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The effect of information technology on learning in professional service organizations

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Abstract

This study examines the relationship between organizational experience and productivity in a professional service organization. The research addresses a gap in the existing literature with respect to organizational experience models in service organizations. Our findings confirm a significant, positive relationship between organizational experience and productivity. In addition, we investigate the effect of information technology on the relationship between organizational experience and productivity. The findings indicate that information technology which becomes a part of the production process is associated with productivity improvements, while information technology which merely documents or collects information is not.

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1. Introduction

Interest in organizational learning (and experience) models has increased recently, as research indicates that effective organizational learning is a critical organizational capability (Argote, 1996; Argyris and Schön, 1996; Senge et al., 1994). Learning curve models represent one dimension of organizational learning. Organizational learning curves measure the association between productivity improvements and an organization's production experience, i.e. cumulative production (Wright, 1936). An association between productivity and production experience has been confirmed in a wide array of manufacturing environments, however, there are only a few studies addressing this relationship in service environments (Argote, 1996; Dutton and Thomas, 1984; Yelle, 1979).

This study analyzes 10 years worth of data from an engineering design firm in order to determine whether there is a significant and positive relationship between productivity and production experience. This is one of few studies evaluating productivity improvements in a professional service context. As the ensuing discussion will show, the innate characteristics of professional service organizations suggest that productivity improvements based on production experience may be more difficult.

In addition, this research evaluates the effects of two different information technology installations on

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the relationship between productivity and production experience. Many past studies of technology's effect on experience-based productivity improvements have typically been restricted to process technologies in manufacturing organizations. In addition to altering the product or service delivery process, information technology has a plethora of uses within organizations (Zuboff, 1988). Examples include the use of information technology as organized repositories of information or even an expert system that can be used for problem solving. The existing research, however, does not evaluate whether different information technologies might demonstrate different relationships with experience-based productivity improvements. This work begins to distinguish the effects that different information technologies may have on production experience-based productivity improvements. Specifically, we consider two types of information technology, one that stores and dispenses information and the other that changes the service delivery process.

The data used in this study permit analysis of learning models in service organizations over 10 years, a longer term than has been undertaken in many past studies (e.g. Darr et al., 1995; Jaber and Bonney, 1997; Lieberman, 1987). Since the accurate measurement of technological impact warrants a long-time frame (Brynjolfsson, 1993), the data permit a more precise analysis of the effect of information technology on the learning curve.

The remainder of the paper is organized as follows. The next section reviews the research on organizational learning curve models, learning curve models in service environments, and the impact of information technology on productivity. Following that is a description of the hypotheses, data, and analysis. We follow the analysis with a discussion of the results. We conclude with a brief summary.

2. Organizational learning curves

The relation between production experience and productivity improvements was first documented by Wright (1936) who observed that the time required to produce successive airplanes decreased at a predictable rate. Wright described this relationship using the following learning curve model, which is still widely used.

$$Y_n = Y_1 n^b, \quad \text{or} \quad \ln Y_n = \ln Y_1 + b \ln n$$

where Y_n is the time or cost required to produce the nth unit, Y_1 is the time or cost required to produce the first unit, n the cumulative number of units produced, b denotes $\ln r/\ln 2$, where r represents the learning rate.

According to this model, each doubling of cumulative production results in a constant reduction in unit production time. The cumulative number of units produced represents experience. As an organization gains production experience, it is able to produce individual units faster and/or at a lower cost.

Wright's log–linear equation is the simplest and most common model of learning curves and it applies to a wide variety of industries (Globerson, 1980). Other log–linear models include the 'Stanford-B' model that is used to model processes where experience carries over from one production run to another. The DeJong log–linear model is used to model processes where a portion of the process cannot improve or has reached a plateau. The '*S*-Curve' model combines the Stanford-B and DeJong models to incorporate processes where experience carries over from one production run to the next and where a portion of the process cannot improve. For a detailed overview of these models, the reader is directed to Yelle (1979).

Starting with Wright's (1936) study, research in manufacturing organizations has consistently established the relation between productivity improvements and cumulative production experience. A number of researchers have examined whether time or cumulative number of units produced (or the number of projects completed in project-based organizations) is a better measure of cumulative production experience (Lieberman, 1984; Sheshinski, 1967; Womer, 1984). Their findings indicate that cumulative number of units produced is a better measure of production experience. They found that time became statistically insignificant once cumulative number of units produced was incorporated into their model.

