagnostic tests are among the most costly (Kwok and Jones, 2005 and Mekhjian et al., 2003). Nearly seven billion lab tests are conducted each year (McCormack, 2011). Of these, 20 percent or more are unnecessary duplications or inappropriate requests (Grunden, 2009 and Kwok and Jones, 2005). The Congressional Budget Office (CBO) estimates that five percent of the nation's GDP, about $700 billion dollars per year, goes towards unnecessary tests and procedures (Kendall, 2009). The effort to reduce waste has therefore centered on the implementation of Health Information Technologies (HITs) that can address the information asymmetries and unnecessary redundancies found in orders for laboratory tests, radiology studies, and other tests.

Electronic laboratory order entry and management (eLAB) systems provide important opportunities for technology to play a transformative role in the care provision across four foci of health reform. First, laboratory order entry has a well-defined ontological system (i.e., HL7) that lends itself to computerization and standardization (Gardner, 2003). Second, the large volume of such tests coupled with their high costs makes these procedures a good target for systemic savings through better information management and waste reduction (Hillestad et al., 2005). Third, eLAB technologies are sufficiently mature and cost effective (Chaudhry et al., 2006). Finally, eLAB systems have been found to serve as the foundation upon which EHRs are implemented, often serving as a leading-edge indicator of technological adoption among non-computerized facilities (American Hospital Association Annual Survey, 2009).

With potential savings in the billions of dollars over the next decade, eLAB systems are an integral part of the federal government's ‘Meaningful Use’ rewards and incentives program (Jain, Seidman, & Blumenthal, 2010). Hospitals, in particular, are targeted for adoption because they make extensive use of the most expensive laboratory and diagnostic procedures. However, as of 2009, eLAB systems were not widely implemented throughout U.S. hospitals (Jha, DesRoches, Kralovec, & Joshi, 2010). Therefore, hospitals must switch from paper-based systems to electronic systems in relatively short time frames in order to meet the government's Meaningful Use targets and avoid such penalties. It is unclear how implementing eLAB systems in short time frames impacts hospitals’ productivity levels, but the studies to date have found mixed results at best (Hillman and Given, 2005 and Jha et al., 2009).

The purpose of this study is to analyze how implementing eLAB systems impact facility productivity in U.S. hospitals. First, taxonomy of eLAB systems implementation strategy is developed based on the stages of meaningful use for U.S. hospitals. Specifically, the taxonomy classifies facilities based on the change in percentage of orders processed using eLAB systems across two points in time—2007–2008. Next, using the Malmquist total factor productivity (TFP) Index and it underlying factors (viz., technical efficiency change (EFFCH) and technological change (TC)), facility relative productivity levels are measured and compared. The results and implications are discussed followed by a brief description of the study's limitations and potential future research.

With the federal government promoting the accelerated implementation of health information technologies (HITs) through large-scale investments, hospitals need guidance on the differential productivity outcomes associated with various strategies. With high profile implementation failures, such as the one experienced at Cedar-Sinai (Connolly, 2005), this paper seeks to illuminate how strategy selection impacts organizational productivity. For policymakers as well as healthcare executives, this paper not only demonstrates a positive link between eLAB systems use and productivity that would justify the major capital investments these systems require but provides an evidentiary basis for strategy decisions.

## 2. Background on eLAB systems

Computerized Provider Order Entry (CPOE) systems were first introduced in 1969 and have been evolving slowly ever since (Goolsby, 2002). There are three major classes of CPOE systems. The most frequently discussed is electronic prescribing (ePrescribing or eRx), often because of the focus on patient safety, and the significant role medication errors play in compromising care quality (Yu et al., 2009). Physicians have been financially incentivized to adopt eRx and its use has grown rapidly.

The second class of CPOE involves the standardization of clinical order set entry and use. Clinical order sets describe the activities of care that a patient is to receive. For example, post-operative order sets may describe the dietary restrictions, physical therapy and wound care that a patient should receive in accordance with evidence-based medicine (Payne, Hoey, Nichol, & Lovis, 2003). The use of these systems has been the slowest to take hold because of the difficulty associated with moving physicians away from their traditional practice and towards standardized regiments of care (Stolle, 2010).

