Organizational Differences in Rates of Learning: Evidence from the Adoption of Minimally Invasive Cardiac Surgery

Gary P. Pisano • Richard M.J. Bohmer • Amy C. Edmondson
Harvard Business School, Soldiers Field Road, Boston, Massachusetts 02163
gpisano@hbs.edu • *rbohmer@hbs.edu* • *aedmondson@hbs.edu*

This paper examines learning curves in the health care setting to determine whether organizations achieve performance improvements from cumulative experience at different rates. Although extensive research has shown that cumulative experience leads to performance improvement across numerous contexts, the question of how much of this improvement is due to mere experience and how much is due to collective learning processes has received little attention. We argue that organizational learning processes may allow some organizations to benefit more than others from equivalent levels of experience. We thus propose that learning curves can vary across organizations engaged in the same "learning task," due to organizational learning effects. To investigate this proposition, we investigate cardiac surgery departments implementing a new technology for minimally invasive cardiac surgery. Data on operative procedure times from a sample of 660 patients who underwent the new operation at 16 different institutions are analyzed. The results confirm that cumulative experience is a significant predictor of learning, and further reveal that the slope of the learning curve varies significantly across organizations. Theoretical and practical implications of the work are discussed.
(*Organizational Learning; Learning Curves; Process Improvement*)

1. Introduction

The concept of organizational learning has long fascinated scholars from a range of management and social science fields. The learning curve in particular has been the subject of extensive study and discussion in the fields of operations management, economics, competitive strategy, and technology management. More recently, scholars and practitioners have shown renewed interest in learning because of its intimate link to emerging theories of core competencies, dynamic capabilities, and resource-based views of the firm.[1] Quite simply, without learning, organizations are not likely to cultivate the unique skills and capabilities that underlie competitive advantage. Understanding the processes by which organizations learn, and how these processes might be better managed, are issues of central importance of scholars and practitioners alike.

Learning is often equated with experience. Indeed, the terms "learning curve" and "experience curve" are frequently used interchangeably. An extensive number of empirical studies have documented the link between cumulative experience (e.g., cumulative production volume, cumulative production time) and some measure of operational performance improvement (e.g., cost reduction, yield improvement, productivity improvement).[2] The implications of the

[1] Teece et al. (1997), Edmondson and Moingeon (1996), Teece and Pisano (1995), Prahalad and Hamel (1990), and Wernerfelt (1984).

[2] Sinclair et al. (forthcoming), Hatch and Mowery (1998), Argote (1996), Argote et al. (1995), Gruber (1994), Jarmin (1994),

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learning curve—that "practice makes perfect" and performance improves with experience—have held up remarkably well over time. In recent years, however, researchers have begun to question the extent to which performance improvement is an "automatic" benefit of cumulative experience versus a result of more subtle processes of "organizational learning."[3]

Theories of organizational learning suggest that organizations vary in their capacity for learning.[4] This work argues that organizations facing similar changes in the environment can learn (or fail to learn) in different ways, due to cognitive (Senge 1990), interpersonal (Argyris and Schon 1978), structural (Duncan and Weiss 1979), or managerial (Dutton and Thomas 1984) factors. However, as most studies of learning curves have focused on detailed longitudinal data within one or a small number of companies, or within multiple facilities owned by the *same* firm (e.g., Hayes and Clark 1986), it has been difficult to identify the effects of organizational-level learning processes that contribute to performance improvement above and beyond experience. Further, studies involving multiple firms have included differences in technology that make it difficult to compare learning across sites. Thus, although some studies support the idea that learning curves differ across organizations (Dutton and Thomas 1984, Argote and Epple 1990), further conceptual and empirical work is needed to better understand this phenomenon.

In this paper, we directly investigate the possibility of differences in rates of improvement across independently owned organizations, using data on the adoption of a particular new technology for minimally invasive cardiac surgery. We obtained detailed data on procedure times and other aspects of surgical performance on a sample of 660 patients who underwent this operation at 16 institutions over the time period 1996–1998. This unique data set allows us to estimate learning curves and to explore differences in learning outcomes across highly similar organizations, We predict that cardiac surgery departments will achieve benefits from cumulative experience at different rates. In short, we propose that some organizations will undergo greater organizational learning than others. To develop this proposition more fully, the next section of this paper draws from relevant literature on learning and learning curves. Section 3 then provides a brief overview of the particular surgical technology and procedure studied. In §4, we develop and test a set of statistical models of performance improvement (in the form of procedure-time reduction). Section 5 probes factors contributing to differences across institutions in the rate of learning, and §6 discusses the implications of these results for future research.

Gruber (1992), Epple et al. (1991), Adler (1990), Argote et al. (1990), and Wright (1936).

[3] Adler and Clark (1991).

[4] Miller (1990), Senge (1990), Duncan and Weiss (1979), and Argyris and Schon (1978).

2. Anticipating Differences in Rates of Learning

The present study draws from three research streams: (1) learning-curve studies in industrial settings, (2) volume-outcome studies in medicine, and (3) theoretical work on organizational learning. Although a comprehensive review of these literatures is beyond the scope of this paper, central themes from each can be highlighted to identify an important gap in our understanding of learning in organizations.

Learning-Curve Studies. Few concepts in management and economics have drawn more empirical attention than the learning curve. Starting with Wright (1936), many studies have demonstrated the link between cumulative experience and performance improvement and established a fairly robust association between cumulative experience (e.g., cumulative production volumes) and performance improvement (e.g., cost reduction) in a variety of industrial settings, providing an empirical basis for the concept of learning-by-doing.[5] Despite the extensive body of research on learning curves, two topics have received comparatively little attention. First—although von Hippel (1976) and Rosenberg (1976) have highlighted

[5] Sinclair et al. (forthcoming), Hatch and Mowery (1998), Argote (1996), Argote et al. (1995), Gruber (1994), Jarmin (1994), Gruber (1992), Epple et al. (1991), Cohen and Levinthal (1990), Adler (1990), Argote et al. (1990), and Wright (1936).

the critical role of user learning for several technologies, "learning-by-using" has received comparatively little empirical attention in the learning-curve literature. Given the powerful influence of users in the innovation process (von Hippel and Tyre 1995, von Hippel 1982), user learning curves present an important area for research.