2.1. Organizational learning curve models in services

Most research examining learning curves has been conducted in manufacturing organizations (Argote and Epple, 1990; Dutton and Thomas, 1984; Reis, 1991; Yelle, 1979). Services are significantly different from manufactured products (Fitzsimmons and

Fitzsimmons, 1998; Lovelock, 1992; Morris and Johnston, 1986). The distinctive characteristics of professional services, high labor intensity, and high product variability with frequent customer interaction, potentially affect learning (Schmenner, 1986). In professional services, the production units are usually projects which take several days or even weeks to complete (McLaughlin et al., 1995). The major input is labor hours.

Most previous studies of learning curves in service organizations have focused on organizations with less product variability and customer interaction (Darr et al., 1995; Reis, 1991). The proportion of human labor and product variety have both been shown to affect the relationship between productivity and production experience.

Human labor has demonstrated a greater capacity for learning than machine labor (Andress, 1954; Hirschmann, 1964a,b). Production processes using higher proportions of human versus machine labor typically have steeper learning curves and plateau more slowly than less labor intensive processes (Baloff, 1971; Yelle, 1979). Nonetheless, researchers have found moderate learning curves in service organizations. For example, Darr et al. (1995) found that the learning rate in a network of pizza restaurants was lower than the 80% learning rate found in most manufacturing firms.

Professional services display considerable variety in the service product and the service creation process (Schmenner, 1986). High product and process variety may dampen learning as follows. Subsequent customers typically do not request the same or a similar service product. As a result, some time passes before similar products are reproduced. The time between reproduction of similar service products can be thought of as a production break for a particular product type. Production breaks are associated with organizational forgetting or unlearning (Jaber and Bonney, 1997). Forgetting is a function of the length of the production break, the number of dissimilar products produced during the break, and the production time before the break (Globerson, 1980; Globerson et al., 1989; Jaber and Bonney, 1997). Forgetting can occur at the individual and organizational level (Bailey, 1989).

In the organization under study, this means that the production time of a given project will depend on the amount of time since a similar project was completed by the same worker, by the organization, and the proficiency (i.e. production time) the organization and the worker demonstrated on the last similar project.

High service product variety does not necessarily nullify the relationship between productivity and production experience. Hirschmann (1964a) found an 80% learning curve in one make to order environment. In a study of a food service contractor, Reis (1991) found that the learning rates ranged from 85 to 95% and the learning curve plateaued after 4–8 months.

2.2. Information technology and organizational learning curves

The amount of productivity improvements that an organization will realize from production experience depends on a variety of factors, including the time frame (Dutton and Thomas, 1984; Globerson, 1980), workforce training (Adler and Clark, 1991), management techniques (Adler, 1990; Globerson, 1980), and methods of planning and control (Globerson, 1980). Process technologies are indicated as one of the most important factors governing the rate of productivity improvement (Hirsch, 1952;Hirschmann, 1964a,b; Itami and Numagami, 1992; Pavitt, 1990; Yelle, 1979).

More recently, researchers have suggested that technology's ability to capture, retrieve, and share individual knowledge and information is critical to maximizing the productivity benefits from production experience (Adler, 1990; Globerson, 1980; Huber, 1991; Williams and Kotnour, 1993). In their discussion of information technology and learning in professional services, Williams and Kotnour (1993) concluded that information technology that only supplies data would not alter learning rates. In order for information technology to substantially improve productivity, it must assist with problem solving; or it must store, organize, and induce knowledge from past experiences (Argyris and Schön, 1996; Huber, 1991).

At the same time, new technology implementations have been found to disrupt the relationship between production experience and productivity improvements when it is obsolete, inappropriate, or difficult to use (Adler and Clark, 1991; Argote, 1996). These disruptions can be permanent or of very long duration in organizations that are already relatively low performers, where information technology limits information flows, or where the information technology is inappropriate for the application (Argote, 1996; Hitt and Brynjolfsson, 1996).

The process reengineering literature points to the importance of process change accompanying the implementation of information technology (Davenport, 1994; Foster and Flynn, 1984). Information technology is associated with significant improvements in productivity when processes are reevaluated and changed to reflect the capabilities of the technology and the needs of the organization without respect to functional boundaries (Hammer and Champy, 1993).