The third class of CPOE, and the subject of this research, is the use of eLAB systems for ordering of diagnostic tests that are conducted in a controlled manner such as imaging (e.g., radiology) and hematology (e.g., blood work). eLAB systems provide a structured and auditable framework in which laboratory data may be captured and communicated. Through the establishment of a single point of contact for laboratory ordering and results, the basic principal of eLAB systems is that redundant tests can be minimized and clinical decision-making is further supported. The use of eLAB systems is a necessary component in achieving the policy aims of automating public health registry reporting and providing patients with test results that can be stored in an electronic personal health record (Hinman and Ross, 2010, Tripathi et al., 2009 and Williams and Boren, 2008).

The HIT system required to make eLAB systems work requires an ecosystem that makes their adoption more complicated than stand-alone technologies, which has slowed their widespread use (DeVore & Figlioli, 2010). The ability to integrate eLAB system data into existing information technologies, such as revenue cycle management systems, can also slow adoption. Such issues have been at the heart of the interoperability challenges highlighted in the literature and are consistently noted as a significant barrier to HIT adoption (Lovis, Spahni, Cassoni, & Geissbuhler, 2007).

In addition to concerns about technical issues, there is a reticence to move forward as a result of several reports of costly implementation failures (Heeks, 2006). The implementation of a high performing eLAB system requires extensive workflow redesigns across the hospital's service and support units. In fact, this is one of the concerns that led the American Hospital Association (AHA) to petition the Office of the National Coordinator for Health Information Technology to delay demonstrating 'Meaningful Use' of eLAB systems as part of the Patient Protection and Affordable Care Act (PPACA) requirements (Segal, 2010).

On the other hand, there are several significant factors helping to accelerate eLAB system adoption. One of the most common benefits discussed in support of increased eLAB system adoption is the savings that result from eliminating unnecessary or duplication orders. The labor costs associated with a laboratory order include staff time preparing the patient (e.g., X-rays, blood draws, and other screening), materials costs, and coordination and transportation. The latter of these often requires a patient hand-off, which creates a source of potential medical errors that can prove costly (Catalano, 2009). When inpatient services are provided, these duplicative services create unbillable expenses and unnecessary costs, which are not reimbursed and must be absorbed by the hospital.

eLAB systems can also increase the availability of electronically compiled information supporting payment claims. This information often plays a key role in efforts to maximize reimbursement rates through better documentation of clinical activities (e.g., Medicare's Premier pay-for-performance program; Becker, 2003 and Tieman, 2003). These changing payment schemes create important external influences on technology innovation that can impact adoption rates (Robinson et al., 2009).

Finally, there is a change in the generation expectations associated with newly trained physicians. Residents and medical students are bringing with them an increased familiarity and comfort with technology. This evolutionary shift within the medical field has changed the expectations for technology innovation (Ford, Menachemi, & Phillips, 2006).

Cultural expectation, technological availability and challenges, and policy forces are working together to shape implementation strategies. What is missing is evidence on the effect of eLAB systems implementation on hospital productivity. Without this data, it would be difficult to determine a pathway to the most likely cost efficiencies that will help bend the healthcare inflation curve.

## 3. Methods

### 3.1. Taxonomy of eLAB system adoption rates

In 2007, hospitals were asked (from the AHA annual survey) to categorize the percentage of physicians in the facility that “routinely order laboratory or other tests electronically.” The answer set was anchored at ‘0%’, and had options of ‘1–24%; ‘25–49%’; ‘50–74%; and ‘75–100%’. In 2008, hospitals were asked the same question. Based on changes in the percentage of lab orders entered from one year to the next, a taxonomy of change was created.

The taxonomy is as follows: The first group, the ‘Never Adopter’ (NA: n = 895) hospitals are those facilities that reported no system in place in either 2007 or 2008. The second group is facilities that reported less than 50 percent usage in 2007 and ‘No Change’ (NC1: n = 312) in adoption level in the usage of the system in the next year. Hospitals in this group have physicians using the system; however, this group is separated from the subsequent group to discriminate between facilities that met the standard and those that need to increase eLAB use to qualify. The third designation is for hospitals with ‘No change’ (NC2: n = 190) in utilization from 2007 to 2008, but a baseline usage of greater than 50 percent of orders being entered using the CPOE system.

