

Learning and Knowledge Depreciation in Professional Services

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Organizational knowledge is a critical source of competitive advantage for professional service firms. Learning from experience and sustaining past knowledge are critical to the success of such knowledge-driven firms. We use learning curve theory to evaluate learning and depreciation in professional services. Our results, based on seven years of project data collected from an architectural engineering (A/E) firm, show that (a) professional services exhibit learning curves, (b) there is virtually no depreciation of knowledge and, (c) the rate of learning accelerates with experience.

Key words: learning; depreciation; professional services

History: Accepted by Linda Argote, organizational behavior, performance, strategy, and design; received March 10, 2000. This paper was with the authors $3\frac{1}{2}$ years for 3 revisions. Published online in *Articles in Advance* May 30, 2008.

1. Introduction

The organizational learning curve refers to the increases in productivity that are realized as organizations gain production experience. Wright (1936) was the first to document the relationship between production experience and productivity improvements. Wright observed that unit labor cost in airframe production declined at a constant rate with each doubling of cumulative output. Organizational learning curves exhibiting this inverse log-linear relationship between productivity improvements and cumulative experience have since been empirically observed in a wide variety of industries (Argote and Epple 1990, Dutton and Thomas 1984, Yelle 1979). However, much of the empirical evidence for organizational learning curves has centered around manufacturing or massservice environments. We extend this body of work by empirically estimating learning curves in professional service organizations. Specifically, we use seven years of project data from an architectural engineering (A/E) firm to examine productivity gains.

Professional services provide a new business context to study learning curves. Professional services (examples include consultants, engineers, lawyers, etc.) sell business solutions to their clients. Unlike past learning curve studies, projects undertaken by a professional service firm tend to be highly variable (they often span multiple solution types in multiple industries), are nonrepetitive, exhibit high levels of customization to client needs, and involve highly trained professionals from multiple disciplines. Indeed, the core competency of professional service firms is their knowledge stock; understanding the dynamics of how well they leverage this knowledge is key to firms' success.

A further contribution of this paper is the estimation of organizational knowledge depreciation in professional service firms. Empirical evidence from organizations in multiple business settings such as shipbuilding, aircraft production, automotive assembly, and pizza production has indicated that the knowledge stock depreciates with time (Argote and Epple 1990, Benkard 2000, Darr et al. 1995, Epple et al. 1996). Professional service firms compete on the basis of their domain expertise, and depreciation of knowledge stock can potentially endanger the competitive advantage of these firms. Given the significant gains in systems that capture and aid in leveraging a firm's work product, evaluating depreciation will provide managers and planners in professional service firms insights into devising strategies to codify and sustain the firm's knowledge stock.

The remainder of this paper is organized as follows. Section 2 provides background literature on organizational learning curves and knowledge depreciation. In §3, we describe our data sources and our method of analysis. In §4, we discuss our results.

2. Background

Since Wright's (1936) pioneering study of learning curves in aircraft production, there has been a widespread acceptance of the 80% learning curve implying a 20% productivity gain for every doubling of cumulative output. While the modal learning rate may be around 80%, there is a wide variation in how fast firms accrue productivity gains. Although there are no definitive answers in the literature to explain why some firms learn fast and others learn more slowly, the form of learning is a useful framework to understand this variation in productivity gains (Benkard 2000, Argote et al. 1990).

In one extreme, in capital-intensive industries such as petrochemical refining, learning is often instantiated in the production technology. Firms observe outcomes and optimize production processes for productivity gains. In the other extreme, in laborintensive industries such as shipbuilding, productivity gains are primarily a result of workers performing repetitive tasks (Benkard 2000). In many industries, especially in professional services, knowledge resides in both the production technology and in the worker.

Professional services are different from other manufacturing or services studied in the learning-curve literature in a fundamental way-they provide customized solutions to their clients using highly trained labor. Even similar services that are provided to the clients are highly context sensitive.¹ However, as Ofek and Savary (2001, p. 1442) point out, "business solutions are not created from scratch, but rather, they are generated using the collective experience of the firm." The learning process is not derived from direct repetition but rather through insights generated from prior projects. Productivity gains depend, on one hand, on the production technologies that codify and map this collective experience and, on the other hand, on the ability of highly trained professionals to locate, interpret, partially reuse, or adapt prior solutions. In addition, professional service firms can accrue productivity gains by codifying processes (developed from prior experience) to complete routine tasks. These could take the form of a set of rules to complete a task or the form of techniques, methods, and templates that can be reused (Stewart 1997).²

Productivity gains also result from better communication among the professional workers, helping project teams "track down relevant colleagues" (Ofek and Savary 2001, p. 1442) to solve problems at hand. In addition to facilitating communication, professional services can access tacit knowledge from their employees by having formal routines that synthesize insights from past projects to create "new" knowledge that can then be codified and used in anticipation of future service requests (Skyrme and Amidon 1997).

