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From: Argote, Linda (1999), Organizational Learning, Norwell, MA: Kluwer.

Chapter 1

Organizational Learning Curves: An Overview

1.1 Introduction

"Learning curves" have been found in many organizations. As organizations produce more of a product, the unit cost of production typically decreases at a decreasing rate. A learning curve for the production of an advanced military jet built in the 1970s and 1980s is shown in Figure 1.1. The number of direct labor hours required to assemble each jet aircraft is plotted on the vertical axis; the cumulative number of aircraft produced is plotted on the horizontal axis. As can be seen from Figure 1.1, the number of direct labor hours required to assemble each aircraft decreased significantly as experience was gained in production, and the rate of decrease declined with rising cumulative output. This and related phenomena are referred to as learning curves, progress curves, experience curves, or learning by doing.

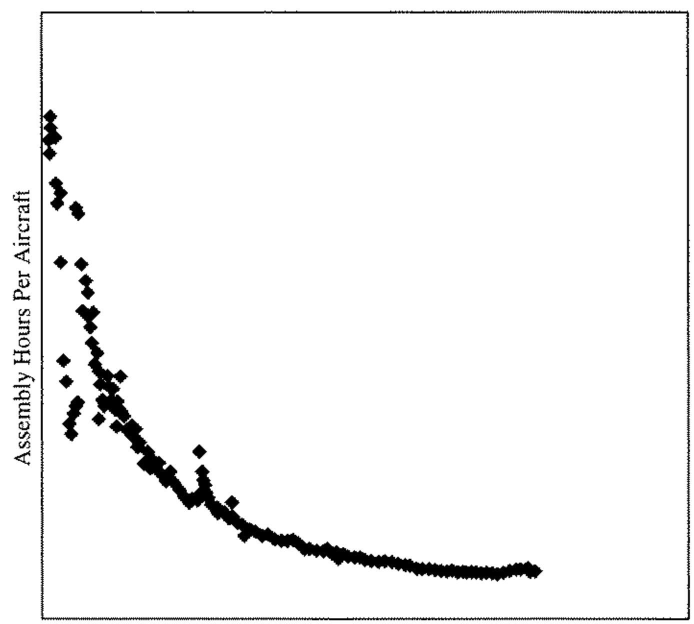
This learning-curve pattern has been found in many organizations. Figure 1.2 shows a learning curve for a truck assembly plant. The number of direct labor hours required to assemble each vehicle is plotted on the vertical axis; the cumulative number of trucks produced is plotted on the horizontal axis. Figure 1.2 depicts the classic learning-curve pattern: the number of labor hours required to assemble each vehicle decreased at a decreasing rate as experience was gained in production.

The unit cost of producing discrete products such as aircraft (Alchian, 1963; Asher, 1956; Wright, 1936), ships (Rapping, 1965), trucks (Epple, Argote & Murphy, 1996), and semiconductors (Gruber, 1994) have all been shown to follow a learning curve. The production of continuous products such as refined petroleum (Hirschmann, 1964) and chemicals (Lieberman, 1984) have also been found to exhibit learning. Additionally, learning curves have been found to characterize a wide range of outcomes in very different settings, including success rates of new surgical procedures (Kelsey, Mullin, Detre, Mitchell, Cowley, Gruentzig & Kent, 1984), nuclear

plant operating reliability (Joskow & Rozanski, 1979), and productivity in kibbutz farming (Barkai & Levhari, 1973) and pizza production (Darr, Argote & Epple, 1995).

The productivity gains derived from organizational learning are significant. For example, during the first year of production of Liberty Ships during World War II, the average number of labor hours required to produce a ship decreased by 45%, and the average time it took to build a ship decreased by 75% (Searle & Gody, 1945). During the first year of operation of a truck assembly plant, the plant's productivity grew by approximately 190% (Epple, Argote & Devadas, 1991).

Figure 1.1
The Relationship Between Assembly Hours Per Aircraft and Cumulative Output



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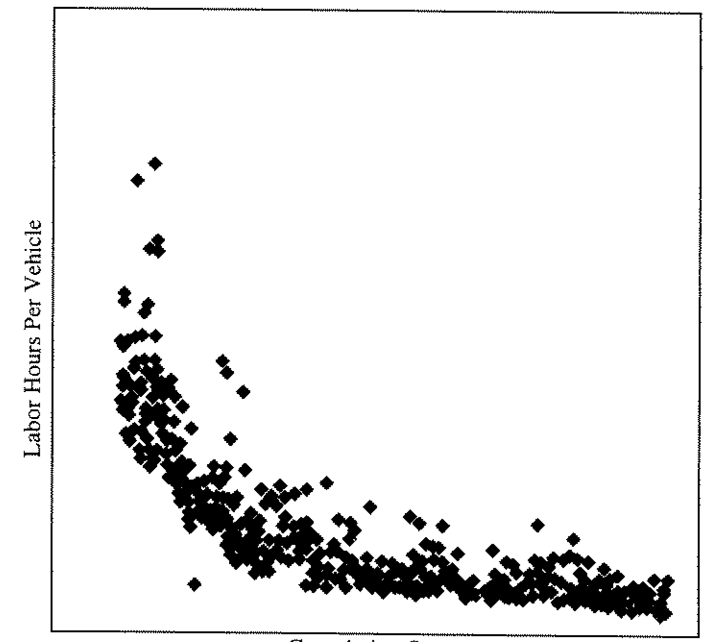
Although the learning-curve pattern has been found in many organizations, organizations vary considerably in the rates at which they learn (Argote & Epple, 1990; Dutton & Thomas, 1984; Hayes & Clark, 1986). Some organizations evidence extraordinary rates of productivity growth with experience; others fail to exhibit productivity gains from learning. Understanding the contrast between organizations that evidence little or no productivity growth with experience and those that show remarkable rates of learning is an important undertaking. For organizations to compete effectively, we need to understand why some organizations show

Figure 1.2
The Relationship Between Labor Hours Per Vehicle and Cumulative Output



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rapid rates of learning and others fail to learn. A greater understanding of factors responsible for the variation observed in organizational learning rates is needed.

Many researchers have emphasized the importance of understanding the variation observed in organizational learning rates. Dutton and Thomas (1984), Lieberman (1984), and Lucas (1993) concluded that the dynamics underlying the learning curve need to be understood better. Similarly, Yelle (1979) indicated that a better understanding of the contributions of various factors to learning curves is needed. This monograph aims to advance knowledge about factors explaining the variation observed in organizational learning curves—to explain why some organizations are better at learning than others.

This chapter began with a discussion of the classic learning curve. It continues with a brief historical overview of the phenomenon, and recent trends in research are noted. How organizational knowledge is typically measured in the learning-curve framework is described and how learning is assessed is discussed. The chapter then presents evidence that learning rates vary tremendously across organizations. Empirical studies that assess the contribution of various factors to organizational learning curves are described. Theoretical models that aim to explain the variation observed in learning rates are presented. The chapter concludes with a discussion of learning-curve applications aimed at improving firm performance.