The facilities most relevant to the study question varied in the percent of laboratory or other tests ordered electronically between years. The group, labeled ‘Simple Introduction’ (SI: n = 94), consist of hospitals that reported no eLAB system usage in 2007 and less than 25 percent usage in 2008. It should be noted that the move to simple introduction belies a significant transition from no eLAB system to the presence of an electronic system—and with it, all the accompanying organization change and work redesign required. The group of hospitals labeled ‘Incremental Progress’ (IP: n = 74) represents facilities reporting a 25 percent or less increase in usage from one year to the next. The group labeled ‘Major Progress’ (MP: n = 31) contains facilities reporting a two- (26 percent or more) or three-step (51 percent or more) increase in CPOE usage, which is a significant increase in eLAB system use. The group called the Big Bang (BB: n = 60) represents the transition from no usage to usage greater than 50 percent in the single year between reports. We call this a ‘Big Bang’ because the transitional impacts on the organization of moving from no system at all to widespread use are expected to be significant ( Heichert, 2008 and Roberts, 2004). Table 1 illustrates the taxonomy.

Table 1. Typology of technology adoption.

Percent of laboratory or other tests ordered electronically.

| | | 2008 | | | | |
|---|---|---|---|---|---|---|
| | | No eLABS Use | 0–24% | 25–49% | 50–74% | 75% or more |
| 2007 | No eLABS Use | NA | SI | BB | BB | BB |
| | 0–24% | NG0 | NC1 | IP | MP | MP |
| | 25–49% | NG0 | NG1 | NC1 | IP | MP |
| | 50–74% | NG0 | NG1 | NG1 | NC2 | IP |
| | 75% or more | NG0 | NG1 | NG1 | NG1 | NC2 |

NA: never implemented eLAB system; NG0: negative growth moving to zero use (e.g., dis-adoption); NG1: negative growth, but still using eLAB system (e.g., decline in use); SI: simple introduction; IP: incremental progress; NC1: no change in use level, not meeting the Meaningful Use standard; NC2: no change in use, Meaningful Use Stage 1 standard met; BB: big bang; MP: major progress.

There were facilities that reported eLAB system use in 2007 but had a decline in use the subsequent year. One group of hospitals reported using eLAB system in 2007 then reported no use in 2008 (e.g., 'Negative Growth to Zero' (NG0: n = 60)). This category represents the abandonment of eLAB system by those hospitals. The second group within this category contains hospitals that have a negative change in implementation level; however, they are still indicating usage of an eLAB system (NG1: n = 37). This category represents a decrease in eLAB system utilization, but not a complete abandonment of the technology.

## 3.2. Measuring hospital efficiency, technological change and productivity

The Agency for Healthcare Quality and Research (AHRQ) defines efficiency "as an attribute of performance that is measured by examining the relationship between a specific product of the health care system (also called an output) and the resources used to create that product (also called inputs)" (McGlynn, 2008). While the use of regression analysis in comparative efficiency calculations is common, Data Envelopment Analysis (DEA) is gaining increased traction in healthcare. DEA allows for multiple output variables to be used in the calculation along with multiple input variables—allowing a more holistic perspective on efficiency than is provided by simple output or ratios alone. The advantages of frontier analysis over regression are described below.

DEA takes a fundamentally different approach from standard regression methods by establishing a mathematical frontier associated with best demonstrated practices and then building a metric based on that benchmark. The average of this index across all decision-making units is then an overarching measure of relative transformational efficiency. Put more simply, regression analysis identifies the line that best represents the relationship among variables; whereas frontier analysis identifies the line that represents the best relationship among variables.

Fig. 1, adapted here from the work of McGlynn (2008), provides a more in-depth illustration of the linkage between efficiency and the frontier. The figure illustrates the case of a single output (Y) that is produced using two inputs (X1, X2), and that the production function, Y = f(X1, X2) is linearly homogenous. As such, Fig. 1 represents the trade-offs made between consumption of X1 and X2 in the production of a single unit of Y. Q represents a decision-making unit that is efficient, that is, it lies on the frontier of efficient outputs given the multitude of input combinations possible. P represents a decision-making unit that requires higher levels of inputs to produce a single unit of Y. The magnitude of the efficiency can be expressed as the ratio between optimal and actual resource use (OR/OP). Further, allocative efficiency can be expressed as the ratio between minimum and actual cost (OS/OR) along the iso-cost line.