Past research has shown that both the proportion of human labor and production volumes impact productivity gains. Human labor has demonstrated a greater capacity for learning than machine labor (Hirschmann 1964a, b). On one hand, production processes using higher proportions of human versus machine labor—like professional services—typically have steeper learning curves and plateau more slowly than less labor-intensive processes (Yelle 1979). On the other hand, learning curves are most frequently associated with the higher volume settings such as line and batch production (March et al. 1991). In professional services, the overall volumes are low which may impact productivity gains.

2.1. Knowledge Depreciation

Knowledge depreciation refers to ongoing erosion in the knowledge stock, and indicates that the experience-based knowledge stock is not accurately represented by total accumulated production. The net result of depreciation is that in order to predict productivity at a given point in the production history, the basic learning curve must be modified to show that not all production experience is reflected in productivity. Using geometric weighting of past output to allow for depreciation of knowledge stock, several researchers have computed the rate at which the knowledge stock erodes in a variety of industrial settings such as aircraft production (Benkard 2000, Argote and Epple 1990), shipbuilding (Argote et al. 1990), automotive assembly (Epple et al. 1991), Israeli Kibbutzim (Ingram and Simons 2002), and pizza franchises (Darr et al. 1995). With the exception of Ingram and Simons (2002) who did not observe any depreciation in Israeli Kibbutzim, the results indicate that depreciation is significant but varies widely across these industries. There are few answers in the literature as to why knowledge depreciates at different rates, but researchers (see Darr et al. 1995, Ingram and Simons 2002) cite specialization of work, stability and motivation of workers, turnover, sophistication of the

¹ For example, in a routine commercial service such as trucking, the service delivery is insensitive to who is shipping the product. So experience from one instance of service delivery is directly applicable to the next, and learning is achieved via repetition. In professional services such as A/E, two clients asking for the same service—say, the design of an HVAC system—will have different solutions depending on the context and client requirements.

² An anonymous reviewer pointed out that while the projects themselves are unique, the processes employed across projects are typically the same. Indeed, the processes that characterize services as "professional" are common between projects. That referee also

characterized the A/E environment accurately: "...firms also have templates for specific functions, workflows, and computer-aided-design (CAD) systems that substantially aid in making even the design process a methodical one."

production technology, and demand rate as possible explanations.

Professional service workers share a common body of codified knowledge through formal education and training. In many professional services, especially in A/E, there are mandated and well-documented standards, protocols, and procedures that must be followed for service delivery. For example, an electrical engineer must comply to local and state codes, and design of electrical circuits should confirm to wellestablished scientific and design principles. Many professional service firms require their workers to be accredited (pass the bar exam or be a licensed professional engineer) and, in addition, seek continuing education to keep them abreast with the latest developments in the profession. Such specialized and consistent know-now and its continued use in ongoing project work makes the professional worker resistant to knowledge depreciation. On the other hand, productivity gains in professional services may be sensitive to worker turnover (or layoff). Professional workers are primarily responsible for generating insights from prior projects to solve current client problems. When a worker leaves, the unique knowledge he or she has also leaves, depreciating the knowledge stock. In the analysis of shipyards, Argote et al. (1990) found that labor turnover of around 10% did not affect productivity, but suggested that in environments characterized by highly skilled labor, turnover may be significant.

Over the last two decades, gains in storage, retrieval, and communication systems have made it easier for professional service firms to codify, access, and leverage a firm's knowledge stock (Hansen et al. 1999). Firms that are able to successfully leverage these "knowledge management" systems may resist depreciation. However, firms that have less sophisticated production technologies-those that are unable to codify or disseminate past experience into a usable form-may be vulnerable to depreciation (see Darr et al. 1995). If routine tasks are not codified or current teams cannot locate or access past projects that may aid the current project, the cumulative knowledge stock is not used. Additionally, if project teams are unable to identify or communicate with workers who may be able to solve the problem at hand, the tacit stock of knowledge in the workers is not used.