1.2 Historical Overview

Psychologists were the first to discover learning curves. These researchers focused on the behavior of individuals. Psychologists found that the time individuals took to perform a task and the number of errors they made decreased at a decreasing rate as experience was gained with the task (Ebbinghaus, 1885/1964; Thorndike, 1898). For example, Thurstone (1919) found that the learning-curve pattern shown in Figure 1.1 characterized the performance of students as they progressed through a typing course.

Mazur and Hastie (1978) provided a review of research on learning curves at the individual level of analysis. Researchers working in the individual psychological tradition often fit their data to an exponential rather than a power function, as is customary in organizational learning-curve analysis. There is evidence, however, that power functions may fit individual learning data better than exponential functions (Newell & Rosenbloom, 1981). Further, Delaney, Reder, Staszewski and Ritter (1998) found that the fit of power functions could be improved by plotting learning curves separately for each problem-solving strategy individuals used. When

estimating learning-curve data, one should be sensitive to the choice of the appropriate functional form. Issues that arise in estimating learning rates are discussed later in this chapter and in Chapter 2.

Additionally, learning curves have been found at the group level of analysis. For example, in their studies of the effects of various communication networks on the performance of groups, Guetzkow and Simon (1955) and Leavitt (1951) found that the errors made by groups and the time groups took to complete tasks decreased at a decreasing rate as groups gained experience. Similarly, in their analysis of the effect of planning on group performance, Shure, Rogers, Larsen and Tassone (1962) found that group performance followed a learning curve.

Learning curves have also been found at the organizational (e.g., Wright, 1936) and industry levels of analysis (e.g., Sheshinski, 1967). Some researchers distinguish among learning curves, progress curves, and experience curves as a function of the level of analysis. According to Dutton and Thomas (1984), the term "learning curve" is frequently used to describe labor learning at the level of an individual employee or a production process. The term "progress curve" is often used to describe learning at the level of the firm. Experience curves are used to describe learning at the level of an industry. These distinctions, however, are not made universally in the literature. I use the term learning curve to encompass these related phenomena and specify the level of analysis of the phenomenon.

The focus of this monograph is on learning at the organizational (or organizational subunit) level of analysis. Relevant work at the group and at the interorganizational levels of analysis will be incorporated when it has implications for learning at the level of the organization. Research on group learning provides some of the micro underpinnings of organizational learning. These micro underpinnings of organizational learning are developed in Chapter 4. Research on interorganizational or population-level learning (Miner & Haunschild, 1995) provides the macro context in which organizational learning takes place and also has implications for how one organization learns from another. The implications of interorganizational learning for organizational learning and productivity are discussed in Chapter 5. Interesting tensions or trade-offs that emerge across learning at different levels of analysis are developed in Chapter 6.

An influential early documentation of a learning curve at the organizational level of analysis was published by Wright in 1936. Wright (1936) reported that the amount of labor it took to build an aircraft decreased at a decreasing rate as the total number of aircraft produced, cumulative output, increased. Dutton, Thomas and Butler (1984) noted that Rohrbach had reported that the same pattern characterized the production of

aircraft in Germany in the 1920s. Alchian (1963) found that the learning-curve pattern characterized the production of a variety of aircraft.

Many studies were conducted after the publication of Wright's classic paper that investigated whether the learning-curve pattern characterized the manufacture of other products as well. Dutton, Thomas and Butler (1984) provided an excellent review and interpretation of research on organizational learning curves through the mid 1980s (see also Dutton & Thomas, 1984; and Yelle, 1979). A few of the particularly important early studies on learning are highlighted here.

One early study compared rates of learning in different types of production work. Hirsch (1952) found that improvements in unit labor costs associated with cumulative output were greater in assembly than in machining work. Hirsch's finding has been interpreted as providing evidence that learning curves are steeper in labor-intensive than in machine-intensive industries. This finding has received mixed support in subsequent studies (cf. Adler & Clark, 1991). In a similar vein, Baloff (1966, 1971) found that the tendency for learning curves to "plateau" or level off was greater in machine-intensive than in labor-intensive industries.

Although early work on learning curves focused on industries that manufactured discrete products such as planes, trains and automobiles, learning curves have also been found in continuous process industries. For example, Hirschmann (1964) found that petroleum refining followed a learning curve. His finding has important implications because it suggests that learning curves are not due solely to "labor learning" since labor played a relatively minor role in these settings but rather depend on modifications in the organization and its technology as well (see also Baloff, 1966). Dutton, Thomas and Butler (1984) described how these findings on the presence of learning curves in continuous process industries were important in contradicting the prevailing and misguided view that learning curves could be explained mainly by learning on the part of direct production workers.

Productivity, of course, has been found to depend on other factors besides cumulative output. For example, Preston and Keachie (1964) found that unit labor costs depended on the rate of output as well as on the amount of cumulative output. An organization that tries to increase its rate of production dramatically may experience productivity problems independent of learning that are reflected in high unit costs. Preston and Keachie's (1964) work showed the importance of including changes in the rate of output as well as cumulative output in assessing learning rates.

Similarly, Rapping (1965) demonstrated the importance of controlling for additional factors such as economies of scale in assessing learning rates. Rapping (1965) showed that the production of Liberty Ships during World War II followed a learning-curve pattern when inputs of labor and capital were taken into account in the analysis. Although the effects of labor and capital were significant, the effect of cumulative output remained highly significant when these additional factors were included in models of productivity. Thus, Rapping (1965) demonstrated very convincingly that productivity gains associated with cumulative output were not due to increased inputs of labor or capital or to increasing exploitation of economies of scale. Although these factors were important, evidence of learning remained strong when they were taken into account.

Much of the work on organizational learning curves between the publication of Wright's influential piece in the 1930s and the early 1980s focused on studying the phenomenon in different industries. Research during this period also focused on specifying the functional form of the relationship between the unit cost of production and cumulative output (Yelle, 1979). Although attempts were made to identify factors underlying the learning curve, empirical evidence on the importance of various factors was very limited (Dutton & Thomas, 1984).

1.3 Recent Research Trends

1.3.1 Expanded Set of Outcomes

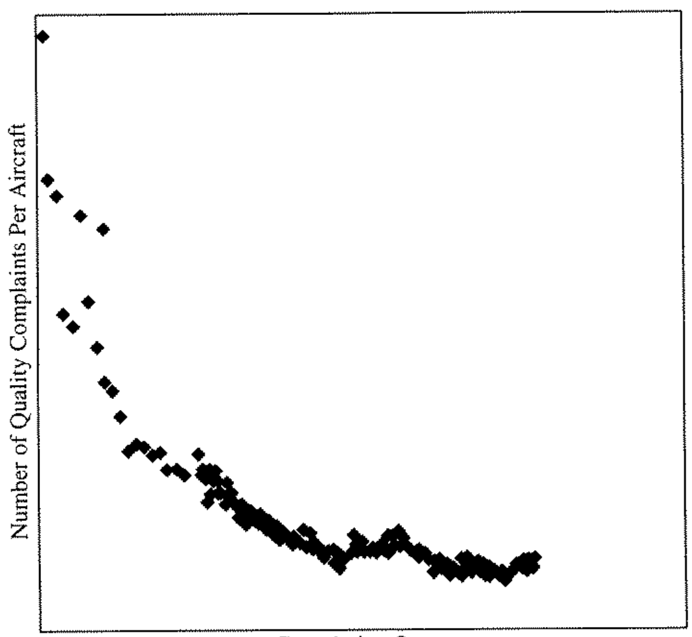
Several important new trends have occurred in research on organizational learning curves in the 1980s and 1990s. First, researchers are expanding the set of outcome measures used as indicators of organizational performance. Research conducted before the 1980s had shown that outcomes in addition to the number of direct labor hours per unit followed a learning curve (e.g., see Greenberg, 1971; Preston & Keachie, 1964). Recent research further expands the set of outcome measures examined as a function of experience. For example, in our research, we have examined the outcome measures of quality, as measured by complaints or defects per unit (Argote, 1993), and service timeliness, as measured by the number of "late" products per unit (Argote & Darr, in press) as outcome variables. Baum and Ingram (1998) focused on the outcome of organizational survival and analyzed how organizations' survival prospects were affected by experience.