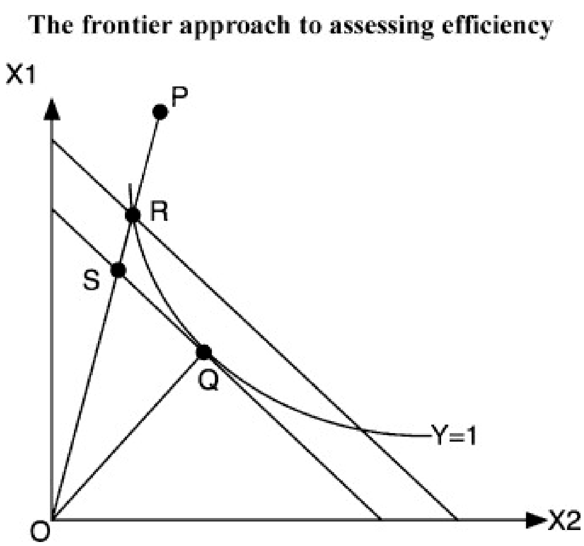


Fig. 1. The frontier approach to assessing efficiency.

Total factor productivity (TFP) is an economic term to describe the transformation of inputs to outputs over time in a manner that accounts for all factors—both endogenous and exogenous. The most common of these time-series measures are the Fisher and Törnquist indices (Reinsdorf, Diewert, & Ehemann, 2002); however, both of these measures require price data to assess productivity. An alternative was developed by Malmquist in 1953 and was further explored by Fare, Grosskopf, and Roos (1995) who proposed the use of linear programming to facilitate analysis. The total factor productivity (TFP) Index focuses on changes in efficiency over time and as such is a longitudinal technique for exploring such efficiency changes (Antonio, 1999). The Malmquist TFP Index is particularly useful when the objectives of the firms are not known, have not been achieved, or differ from firm to firm and when output pricing information is either not available or is unusable because some output values are purposely overstated (Uri, 2001).

The Malmquist index can be understood graphically and is illustrated in Fig. 2. In that figure, we illustrate the productivity of a decision-making unit at both time t and t + 1. On visual inspection, it would seem that the decision-making unit has become more efficient at time t + 1, in part because over twice the output is being produced with only a marginal increase in the input. The Malmquist indices enumerate the magnitude of that change as an index centered on one. It does so by implementing a benchmark “technology” at t, $T_c^t$, with a similar technology benchmark based on t + 1, $T_c^{t+1}$. The Malmquist is then expressed as the relationship of each point to these two benchmarks, expressed as the geometric mean of these two distance functions.

$$M_{oc}(x^t, y^t, x^{t+1}, y^{t+1}) = \left[\frac{D_{oc}^t(x^{t+1}, y^{t+1})}{D_{oc}^t(x^t, y^t)} \times \frac{D_{oc}^t(x^{t+1}, y^{t+1})}{D_{oc}^{t+1}(x^t, y^t)}\right]^{1/2}$$
$$= \left[\frac{Q}{M} \times \frac{P}{N}\right]^{1/2}$$

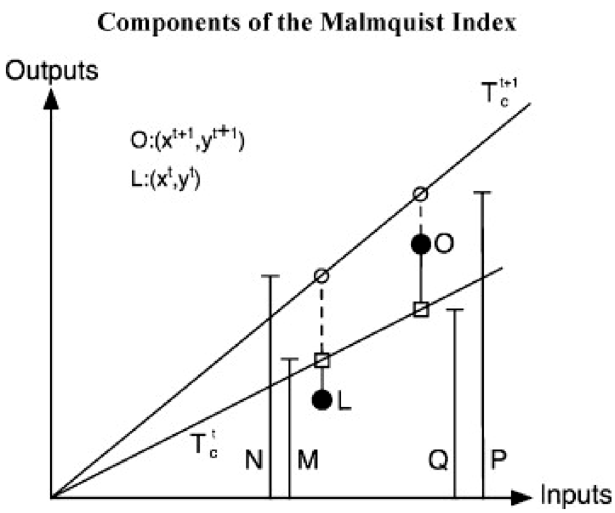


Fig. 2. Components of the Malmquist index.

The result is an index that may take a value less than, greater than or equal to one based on whether the decision-making unit retreated, advanced or remained stagnant against the shift in the technology benchmark. As further described in Eq. (2), the Malmquist index can be decomposed into two components, one measuring the change in efficiency and the other measuring the change in the frontier technology ($T_c^t$). In Färe, Grosskopf, Lindgren, and Roos (1992), the technology was determined by the efficient frontier estimated using DEA for a set of decision-making units. However, the benchmark frontier technology for each particular decision-making unit under evaluation is only represented by a portion of the DEA frontier.