Second, firm-level and organizational-level differences in slopes of learning curves have received relatively little attention. A few studies have established the possibility that learning curves can vary across plants or organizational subunits *within* the same company (e.g., Hayes and Clark 1986). These differences were not explained by product or technology differences, suggesting the possibility of organizational learning effects—in addition to experience effects—as a contributor to performance improvement. In general, research has not compared learning curves across independent organizations in the same industry. An exception to this is Jarmin's (1994) study of early U.S. rayon production, in which he noted that the relationship between cumulative experience and performance improvement might differ across producers. He analyzed learning curves for two rayon producers and a third composite firm for the years 1911–1928, and found differences in the abilities of rayon producers to benefit from their own cumulative production experience. Although this finding is limited by the very small number of "firms" and by the historical nature of the data, it suggests that further research into differences in the magnitude and drivers of learning curves across firms is worthwhile.

Volume and Outcomes in Medicine. An extensive literature documents the effects of cumulative experience on clinical performance in health care settings (see Luft et al. 1990 for a comprehensive review). These studies have been consistent in finding an association between clinical performance (e.g., lower rates of mortality) and case volume across a range of surgical procedures.[6] As in industrial settings, no attempt has been made in medical research to discern whether all hospitals or surgical units learn at the same rate. Instead, the research presents an implicit assumption that, after taking into account other factors, the effect of volume on clinical outcomes is the same across institutions. Also, these studies have consistently used volume per year as a proxy for experience, which confounds dynamic learning-curve effects and static scale economy effects. As Luft et al. (1990) point out:

> Given the available data, it has been impossible to distinguish the learning effect from the scale effect. To do so, one would have to measure both the current volume and the accumulated experience of the relevant professionals and organizations (p. 12).

Finally, studies in the medical literature have tended to examine improvement in procedures that were in place for a number of years prior to the sampling period. As a result, this research has not shed light on the relationship between cumulative case volumes and outcomes during the initial adoption period when opportunities for organizational learning are likely to be greatest. Moreover, organizational learning processes may influence performance improvement in new procedures more than in mature medical procedures. To better understand learning processes in organizations, we propose studying organizations soon after they have adopted new technologies that require the development of significantly new routines and skills.

Organizational Learning. In contrast to learning-curve research, organizational learning has drawn more theoretical attention than empirical analysis. Although a broadly accepted framework for understanding organizational learning has remained elusive (Edmondson and Moingeon 1998), two themes in this literature about which there is broad agreement suggest that variance across organizations facing a similar learning opportunity is likely.

First, organizational learning is viewed as a process of seeking, selecting, and adapting new "routines" to improve performance (Nelson and Winter 1982, Levitt and March 1988). In any sufficiently complex situation, there are many combinations and permutations for how a given activity might be performed; thus, a theoretically optimal approach may exist but is likely to be extremely difficult or even impossible to iden-

[6] For example, after controlling for the patient's comorbidities, the probability of death in a coronary artery bypass graft operation is significantly lower at hospitals performing 125 or more of these procedures per year (Crawford et al. 1996).

tify. New routines thus evolve through both deliberate choice (e.g., "let's try eliminating this step to save time") and through more path-dependent trial-and-error processes (Nelson and Winter 1982). The learning process is thus complex and unpredictable.

Second, the literature on organizational learning suggests that organizations have different capacities for learning (e.g., Cohen and Levinthal 1990, Miner and Mezias 1996). Learning from experience is not automatic, but rather may result from action and reflection within the organization. Experience may provide the opportunity to learn, but a range of factors has been posited as influences on whether this opportunity is actually exploited (Senge 1990, Argyris and Schon 1978, Duncan and Weiss 1979, Dutton and Thomas 1984). This literature leads us to expect that such factors as team structures, incentives, use of analytic tools for capturing and anaylzing information, and psychological safety (Edmondson 1999) are a moderating influence between experience and performance improvement. In summary, drawing from three research streams, we argue that the slope of a performance improvement learning curve in different organizations undertaking the same learning task will vary. Specifically, organizational learning processes will allow different organizations with equivalent experience levels to exhibit different levels of performance improvement. Thus, the core proposition in this paper is that documented performance improvements in so-called learning curves are a function of both experience *and* organizational learning.

3. Research Design and Context

To investigate this proposition, we collected data from cardiac surgical units in 16 hospitals adopting a specific new technology for minimally invasive heart surgery. The technology was developed by a private company and received FDA approval in 1996. By holding constant the technology, the study design enables us to isolate differences in learning rates that are due to organizational, as opposed to technological, factors.

This technology was particularly conducive to exploring the research proposition presented above. First, all adopting hospitals received the same three-day training session prior to performing operations on patients, such that all of the operating-room teams in our sample had the same starting base of experience and competence with the procedure prior to the first real case. Second, the technology had been in commercial use for approximately two years—a long enough time horizon over which to observe significant performance improvements by adopters, and short enough to allow interviews with people directly involved in early use of the technology who could accurately recall these early experiences. In addition, the newness of this technology enabled us to trace learning curves for each site from the first use of the technology after the training. Third, the company that developed the technology had assembled a comprehensive database documenting all operations with the new technology. This database contained detailed information on procedure times, surgical outcomes, patient characteristics, and other relevant variables, and because the data were to be used for clinical study purposes, they were collected under strict clinical protocols.[7] The company agreed to provide us with access to these data under standard conditions of confidentiality,[8] and helped us to obtain access to personnel at the adopting hospitals. Finally, as described below, adopting of this technology required more than mastering the surgical technique; it required a significant degree of change in the way different members of the surgical team interacted and communicated.

Minimally Invasive Cardiac Surgery. Most cardiac surgery comprises three phases: gaining access to the heart, operating on the heart, and exiting the chest. The surgeon obtains access to the heart by splitting the breastbone and separating the ribs. The patient's blood is then rerouted from their chest to a "heart-lung machine," which supports the blood pressure and oxygenates the blood while the heart is stopped. During the operation, a clamp is placed on the aorta to prevent blood from flowing backward into the heart during the operation. The most common cardiac surgical procedure is coronary artery bypass graft

[7] Data were collected by individual hospitals and checked and cleaned by an independent contract research organization.

[8] All patient names and identifiers were scrubbed from the database prior to its transfer to us.

(CABG), in which a blocked artery is bypassed with either a vein taken from the leg or an artery dissected from the inside of the chest wall. Other types of procedures included replacement and repair of mitral vales (MVR) and repair of atrial septal defects (ASD). Once the operation is complete, the heart is allowed to resume beating, fill with blood, and gradually take over responsibility for generating blood pressure. At this point the patient is weaned from the pump and the chest is closed.

The most important difference between minimally invasive cardiac surgery and the conventional procedure is that the breastbone is not cut and split. Instead, the heart is accessed through a small incision between the ribs using specially designed instruments. Because the incision is too small to admit the tubes that take the blood from the patient to the pump, these tubes are placed in the artery vein in the groin. Instead of clamping the aorta externally, a catheter is threaded through the groin up into the aorta and then a balloon is inflated to stop the blood flowing backwards. The technology poses both a technical challenge for the surgeon, who must operate in a substantially reduced space, and an organizational challenge for the operating-room team, which must learn a new interpersonal routine.