3. Hypotheses

The objective of this study is to first examine the relationship between production experience and productivity in a professional service organization. We then investigate the effect that experience with information technology has on this relationship. The basic model evaluates the relation between production experience and productivity. We then expand this basic model to include the impact of experience with two different information technologies on productivity (Table 1).

As indicated earlier, research investigating learning curves in services is sparse. However, the findings of researchers such as Hirschmann (1964a), Reis (1991) and Darr et al. (1995) indicate that production experience is associated with productivity in service organizations. This leads to our first hypothesis, where our intent is to test if organizational production experience is a meaningful predictor of organizational productivity:

Hypothesis 1. Production experience, measured via cumulative number of units produced, will be positively associated with productivity in a professional service organization.

The dependent variable, organizational productivity, is defined as the number of projects completed during a specified time period. This is analogous to the number of units produced in a manufacturing environment. We expect that the organizational productivity will be partially attributable to the production experience the organization has accumulated.

There is innate variability in the demand for the service product produced by the organization studied. The high level of customization present in this organization means that inventory cannot be used to level production. As a result, demand variability will be reflected in productivity. All else being held equal, when demand is down, productivity will be lower because there are fewer customers to service. To control for the demand variability, a measure of the overall workload is included in the model. This is consistent with the work of Epple et al. (1996) who included workload measures in their investigation of the association between productivity and experience at shipyards. This ensures that the variability in productivity attributable to demand fluctuations will not be captured by the experience measure.

In addition, there is a lot of variability from project to project. Some products are more complex and require more time, and vice versa. This may result in variability in the productivity as well. To control for this to some extent, total labor hours expended is included in the model. This assumes that differences in project complexity and scope will be reflected in labor hours. The use of labor hours is consistent with Epple et al. (1991) who included total labor hours as a control variable when analyzing learning curves in a North American truck-plant producing a single product.

Table 1
Basic model result[a]

	Pre-technology	Post-PMS, Pre-AutoCAD	Post-AutoCAD
$\beta_{\text{labor hours}}$	0.529 (0.000)	0.518 (0.000)	0.508 (0.000)
$\beta_{\text{department experience}}$	0.377 (0.000)	0.379 (0.000)	0.487 (0.009)
$\beta_{\text{organization experience}}$	0.125 (0.091)	0.154 (0.026)	0.096 (0.051)
log(likelihood)	−4530.31 (0.000)	−2120.75 (0.000)	−2350.55 (0.000)
Pseudo-R^2	0.295	0.279	0.175
n	246	94	152

[a] P-values given in parenthesis.

The literature suggests that information technology installations can lead to improvements in productivity. However, information technologies that serve as a passive dispenser of knowledge are not expected to improve productivity (Williams and Kotnour, 1993). Moreover, as indicated by a number of authors (Hitt and Brynjolfsson, 1996; Davenport, 1994) productivity improvements, and as a result, learning rates are likely to be affected by information technology that becomes a core part of the process. This leads to the next two hypotheses

Hypothesis 2. Production experience with information technology that is used solely to acquire data and dispense information will not be associated with changes in organizational productivity.

Hypothesis 3. Production experience with information technology which is an integral part of the service production process will be positively associated with productivity.

Earlier studies in manufacturing firms have demonstrated that new process technology is likely to be associated with productivity improvements (Hirsch, 1952; Hirschmann, 1964a,b; Hollander, 1965; Itami and Numagami, 1992).

4. Data sources

Data to test the hypotheses were collected from a multi-disciplinary engineering organization. The organization comprises of four departments: architects, electrical, mechanical and civil engineers. The organization operates in a project process environment, creating drawings, technical specifications and cost estimates to meet customer requirements. The projects are highly variable, ranging from very simple designs, such as the installation of a single piece of equipment, to very complex designs, such as the complete design of a building. The organization sub-contracts projects it does not have the skills or time to complete.

The organization provided data on labor hours and completion dates for all projects started between 1986 and mid-1997. The project data was supplemented with information from interviews with employees. Data were collected on 3312 projects. Data relevant to this study consisted of project descriptions, estimated labor hours, the actual labor hours expended, the start date, the finish date, and the engineer-architect in-charge. Project records that contained incomplete data, projects that were subcontracted, projects that were canceled before completion and records of engineering studies that did not produce designs were excluded from the analysis. This reduced the data set to 1512 projects.