A couple of figures illustrate the wide range of outcomes that have been found to follow a learning curve. Figure 1.3 shows an example of a learning curve for quality. The figure is based on data from the production of the same advanced jet aircraft discussed earlier. Figure 1.3 plots the number of complaints made to quality assurance per aircraft as a function of cumulative output. These complaints, which are made internally to the firm,

identify problems that are to be corrected before the product is shipped. As Figure 1.3 indicates, the number of quality complaints made per aircraft decreased at a decreasing rate as the organization gained experience in production. Thus, experience in production was associated with improvements in quality.

Figure 1.4 shows an example of a learning curve for service timeliness for a very different production process—pizza production. The figure is based on one and a half years of data from a pizza store. The cumulative number of pizzas produced is plotted on the horizontal axis; the number of "late" pizzas per unit is plotted on the vertical axis. The

Figure 1.3
The Relationship Between Number of Complaints About Quality Per Aircraft and Cumulative Output



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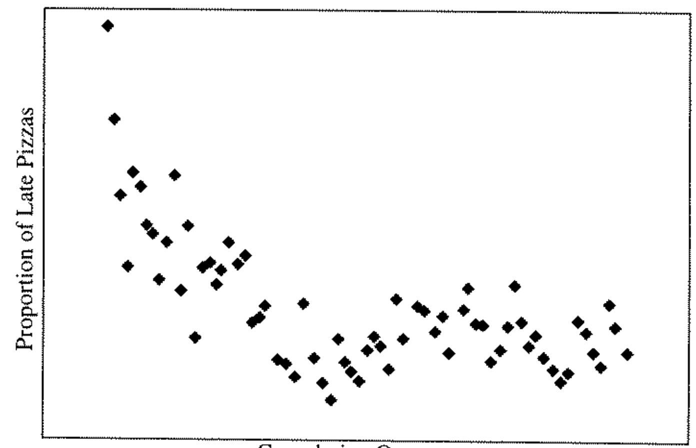
corporation's metric for assessing whether a pizza was late was adopted: if the number of minutes that elapsed from when an order was received to when the pizza was completely prepared exceeded a prespecified limit, then the pizza was coded as late. Figure 1.4 depicts the classic learning-curve pattern: the number of late pizzas per unit decreased at a decreasing rate as experience was gained in production.

Figure 1.4
The Relationship Between Proportion of Late Pizzas and Cumulative Output



Note: Units omitted to protect confidentiality of data.

1.3.2 Understanding Productivity Differences

Another trend in recent research on organizational learning curves is a resurgence of interest in identifying factors explaining the variation observed in organizational learning rates (e.g., see Adler & Clark, 1991; Argote, Beckman & Epple, 1990; Bahk & Gort, 1993; Hayes & Clark, 1986; Ingram & Baum, 1997; Lester & McCabe, 1993; Lieberman, 1984). This work focuses on understanding why some organizations are more productive than others. Research on these productivity differences was stimulated by both practical and theoretical concerns. On the practical side, many manufacturing organizations in the United States in the 1980s experienced enormous productivity problems (Minabe, 1986). While the U.S. had once

enjoyed a very large productivity advantage relative to other industrial countries, the productivity of firms in other countries caught up with and even surpassed U.S. productivity in many sectors during this period (Krugman, 1991). Understanding sources of productivity differences became a central concern.

On the theoretical side, many scholars at this time were shifting to the view that interesting performance variation occurred at the firm rather than the industry level. Resource-based and evolutionary views of the firm were gaining momentum in the fields of strategy and organizational theory (Barney, 1991; Henderson & Cockburn, 1994; Lippman & Rumelt, 1982; Montgomery, 1995; Nelson, 1991; Prahalad & Hamel, 1990; Teece, 1998; Winter, 1995). These theoretical perspectives emphasize differences across firms and aim to understand the source of the differences. Thus, research identifying factors contributing to organizational learning curves occurred against a backdrop of intense concern about productivity problems and a theoretical shift to the firm as a fundamentally important unit of analysis.

1.3.3 Organizational Forgetting

A third important new trend in research on organizational learning curves is examining the dynamics of knowledge acquisition (and loss) by firms. Research in this area examines whether organizational knowledge is cumulative and persists through time or whether it decays or depreciates (e.g., Argote, Beckman & Epple, 1990; Benkard, 1997). This stream of research occurred amidst the same currents discussed previously as motivating work on organizational productivity since differences in the ability to retain knowledge can contribute to productivity differences across organizations. Research on the dynamics of knowledge acquisition and retention also occurred against a backdrop of increased interest on the part of many scholars in applying cognitive principles to understand organizational phenomena (Walsh, 1995). Developments in computing and information systems (Stein & Zwass, 1995) also stimulated and were stimulated by work on organizational knowledge acquisition and retention since a potential benefit of these systems is their enhanced capacity for capturing and retaining knowledge.

1.3.4 Knowledge Transfer

The area of research on organizational learning curves that has exploded in recent years is work on the transfer of knowledge across organizations (e.g.,

Argote, Beckman & Epple, 1990; Baum & Ingram, 1998; Darr, Argote & Epple, 1995; Haunschild and Miner, 1997; Henderson & Cockburn, 1996; Powell, Koput & Smith-Doerr, 1996; Szulanski, 1996; Zander & Kogut, 1995). This research examines whether productivity gains acquired in one organization (or unit of an organization) transfer to another. That is, the research examines whether organizations learn from the experience of other organizations—whether one organization benefits from knowledge acquired at another. For example, research might examine whether one shift learns from another at a manufacturing plant (Epple, Argote & Murphy, 1996), whether one hotel learns from others in its chain (Baum & Ingram, 1998), or whether one biotechnology firm learns from others linked to it through a Research and Development (R&D) alliance (Powell, Koput & Smith-Doerr, 1996).