In conventional surgery, the roles of each team member are well established. In addition, because the chest is open, everyone has direct visual access to the operative field and the surgeon has both visual and tactile access. This allows team members to monitor progress of the operation and to use visual cues to anticipate what actions will be needed. For instance, the clamping of the aorta is visually apparent to everyone in the operating room and is a signal to the scrub nurse that the surgeon will soon begin the actual repairs to the heart.

In the new procedure, because of the much smaller incision, direct visual and tactile access are severely limited. As a result, communication between team members becomes critical in monitoring progress and in coordinating actions. A good example of the required change is the clamping of the aorta. In conventional heart surgery, clamping the aorta requires virtually no coordination or communication. It is done by the surgeon and is visually apparent to everyone on the team. In the new procedure, the aorta is "clamped" by placing a deflated balloon at a precise location in the aortic arch (just outside the heart) and then inflating it to the requisite level of pressure. The process begins with the surgeon threading a catheter into the groin and up the aorta toward the heart. It is critical to monitor the progress of the catheter to ensure that it is passing safely through the aorta. Because the surgeon cannot directly see the tip of the catheter inside the aorta, he must rely on other team members for the critical information. Transesophageal echo[9] (TEE) images provide critical information on the location of the catheter and the balloon. However, because only the anesthesiologists are typically trained in TEE, the surgeon is heavily reliant on them for this delicate part of the procedure. Perfusionists (specially trained technicians who operate the heart-lung machine) typically monitor balloon pressure. The nurses consult monitors that display patient vital signs; a dramatic difference in blood pressure between one side of the body and another is a sign that the balloon is not located properly. Proper placement of the balloon requires that team members share information among themselves (to identify warning signs) and to relay information on a continuous basis to the surgeon who makes adjustments to the balloon through a catheter. Only after the balloon is properly placed and inflated, and the aorta occluded, can the surgeon begin performing repairs to the heart. Through interviews with members of the operating-room teams, we learned that problems of accurately placing the balloon were one of the single biggest causes of delays in the operation.

The placement of the balloon provides an example of the expanded roles of nonsurgeon team members during the new procedure. The anesthesiologist, who in a conventional case had little to do while the patient is supported by the pump, plays a key role in monitoring balloon placement through the TEE images. The scrub nurse, who formerly could see the operative area to follow the surgeon's progress

[9] Transesophageal echo, or TEE, is a kind of ultrasound technology primarily used by cardiologists and anesthesiologists.

and anticipate what to do next, has to consult monitors and communicate with both the surgeon and other team members on the progress of the operation. The perfusionist, who worked exclusively with the surgeon in a conventional case, has to work collaboratively with the anesthesiologist and scrub nurse in placing the balloon and monitoring its movements. Conventional surgery could be described as a "modular" process whereby task boundaries are well established and fairly independent; the new procedure is a far more integral process in which task boundaries are more blurred and tasks are interdependent. Thus, the technology disrupted the smooth flow of the operative routine and required the development of new communication behaviors and new routines to enable the execution of more interdependent set of processes.

Data. To document rates of learning at the organizational level, we obtained access to operative histories of 660 patients who had received the new procedure at 16 institutions nationwide. Of these 16, nine were academic medical centers ("teaching hospitals") and seven were nonacademic ("community") hospitals. The average hospital in our sample undertook a fairly high volume of cardiac surgeries on an annual basis (approximately 1,400/year); total annual cardiac surgery volumes ranged from 400–3,500 cases per year. All of the hospitals in our study were nonprofit entities. Most of the hospitals had extensive experience adopting new cardiac surgery innovations, and all had at least some prior experience with innovation. The company that introduced the technology had targeted these institutions because they were considered to have "first tier" cardiac surgery departments (with moderate to high total case volumes, reputable surgeons, and a reputation for high-quality care and excellent clinical outcomes).

For each institution, we assembled a fairly complete case series that spans the first case performed at a hospital through the last case performed as of November 1998. The average number of cases for a site in our sample was 40, with a low of 11 and a high of 95. Differences in number of cases performed across sites were generally the result of two factors. Although all 16 hospitals in our sample were considered "early adopters" (because they adopted within the first year of FDA approval), there were differences in the exact time of adoption, which influenced the number of cases performed by November 1998. The site with 95 cases, for instance, was the first adopter of the technology. In addition, sites also varied in the rate (number of cases/month) at which they were able to do the procedure (due to availability of appropriate patients and interests of the adopting surgeon). Most of these data were obtained from a database compiled for clinical study purposes, but we obtained missing data directly from the databases created by the hospitals and surgical departments. The resulting database contained the following information for each patient in the sample: characteristics of the patient (e.g., age, sex, height, and weight), indicators of health status prior to the operation (e.g., presence of diabetes or chronic lung disease), the type of cardiac surgery performed (CABG, MVR, ASD, or multiple procedures), the type and number of arteries bypassed (when relevant), the date of the operation, the ordinal sequence a case represented for the hospital (first case, second case, etc.), and times required to complete various phases of the operation.

We conducted interviews with cardiac surgeons, cardiologists, anesthesiologists, nurses, perfusionists, and administrators at each of the 16 hospital sites. These interviews provided important technical information that informed the design of our statistical models, and provided data on how each site approached adoption, management practices, and organizational climate.

4. Statistical Models and Analysis

In any context, there may be multiple ways to measure learning. In this paper, we focus on one dimension: reduction in the time required to perform the minimally invasive cardiac surgery *(procedure time)*. For several reasons, investigation of this dimension of learning provides a critical lens through which to examine organizational learning.

First, previous case studies have indicated that procedure time is perhaps the single most important factor driving the total costs of treating and caring for a cardiac surgery patient.[10] This view was further corroborated during our interviews with administrators

[10] See, e.g., "Partners HealthCare System, Inc. (B): Cardiac Care Improvement," Harvard Business School case number 9-696, and

at hospitals in our study. Long procedure times cut into the available capacity for performing surgeries, and thus have a high opportunity cost in terms of foregone revenue. In addition, cardiac surgery teams consist of highly trained professionals. Typically, hospitals and physicians are each paid a set fee for performing a specified type of cardiac surgery (e.g., single-vessel coronary artery bypass or mitral valve repair). No additional compensation is provided for using a new technique that takes longer to treat a particular condition. Thus, if a new technique requires an additional three hours to perform compared to a conventional procedure, the additional cost is borne by the hospital.[11] And, in recent years, as hospitals have faced significant price restraints from both public payers and private managed-care insurers, the issue of cost has become a critical area of focus.