The service organization under consideration implemented an information technology called the Project Management System (PMS) in 1989. The PMS is used to collect data on the design projects. At the completion of each project, the architect-engineer is responsible for entering a variety of information regarding the project, including date completed, estimated labor hours, actual labor hours used, and a summary description of the project. The data is typically used to prepare annual performance reports, e.g. number of projects completed, average time for completion, etc. The system is not integrated with support tools and does not aid project completion. Essentially, this system serves only as a knowledge acquiring information technology (Huber, 1991).

When first introduced, the system was considered disruptive and bothersome by many of the architect-engineers. Before the implementation of the system, the same information was written on a cover sheet attached to each completed design. Secretaries would then collect and file the information. Many architect-engineers felt they were taking on additional "non-productive" tasks. The PMS implementation was not accompanied by any other significant process changes. As a result, we expect that this information technology will not have a significant, positive effect on the organization's learning curve.

The second information technology used in the service organization under study is a networked AutoCAD system. The technology implementation made AutoCAD available in a personal computer on the desk of every architect-engineer. Before the implementation of AutoCAD, workers could complete drawings using a mainframe CAD or by hand. Most workers, especially older engineers and technicians, preferred to complete all drawings by hand, believing they could draw faster. After the installation of the AutoCAD system, management mandated AutoCAD use for project completion.

In contrast to the first information technology, this information technology was accompanied by some important changes. The process for collaborating on designs was changed immediately to take advantage of the capabilities of AutoCAD. In addition, a multi-functional team was created to identify ways to better use the technology. Many architect-engineers feel that the system has dramatically enhanced their productivity. They believe that they are able to produce work of consistent quality much more quickly than before the AutoCAD implementation. In their case study of a CAD system implementation in a similar organization, Yetton et al. (1994) found that CAD increased the speed of production. We expect the AutoCAD to enable a new economy of operating which will be reflected in the organizational learning curve.

5. Methodology

We adapt the model used by Epple et al. (1996) and Argote et al. (1990). The basic idea in these models, as in Wright's, is that current productivity can be predicted from past production experience, i.e. cumulative number of units produced.

In our study, we evaluate the relationship between productivity and production experience on a monthly basis. Production experience in any given month is measured using the cumulative number of projects that have been completed before that month (Epple et al., 1996; Lieberman, 1984).Production experience is measured at the department and the organizational level. The number of projects completed by department i ($i = 1, \dots, 4$, recall that there are four departments) up to the start of month t (Q_{it}) serves as a measure of departmental experience while the total number of projects completed up to month t (O_t) measures organizational experience. There is more homogeneity among projects at the department level. In addition, there is more interaction and communication among workers within departments than among workers between departments. As a result, there is likely to be more transfer of learning within departments than between departments (Cohen and Levinthal, 1990).

Productivity is measured using the number of projects completed by each department in a given month. This is similar to the study by Argote et al. (1990), which used the accumulated production experience from a set of shipyards to predict the productivity of individual shipyards. The department in our study is analogous to individual shipyards in that study. In effect, we are studying the effect of accumulated departmental and organizational experience on departmental productivity. Project size and complexity are controlled for, by including the number of labor hours expended on every completed project (over their entire duration) by department i in month t (l_{it}). Admittedly, this only partially controls for project size and complexity. The use of l_{it} also eliminates the potential bias of aggregate data by including only those labor hours expended on the projects completed in each month (Womer, 1984).

We use the following variables. The specific functions of some of these variables are deferred until they are introduced into our models.

- C_t — a dummy variable which is 1 if t is a month after the implementation of the AutoCAD system, and 0 otherwise.
- i — the index for the department in which the project was performed; $i = 1, \dots, 4$, representing architects, electrical, mechanical and civil engineers, respectively.
- l_{it} — the number of labor hours expended on projects completed by department i in month t.
- O_t — the cumulative number of projects completed by the organization up to month t.
- q_{it} — the number of projects completed by department i in month t.
- Q_{it} — the cumulative number of projects completed by department i up to month t.
- S_t — a dummy variable which is 1 if t is a month after the implementation of the project management system, and 0 otherwise.
- t — the index for time periods in months, $t = 1, \dots, 146$.
- ε_{it} — the estimation error.

To facilitate the analysis, we organize the data so that for each month, there are four observations, each corresponding to the four individual departments. For example, for month five, q_{15}, l_{15}, and Q_{15} represent the total number of projects completed, the total labor hours expended on these projects, and the cumulative number of projects completed by the architecture department ($i = 1$) in the first 4 months. Meanwhile,

O_5 represents the cumulative number of projects completed by the organization (i.e. all four departments together) in the first 4 months. Data were collected over 146 months for a total of 584 observations.