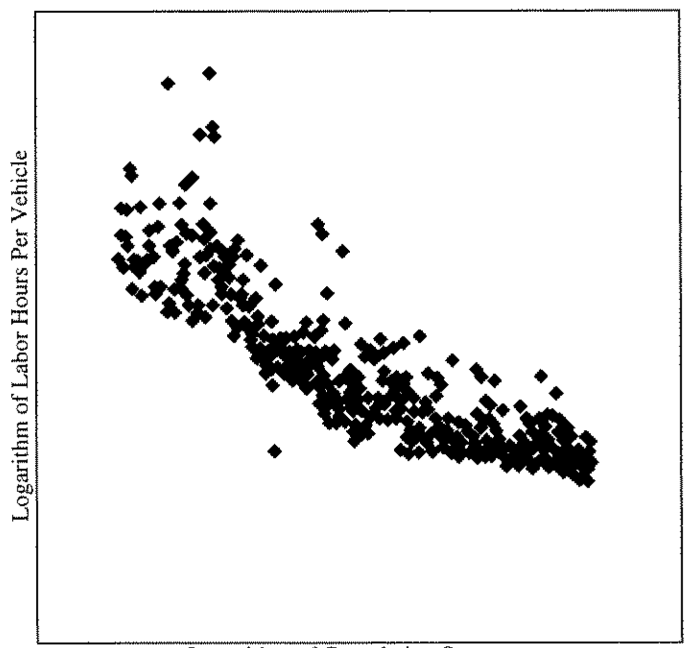
Research on knowledge transfer was shaped in part by the same concerns about productivity that shaped the trends noted previously. An organization that is able to transfer successfully a productivity improvement made at one establishment to another will be more productive than its counterparts who are ineffective at knowledge transfer. Advances in computing and in information systems also stimulated and were stimulated by interest in knowledge transfer since these systems have the potential for facilitating knowledge transfer across geographically distributed sites (e.g., Goodman & Darr, 1996).

In addition, interest in knowledge transfer was stimulated by a shift in the mode of organizing used at many firms from large integrated facilities to small, distributed sites (Galbraith, 1990). This shift enables firms to take better advantage of differences in expertise, labor costs and demand for their product around the world. For example, rather than have all product-development activities occur at one centralized site, an organization might have small teams with expertise in aspects of product development distributed around the world. Similarly, aspects of manufacturing are becoming separate and distributed rather than concentrated at one site ("Survey of manufacturing," 1998). More manufacturing is being done by multinational companies that are able to capitalize on differences in capabilities around the world. Blumenstein (1997) described how General Motors (GM) is taking advantage of such distributed expertise. Blumenstein quoted Basil Drossos, President and Managing Director of GM Argentina, as saying: "We are talking about becoming a global corporation as opposed to a multinational company; that implies that the centers of expertise may reside anywhere the best reside" (Blumstein, 1997, p. A4). Effective operation requires that this distributed expertise be coordinated—that knowledge be transferred from one expert to another and from one site to

another. Thus, the successful use of this organizational form requires the ongoing transfer of knowledge.

Increased interest in organizational learning curves occurred in the context of increased interest in the more general topic of organizational learning. Many theoretical pieces have been written on the topic (see Huber, 1991, for a review). The amount of empirical work is increasing rapidly (Miner & Mezias, 1996). Numerous books and articles have appeared in the business and popular press (Garvin, 1993; Senge, 1990).

Figure 1.5
The Relationship Between Logarithm of Labor Hours Per Vehicle and Logarithm of Cumulative Output



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Research on factors affecting organizational learning curves and the persistence and transfer of productivity gains from learning has occurred in the context of increased interest in the general topic of organizational learning.

Agreement has not emerged about exactly what is meant by the concept of organizational learning. In my view, the concept of organizational learning is likely to remain an "umbrella" concept for many related concepts (see also Easterby-Smith, 1997). What is critical for advancing our understanding of organizational learning issues is for researchers and practitioners to be precise about the approaches they take and to develop the theoretical and practical implications that can be derived from those approaches.

This monograph aims to present and integrate research on these new trends in research on organizational learning curves. This chapter summarizes empirical work directly aimed at assessing the contribution of particular factors to organizational learning curves. Chapter 2 describes and integrates work on the dynamics of knowledge acquisition and loss in organizations. Chapter 3 discusses organizational memory and develops the implication of where knowledge resides for organizational performance. Chapter 4 discusses the micro underpinnings of organizational learning, with particular attention to factors promoting the acquisition or creation of knowledge by groups. Research on knowledge transfer in organizations is presented in Chapter 5. Theoretical and managerial implications of the work are developed in Chapter 6. Before these new research findings are presented, an explanation of how knowledge is measured and how learning is assessed in the learning-curve framework is required. The next section addresses these issues.

1.4 Measuring Knowledge and Assessing Learning

The classic form of an organizational learning curve is:

$$y_i = a x_i^{-b} \tag{1.1}$$

where

y = the number of labor hours required to produce the ith unit
a = the number of labor hours required to produce the first unit
x = the cumulative number of units produced through time period i
b = the learning rate
i = a time subscript

Researchers have found that other outcomes such as defects per unit (see Figure 1.2) or accidents per unit (Greenberg, 1971) follow a learning-curve pattern. Thus, y in Equation (1.1) may represent a range of outcomes associated with the production of the xth unit.

For estimation purposes, Equation (1.1) can be rewritten in logarithmic form:

$$\ln y_i = c - b \ln x_i \qquad (1.2)$$

When converted to logarithmic scales, relationships in the form of the power function shown in Equation (1.1) become a straight line. Figure 1.5 plots the same data shown in Figure 1.2 using logarithmic (log-log) scales. That is, Figure 1.5 expresses the logarithm of direct labor hours per vehicle as a function of the logarithm of the cumulative number of vehicles produced. As can be seen from Figure 1.5, when plotted on logarithmic scales, the data more closely resemble a straight line. Analytic techniques for dealing with any curvature remaining in the data after it is converted to logarithmic scales are described later in this chapter.

The standard measure of organizational experience in the learning curve formulation is the cumulative number of units produced. This measure is computed by summing the total number of units of output produced from the start of production through the end of each time period. The cumulative number of units produced is a proxy variable for knowledge acquired through production. If unit costs change as a function of this knowledge, other variables being equal, we infer that learning has occurred. That is, if the coefficient of the cumulative output variable is significant when Equation (1.2) is estimated with appropriate control variables, organizational learning is said to occur. Thus, the basic principle underlying the learning curve is that production experience creates knowledge that improves productivity (Arrow, 1962).

Knowledge is a difficult concept to measure (Barsalou, 1992). A significant component of the knowledge acquired as organizations gain experience is tacit and difficult to assess directly (Nonaka, 1991; Polanyi, 1966). Further, the scale of many organizations and the uneven distribution of member knowledge makes it difficult to assess knowledge. For example, in a large manufacturing plant with thousands of employees it is virtually impossible to chart all the knowledge that is acquired as organizations gain experience in production. The learning-curve framework uses the cumulative number of units produced as a proxy variable for this knowledge acquired through experience.

A few studies have tried to measure the knowledge organizations acquire as they gain experience more directly. Although these studies provide only a partial picture of knowledge acquisition, they provide useful information about the content of what is being learned with experience. Many of these studies have focused at the group level rather than the organizational level of analysis and hence are discussed in Chapter 4 on the micro underpinnings of organizational learning.