Second, procedure time is a good proxy for organizational learning. As described earlier, minimally invasive cardiac surgery requires a new type of coordination among several professionals, involving intensive learning by an operating-room team. Improved coordination and communication occur through developing and refining team routines, thereby allowing shorter procedure times. Finally, use of procedure time as a dependent variable alleviates the problem of "selective referral," which has faced prior medical learning-curve studies. Using medical outcome (such as mortality) as a dependent variable leaves open the possibility that hospitals and surgeons with better outcomes get more referrals, confounding the causal linkage. In contrast, because procedure time is not a basis for referral of a patient to a surgeon or hospital, it is extremely unlikely that procedure-time results are confounded by selective referral biases.

One potential concern of focusing on procedure time is the possibility that other dimensions of performance—particularly clinical outcomes—may suffer when procedure times are reduced. Reducing procedure times and reducing the risk of complication or death, however, are not necessarily in conflict. The incidence of central nervous system complications tend to rise with the length of time the patient is on the heart-lung machine (Roach et al. 1996).[12] Thus, the surgeons we interviewed indicated that reducing procedure time was desirable from the perspective of a patient's well-being. Clearly, however, "rushing" an operation could lead to poor clinical outcomes. The impact of procedure time on clinical outcome in any given case is extremely difficult to determine; however, the surgeons we interviewed explained that reducing procedure time, while important, was far less important than achieving optimal clinical outcomes. We had no reason to disbelieve surgeons' reports that efforts to reduce procedure times were taken within the confines of delivering high levels of care.[13]

Dependent Variables. Procedure time reduction—a measure of efficiency improvement—can occur due to increased surgeon skill, as well as due to improved coordination within the operating-room team. To distinguish between these two factors, we used two measures of procedure time. *Total procedure time* is the time from the point of the first incision to the completion of the operation; this measure directly relates to the total resources used and cost of the procedure to the hospital, and thus has important managerial implications. We calculated a second dependent variable by subtracting out the time for the *aortic occlusion* phase of the operation from total procedure time. Aortic occlusion occurs *after* the heart is completely stopped and the balloon clamp has been successfully placed and inflated. During aortic occlusion, the surgeon performs repairs to the heart itself. Individual surgeon

"Massachusetts General Hospital: CABG Surgery (A)," Harvard Business School case number 9-696-015.

[11] Medicare and some private insurers make reimbursement provisions for "outlier" patients. However, such extra reimbursements typically only apply when there is a very large difference in the cost of treating a specific patient relative to the average (e.g., the patient experienced complications and was hospitalized for 30 days instead of the normal 5-day period).

[12] We attempted to discern whether shorter procedure times were associated with higher postoperative patient mortality rates in our sample. Detecting any correlation, however, was made impossible by the extremely low mortality rate in our sample.

[13] Finally, as a check, the data set allowed us to check for differences in mortality and complication rates; the result that there were no differences across hospitals in either outcome supports the claim that some hospitals did not attempt to reduce procedure time at the expense of clinical outcomes.

speed, rather than team coordination, is likely to be the dominant influence on how long the aortic occlusion phase lasts. By netting out aortic occlusion time from total procedure time, we constructed a measure that more closely captures the effects of team coordination—called *net adjusted procedure time.*

Control Variables. To isolate the effects of cumulative volume on procedure time, we needed to include in our model as many factors as possible that also impact procedure time. Obviously, in any operation on any given patient, there are many factors that ultimately determine the procedure time. For our purposes, it was critical to identify systematic factors: those that might cause large differences in procedure time *and* that varied systematically across the time series of cases at any given site. We attempted to identify as many of these factors as possible through surgeon interviews and through review of relevant medical literature.

First, the particular procedure being performed is likely to affect procedure time. The technology studied can be used for several types of heart repairs, including coronary artery bypass, atrial septic defect repair, and mitral valve repair or replacement. In some cases, a combination of repairs is performed during the same operation. The procedure mix varied across sites in the sample. We controlled for the effects of different procedures by including dummy variables for the following procedure types: CABG, ASD repairs, and multiple procedures (mitral valve repair/replacement is the excluded category). The distribution of procedures in our sample was as follows: CABG (49%), valve repair/replacement (43%), ASD repair (4%), and multiple procedures (4%). Data provided by the company indicated that the distribution of procedures in our sample was very similar to the distribution of procedures performed by all adopters of the technology.

Second, we controlled for the number of grafts in the CABG operation; each graft takes time to sew, hence lengthening procedure time. Third, characteristics of the patient can also influence operative times. Surgery on sicker patients is likely to take longer due to the risk of complications. We used a slightly modified version of a standard measure of patient health known as the Higgins Score. The Higgins Score, a predictor of the probability of death, is a composite of several preoperative factors.[14] Our measure is a modified Higgins Score (without anemia, a variable that was not collected in the clinical database we accessed).

One potential factor that might influence operative times is the vintage and type of equipment available to the teams in our sample. We did not include this factor in our analysis because the 16 sites had no major differences in basic cardiac surgery operating-room equipment. Second, the company that developed the technology required all adopting sites to use a consistent, specific set of specialized instruments and catheters for the operations, as this set was approved by the FDA. The company also specified the use of certain other types of equipment for its procedure (notably, fluroscopy and TEE cardiographs). Thus, adopting sites had limited degrees of freedom in their choice of equipment. Finally, even if there were small differences in equipment across sites that affected procedure times, these differences would be reflected in the intercept term rather than the site-specific learning-curve slope coefficients.

We estimated the following model:

$$\begin{aligned}
&\ln(\text{Procedure Time}_i)\\
&\quad = \alpha_0 + \beta_0 \text{CABG}_i + \beta_1 \text{Grafts}_i\\
&\qquad + \beta_2 \text{ASD}_i + \beta_4 \text{Multi-Procedure}_i + \beta_5 \text{Higgins}_i\\
&\qquad + \beta_6 \ln(\text{Cumulative Volume}_{ij}) + \beta_{7j} \text{Hospital}_j\\
&\qquad + \beta_{8j} \text{Hospital}_j * \ln(\text{Cumulative Volume}_{ij}) + e_{ij},
\end{aligned}$$

where each of the variables is defined as follows:

Procedure Time$_i$. Time in minutes required to perform the procedure on the ith patient.

CABG$_i$. A control variable coded 1 if the procedure was a coronary artery bypass, and 0 otherwise.

Grafts$_i$. A control variable indicating the total number of sites where veins or arteries were stitched to the cardiac arteries being bypassed on the ith patient.