6. Analysis

The basic model, which tests the first hypothesis, estimates the effect of cumulative production experience on productivity before the introduction of either information technology.

$$\begin{aligned}\ln(q_{it}) = \beta_0 &+ \beta_{\text{labor hours}} \ln(l_{it}) \\ &+ \beta_{\text{department experience}} \ln(Q_{it}) \\ &+ \beta_{\text{organization experience}} \ln(O_t) + \varepsilon_{it} \qquad (1)\end{aligned}$$

The results from this model will indicate whether productivity is positively associated with departmental and/or organizational experience.

In order to test our technology-related hypotheses, we add the dummy variables S_t and C_t. The model, shown in Eq. (2), test whether the PMS technology is a significant predictor of productivity.

$$\begin{aligned}\ln(q_{it}) = \beta_0 &+ \beta_{\text{labor hours}} \ln(l_{it}) \\ &+ \beta_{\text{department experience}} \ln(Q_{it}) \\ &+ \beta_{\text{organization experience}} \ln(O_t) \\ &+ \beta_{S_t \times \text{department experience}} \ln(Q_{it}) S_t + \varepsilon_{it} \qquad (2)\end{aligned}$$

This model adds an interaction term, $\ln(Q_{it})S_t$, to the basic model. If the coefficient $\beta_{S_t \times \text{department experience}}$ is significant, then the PMS technology has a significant impact on productivity.

The third model tests the relationship between productivity and cumulative experience with the AutoCAD technology. The goal is to determine whether the AutoCAD system is a significant predictor of productivity. The model tested is

$$\begin{aligned}\ln(q_{it}) = \beta_0 &+ \beta_{\text{labor hours}} \ln(l_{it}) \\ &+ \beta_{\text{department experience}} \ln(Q_{it}) \\ &+ \beta_{\text{organization experience}} \ln(O_t) \\ &+ \beta_{C_t \times \text{department experience}} \ln(Q_{it}) C_t + \varepsilon_{it} \qquad (3)\end{aligned}$$

As before, an interaction term, $\ln(Q_{it})C_t$, is added to the basic model. If $\beta_{C_t \times \text{department experience}}$ is significant, we can conclude that the AutoCAD has a significant effect on organizational productivity.

7. Results

Negative binomial regression is used to estimate the models. Negative binomial is a more general version of the Poisson model, which accounts for the count nature of the data (Cameron and Trivedi, 1986; Lieberman, 1987). In addition, while the Poisson assumes equality of the mean and variance, the negative binomial model allows for over dispersion of the errors.

7.1. Organizational learning curves in professional services

We first estimate the basic model after dividing the data into three separate groups. The first group contains only projects completed before the implementation of either technology. There are 62 months (246 observations) in this group. The second group contains projects completed after the implementation of the PMS and before the AutoCAD. There are 24 months (94 observations) covered in the second group. The third group contains only projects completed after the implementation of the AutoCAD. There are 38 months (152 observations) in the last group.

The overall model is significant ($P < 0.001$) and supports the first hypothesis, i.e. production experience is positively associated with productivity in this professional service organization.[2] The positive values for $\beta_{\text{labor hours}}$ indicate that productivity increases as more manpower is applied to production. In addition, it suggests that some of the variability in productivity can be attributed to project size and complexity differences.

The positive values for $\beta_{\text{department experience}}$ and $\beta_{\text{organization experience}}$ indicate positive returns to departmental and organizational experience. As experience increases so does productivity. There is some correlation between the two (see Table 2). However, organizational experience has less predictive power than department experience. The cumulative number of projects completed by the department is a signif-

[2] We also tested to determine whether there were significant departmental effects. None were found.

Table 2
Correlation matrix

	Labor hours	ln(department experience)
ln(department experience)	0.268	
ln(organization experience)	0.236	0.4020

icant predictor of departmental productivity, while the cumulative number of projects completed by the organization is only significant at the 0.091 level.

As indicated by Darr et al. (1995), the coefficient $\beta_{\text{organization experience}}$ represents the production experience that is transferred from the organization to the department. The transfer of organizational experience to departments may be undermined by a number of factors. Within-department affiliations are much stronger than organizational affiliation. Departmental experience may be more significant because workers within each department share the same skills and knowledge sets. This forms a basis of common knowledge and discourse that does not necessarily exist among different departments. Information is more likely to be shared formally and informally within departments than between departments (Midgley et al., 1992; Zander and Kogut, 1995). Typically, workers go to others within their same departments with questions or concerns.