Debate has occurred among researchers about whether the cumulative number of units produced at an organization is better than calendar time as a measure of experience. The cumulative output measure reflects experience at a particular organization (or unit of an organization). For example, as organizations acquire experience, members might learn who is good at what, how to structure their work better, or how to improve the layout of the production area. By contrast, the calendar time measure reflects general technological improvements in the external environment (Solow, 1957). For example, as time passes, properties of materials may improve or computing power may increase. These improvements in the general environment could translate into a reduction in a firm's unit costs. Further, these improvements may be correlated with cumulative output. Thus, it is important to control for the passage of time in analyzing learning rates. This will enable one to determine the extent to which productivity gains are due to technological improvements in the larger environment versus experience at the particular organization.

Studies of organizational learning that have included both calendar time and cumulative output as predictors of unit costs generally find that cumulative output is a better predictor of an organization's unit costs than time is (e.g., see Darr, Argote & Epple, 1995; Lieberman, 1984; Rapping, 1965). For example, Lieberman (1984) and Rapping (1965) found that time was not significant but cumulative output was when both variables were included as predictors of organizational performance. In one of our studies, we found that productivity increased significantly with the passage of time—and with increases in cumulative output (Argote, Epple, Rao & Murphy, 1997). That is, when both variables were included in the productivity models, both were significant. The magnitude of the effect of the cumulative output variable, however, was greater than the effect of calendar time. Thus, it is important to account for the passage of time since it can have a significant effect on productivity. For organizations that produce things with some degree of repetition, cumulative output is generally a more powerful predictor of productivity than simply the passage of time (see also Lieberman, 1987).

Debate has also occurred about whether organizational learning should be defined in terms of changes in knowledge or changes in behavior. This discussion is reminiscent of an earlier discussion in the psychological literature about individual learning. Certain individual learning researchers

defined learning as changes in individual behavior that occurred as a result of experience (e.g., see Hilgard & Bower, 1975). Acknowledging that individuals may acquire knowledge that does not manifest itself directly in changes in behavior, other researchers defined individual learning in terms of changes in "behavior potentiality" that occurred as a result of experience (e.g., see Houston, 1986; Kimble, 1961). Still other researchers of individual learning defined learning as a change in either behavior or knowledge brought about by practice or experience (e.g., see Wingfield, 1979).

At the organizational level of analysis, Duncan and Weiss (1979) and Fiol and Lyles (1985) defined learning in terms of changes in knowledge. Huber (1991) took an approach to defining organizational learning similar to the approach Houston (1986) and Kimble (1961) used at the individual level of analysis. Huber (1991) defined organizational learning in terms of changes in the "range of potential behavior."

The organizational learning curve approach does not assume that behavior changes as a result of experience but rather examines empirically whether such behavioral change occurs as organizations acquire experience. Thus, by examining the coefficient on the cumulative output variable in Equation (1.2), one infers whether learning has occurred. If the cumulative output coefficient is significant, learning has occurred—productivity has changed as a result of experience. A positive coefficient on the cumulative output variable suggests that learning is adaptive for the organization since experience improves performance, whereas a negative coefficient suggests that learning is maladaptive since experience impairs performance. Thus, the learning curve approach allows one to assess empirically whether organizational behavior has changed as a function of experience.

Part of the success of the approach of examining the relationship between cumulative output and the unit cost of production to assess whether organizational learning has occurred hinges on one's ability to control for other factors besides cumulative output that may affect productivity. As noted previously, other factors in addition to experience have been shown to affect the rate of productivity gains in firms. For example, Rapping (1965) showed that economies of scale contributed to the productivity gains observed in the Liberty ship production program. It is important to control for these additional factors that affect productivity since failure to do so may lead to erroneous estimates of the rate at which organizations learn.

The production function[1] approach allows one to control for factors in addition to organizational experience that may affect production. For example, if economies of scale are present, as they were in the Liberty Ship production program, such that a given increase in inputs results in a more than proportionate increase in output and if the scale of operation is

increased over time, productivity will rise over time because of increasing exploitation of economies of scale. If one estimates the rate of learning without controlling for the changing scale of operation, this increasing exploitation of scale economies will result in an overestimate of the amount of learning. Womer (1979) argued for the importance of integrating estimation of learning with production function estimation as a vehicle for controlling for the effects of factors other than cumulative output on productivity.

Issues that must be addressed in using a production function approach to estimating learning rates are discussed in Argote and Epple (1990). These issues include selection of functional form, choice of variables in the model, specification of the properties of factors affecting the production process, and choice of an appropriate method of estimation. An important issue that arises in estimating learning rates is choosing a flexible enough functional form to accommodate a leveling off or slowing down of the rate of learning. Even when learning curves are expressed in logarithmic form, as in Figure 1.5, there may be a slowing down of the rate of learning over time. The possibility of this leveling off or "plateau" effect is documented in Baloff (1966, 1971) and Conway and Schultz (1959). Including a quadratic function of the knowledge variable and evaluating it at values less than the value at which the function reaches a minimum can approximate a function with a positive asymptote. Thus, including a squared term for the experience variable allows for the possibility that the rate of learning plateaus or levels off.

It is also important to correct for problems that may arise if data are collected on a per period basis when several periods are required to produce each unit (Womer, 1984). For example, it may take more than one month to build a ship or assemble a plane. If it takes more than one time period to build a product, it is important to deal with this in the analysis by using measures of the fraction of product produced each time period. For example, Rapping (1965) measured the monthly productivity of shipyards by the tonnage of ships produced per month. Tonnage produced per month is the weight of all ships or portions of ships produced during a month. Thus, Rapping's measurement approach captured all the output, including fractions of ships, produced each time period.

The choice of variables to be included in the model is another issue that must be addressed. The choice of variables varies according to the production process being studied. For example, in a single plant with unchanging physical facilities, labor hours may be the only input that varies over time. Thus, in estimating productivity, one would need to include measures of labor hours but not measures of physical facilities, since these do not change. In studying multiple plants, however, it is important to

include measures of capital investment and other inputs that differ across plants. Such measures would also be needed if the facilities in a given plant change over time.

When production occurs at several plants, additional variables such as cumulative output aggregated across plants may be included in addition to a plant's own cumulative output to assess whether plants benefit from the experience of other plants. This phenomenon, the transfer of knowledge across organizations, will be discussed more fully in Chapter 5. If the plant has the potential to benefit from improvements in technical knowledge in the larger environment such as developments in materials or computing power, proxies for the pace of such improvements should be included. As noted previously, one such proxy is calendar time (Solow, 1957).

It may also be necessary to control for factors such as product mix and adjustment costs associated with changing the rate of production. For example, some plants may produce a more difficult product mix. Perhaps more complex products or a wider range of models are manufactured at one plant than another. The plant with the more complex product mix may have a higher unit cost than its counterparts that is not due to deficiencies in its learning processes but rather due to the complexity of its product line. Thus, in multi-plant comparisons of learning rates, it is important to control for these differences in product mix since failure to do so will result in misleading estimates of the rate of learning. If the product mix changes over time within a plant, it would also be important to control for product mix in single plant studies.