[14] The factors are the extent to which the operation is an emergency case, patient weight and age. the level of serum creatinine, severity of left ventricular dysfunction, the number of previous cardiac surgeries on the patient, the level of mitral valve insufficiency, prior vascular surgery, the presence of chronic obstructive pulmonary disease, diabetes, anemia, cerebrovascular disease, and the presence of aortic valve stenosis.

ASD_i. A control variable coded 1 if the procedure was an atrial septal defect repair, and 0 otherwise.

Multi-Procedure$_i$. A control variable coded 1 if multiple types of repairs were performed on the heart during the operation.

Higgins$_i$. A control variable based on the Higgins Score to adjust for the health status of the ith patient at the time of the operation.[15]

Cumulative Volume$_{ij}$. The number of prior cases of the minimally invasive procedure performed at hospital j when patient i had his/her operation.

Hospital$_j$. A vector of j dummy variables indicating at which hospital patient i had his/her operation.

This model enables isolation of the effects of cumulative volume on procedure time (the main effect) and determination of whether this effect is different across sites in the sample (the interaction term). Many site-specific factors might affect this result. For example, previous research has shown that *the rate* of experience accumulation can have an impact on learning through "forgetting" effects (Argote et al. 1990). In this study, rate of experience could be an important factor, along with characteristics of the surgical team (e.g., experience or leadership style) and of the institution (e.g., size or hospital type). Our analytic strategy is to first test for differences in learning-curve slopes across institutions, and then to examine factors that might explain these differences.

We estimated the model using log specifications of the dependent variable procedure time and the independent variable, cumulative volume.[16] This approach follows the convention of prior learning-curve studies and is consistent with the fact that, in absolute terms, procedure times cannot decline at a linear rate forever. As an organization reduces its procedure time, we expect marginal reductions in absolute times to become progressively more difficult and thus smaller. Eventually, we would expect procedure times to approach an asymptote.

The coefficients of the model can be interpreted as follows. β_6, the coefficient on ln(*Cumulative Volume*), captures the average impact of case volume experience on procedure time across all institutions. Previous learning-curve studies lead us to expect this coefficient to have a negative sign. That is, on average, we expect procedure times to fall in proportion to case volume experience (holding constant other variables). β_{7j} is a vector of coefficients that captures how the average procedure times across institutions vary. β_{7j} can be viewed as shifting up or down the procedure time estimate for any given hospital.

β_{8j} is a vector of the coefficient that captures the extent to which the slope of the learning curve for a given institution varies from the average. β_6–β_{8j} can be interpreted as the learning-curve coefficient for site j. The central proposition of this paper is that—while cumulative experience generally leads to performance improvement—organizational learning processes are likely to lead to differences in the rates of learning across institutions. A result obtaining significant differences among the β_{8j} estimates would support this proposition.

We estimated one model that pooled observations across sites and included dummy variables for hospitals and an interaction term. With this approach, we used the larger pool of data to estimate common effects, while isolating the predicted institution-specific differences through dummy variables and interaction terms. An alternative approach would have been to estimate a separate regression model for each of the 16 sites (and exclude the site dummy and interaction term). However, this would require including the entire set of independent variables in each equation (less site dummy and interaction terms), and thus would not be an efficient use of degrees of freedom. We used the approach that assumed that the effects of control variables (*Higgins*, *CABG*, *Grafts*) on procedure time were the same across institutions in our sample, because the surgeons in our study, although from different institutions, consistently identified the same set of factors as influencing procedure times. Moreover, the Higgins index was constructed by statistical research in the medical

[15] In our preliminary analyses, we estimated several versions of the model using separate components of the Higgins index. These did not improve the fit or statistical power of the model.

[16] We ran tests for autocorrelation, and found an autocorrelation estimate for the full ln(*Procedure Time*) model of −0.022, with a 95% confidence interval (−0.105, 0.061). For the full net adjusted procedure time model, the autocorrelation estimate is −0.017, with a 95% confidence interval (−0.107, 0.070). For both models, the results are not different from zero, indicating a lack of autocorrelation.

community on very large samples of patients across many institutions, suggesting that the index has fairly similar effects across institutions. Finally, in preliminary statistical analyses we estimated separate models for each site and found that effects of the control variables were consistent across sites.

Results. Table 1 shows the results of the total procedure-time models. For clarity of presentation, Table 1 does not report the individual coefficients on site-specific estimates (*Hospital*$_j$ and *Hospitalj** ln(*Cumulative Volume*$_{ij}$)), but simply denotes whether the vector is statistically significant from 0. Table 2 shows the analogous results for the net adjusted procedure-time models.

In the total procedure-time models (Table 1), all control variables except *Higgins* have the expected sign and are statistically significant in all specifications. Model 2 considers the effect of cumulative volume. Consistent with previous learning-curve studies, the estimated coefficient is negative and statistically significant; on average, total procedure time falls with the institution's cumulative experience with the technology. Model 3 adds a dummy variable for each hospital site. The vector of dummy site variable coefficients (B_{7j}) is statistically significant and improves the overall fit of the model.

Next, we address the question of whether hospital effects are different from each other. Results of the F test show that the magnitude of site-specific effects on procedure time varies significantly across hospitals ($F = 14.11$, $p < .0001$). Because the site dummies affect the intercept, this finding suggests that initial procedure times varied significantly across hospitals in our sample. This finding is interesting given that all adopting sites received highly standardized training in how to conduct the procedure. The company invested heavily in this training, both in the development of supporting documentation and training materials and in providing technical support in the field. Despite these efforts, these results indicate that some adopters start off faster than others.

Model 4 addresses the core research question of the study—whether sites learn at different rates. To do this, it includes an interaction term between the hospital dummy and cumulative experience. Whereas Model 3 helped us identify differences across hospitals in the intercepts, Model 4 isolates differences in slopes. These results show, first, that the vector of coefficients corresponding to the interaction term is statistically significant. Second, affirmatively answering our core research question, the results show that these site-specific slope coefficients are statistically different from each other. To test this, we calculated an F statistic from the vector of coefficients β_{8j}. The results supported our hypothesis, revealing significant differences in the slopes of the learning curves across sites ($F = 3.44$, $p < .0001$). Model 4 also shows that, even after taking into account site-specific effects on the slope, significant differences in the intercepts across sites still persist.