3. Data

Data were collected from an architecture engineering firm that primarily provides facilities engineering services to its clients. The firm has expertise in four disciplines: architectural, electrical, mechanical, and civil/structural engineering. Examples of projects include the design of commercial buildings and specialized structures like cranes and communication towers. This firm also designs technical drawings and estimates costs for systems such as power generation and distribution, lighting, controls, HVAC, plumbing, and fire protection.

Most of the projects require input from multiple disciplines. When a firm is hired for a project, a team is created drawing on engineers from the disciplines that are required for the project. This project team has meetings with the client and visits the project site to finalize client requirements and evaluate design constraints. The team of engineers work on the design in a networked, computer-aided-design (CAD) environment, collaboratively developing the drawings. The output of a project is a set of drawings that completely specify the project. For example, the design of an electrical substation may include the general arrangement of structures, cable, and trench layouts from the architectural engineer; electrical and control schematics from the electrical engineer; and topographical surveys and foundation design from the civil and structural engineers. As the projects get bigger and more complex, a larger set of drawings are required to specify it.

The drawings are also used to generate a "bill of materials" for cost estimation. There is considerable variability among projects, although some project tasks such as client and site visits and cost estimation are similar across projects. And, indeed, all projects draw on common bodies of knowledge. Architectural and engineering rules seldom change, though designs may.

We have monthly data starting in late 1992 for 86 months on the number of projects completed by this firm, the total number of drawings produced, and the labor hours used by the engineers in each of those 86 months. The start of our time series also coincides with the implementation of a desktop-based CAD system. Our analysis focuses on the relationship between productivity, measured as the number of drawings per hour in any given month, and cumulative knowledge stock, measured as the number of drawings produced until the previous month.

4. Models and Results

4.1. The Traditional Learning Curve

The traditional form of learning curve is often written as (see Epple et al. 1991):

$$l_t/q_t = AQ_{t-1}^{-\gamma},\tag{1}$$

where l_t is the labor hours worked by the engineers in month *t* (input), q_t is the number of drawings produced in a month *t* (the output), and Q_{t-1} is the cumulative number of drawings (knowledge

Estimates of Model Coefficients

Table 2

					Correlations		
	Mean	Std. dev.	Min.	Max.	(b)	(C)	(d)
(a) Drawings	3.483	0.918	0	5.37	0.882	0.027	0.0067
(b) Labor hours	6.986	0.965	3.806	9.108		-0.206	-0.247
(c) Experience	7.298	1.111	3.044	8.272			0.991
(d) Experience ²	54.493	13.937	9.269	68.439			

Table 1Basic Statistics (Logged Data)

stock) up to month *t* or $Q_{t-1} = \sum_{i=1}^{t-1} q_i$, $q_0 = 0.^3 A$ and γ are positive constants. The rate of learning can be expressed by the progress ratio $p = 2^{-\gamma}$, which is the percentage decrease in labor hours to create a drawing for every doubling of drawings produced. For estimation, (1) can be rewritten in the commonly used form (Epple et al. 1991):

$$\ln(q_t) = \alpha + \beta \ln l_t + \gamma \ln Q_{t-1} + \epsilon_t, \qquad (2)$$

where $\alpha = 1/\ln(A)$, β , and γ are all coefficients that need to be estimated and ϵ_t is the error term.⁴ Table 1 contains the basic description of the data (all variables are logged) and Table 2 shows the estimated parameters using ordinary least squares for all models considered in the paper.⁵

³ Past research has routinely used "0" or "1" as the stock of knowledge at t = 0. An anonymous referee pointed out that, especially for professional services, not accounting for past history may alter the model coefficients. While we acknowledge that accounting for prior experience will produce more precise results, the issues associated with the assumption of zero knowledge stock at t = 0 are less problematic in our research because a desktop-based CAD system was introduced at the beginning of our time series. The CAD system significantly changed how project teams collaborated, replacing manual processes-such as drafting and routine engineering calculations-with automated ones. The CAD system also brought with it the ability to create templates and the capability to quickly reuse and adapt past designs. In effect, we track the experience on a new production technology. Because the logarithm of zero is not defined, the first observation is not used for estimation; rather, q_1 is used as a starting value to generate the Q_t series.

⁴ Our models assume that the labor hours are exogenously determined. The impact of this assumption is minimal because every project goes through a "scoping" phase where the labor hours are estimated *prior* to the start of the project. The estimate for the labor hours is typically based on project type, specific client requirements, and the complexity of the project—a process that is largely exogenous to the models we estimate. Additionally, the estimated labor hours are seldom adjusted based on the status of concurrent projects. The potential for simultaneous equation bias is therefore minimal.