Cohen and Levinthal (1990) suggest that the ability of prior experience to influence subsequent efforts depends on effective communication within the organization, and between the organization and the external environment. In addition, intensity of information sharing is directly proportional to the distance between firms or units, the closer the units, the faster the transfer of new knowledge (Rothwell, 1994). In addition, geographically closer organizations or units are more likely to experience richer knowledge transfer, which includes tacit as well as codified knowledge. Physical barriers that separated the departments may have stymied inter-departmental communication. At times, departments were housed in separate buildings or on separate floors of the same building. Workers confirmed that this resulted in frequent, informal intra-departmental interaction and reduced informal, inter-departmental interaction.

Informal communication networks are important for the transfer of non-technical information (Cohen and Levinthal, 1990). This includes information about "who knows what, who can help with what problem, or who can exploit new information." In the organization studied herein, workers tend to search for almost all informations within their home departments. Moreover, workers may resist sharing information across departments if hoarding the information gives the worker a sense of power or control (Davenport, 1994).

7.2. Information technology and organizational learning curves

The results presented in Table 3 show the effects of the PMS and AutoCAD on experience-based productivity improvements. As expected, $\beta_{S_t \times \text{department experience}}$ is not statistically significant, confirming the hypothesis that the PMS technology does not significantly affect productivity. The findings suggest that the relationship between information technology implementation and productivity is determined in part by the use of the technology. As expected, the project management technology did not significantly alter the relationship between productivity

Table 3
Technology results

	(2)		(3)	
$\beta_{\text{labor hours}}$	0.532 (0.000)	0.522 (0.000)	0.524 (0.000)	0.518 (0.000)
$\beta_{\text{department experience}}$	0.457 (0.000)	0.315 (0.000)	0.419 (0.000)	0.323 (0.000)
$\beta_{S_t \times \text{department experience}}$	−0.060 (0.198)	−0.024 (0.620)		
$\beta_{C_t \times \text{department experience}}$			0.141 (0.000)	0.110 (0.002)
$\beta_{\text{organization experience}}$		0.226 (0.067)		0.161 (0.011)
log(likelihood)	−7670.20 (0.000)	−7570.88	−7590.01 (0.000)	−7530.03 (0.000)
Pseudo-R^2	0.275	0.279	0.283	0.283
n	426	426	426	426

and production experience. The parameter estimate is not significant, and it is negative, which would indicate that the PMS is associated with reductions in productivity.

The results also show that the information technology, the AutoCAD technology, which is incorporated into the production process is associated with increase in productivity. In this case, $\beta_{C_t \times \text{department experience}}$ is positive and statistically significant indicating that the AutoCAD technology significantly affects the relationship between production experience and productivity. The positive value of the parameter estimate suggests that the AutoCAD is associated with an upward positive shift in the learning curve, and increased slope. This indicates that both productivity and productivity improvements increase after the AutoCAD installation. This mirrors the findings of Hirsch (1952) and Hollander (1965) who found that increases in productivity were associated with investments in process technologies.

The magnitude of $\beta_{C_t \times \text{department experience}}$, however, is relatively small. There may be several reasons why the AutoCAD does not have a larger effect on productivity. First, the analysis does not control for the disruptions caused by the initial installation. Process changes, such as the AutoCAD installation, are associated with disruptions in productivity (Adler and Clark, 1991). Any disruptions diminish the measurable effect of the AutoCAD on the model. Next, the magnitude of the effect will depend on the structure of any accompanying process change. Because this work examines the results of a natural experiment, it is difficult to isolate process change from the type of technology. A technology implementation may have a more dramatic and immediate effect, if it is accompanied by radical process changes. Alternatively, the effect of new technology may be smaller and more difficult to measure, if it is accompanied by incremental changes (Davenport, 1994).

Another possible explanation for the relatively small effect of this AutoCAD may be the strategic approach to the implementation. One information systems worker in the organization studied expressed frustration that management "did not view the technology strategically." Yetton et al. (1994) found that strategic installations of CAD were associated with a greater number and magnitude of benefits than tactical CAD installations. Strategic CAD installations led to an increase in product and service quality, improved flexibility, and increased productivity. Tactical CAD installations led to moderate increases in productivity only. Hitt and Brynjolfsson (1996) suggested that managers must view information technology strategically, if they are to maximize the benefits of the technology.