Similarly, it is important to control for adjustment costs associated with changing the rate of output (cf. Preston & Keachie, 1964). Lockheed's production of the L-1011 is an example of a production program that evidenced wide variation in the rate of output. Lockheed experienced considerable difficulties in trying to scale up its rate of output very quickly. These difficulties could result in lowered productivity, independent of the organization's learning rate. Failure to control for adjustment costs may lead to inappropriate conclusions about the rate of learning in firms.

Learning curves are often characterized in terms of a progress ratio, p. With the learning curve in Equation 1.1, each doubling of cumulative output leads to a reduction in unit cost to a percentage, p, of its former value. An 80% progress ratio means therefore that with each doubling of cumulative output, unit costs decline to 80% of their previous value. Thus, an 80% progress ratio means that every time cumulative output doubles, costs decline by 20%. The parameter, b, in Equation 1.1 is related to the progress ratio, p, by the following expression:[2]

$$p = 2^{-b} \tag{1.3}$$

The progress ratio is the measure typically used by firms to characterize their learning rates.

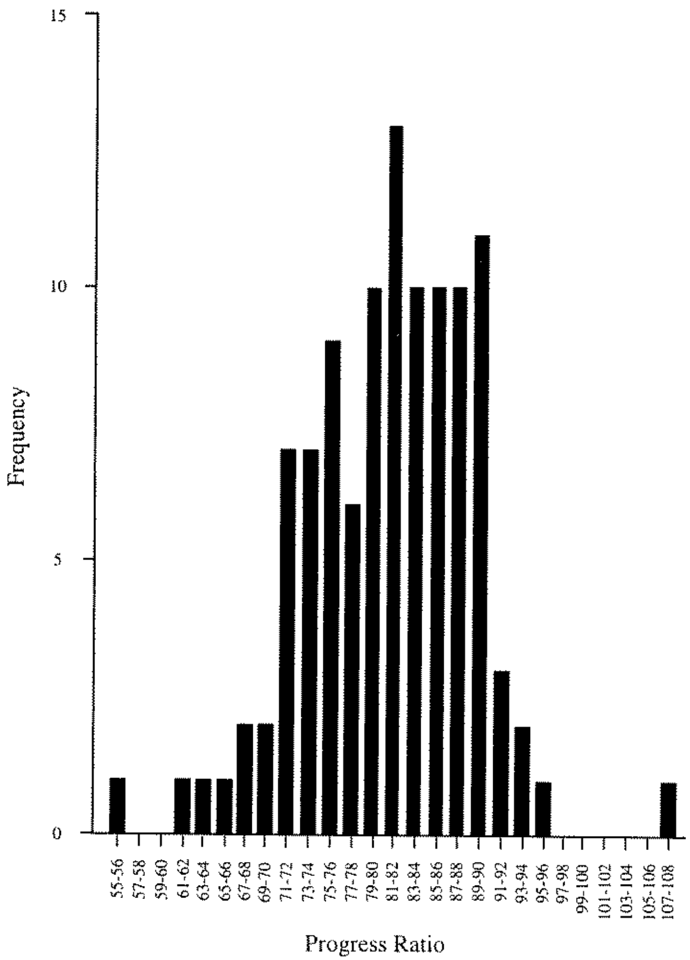
1.5 Organizations Vary in Their Learning Rates

Organizations vary dramatically in the rate at which they learn. Some organizations show remarkable productivity gains with experience, whereas others evidence little or no learning. A study by Dutton and Thomas (1984) nicely illustrated the tremendous variation observed in organizational learning rates. Dutton and Thomas plotted a frequency chart or histogram (see Figure 1.6) of the progress ratios found in more than 100 different production programs in field studies of organizational learning. The field studies were conducted in a variety of industries including electronics, machine tools, papermaking, aircraft, steel and automotive. As can be seen from Figure 1.6, there was a tremendous variation in the rate at which these organizations learned. The lowest progress ratio was 55%, indicating that unit costs declined to 55% of their previous value when cumulative output doubled—an amazingly rapid rate of learning! The highest progress ratio was 107%, indicating that unit costs increased rather than decreased with each doubling of cumulative output. The modal progress ratio found in the Dutton and Thomas analysis fell at 81-82%—perhaps giving rise to the often made assumption of an "80% learning curve." Although an 80% learning curve is the most frequently observed, Figure 1.6 underscores the enormous variation in learning rates.

Although differences in product contribute to the variation observed in learning rates, the different rates of learning are not simply a function of the different products studied. Dutton and Thomas (1984) found that learning rates differed not only across different industries, processes and products but also within the same or similar processes and products. There is often more variation across organizations producing the same product than within organizations producing different products. For example, there was more variation in productivity gains across World War II shipyards that produced the same ship than there was within the shipyards that produced different ships (Searle & Gody, 1945). In a similar vein, Hayes and Clark (1986) found considerable variation in the rate of learning across plants in the same firm producing the same product.

Similarly, Chew, Bresnahan and Clark (1990) documented large differences in productivity across plants in the same firm that produced the same or similar products with similar technology. The researchers described dramatic differences in performance between the best and the worst plants in a firm. After controlling for differences in plant size, age, location and

Figure 1.6
Distribution of Progress Ratios Observed in 22 Field Studies (n=108)

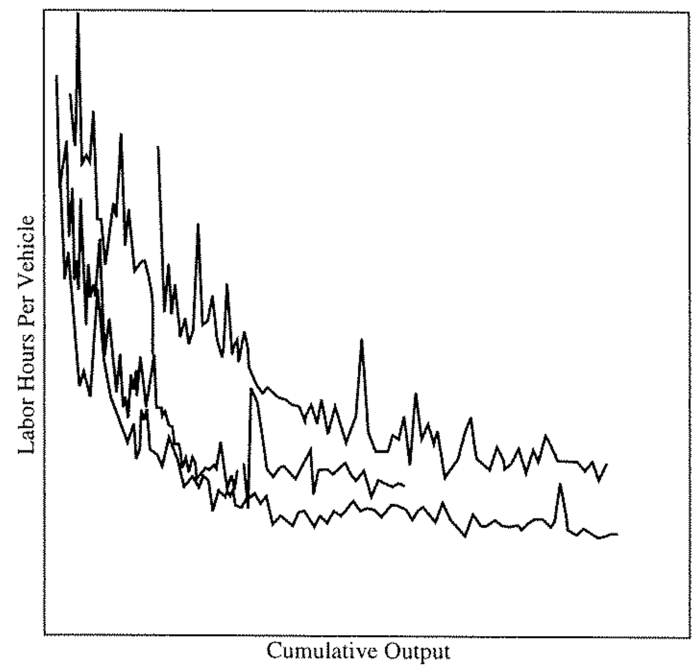


Note. Reprinted with permission from J. M. Dutton and A. Thomas, Treating progress functions as a managerial opportunity, *Academy of Management Review*, Volume 9, Number 2, (April, 1984). Copyright 1984.

technology, performance differences on the order of 2:1 between the best and the worst performer remained (Chew, Bresnahan & Clark, 1990).