⁵ In Table 2, models (2) and (2') employ robust standard error corrections. We recovered all parameter and standard errors in Models (3) and (4) using nonparametric bootstrap techniques (proposed by Freedman 1981 and discussed in Davidson and MacKinnon 2006). Results use 10,000 replicates with a grid search over λ in increments of 0.001. Breusch-Godfrey tests for first-order autocorrelation for all models (evaluated at optimal λ) are rejected at the 10% level. In addition to rejecting first-order autocorrelation at the parameters (including λ) providing the best fit to the OLS model,

Parameter	Model (2)	Model (3)	Model (2')	Model (4)
Constant (α)	-4.009 [†]	-4.0354 [†]	—1.355	-0.550
	(0.509)	(1.740)	(1.111)	(0.526)
Man hours (β)	0.8831 [†]	0.8805 [†]	0.9380 [†]	0.9325 [†]
	(0.051)	(0.052)	(0.045)	(0.047)
Experience (γ)	0.1811 [†]	0.1847 [†]	-0.8752 [†]	−0.9874 [‡]
	(0.0429)	(0.058)	(0.343)	(0.501)
Experience ² (δ)			0.0857 [†] (0.026)	0.0942 [†] (0.043)
Depreciation (λ)	1	0.9934 [†] (0.077)	1	0.9983 [†] (0.032)
R ²	0.826	0.825	0.850	0.851
N	85	85	85	85

Note. Standard errors in parentheses.

[†] p < 0.05, [‡] $0.05 \le p < 0.10$.

4.2. Depreciation of Knowledge

Traditional models assume that all knowledge acquired through learning by doing is carried forward to succeeding periods. The model in (3) allows for depreciation in knowledge stock. If K_t is the stock of knowledge at time t, then $K_t = \lambda K_{t-1} + q_t$, $0 \le \lambda \le 1$, and $K_0 = 0$. The parameter λ represents the proportion of knowledge from previous months that is available during future months. Equation (2) can be generalized to

$$\ln(q_t) = \alpha + \beta \ln l_t + \gamma \ln K_{t-1} + \epsilon_t, \qquad (3)$$

where $K_{t-1} = \sum_{i=1}^{t-1} \lambda^{t-i-1} q_i$. Equation (2) is a special case of (3) when $\lambda = 1$. If $0 \le \lambda < 1$, then some of the knowledge gained from accumulated production is lost, i.e., it is not all available for use in the current month. Model (3) in Table 2 shows the parameter estimates for (3). The value of λ is 0.9934, with a standard error of 0.077, indicating that while some depreciation of knowledge does occur, it is not significant to reject the hypothesis that $\lambda = 1$.⁶

4.3. Changing Rate of Learning with Knowledge Stock

The next model tests the impact of growing knowledge stock on the rate of learning. In Equation (4), $\delta < 0$ would imply that the rate of learning slows with increasing knowledge stock; $\delta > 0$ would imply that learning increases with the knowledge stock. When $\delta = 0$, Equation (4) reduces to (3):

$$\ln(q_t) = \alpha + \beta \ln l_t + \gamma \ln K_{t-1} + \delta (\ln K_{t-1})^2 + \epsilon_t. \quad (4)$$

⁶ We use the nonnested hypothesis test proposed by Vuong (1989).

we performed grid searches over λ using the Prais-Winston AR(1) regression model and find optimal λ and other model parameters that are very similar to the OLS model. The conclusions we draw, therefore, are not sensitive to assumptions concerning the error structure.

The columns labeled Model (2') and Model (4) in Table 2 are the estimates for Equation (4), restricting $\lambda = 1$ and freely estimating it, respectively. $\delta = 0.0942$ indicates that the rate of learning increases with the knowledge stock. Learning is now represented by the term $\gamma \ln K_{t-1} + \delta (\ln K_{t-1})^2$, and because δ is significantly different from zero, the change in γ is expected.^{7, 8}

5. Discussion and Conclusions

The findings indicate significant association between experience-based knowledge and productivity increases in professional services. The progress ratio for this firm was 0.8798,⁹ suggesting that for every doubling of output (drawings), productivity increases approximately by 12%. While this is slower than the modal "80% learning curve" found in manufacturing firms, it falls within the range of learning rates observed in past studies (Dutton and Thomas 1984, Argote and Epple 1990).