Next, as indicated earlier, high product and process variety may have limited the applicability of prior experience and learning to successive projects. At the same time the AutoCAD may have enabled even greater process variety. According to several workers, the AutoCAD installation was accompanied by an increase in their responsibilities. They believed that they became responsible for more project activities, tasks that were previously carried out by clerks or managers or technicians. An increase in project responsibilities could partially undermine productivity gains from the AutoCAD. What is not clear is whether transferring the responsibility of these tasks to the architect-engineers increased the value of the service product.

Finally, the workers reported that the AutoCAD system allowed them to complete projects that they had been subcontracted in the past. The evidence indicates that the organization subcontracted fewer projects in the years after the introduction of AutoCAD: approximately 32% of all projects, versus approximately 50% in earlier years for which data are available. There appears to be a trade-off between increasing productivity and increasing project variety within this organization.

8. Conclusions

The basis of organizational learning curves is the relationship between production experience and productivity. We find a significant relationship between production experience and productivity which verifies the existence of an organizational learning curve in this professional service organizations.

The magnitude and type of benefit that an organization can expect from information technology will depend on the use of the technology. As theorized in earlier research, information technology that does not add value to the information that it collects will not improve organizational performance. Our findings suggest that information technology must also help users gain insights or knowledge in order to significantly improve productivity.

The AutoCAD implementation suggests that benefits of increased flexibility may offset expected increases in productivity. Managers that expect to realize dramatic increases in organizational productivity from information technology may be disappointed if the technology also increases organizational flexibility.

Additional studies can examine the existence of learning curves in other types of service organizations. Existing studies have only investigated learning curves in two of the four types of services proposed by Schmenner (1986). Future work can examine the nature of learning curves in all types of service organizations. This type of analysis would allow the construction of descriptive framework with respect to learning curves in service organizations.

References

Adler, P.S., 1990. Shared learning. Management Science 36 (8), 938–957.

Adler, P.S., Clark, K.B., 1991. Behind the learning curve: a sketch of the learning process. Management Science 37 (3), 267–281.

Andress, F.J., 1954. The learning curve as a production tool. Harvard Business Review 32, 87–97.

Argote, L., 1996. Organizational learning curves: persistence, transfer and turnover. International Journal of Technology Management 11 (7/8), 759–769.

Argote, L., Epple, D., 1990. Learning curves in manufacturing. Science 247, 920–924.

Argote, L., Beckman, S., Epple, D., 1990. The persistence and transfer of learning in industrial settings. Management Science 36 (2), 140–154.

Argyris, C., Schön, D.A., 1996. Organizational Learning. II. Theory, Method and Practice. Addison-Wesley, Reading, MA.

Bailey, C.D., 1989. Forgetting and the learning curve: a laboratory study. Management Science 35 (3), 340–352.

Baloff, N., 1971. Extension of the learning curve: some empirical results. Operational Research Quarterly 22 (4), 329–340.

Brynjolfsson, E., 1993. The productivity paradox of information technology. Communications of the ACM 36 (12), 67–77.

Cameron, A.C., Trivedi, P.K., 1986. Econometric models based on count data: comparisons and applications of some estimators and tests. Journal of Applied Econometrics 1, 29–53.

Cohen, W.M., Levinthal, D., 1990. Absorptive capacity: a new perspective on learning and innovation. Administrative Science Quarterly 35 (1), 128–152.

Darr, E., Argote, L., Epple, D., 1995. The acquisition, transfer and depreciation of knowledge in service organizations: productivity in Franchises. Management Science 41 (11), 1750–1762.

Davenport, T.H., 1994. Managing the new world of process. Public Productivity and Management Review 18 (2), 133–147.

Dutton, J., Thomas, A., 1984. Treating progress functions as a managerial opportunity. Academy of Management Review 9 (2), 235–247.

Epple, D., Argote, L., Devadas, R., 1991. Organizational Learning Curves: A Method for Investigation Intra-Plant Transfer of Knowledge Acquired through Learning by Doing. In: Cohen, M., Lee, S.S. (Eds.), Organizational Learning. Sage Publications, Thousand Oaks, CA, pp. 83–100.