$Moc(xt,yt,xt+1,yt+1)=TE\Delta oc(xt,yt,xt+1,yt+1)\times T\Delta oc(xt,yt,xt+1,yt+1)$

$TE\Delta oc$ is a measure of the contribution of technical efficiency change (EFFCH) to the Malmquist index and represents the shift in productivity of the decision-making units experienced from $t$ to $t+1$. As such, it may take a value less than, greater than or equal to one based on whether the decision-making unit retreated, advanced or remained stagnant in terms of its technical efficiency. Visually, a decision-making unit that experiences no change in TE produces the same number of outputs for every unit input in both $t$ and $t+1$, and would result in a decision-making unit with a $TE\Delta oc$ of one. The movement from point L to point O is indicative of $TE\Delta oc$ greater than one in Fig. 2. $T\Delta oc$ is a measure of the contribution of technical change (TC) to the Malmquist index and is illustrated by the shift in the line from $T_c^t$ to $T_c^{t+1}$. The upward shift in the technology benchmark from $t$ to $t+1$ is indicative of $T\Delta oc$ greater than one in Fig. 2.

The decomposition of TFP productivity has been widely explored in the literature, and more specifically, it has been used to explore issues in healthcare (Kontodimopoulos & Niakas, 2006). The EFFCH component, on one hand, is an indicator of the 'management effect' on organizational performance. It occurs when more of each input is used than should be required to produce a given level of output in specific organizational activities (Isik, 2007). It is typically attributed to insufficient competitive pressures that allow management to engage in suboptimal productivity. Under competitive pressure, managers are incentivized to improve their underlying organizational processes in order to keep pace with other firms in the market through innovation.

On the other hand, the TC index measures shifts in the TFP frontier that arise from organizational innovation. It is interpreted as the change of the "best practice" frontier over time typically due to improvements in the "technology" of organizational processes (Salehirad & Sowlati, 2006). The term "technology" has a general meaning here and refers not only to information or clinical technology innovations. The most significant technological changes in an organization often rely on behavior modifications; for example, to research and development, education and human capital investments, policy improvements (e.g., transparency in reporting), better design of workflows (e.g., the use of intensive care unit physician specialists), regulations (e.g., the implementation of safe practices), and an organization's culture. Collectively evaluating changes in hospitals' efficiency and technological acumen are thus critical to evaluating improvements in the productivity of such facilities.

The use of TFP, EFFCH and TC to explore issues in healthcare is diverse. One study, conducted by Kontodimopoulos and Niakas (2006) used these three measures to explore productivity among dialysis treatment facilities in Greece. In that article, Malmquist indices were calculated for dialysis facilities in Greece over a 12-year period, using nationally representative panel data. Similarly, we decomposed the Malmquist TFP into technical efficiency change (EFFCH) and technological change (TC) to assess US facilities' relative performance upon implementing eLAB systems.

### 3.3. Malmquist model specification and dataset description

The analysis used 3 inputs and 5 outputs drawn from the American Hospital Association's (AHA) annual survey. Drawing on this data, we selected total of licensed beds (AHA variable: BDTOT) as a proxy for the size of the facility. Staffing was measured using both total FTE minus the nursing staff (AHA variable: FTE) and the total number of FTE in the licensed nursing staff (AHA variable: FTERN + FTELPN). In effect, the nursing staff is broken out as their own input with all other employees being their own input.

Our output measures focus on facility usage. To identify those with heavy outpatient surgical loads, we included the number of surgical outpatient procedures (AHA variable: SUROPTOT). As is a common measure in DEA, adjusted admissions were multiplied by Case Mix Index (CMI) to calculate a CMI-adjusted admission count for the facility (AHA variable: ADJADM × CMI). AHA reports adjusted patient days of care to take into account the outpatient care provided by the hospital because staffing level data does not distinguish between in- and out-patient staffing. CMI was taken from the public data file from CMS for each year and reconciled against Medicare Number (AHA variable: HCFAID or MCRNUM) and is consistent with the move among scholars in DEA settings (Li and Rosenman, 2001 and O'Neill et al., 2008). Additionally, the number of patient days beyond the admission day (AHA variable: ADJPD − ADJADM) provided the length of stay measure and together with the admission variable were used to capture the average daily census. Finally, the volume of emergency room visits (AHA variable: VEM) and outpatient encounters (AHA variable: VTOT) were added to the outputs because they consume hospital resources.