Different plants producing the same product that have different rates of learning are shown in Figure 1.7. The figure is based on data from three truck plants that assemble the same product within the same firm. The number of direct labor hours required to assemble each truck is plotted as a function of the cumulative number of trucks assembled. Figure 1.7 illustrates that although unit costs decreased at a decreasing rate with

Figure 1.7
The Relationship Between Labor Hours Per Vehicle and Cumulative Output for Three Plants



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experience for each plant, the rate of the decrease differed dramatically across the three plants. There was considerable variation in the rate at which productivity grew with experience across the three plants—considerable variation in the rate at which they learned.

1.6 Sources of Variation in Learning Rates

What explains the variation in the rate at which organizations learn? Many researchers have speculated about factors explaining organizational learning curves and contributing to the variation observed in organizational learning rates. For example, Hayes and Wheelwright (1984) discussed the following factors as facilitators of organizational learning: individual learning, better selecting and training of new members, improved methods, better equipment and substitution of materials and/or capital for labor, incentives, and leadership. Joskow and Rozanski (1979) identified several factors as contributors to the productivity gains associated with experience: routinization of tasks, learning by management that leads to more efficient production control, learning by engineers who redesign the equipment and improve routing and material handling, and learning by suppliers who are able to provide a speedier and more reliable flow of material. Dutton, Thomas and Butler (1984) noted that productivity gains derived from improvements in capital goods, labor skills, materials, engineering, and managerial expertise. Lieberman (1987) indicated that the productivity gains stemmed from a variety of underlying sources, including improvements in capital equipment, improvements in product and process designs, and improved organizational and individual skills. In our interviews with managers at aerospace and truck plants regarding their perceptions of the most important determinants of organizational learning curves, the managers emphasized: improvements in the performance of individual workers; improvements in the technology, tooling and layout; improvements in the organization's structure; and better understanding of who in the organization is good at what (Argote, 1993).

Thus, a very large set of factors have been hypothesized to contribute to the productivity gains associated with increasing experience. The factors can be grouped into three general categories: increased proficiency of individuals, including managers, engineers and direct production workers; improvements in the organization's technology; and improvements in its structure, routines and methods of coordination.

As noted previously, there has been a resurgence in studies assessing the contribution of various factors to organizational learning rates. These studies aim to open up the "black box" of organizational learning

curves by identifying the factors that drive the productivity gains associated with experience. Organizational performance does not improve automatically with experience. The variation observed in organizational learning rates clearly indicates that productivity improvements are not guaranteed to occur as experience increases. A goal of much research on organizational learning rates is to identify the specific factors that lead to productivity improvements.

Working in this tradition, Lieberman (1984) found that investment in Research and Development appeared to accelerate the rate of learning among firms in the chemical processing industry. Similarly, Sinclair, Klepper and Cohen (1997) found that Research and Development appeared to drive the productivity improvements observed in a chemical firm.

Hayes and Clark (1986) investigated the effect of a variety of factors on the productivity of factories. Hayes and Clark found that reducing the work-in-process inventory, reducing the number of rejects, and decreasing the number of engineering change orders improved productivity. The researchers also found that investment in capital had a positive effect on productivity but cautioned about the importance of managing the introduction of new technology appropriately and adapting it to the organizational context. Surprisingly, investment in training showed a consistently negative relationship to productivity in the Hayes and Clark (1986) study. This latter finding, of course, does not imply that training necessarily hurts productivity but rather suggests that many training programs may be counterproductive or are used as a corrective device once productivity problems have appeared. Chapter 4 discusses how new results on organizational learning can inform the design of training programs to increase their effectiveness.

Galbraith (1990) examined factors explaining the productivity of "recipient" organizations after attempts to transfer advanced manufacturing technology to them had been made. Galbraith (1990) found that the time it took the recipient site to reach the level of productivity achieved by the donor before the transfer was greater when the organizations were geographically far apart and when the technology was complex. Conversely, the time to recover was faster when co-production occurred at the donor site, when an engineering team was relocated from the donor to the recipient site for more than one month, and when individuals involved had a financial stake in the success of the transfer. Similar to the Hayes and Clark (1986) result, training was associated with greater productivity loss. The measure of training did not reflect the appropriateness or quality of the training program.

Adler and Clark (1991) investigated the effect of two learning process variables, engineering activity (measured as the cumulative number

of hours spent by direct personnel on product development changes, running experiments, or learning new specifications) and training activity (measured as the cumulative number of hours spent in training by direct personnel), on the productivity of two manufacturing departments. The researchers found that the two learning process variables had different effects in the two departments. In one department, training facilitated productivity, whereas engineering changes impaired it; in the other department, training impaired productivity, whereas engineering changes had a direct positive but (through their effect on training) an indirect negative effect on productivity. The researchers suggested that in the department where engineering changes had a negative effect on productivity, the changes were made for product performance concerns whereas in the department where engineering changes had a positive effect they were motivated by manufacturability concerns. Training had a more positive effect in the capital-intensive department where it was less disruptive to production than in the labor-intensive department where the training was seen by management as lacking discipline.

Whether organizations are specialists or generalists has been found to affect their rate of learning. Barnett, Greve and Park (1994) found that specialist banks had higher returns on average assets as a function of experience than generalist banks and that generalist banks did not exhibit performance increases as a function of experience. Similarly, in a study of the survival of hotels, Ingram and Baum (1997b) found that "geographic generalists" that operated over a large physical area were less affected by their own experience than specialists who concentrated in a smaller number of areas. Thus, generalists seem to benefit less from experience than specialists. This finding may reflect the difficulty generalist organizations have transferring knowledge across very different units and the greater likelihood that knowledge acquired in one unit will not be relevant for another.

These studies are an important first step at understanding variation observed in organizational learning rates. The studies described in this section are important because they analyze productivity in actual organizations and document performance differences across them. A challenge with the approach, however, is that the same independent or predictor variable may be implemented very differently in different organizations. For example, two firms may make the same number of engineering changes: one chooses the changes judiciously based on analyses of how to improve manufacturability of the product; the other makes the changes on an ad hoc basis. The changes at the former firm are more likely to improve productivity than those at the latter. Yet both firms would have the same value for the engineering change variable since the

firms made the same number of changes. Thus, measuring organizational phenomena in such an aggregate form can mask important differences in the phenomena. These more aggregate studies of productivity are useful in suggesting that a variable may make an important contribution to productivity. The aggregate studies can be complemented by more fine-grained studies that specify the conditions under which the variable has a positive or negative effect on productivity. These more fine-grained studies are described later in this monograph (see Chapters 3-5 in particular).

In our work, we have found that differences in organizations' abilities to retain and transfer knowledge are major contributors to differences observed in organizational learning rates. For example, a firm that is consistently better at retaining knowledge will typically have a faster productivity growth rate than one where knowledge is lost. Empirical results on the acquisition and loss of knowledge are discussed in chapters on Organizational Forgetting (Chapter 2) and Organizational Memory (Chapter 3). Furthermore, a firm that is better at learning from other organizations will generally have a faster rate of productivity growth than one less adept at learning from others. Jarmin (1994) also found that firms differed in the extent to which they benefited from knowledge acquired at other firms. Empirical findings on the transfer of knowledge are presented in Chapter 5.