Table 1 **Estimated Coefficients for Total Procedure-Time Regression Model (Standard Errors in Parentheses)**

	Models			
Variables	1	2	3	4
Constant	5.60***	5.79***	6.01***	6.11***
	(0.03)	(0.05)	(0.07)	(0.15)
CABG	−0.22***	−0.24***	−0.13***	−0.12**
	(0.04)	(0.04)	(0.04)	(0.04)
Grafts	0.09***	0.10***	0.08***	0.07***
	(0.01)	(0.01)	(0.01)	(0.01)
ASD	−0.38***	−0.37***	−0.31***	−0.30***
	(0.06)	(0.06)	(0.06)	(0.05)
Multi-Procedure	0.19***	0.19***	0.11*	0.11*
	(0.06)	(0.06)	(0.05)	(0.05)
Higgins	0.00	0.00	0.01	0.01
	(0.01)	(0.01)	(0.00)	(0.00)
log*(Cumulative Volume)*		−0.06***	−0.04***	−0.04*
		(0.01)	(0.01)	(0.02)
Hospital Dummies			***	***
log*(Cumulative Volume)** *Hospital Dummies*				***
N	669	669	669	669
F	24.02***	24.69***	20.52***	14.23***
R^2	0.15	0.18	0.40	0.45

Note. Dependent variable: ln(*Procedure Time*).
$^{***}p < 0.001$.
$^{**}\bar{p} < 0.01$.
$^{*}\bar{p} < 0.05$.

Table 2 Estimated Coefficients for Net Adjusted Procedure-Time Regression Model (Standard Errors in Parantheses)

	Models			
Variables	1	2	3	4
Constant	5.14***	5.39***	5.62***	5.69***
	(0.04)	(0.06)	(0.09)	(0.20)
CABG	0.09	0.07	0.20***	0.23***
	(0.05)	(0.05)	(0.05)	(0.05)
Grafts	0.07***	0.08***	0.06***	0.05***
	(0.02)	(0.02)	(0.01)	(0.01)
ASD	−0.10	−0.08	−0.03	−0.02
	(0.08)	(0.08)	(0.07)	(0.07)
Multi-Procedure	0.19**	0.20**	0.11	0.12*
	(0.07)	(0.07)	(0.06)	(0.06)
Higgins	0.01†	0.00†	0.02*	0.02*
	(0.01)	(0.01)	(0.01)	(0.01)
ln*(Cumulative Volume)*		−0.08***	−0.05***	−0.05***
		(0.02)	(0.02)	(0.02)
Hospital Dummies			***	***
ln*(Cumulative Volume)** *Hospital Dummies*				***
N	628	628	628	628
F	16.96***	19.74***	15.57***	11.96***
R^2	0.12	0.16	0.35	0.42

Note. Dependent variable: ln(*Team Time*).
***$p < 0.001$.
**$\bar{p} < 0.01$.
*$\bar{p} < 0.05$.
†$\bar{p} < 0.10$.

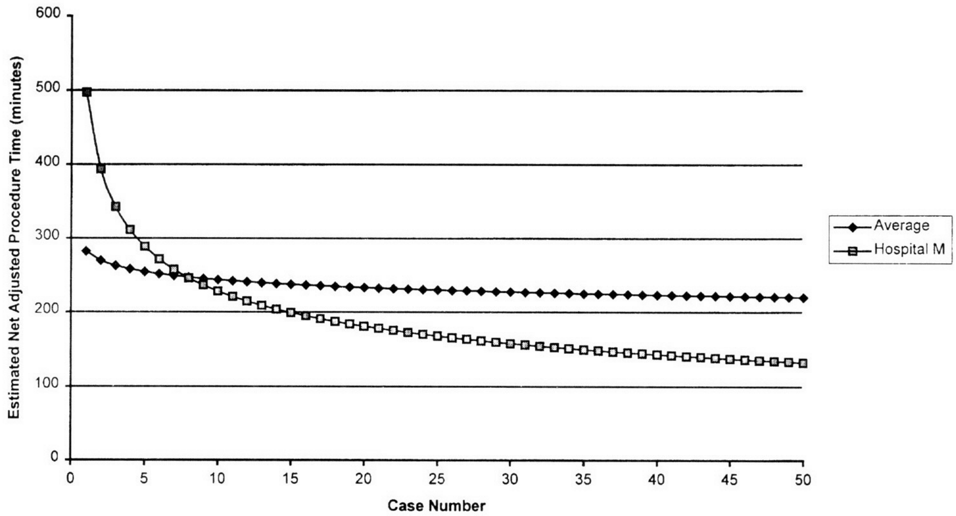
Table 2 presents the results for the *net adjusted procedure-time* models. With the exception of some differences in control variables (*ASD* and *Higgins*), the overall impact of the variables of interest is consistent with those presented for the total procedure-time models. There is an overall tendency for procedure times to fall with cumulative experience. At the same time, we also find statistically significant differences in both the slope and intercept of the learning curves across our sample of 16 sites. These results give us further confidence that organizational or team learning plays an important role in reducing procedure time because the effects of cumulative experience are different across sites, even when surgeon learning (improvements in stitching time) is removed from the analysis. In sum, cumulative experience remains a significant contributor to reductions in procedure time; however, these data reveal differences in the rates at which individual hospitals learn from experience.

The parameter estimates from the models above provide insight into the substantive impact of learning-curve differences across sites. To illustrate this, Figure 1 shows the time obtained when we hold procedure type constant (a single-vessel CABG performed on a patient of typical health status—a Higgins score of 2.5), and trace the estimated net adjusted procedure times for the first 50 cases for the site with one of the steepest, statistically significant learning curve coefficients (Hospital M). The learning curve for Hospital M is juxtaposed against the estimated average learning curve across all 16 sites in the study. As can been seen in Figure 1, Hospital M had slower than average predicted procedure times for its first seven cases. Our models suggest, however, that by Case 50, the team at Hospital M would be able to undertake a comparable procedure significantly faster than the typical team in our sample. The estimated net adjusted procedure time for Hospital M at Case 50 would be approximately 132 minutes, versus 220 minutes for the sample average.

Hospital M's reduction procedure time is substantial both in terms of raw time and the associated costs. We estimate that Hospital M was able to reduce its net adjusted procedure time from approximately 500 minutes on Case 1 to 132 minutes by Case 50. Using a standard industry assumption that a cardiac operating-room suite costs approximately $1,500 per hour, this 6-hour reduction translates into a potential cost savings of $9,000 per case. Hospital M's 88-minute procedure-time advantage over the average hospital is also by no means trivial. At $1,500 per hour, this translates into approximately a $2,250 per case advantage. A 368-minute improvement at Hospital M allows the surgeons to do one more revenue-generating procedure per day.[17] In

[17] Medicare reimbursement for a coronary artery bypass graft admission ranges between $33,000 and $36,000. The cumulative effect of this over the course of a year can be quite substantial.