Data for this study were taken from the American Hospital Association's (AHA's) Annual Survey for fiscal years 2005 through 2008 (sample size availability: 2005: n = 6349; 2006: n = 6346; 2007: n = 6312; 2008: n = 6407). The datasets used in this study were merged, cleaned, and cross-validated in Microsoft Excel using their Medicare Identification Numbers. In order to be included in the analyses, it was necessary to limit the sample to facilities with complete data over the entire time span. Altogether, 2849 hospitals had complete responses for the four years included in the study. DEAP was used to calculate the TFP, EFFCH and TC measures (Coelli, Rao, O'Donnell, & Battese, 2005). The four-year average of the Malmquist index, its standard deviation, and value range are presented in Table 2 below.

Table 2. The Malmquist indices summary of U.S. hospitals' means (2005–2008).[a]

| | Technical efficiency change (EFFCH) | Technological change (TC) | Total factor productivity (TFP) |
|---|---|---|---|
| Mean[b] | 1.0184 | 0.9916 | 1.0088 |
| s.d.[c] | 0.0756 | 0.0412 | 0.0750 |
| Min.[c] | 0.5219 | 0.8269 | 0.5437 |
| Max[c] | 1.4405 | 1.7981 | 2.5904 |

a

*n* = 2849.

b

All indices are geometric averages.

c

The s.d., minimum and maximum values are for individual facilities.

4. Results

The data from respondents to the AHA eLAB items were used to evaluate the Malmquist TFP index using a one-way Analysis of Variance (ANOVA) across these adoption patterns. Post hoc multiple comparisons of means were also conducted to determine whether the significance tests for each group followed a consistent pattern. Given the hierarchical nature of the groupings, we would expect consistent increases in significance with increases in electronic laboratory order usage.

The Malmquist productivity and efficiency indices described earlier were used to evaluate U.S. hospital performance. Table 2 summarizes the three indices' geometric means for the period from 2005 to 2008. Hospitals experienced an average annual increase of 1.8 percent in EFFCH, which translates into a cumulative 7.5 percent increase over the four-year period. However, the gains in the EFFCH factor are largely offset by the TC component of the productivity measure. Overall, the Malmquist analysis indicates that TFP increased approximately nine-tenths of one percent over the period studied (mean = 1.0088) in the 2849 hospitals that provided a full response (to the variables used in the model specification) from the AHA annual survey for each year of the analysis.

To determine if there was a response bias between those hospitals that submitted data on CPOE and those that did not, t-tests were used. In the case of both EFFCH ($p = 0.018$) and TC ($p = 0.007$), the results were found to be statistically different. Hospitals that reported data in both years on laboratory ordering were less technically efficient that their counterparts; however, they were more technologically advanced as indicated by the TC component. With respect to TFP, the difference between those that responded to the CPOE survey item in the AHA dataset and non-respondents were NOT significantly different ($p = 0.425$).

In our initial assessment (Table 3), we found that linking EFFCH (p = 0.071) and TC (p = 0.352) with eLAB system use level was not significant. However, we found statistically significant differences in the TFP indices for hospitals that were actively expanding the use of eLAB systems during the study (p = 0.021). Therefore, there is some support that TFP would be positively related to greater levels of eLAB system use.

Table 3. ANOVA for Malmquist indices and the use of electronic laboratory ordering by hospitals.[a]

| Variable | | Sum of squares | df | Mean square | *F* | Sig. |
|---|---|---|---|---|---|---|
| EFFCH | Between groups | 0.079 | 8 | 0.01 | 1.807 | 0.071 |
| | Within groups | 9.487 | 1744 | 0.005 | | |
| | Total | 9.566 | 1752 | | | |
| TC | Between groups | 0.016 | 8 | 0.002 | 1.112 | 0.352 |
| | Within groups | 3.132 | 1744 | 0.002 | | |
| | Total | 3.148 | 1752 | | | |
| TFP | Between groups | 0.106 | 8 | 0.013 | 2.257 | 0.021 |
| | Within groups | 10.23 | 1744 | 0.006 | | |
| | Total | 10.336 | 1752 | | | |

a

This ANOVA only includes the respondents who had either no change or indicated increased usage.