1.7 Theoretical Models of Organizational Learning

Several theoretical models of organizational learning curves and related phenomena have been proposed (e.g., Dorroh, Gulledge & Womer, 1994; Levy, 1965; Muth, 1986; Roberts, 1983). Muth (1986) provided an excellent review of these models and developed a new one. Muth (1986) generated the power law relationship between unit cost and experience (see Equation 1.1) by a model that involves a firm searching randomly for lower cost methods from a fixed population of technological improvements. Muth's model did not aim to explain the variation in learning rates observed across firms.

By contrast, Huberman (1996) developed a theoretical model of organizational learning that aimed at explaining the variation in learning rates observed across firms. In Huberman's model, the production process is mathematically represented by a connected graph whose nodes represent stages in the production process and whose links represent the routines connecting them. Since there are multiple ways in which products can be assembled, the goal node representing the finished product can be reached along a variety of paths. The total cost of manufacturing a product is proportional to the number of steps (or links in the graph) that are needed to

reach the goal. The more steps, the greater the cost. The learning process involves finding decreasingly shorter paths from the initial state to the final product.

Learning occurs through two mechanisms in Huberman's model. First, a shortcut or new routine for going from the initial to the final node can be discovered. For example, the organization might discover a shortcut for painting a product that involves fewer procedures.

Second, the organization can improve at selecting routines (or choosing links in the graph). That is, of the many possible links leading from one node to another, the organization improves its ability to select the more efficacious links. For example, members of an organization might learn who is good at what so they know whom to go to for advice or assistance. When an issue arises in a particular domain, members of the organization go to the person with the most expertise in the domain, and thus save considerable time. These two learning mechanisms lead to a shorter path from the initial to final stage.

Huberman's model generates a power law decrease in the number of steps to assemble a product. The model also generates variation in organizational learning rates: changes in the effectiveness of the procedure for selecting routines lead to differences in the learning rates. Huberman's model also produces other empirical regularities found to characterize organizational learning such as "organizational forgetting." Thus, his model is very consistent with observed empirical regularities.

Research is needed to test whether Huberman's model corresponds to the process by which learning occurs in organizations. The correspondence of his model with known empirical regularities about organizational learning makes it attractive, and it is intuitively appealing. As organizations acquire experience, they reduce the number of steps or shorten the number of links in a production process. For example, an organization might learn that its layout is inefficient and rearrange equipment to minimize the number of steps required to produce a product. Or an organization might learn that its structure is unwieldy and shift to a structure where individuals who interact on a recurring basis are grouped together. Thus, the number of links required for them to communicate are reduced. Alternatively, members of an organization might learn who is expert about particular domains and therefore choose more effective links in the production process. Thus, in this framework, organizational learning involves building faster and more effective connections for getting work done. In my view, this is a very attractive way of conceptualizing organizational learning.

1.8 Learning Curve Applications

We turn now to a brief overview of applications for improving firm performance that are based on the learning curve. Organizations use learning curves as planning and forecasting tools. Analyses based on organizational learning curves have been used in many applications geared at improving firm performance (Dutton, Thomas & Butler, 1984). Learning curves have been used to plan and manage the internal operations of firms as well as to make strategic decisions regarding their behavior vis-à-vis other firms. For example, on the internal side, learning curves are used for planning production schedules, setting labor standards, planning for training, deciding about subcontracting, making delivery commitments, budgeting, monitoring performance, and determining manufacturing strategy (Ghemawat, 1985; Hayes & Wheelwright, 1984; Jucker, 1977; Levy, 1965). On the external or strategic side, firms use forecasts based on learning curves to predict competitor's costs (Henderson, 1984) and to decide about whether to enter a market and how to price their products.

At a more macro level, the rate and transfer of learning are also important issues for antritrust policy (Spence, 1981), trade policy (Baldwin & Krugman, 1988; Gruenspecht, 1988; Young, 1991), and market structure and performance (Dasgupta & Stiglitz, 1988; Ghemawat & Spence, 1985). Developing the implications of organizational learning and its persistence and transfer for these phenomena is an important undertaking and worthy of future research. The implications of learning for antitrust and trade policy are, however, beyond the scope of this monograph.

Dutton, Thomas and Butler (1984) vividly described the problems associated with some applications of the learning-curve concept that were too simplistic. The learning curve came into vogue as a management tool in the 1960s and 1970s (e.g., see Conley, 1970). It was promoted by consulting groups and by the United States government's requirement that defense contractors include estimates of progress rates in their proposals. Unfortunately, some of these applications treated learning as though it were automatic. Relatedly, there was also a tendency to adopt the "80 percent learning curve" as the norm. Proponents of this view believed that all production programs should achieve an 80% learning rate—that is, with each doubling of cumulative output unit costs would decline to 80% of their previous value. Indeed we have encountered a few organizations where managers were fired because their operations did not achieve an 80% learning curve. This belief in an 80% learning curve is too simplistic and neglects the many factors that affect rates of learning. The overly simplistic use of the learning curve led to some disgruntlement with it in the 1980s (Kiechel, 1981).

The 1990s have enjoyed a resurgence of interest in organizational learning. More recent analyses of learning curves are more appreciative of the many factors affecting learning than earlier treatments were. Academic interest in organizational learning has increased dramatically in recent years. The many popular books and articles on organizational learning and knowledge management reflect concern on the practitioners' side. Subsequent chapters of this monograph return to learning curve applications and develop the operational and strategic implications of new results on organizational learning for firm performance.

1.9 Conclusion

Large increases in productivity typically occur as organizations gain experience in production. Although these learning curves have been found in many organizations, organizations vary tremendously in the rates at which they learn. Some organizations show remarkable productivity gains, whereas others evidence little or no learning. Researchers are beginning to understand the variation observed in organizational learning rates. Empirical research on this important issue is underway. Research is also underway on the dynamics of knowledge acquisition, retention, and transfer in firms. Understanding sources of variation in organizational learning and its persistence and transfer is an important research agenda as well as a source of competitive advantage for firms. The remainder of this monograph is devoted to summarizing what we know about the acquisition, retention, and transfer of knowledge in organizations.

Notes

1. The classic learning curve in Equation (1.1), $y = ax^{-b}$, can be expressed as a production function. The dependent variable in Equation (1.1) is labor hours per output ($y = h/q$). Equation (1.1) can be rewritten as $q = a^{-1}hx^{b}$. Thus, the production function implicit in the conventional learning curve has a single input, labor hours (h), and a single measure of organizational knowledge—cumulative output (x). The conventional formulation also imposes the assumption of proportionality between output and labor hours. Thus, the conventional formulation of the learning curve is a special case of the more general production function approach.

2. The relationship between the progress ratio and the learning rate from Equation (1.1) can be derived as follows:
   Let y_1 = unit cost of producing unit x;
   y_2 = unit cost of producing unit $2x$;
   Then $y_1 = ax^{-b}$,
   $y_2 = a\,(2x)^{-b}$; and
   $y_2 / y_1 = 2^{-b}$.

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