This study also indicates that there is only a small (nonsignificant) depreciation of knowledge in this organization. Approximately 99.8% of the knowledge stock is carried over from one month to the next. Prior studies, with the exception of Ingram and Simons (2002), have all observed significant levels of knowledge depreciation. In manufacturing settings, the percent of knowledge stock retained month to month varies widely, anywhere from 67% to 96%.¹⁰ In pizza franchises—a service setting—Darr et al. (1995) estimated that only 47% of knowledge stock at the beginning of the month was carried to the next month.

Based on our interviews with managers and engineers of this firm, we conjecture that productivity gains and the lack of depreciation were due to a number of reasons. First, every project in the data set was done in a CAD-based environment, so there is an electronic copy of all the past designs. This electronic repository is accessible by all the engineers in the firm. The firm also maintained a separate database of details about each project which served as an index to the design repository. This index had the "project number" (a unique project identifier that linked the project to the CAD file), name of the client, description of the project, project start and end dates, the names of associated engineers, and comments on project details by the engineers who worked on the project. An engineer who is working with a client can access this index and search for similar projects from her workstation, making it easy to access, reuse, or adapt past designs.

Second, this is also a relatively small engineering design firm with approximately 30 engineers in each of the four disciplines. Many of the engineers had worked together for a number of years, knew each other well, and were aware of the projects their colleagues had worked on. Several of the senior engineers themselves served as "indexes," telling project teams which projects to "look up" in order to gain insights into solving current client problems. Additionally, in our conversations with the engineers, there was broad recognition of who the "experts" were in each of the disciplines. Project teams routinely sought advise from these experts for solving client problems. Our model in this paper does not control for this interaction between engineers. While this is a question for future study, our interviews suggest that this is an important source of productivity gains.

A third reason for low levels of knowledge depreciation rates in this firm may be a result of low turnover rates. Over the course of the seven-year span of this data, the annual turnover was approximately 3%, with most of the senior engineers staying with the firm. Darr et al. (1995) conjecture that turnover rates of 300% among employees and 50% among managers may have contributed to high knowledge depreciation in pizza franchises. Further research is needed to determine if turnover rates impact productivity gains in professional services.

Another finding in this paper is that the rate of learning increases with increasing experience. Past studies (Argote et al. 1990, Darr et al. 1995) found that the rate of learning either did not change or decreased with experience. In professional services, each project brings with it unique challenges, and solving those problems adds to the domain expertise of the firm. Our interviews with the managers suggest that once the firm completes a wide variety of projects in a certain domain, it is able to rapidly translate them into solutions to future client problems. For example, HVAC systems can be installed in a variety of environments-in a commercial building, for a client wanting a "green" building, in a research lab that requires high precision temperature control, or in an historical building. The more HVAC installations the firm has completed, the more likely that past solutions can be reused or adapted to complete current HVAC projects. It is unlikely that this or any professional service firm can sustain such productivity

⁷ This parameter narrowly misses significance at the 5% level (p = 0.0522).

⁸ The term $\gamma \ln K_{t-1} + \delta (\ln K_{t-1})^2$ is increasing as long as $\ln K_{t-1} < -\gamma/2\delta$ for $\delta > 0$. In our data set, $\ln K_{t-1} < -\hat{\gamma}/2\hat{\delta}$ for t > 9 (this corresponds to approximately a stock of 190 pages of drawings).

 $^{^9}$ From Model (3) in Table 2, the rate of learning is 0.1847. Thus, the progress ratio is $2^{-0.1847}$.

¹⁰ For example, prior results include monthly knowledge retention rates of 67% in automotive assembly (Epple et al. 1996), 75% in shipbuilding (Argote et al. 1990), 81% in a North American truck plant (Argote et al. 1990), and 96% in aircraft production (Benkard 2000).

growth without major technological change—perhaps a longer time frame of analysis (or a different form of the production function) is needed to observe decreasing returns to scale. Further research is needed to confirm if other professional service firms exhibit similar behavior.

In conclusion, this paper has validated the existence of learning curves in professional services. Another contribution was the finding that there is virtually no depreciation of the knowledge stock. Our intent was to see *if* professional firms exhibit learning curves; we hope that this new business context will add to the debate of *how* firms learn.

Acknowledgments

The authors thank Linda Argote and two anonymous referees for their insightful comments.

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