## 5. Discussion

While hospitals were able to increase the output-to-input ratio and increase technical efficiency levels (EFFCH) in the sector over the four years studied (Maniadakis, Hollingsworth, & Thanassoulis, 1999), efforts to improve the underlying care processes (i.e., TC) are not succeeding to the extent that they made a positive contribution to TFP. Therefore, there has been a trade-off between the EFFCH and TC factors resulting in minor gains in overall TFP.

Within the AHA survey, there are statistically significant differences in two of Malmquist indices between responders and non-responders. Non-responders had a higher score on the EFFCH measure, while responders had a systematically higher score on the TC measure. The net effect was no difference in TFP between responders and non-responders. If one assumes that non-responders are less likely to have implemented an eLAB system application, then adopting the new technology appears to have an adverse impact on efficiency in the near term. The corollary assumption, that responders would be more likely to have implemented an eLAB system application, then adopting the new technology appears to have a positive impact on the TC measure in the near term. Such a paradigm is consistent with the assumption that non-respondents are more likely to be non-adopters of eLAB system technology.

Overall, technical improvements to hospital performance did not exceed unity (TC < 1) over the period studied. Put another way, the TC's contribution to hospital productivity was not positive. Given the use of FTEs as inputs, this analysis could indicate that hospital employees are working harder (i.e., increasing efficiency gains), but not necessarily smarter (i.e., effectively employing new technologies) in order to maintain incremental, but marginal gains in overall productivity. Alternatively, hospitals could be expanding their numbers of licensed beds to gain economies of scale that would increase efficiency, but not influence TC. Given the relatively short time frame of the study, the former seems to be the more plausible explanation as a major change to physical structures are unlikely to have occurred in a widespread, systematic fashion. According to the results, the EFFCH measure accounts for the majority of gains in overall productivity rather than TC.

With respect to eLAB system implementation strategies, as presented in Table 4, the ‘Big Bang’ approach leads to relatively poor overall performance (TFP = 0.983). The high performing strategy with respect to changes in efficiency and productivity is to implement the eLAB system on limited basis and then move to widespread use within a year as indicated by the group labeled ‘Major Progress’ (EFFCH = 1.044; TFP = 1.037). The ‘Simple Introduction’ approach to eLAB system implementation did not have either an adverse or positive impact on changes in efficiency and technology. Given the ‘Simple-Introduction’ tactic is the first step in the ‘Major Progress’ strategy, this provides further evidence that a limited introduction followed by a rapid expansion may be an optimal approach. Lastly, the slowly staged roll-out strategy (i.e., Incremental Progress) is also sub-optimal compared to other approaches (TFP = 0.996). Such an approach is comparable to the ‘stuck-in-the-middle’ problem firms face when they pursue multiple strategies in marketing products to consumers.

Table 4. Means, by category, for EFFCH, TC and TFP.

| Variable | Category | *N* | Mean | Std. Deviation | Std. Error |
|---|---|---|---|---|---|
| EFFCH | Negative change for adopters to no use | 60 | 1.0178 | 0.0697 | 0.0090 |
| | Negative change for adopters still using | 37 | 1.0006 | 0.1116 | 0.0184 |
| | Never adopted | 895 | 1.0162 | 0.0763 | 0.0026 |
| | No change for current users 1–49% | 312 | 1.0161 | 0.0714 | 0.0040 |