Figure 1 Estimated Net Adjusted Procedure Times: Hospital *M* vs. Average



addition, at 132 minutes for the procedure (not including occlusion time), Hospital M's time to undertake the minimally invasive cardiac procedure is very close to the time required to perform a similar phase of the operation using a conventional surgical approach.[18]

One potential concern about interpreting learning-curve coefficients is that some organizations may appear to be "faster learners" by virtue of the fact that they were slow starters. That is, they might reduce procedure time dramatically from an extremely high initial base. While it is true that Hospital M started slower than the average hospital, Figure 1 also indicates that its rate of improvement leads to an overall advantage in procedure time. We calculated estimates for net adjusted procedure time at Case 40 for all hospitals in our study; these times range from 155 minutes to 307 minutes. We chose 40 cases as the point of comparison because 40 was the average number of cases performed at each hospital at the time of our study. We need to be careful interpreting these results for two reasons. First, although nine of the 16 hospitals in our study had performed more than 40 cases, we are extrapolating past the experience base for the others. Second, although these procedure times are point estimates, our statistical models only allow us to say something about the range of estimated procedure times we might expect to observe with some level of confidence. We note this range of procedure times only to provide a rough illustration of the magnitude of learning differences that are possible, rather than to indicate conclusions about differences between specific sites.

Notwithstanding these caveats, these estimates demonstrate that we might expect very large differences in procedure times across sites over a comparable base of experience. Hospital M's estimated 143-minute time (at Case 40) is the shortest net adjusted procedure time in our sample. The largest estimate, 305 minutes, is more than 2.5 hours longer than the time it takes Hospital M to do a case. The estimated procedure time for each hospital's initial case and the estimated procedure time by Case 40 were not negatively (or positively) correlated.

Because cardiac surgery is one of the few services that is capacity constrained in the current health care environment, there are high opportunity costs for long procedure times.

[18] After completing our statistical analysis, we conducted a follow-up interview with the surgeon at Hospital M who performs the minimally invasive procedure. We asked him to tell us how long it now takes his team to perform the minimally invasive operation for a single-vessel graft on a patient in average health. Our statistical estimate of 132 minutes fell within about 10 minutes of what he estimates it now takes his team to do the procedure. In addition, he noted that a minimally invasive cardiac operation for his team now only takes about 20 minutes longer than a similar type of case performed conventionally.

5. Exploring Differences Across Sites

The above statistical analysis provides evidence that rates of learning can differ significantly across independent organizations in the same industry. What might account for these differences? As discussed, all hospitals had similar state-of-the-art operating rooms; all were using essentially the same FDA-approved set of devices; all adopting surgical teams went through the same training course; all of the teams came from respected cardiac surgery departments. One possible source of differences might be the number of surgeons performing the procedure at each hospital. With more surgeons using the new technology, the experience base would be diluted. However, in our sample this does not appear to be a contributing factor. All but one of the hospitals in our study had the same surgeon performing all of the minimally invasive operations. In the one hospital where three surgeons performed the operation, we found no differences across surgeons in speed or the effect of cumulative experience, although the hospital was a slow learner relative to others in the sample. Thus, dilution of experience may have affected this one site, but did not account for differences among the other sites.

Existing theories of organizational learning suggest a number of factors that might explain our observed differences in slope coefficients across sites. One of these concerns time lags. Learning might be reinforced if the time lags between early cases were shorter. To test for this effect, we correlated initial frequency (the number of procedures in the first 30 days at each hospital) with the rate of reduction in procedure time (reverse-scored slopes of individual hospital learning curves). The Spearman rank order correlation (rho = .13, $p = .62$) did not support this proposition.[19] We also examined how the lag between training and conducting the first case for each hospital might have affected learning-curve slopes. This revealed a weak but insignificant association between greater lag and rate of procedure-time reduction (rho = −.26, $p = .37$). Similarly, if later starters could learn from the experience of earlier starters, the timing of adoption might matter; however, there was no association in these data between start date and rate of procedure-time reduction (rho = .09, $p = .73$). Finally, the size of the cardiac surgery departments in our sample hospitals varied substantially (as measured by number of cardiac surgeries per year). To the extent that greater size is associated with more organizational complexity and inhibits focus, it could have a detrimental impact on learning performance. However, the slight negative relationship between department size and procedure-time reduction was not significant (rho = −.18, $p = .52$). Given our small sample of hospitals, these results should be interpreted with caution. It is not possible to dismiss these factors as possible explanations of differences.

Interview data suggested instead that differences in learning performance could be due to differences in underlying organizational processes. To illustrate this possibility, we present a brief description of two cases—Hospital M, the number two learner in the sample, and Hospital R, one of the two slowest learners in the sample. Our intent is to generate plausible hypotheses for future testing.

Hospital M. Hospital M is a well-respected community hospital performing 1,200 cardiac operations a year. Although the cardiac surgery department did not have a history of undertaking major research or cardiac surgical innovation, it had recently hired a recently junior surgeon with an interest in trying new techniques. Several characteristics of Hospital M's adoption of the new technology could plausibly have contributed to their relatively rapid rate of learning.

First, the team that went to the company's three-day training program was not picked randomly or on the basis of seniority (as it was at several other institutions). Instead, the adopting surgeon handpicked the team based on their prior experience working together and their demonstrated ability to work well together. Second, there was evidence of a fairly high degree of cross-department communication and cooperation even before the first case. After returning from

[19] We utilized the nonparametric statistical test, Spearman's rho, to test this, as nonparametric statistics do not require assumptions about the distribution of the population from which the samples were taken, and also do not inflate the correlation due to outlier values (Saslow 1982).

the training, the surgeon organized a series of meetings with other departments that might be affected by the new technology. For instance, he invited the entire cardiology department to a presentation in which he provided an overview of the technology and its indications for use. This was important because it facilitated referrals of appropriate patients by cardiologists. The perfusionists and the operating-room nurses then met to agree upon "standard terminology" that they would use during operations. There was also evidence that these cross-department interactions continued after the first clinical cases. The perfusionists met on an informal but regular basis with both the operating-room nurses and the anesthesiologists to discuss the procedure. A perfusionist noted, "We want to be familiar with what everyone on the team is doing." The surgeon also continued to have weekly meetings with cardiologists to discuss upcoming cases (a practice that was virtually nonexistent in other hospitals in our study).

