Chapter 3
Organizational Forgetting

3.1 Introduction

Do organizations forget? Or do organizations retain the knowledge they acquire as time passes? The classic learning curve assumes that organizational knowledge is cumulative and persists indefinitely through time. Yet, individuals leave organizations. Records can be lost or misplaced. Technologies become obsolete and/or inoperative. Social networks can decay (Burt, 2002).

My colleagues and I began a research program several years ago to examine empirically whether organizational knowledge persists through time as the classic learning curve implies, or whether it evidences "forgetting" or depreciation. The results of our research program on knowledge depreciation, as well as related studies, are described in this chapter.

The chapter begins with an example of a case where unit costs did not follow the classic learning curve—Lockheed's production of the L-1011 TriStar. This production program, which cost Lockheed billions of dollars, evidenced depreciation of knowledge. A method that generalizes the classic learning curve to test empirically for the possibility of knowledge depreciation is presented. Empirical results from several studies that examine whether knowledge depreciates are summarized. The results of our first study of knowledge depreciation in shipbuilding are described in detail to illustrate how we tested empirically for the presence of depreciation. Rates of depreciation found in various industries are compared and contrasted. Factors affecting the rate of depreciation are discussed.

3.2 Knowledge Depreciation

Does knowledge acquired through learning by doing persist through time or does it decay or depreciate? The classic learning curve model described in Chap. 1, which uses cumulative output as the measure of experience, assumes that knowledge

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acquired through learning persists indefinitely through time. More recent research indicates, however, that this characterization might not be accurate.

Several case studies reported that when production was resumed after an interruption at a manufacturing firm such as a strike, unit costs were higher than the level achieved before the interruption (Baloff, 1970; Hirsch, 1952). In addition, De Holan and Phillips (2004) found evidence of forgetting in their case studies of hotels in Cuba. These case studies suggest that organizations might not retain all the knowledge they acquire indefinitely through time and that organizational "forgetting" can occur.

Organizational forgetting has important consequences for organizational performance. If forgetting occurs, organizations will not be as productive in the future as they anticipate. That is, if there is forgetting, forecasts of future production based on the classic learning curve will overestimate future production. Failure to achieve expected levels of productivity can lead to large problems for organizations. Delivery commitments might not be met. Customers can become dissatisfied. Significant financial penalties for late deliveries might be incurred. Inaccurate forecasts of future productivity make it very difficult for organizations to plan and organize their internal operations. Further, strategic analyses based on inaccurate forecasts of future productivity can be very misleading. In extreme cases, an organization's actual productivity is so far below its expected or forecasted productivity that the organization is not competitive. Thus, if forgetting occurs, it is very important for the organization to allow for this forgetting in forecasts of its future productivity. Further, the organization should consider strategies for minimizing forgetting. These strategies for retaining knowledge are discussed in the following chapter on organizational memory.

Theoretical papers (e.g., Batchelder, Boren, Campbell, Dei Rossi, & Large, 1969; Carlson & Rowe, 1976) and simulation results have developed the theoretical implications of forgetting for forecasting, planning, and scheduling (e.g., see Smunt, 1987; Smunt & Morton, 1985; Sule, 1983). Yet empirical studies of organizational learning typically assume that there is no forgetting and use cumulative output as the measure of organizational experience [e.g., see the many studies in the reviews by Dutton and Thomas (1984) and Yelle (1979)]. Similarly, forecasts of future productivity based on the learning curve also do not account for forgetting. Concerns about the possibility of forgetting coupled with the absence of its consideration in empirical studies and forecasts led my colleagues and me to embark on a research program on the extent of forgetting in organizations. Such knowledge would advance our understanding of organizational learning at a theoretical level as well as lead to important information that would enable organizations to improve forecasts and ideally increase their productivity.

My colleagues and I wanted to test empirically whether organizational knowledge was cumulative, as the classic model implied, or whether it depreciated, as the Lockheed example suggested. Dennis Epple, Sara Beckman, and I developed a method for generalizing the classic learning curve to analyze empirically whether knowledge decays or depreciates (Argote, Beckman, & Epple, 1990). The conventional measure, cumulative output, implies that there is no forgetting or depreciation: experience obtained from a unit of output produced in the distant past is as useful as experience obtained from a unit produced yesterday. My colleagues and I tested this assumption by developing a measure of knowledge that embeds the conventional measure as a special case. We introduced a parameter, lambda, to form a geometric weighting of an organization's past output. Estimates of lambda equal to one correspond to the classic cumulative output measure, whereas estimates less than one imply forgetting or depreciation because output in the distant past receives less weight in predicting current productivity than recent output. We have used this approach to test empirically whether depreciation occurs in different industries, most notably shipbuilding, automotive, and fast food.