Epple, D., Argote, L., Devadas, R., Epple, D., Argote, L., Murphy, K., 1996. An empirical investigation of the microstructure of knowledge acquisition and transfer through learning by doing. Operations Research 44 (1), 77–86.

Fitzsimmons, J.A., Fitzsimmons, M.J., 1998. Service Management: Operations, Strategy and Information Technology. Irwin-McGraw Hill, Boston.

Foster, L., Flynn, D., 1984. Management of information technology: its effects on organizational form and function. MIS Quarterly 8, 229–236.

Globerson, S., 1980. The influence of job related variables on the predictability power of three learning curve models. AIIE Transactions 12, 64–69.

Globerson, S., Levin, N., Shtub, A., 1989. The impact of breaks on forgetting when performing a repetitive task. IIE Transactions 21, 376–381.

Hammer, M., Champy, J., 1993. Reengineering the Corporation. Harper Collins, New York.

Hirsch, W.Z., 1952. Manufacturing progress functions. Review of Economics and Statistics 34 (2), 143–155.

Hirschmann, W.B., 1964a. Profit from the learning curve. Harvard Business Review 42, 125–139.

Hirschmann, W.B., 1964b. The learning curve. Chemical Engineering 71, 95–100.

Hitt, L., Brynjolfsson, E., 1996. Paradox lost? firm level evidence on the returns to information systems spending. Management Science 42 (4), 541–558.

Hollander, S., 1965. The sources of increased efficiency: a study of DuPont Rayon Plants. MIT Press, Cambridge.

Huber, G., 1991. Organizational learning: the contributing processes and the literatures. Organization Science 2 (1), 88–115.

Itami, H., Numagami, T., 1992. Dynamic interaction between strategy and technology. Strategic Management Journal 13, 119–135.

Jaber, M., Bonney, M., 1997. A comparative study of learning curves with forgetting. Applied Mathematical Modeling 21, 531–532.

Lieberman, M., 1984. The learning curve and pricing in the chemical processing industries. Rand Journal of Economics 15 (2), 213–228.

Lieberman, M., 1987. Patents, learning by doing, and market structure in the chemical processing industries. International Journal of Industrial Organization 5, 257–276.

Lovelock, C., 1992. Managing Services: Marketing, Operations and Human Resources. Prentice-Hall, Englewood Cliffs, NJ.

McLaughlin, C., Yang, S., van Dierdonck, R., 1995. Professional service organizations and focus. Management Science 41 (7), 1185–1193.

Midgley, D.G., Morrison, P.D., Roberts, J.H., 1992. The effect of network structure in industrial diffusion processes. Research Policy 21, 533–552.

Morris, B., Johnston, R., 1986. Dealing with inherent variability: the difference between manufacturing and service? International Journal of Operations and Production Management 7 (4), 13–22.

Pavitt, K., 1990. What we know about the strategic management of technology. California Management Review 32 (3), 17–26.

Reis, D., 1991. Learning curves in food services. Journal of the Operational Research Society 42, 623–629.

Rothwell, R., 1994. Issues in user production relations in the innovation process. International Journal of Technology Management 9, 629–649.

Schmenner, R.W., 1986. How can service businesses survive and prosper. Sloan Management Review 27 (3), 21–32.

Senge, P.M., Kleiner, A., Roberts, C., Ross, R., Smith, S., 1994. The Fifth Discipline Fieldbook. DoubleDay/Currency Press, New York.

Sheshinski, E., 1967. Tests of the learning by doing hypothesis. Review of Economics and Statistics 49 (4), 568–578.

Williams, K.E., Kotnour, T.G., 1993. An electronic performance support system for organizational learning. Computers and Industrial Engineering 25, 93–97.

Womer, N.K., 1984. Estimating learning curves from aggregate monthly data. Management Science 30 (8), 982–992.

Wright, T., 1936. Factors affecting the cost of airplanes. Journal of Aeronautical Science 3, 122–128.

Yelle, L.E., 1979. The learning curve: historical review and comprehensive survey. Decision Sciences 10 (2), 302–328.

Yetton, P.W., Johnston, K.D., Craig, J.F., 1994. Computer-aided architects: a case study of it and strategic change. Sloan Management Review 35 (4), 57–67.

Zander, U., Kogut, B., 1995. Knowledge and the speed of the transfer and imitation of organizational capabilities: an empirical test. Organization Science 6 (1), 76–92.

Zuboff, S., 1988. In the Age of the Smart Machine. Basic Books, New York.