Third, the early cases (through the first 30) were carefully managed by the adopting surgeon. The surgeon mandated stability of both the surgical team and the surgical procedure in the early cases. Thus, the team that went to the training program performed the first 15 cases before any new members were added or substituted. And, when new members were eventually added, they were required (regardless of rank) to observe four cases and be proctored on two before they were allowed to join the team. The surgeon also deliberately scheduled a set of similar cases such that the team performed six operations in the first week (which occurred four weeks after the team went to training). This allowed the team to keep the surgical procedure stable for the first 30 cases, not modifying anything specified in the training. Moreover, prior to each of the first 10 cases, the entire surgical team met to discuss the proposed procedure for the case in advance. The team also met again after each of the first 20 cases to debrief. Thereafter, the surgical team at Hospital M set up a process through which it could monitor the short- and long-term outcomes of the new operation. The head perfusionist went to the intensive care unit to check on each patient the day after surgery. Other team members collected and analyzed both process and outcome data and presented the results to the referring cardiology group and to national surgical conferences.

Finally, there was some evidence that the surgeon at Hospital M encouraged a high degree of cooperation among members of the team. He saw minimally invasive cardiac surgery as a paradigm shift; he reported that "the surgeon needs to be willing to allow himself to become a partner [with the rest of the team] so he can accept input." He explicitly encouraged input and feedback from other team members in the operating room. One team member (not the surgeon) noted, "With this procedure, the hospital was willing to empower the team. There's a real trusting relationship that allows this to occur."

Hospital R. The approach taken by Hospital R, a large nationally renowned academic medical center, differed markedly from that of Hospital M. The initial phase of adoption at Hospital R differed substantially from the approach observed at Hospital M. The team that was sent to training was picked largely on the basis of availability and willingness to go (the training was scheduled for a weekend). In addition, only three of the four core-team members who attended training together were present for the first case. For each of the subsequent six cases the team composition was slightly different, and the surgeon later noted that "it was a disaster. *Now* [the team] is very stable. We planned the operation so that the same people were here. I won't do it if the team is not here."

Unlike Hospital M, there were no attempts to introduce the technology to other clinical groups that might contribute to or be impacted by its implementation. This lack of cross-departmental communication is also apparent in the phases after the hospital began using the technology on patients. For example, there were no meetings to discuss cases ahead of time. An anesthesiologist noted, "I get no warning of a minimally invasive case until I show up at the hospital." There was also little indication that the staff involved with this procedure viewed themselves as a "team." One nurse noted, "We don't have any real teams here. It's just who gets assigned on any given day." Another added, "The nurses are interchangeable. We know our 'little job' and don't really know what the other people are doing."

Not only was team membership unstable during the early cases, but the surgeon changed the operative process for each early case, noting that "I try to do something new on every case." In addition, there were no specific activities to reflect upon and share the experience gained on the early cases. Hospital R, which published prolifically in the academic medical literature, did not use the high-quality data it collected for research purposes to inform its daily practice. Finally, although the adopting surgeon at Hospital R was affable and respectful of other team members, his focus was largely on mastering the technical aspects of the operation rather than managing the overall adoption process and proactively encouraging input.

In summary, Hospital M's process for adopting the minimally invasive approach differed markedly from the pattern found in Hospital R. First, the hospitals differed in terms of formal procedures for new technology adoption. The presence of standardized training requirements might facilitate learning by ensuring consistency of techniques across different people. Second, crossfunctional communication might facilitate learning, for example, if cardiologists' understanding of the procedure enabled them to make appropriate patient referrals, promoting consistency or simplicity of patient conditions, in the early stages. Third, both team membership stability and operative process stability are likely to promote speed of learning by allowing a consistent group of people to work on a consistent task and thereby improve coordination (e.g., Moreland et al. 1998). Fourth, team debrief activities—including explicit reflection on relevant data—prevalent at Hospital M but missing at Hospital R, can allow a team to reflect on its past actions and design any changes needed to streamline its task (Edmondson 1999), which would likely foster greater efficiency. Finally, surgeon coaching behavior as demonstrated at Hospital M may allow other team members to feel more comfortable to speak up quickly about their observations—for example, related to balloon placement or blood pressure—thus enabling quicker response and ultimately faster operations. In sum, these cases suggest five factors that might account for differences in rate of learning. More investigation of these factors is warranted before conclusions can be drawn.

6. Conclusions and Implications

Consistent with previous studies of the learning curve, this paper provides evidence that learning-by-doing, through cumulative experience, plays a central role in the adoption of new technologies. Our results also suggest, however, that learning from experience is not automatic. Some organizations capitalize on their experience more effectively than others. Two potential implications of this finding for theory and practice are discussed below, followed by issues for future research.

First, learning-by-doing may be a firm-specific capability. As a result, simply increasing output (in order to gain more cumulative experience) may not necessarily lead to a superior cost position. An organization with less cumulative experience than its rivals can still achieve a performance advantage if it more thoroughly exploits its opportunities for learning. Our results offer a strong caution to technology adopters about depending too heavily on output expansion as the key driver of performance improvement. This is particularly important to consider in the context of medical technologies, where the existing volume-outcomes literature has focused administrative and regulatory attention on volume rather than on processes of adoption. Although some level of cumulative experience may be necessary to master a technology, it is unlikely to be sufficient. Unless an organization puts into place mechanisms for capturing knowledge and implementing learning, experience may not translate into competence.

Second, for producers of a new technology the same caution applies. Innovators cannot assume that the initial "teething pains" experienced by adopters will necessarily subside with some specific level of experience. Facilitating collective (or organizational) learning may be an important role that innovators need to play in ensuring the successful adoption of their technology. Training would seem to be a logical strategy, but we must note that significant differences in learning rates in our sample existed despite intensive and consistent training provided by the innovating firm. Certain differences may be rooted in structural and organizational aspects of the adopters themselves and may not be subject to change by the innovator.

Our research to date raises questions to be explored in future work. The first concerns the specific organizational and managerial factors that underlie the differences in learning rates that we observed. Our brief case descriptions of two organizations point in the general direction of certain factors, but much more in-depth comparative work is required to draw more specific conclusions about the drivers of learning. An exploration of organizational-level differences in incentives, organizational processes, management, and practices is clearly warranted. A second fruitful area concerns the complex interaction between performance improvements and future adoption. There may be virtuous cycles and vicious circles at work. Early adopters with initial success (failure) may then have an interest in doing more (fewer) cases. This lead to growing (declining) volume, which, in turn, may stimulate further performance improvement (deterioration). A third avenue for future work concerns different dimensions of learning. This paper focused on procedure-time reduction as one particular manifestation of learning. Learning in the context we have studied can also be manifested in other ways. For instance, some hospitals in our study have begun to use the procedure for a wider range of cardiac procedures than other hospitals. Future work should analyze learning curves associated with these other dimensions of performance. Ultimately, we hope this work will contribute to the empirical base of knowledge about the complex and poorly understood processes by which organizations learn.

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