| Variable | Category | *N* | Mean | Std. Deviation | Std. Error |
|---|---|---|---|---|---|
| | No change for current users 50–100% | 190 | 1.0245 | 0.0648 | 0.0047 |
| | Major progress | 31 | 1.0437 | 0.0703 | 0.0126 |
| | Simple introduction | 94 | 1.0077 | 0.0694 | 0.0072 |
| | Incremental progress | 74 | 1.0050 | 0.0601 | 0.0070 |
| | Big bang | 60 | 0.9992 | 0.0727 | 0.0094 |
| | Total | 1753 | 1.0158 | 0.0739 | 0.0018 |
| TC | Negative change for adopters to no use | 60 | 0.9826 | 0.0360 | 0.0046 |
| | Negative change for adopters still using | 37 | 0.9877 | 0.0367 | 0.0060 |
| | Never adopted | 895 | 0.9944 | 0.0461 | 0.0015 |
| | No change for current users 1–49% | 312 | 0.9947 | 0.0398 | 0.0023 |
| | No change for current users 50–100% | 190 | 0.9914 | 0.0363 | 0.0026 |
| | Major progress | 31 | 0.9928 | 0.0576 | 0.0103 |
| | Simple introduction | 94 | 0.9968 | 0.0401 | 0.0041 |
| | Incremental progress | 74 | 0.9920 | 0.0293 | 0.0034 |
| | Big bang | 60 | 0.9848 | 0.0297 | 0.0038 |
| | Total | 1753 | 0.9932 | 0.0424 | 0.0010 |
| TFP | Negative change for adopters to no use | 60 | 0.9992 | 0.0641 | 0.0083 |
| | Negative change for adopters still using | 37 | 0.9882 | 0.1154 | 0.0190 |
| | Never adopted | 895 | 1.0095 | 0.0845 | 0.0028 |
| | No change for current users 1–49% | 312 | 1.0095 | 0.0648 | 0.0037 |
| | No change for current users 50–100% | 190 | 1.0147 | 0.0595 | 0.0043 |
| | Major progress | 31 | 1.0372 | 0.1091 | 0.0196 |
| | Simple introduction | 94 | 1.0029 | 0.0573 | 0.0059 |
| | Incremental progress | 74 | 0.9964 | 0.0570 | 0.0066 |
| | Big bang | 60 | 0.9832 | 0.0640 | 0.0083 |
| | Total | 1753 | 1.0079 | 0.0768 | 0.0018 |

The availability of electronic clinical information is an essential component of a broader system of hospital changes. To realize productivity and efficiency gains from computers in healthcare settings, managers have to re-engineer the hospital to match workflows with the capabilities of those systems. Therefore, it is a reasonable expectation that implementing an eLAB system would adversely impact hospitals' efficiency levels in the near-term as extra effort is required to redesign processes and workflows.

As such, implementing an eLAB system requires a rethinking of job processes and employees' roles and responsibilities (i.e., scope of practice) as well as organizational hierarchy (Chapman, 1997). The move to a fully integrated and functional EHR involves training the workforce, which would impact EFFCH favorably. However, some organizations retain their same processes and structures because the required changes are initially time consuming. Rather than making the necessary internal changes, it is a common strategy to add a specialist (i.e., outsourcing) to handle specific types of issues in professional domains. One indication of this phenomenon is a new class of workers that serve as 'scribes' for physicians (Anonymous, 2008).

Of greater concern is the push to meaningful use and the implication of these findings to such efforts, especially as eLAB systems are being recommended as part of the second stage. The data suggests that when eLAB system implementations occur too quickly (e.g., the Big Bang), efficiency and productivity are adversely impacted. Comparing the various approaches, facilities may want to consider a Major Progress strategy for eLAB system implementation as a means of qualifying for federal rewards and avoiding future penalties vis-à-vis other options.

## 6. Limitations and future research

The American Hospital Association (AHA) and the Center for Medicare and Medicaid Services (CMS) datasets suffer from two limitations. First, neither data set has complete information on all U.S. facilities for the entire period studied. Case mix index (CMI) is reported only for facilities that accept Medicare for payment—reducing the baseline number of facilities to nearly half. Therefore, the productivity gains for the period studied here are not representative of the entire hospital sector. Further, hospitals in the sample are those that have been established for some time, and as such new facilities may not face the same challenges.

Another limitation is that this study does not include reimbursement information that would allow other forms of productivity analyses to be performed (Herrero & Pascoe, 2004). In particular, it would be useful to generate information on allocative efficiency using the Fisher (1922) and Törnqvist (1936) productivity indices. However, such models require better service pricing information that is not widely available. Indices that include accurate pricing data would be more directly applicable to the study of policy changes designed to increase productivity by using global payment schemes.

The solution to both of the aforementioned limitations would be to use CMS data to conduct hospital productivity analyses. The fidelity of the facilities' submissions would be better assured because false reporting would constitute fraud and be criminally punishable. Because CMS has the payment information related to its Medicare enrollees, other productivity analyses could be conducted. CMS data may provide additional insights, but it is in turn, limited to those facilities that accept Medicare for payment. While this clearly includes over 50 percent of the hospitals in the AHA survey, it creates a bias in the analysis towards hospitals that take both, suggesting that in either case, both analytic approaches may be necessary to get the whole picture.

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