Before turning to the empirical studies, a much publicized production program that appeared to evidence forgetting—Lockheed's production of the L-1011 TriStar—is described. My discussion of the TriStar program is based on information publicly available in newspapers, trade publications, the company's annual reports, and the like. My intention in discussing the TriStar program is not to criticize Lockheed. Indeed, the L-1011 is widely regarded as a major technological success. My intent, rather, is to demonstrate that predictions of Lockheed's productivity based on the classic learning curve were dramatically off the mark. Thus, the classic learning curve was inadequate to describe the Lockheed production program. The pattern of costs Lockheed experienced is consistent with a model in which depreciation occurred. Background information about the Lockheed case is presented to illuminate reasons why knowledge depreciated there. Some of the background information is described to provide context for the example; other information is more suggestive of causes of knowledge depreciation.

3.3 A Case Example

As noted previously, analyses of organizational learning that use cumulative output as the measure of organizational experience have been found at times to contain large errors. The L-1011 TriStar produced by Lockheed throughout the 1970s and early 1980s is an example of a production program for which predictions based on the classic learning curve formulation were not realized.

As can be seen from Table 3.1, the number of L-1011 TriStars produced by Lockheed each year varied considerably. Applying the classic learning-curve formulation to the TriStar program led the firm to predict that unit costs would fall below price around the time Lockheed produced the fiftieth plane (Fandel, 1974). Although Reinhardt (1973) criticized Lockheed's analysis of the L-1011 program for omitting the opportunity cost of nonrecurring expenses for developing technology and facilities for the L-1011, he used the conventional cumulative output measure in his forecast of recurring production costs. Reinhardt arrived at a conclusion similar to Lockheed's: production costs would be below price at about the fiftieth plane. This prediction was borne out: Lockheed reported in 1975 that unit costs were less than the price at which each plane was being sold (Sansweet, 1975).

Table 3.1 Lockheed's production of the L-1011 TriStar

	L-1011 production	
Year	Annual units	Cumulative units
1972	17	17
1973	39	56
1974	41	97
1975	25	122
1976	16	138
1977	6	144
1978	8	152
1979	24	176
1980	25	201
1981	18	219

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Cuts in production occurred in late 1975 (see Table 3.1). Costs rose to exceed price and appeared to remain above price for the rest of the production program (Harris Jr, 1982; "Lockheed loses hope," 1980). In 1982, the L-1011 was sold for $50 to $60 million per plane. Converted to 1975 dollars, this corresponds to $29 to $35 million. By contrast, each plane sold for $20 million in 1975 before the cuts in production occurred. Thus, the unit cost of producing each plane was less than $20 million in real terms in 1975 but greater than $29 million in real terms in 1982! Clearly these data do not follow a learning curve because costs rose rather than fell with increases in cumulative output. In 1980, the Chairman of Lockheed, Ray Anderson, stated that the L-1011 would never break even if all costs incurred since 1968 were taken into account but that the company hoped to reach a point where each plane was selling for at least its current production costs (Hill, 1980). Apparently, this never happened. In December 1981, Lockheed announced that it was phasing out production of the L-1011 (Harris Jr, 1981b), making it the last commercial aircraft Lockheed produced.

In the classic learning-curve model, unit costs decrease as a function of increasing cumulative output. Thus, according to the classic model, unit costs should have continued to fall because cumulative output of the L-1011 continued to rise. Instead, unit costs rose rather than fell with increasing experience.

Many factors contributed to the increasing costs Lockheed experienced. The L-1011 program was plagued by shortages of personnel and parts ("TriStar's trail," 1980). For example, the L-1011 production line was shut down when the company that produced its engines, Rolls Royce, went into receivership (Harris Jr, 1981c). This shutdown delayed the delivery of the first L-1011 aircraft. During this delay in the introduction of the L-1011, McDonnell Douglas' DC-10 made significant gains in the market (Harris Jr, 1981c).

Although personnel and parts shortages hurt every aircraft manufacturer, Lockheed appeared to suffer more than the others because of its attempt to increase production so dramatically in the late 1970s ("TriStar's trail," 1980). Lockheed went from employing 14,000 personnel to employing 25,000 in a 2-year period in California. In order to accomplish this dramatic increase in personnel, Lockheed hired many workers who had no previous experience in aircraft construction and who had not finished high school ("TriStar's trail," 1980). *Business Week* concluded that these inexperienced workers hurt Lockheed's learning curve:

> Inevitably, green workers have wreaked havoc with the TriStar's "learning curve," dramatically boosting the man-hours required to build each airplane ("TriStar's Trail," 1980, p. 90).

Indeed, Lockheed executives spent a significant amount of their time "fighting fires" on the production line ("TriStar's trail," 1980). There was a 6-week strike in 1977 and a threat of one in 1980 ("TriStar's trail," 1980). Further, Lockheed's build-up in production came after Boeing had already purchased a storehouse of materials. Lockheed had to pay a premium for materials it needed ("TriStar's trail," 1980).

Another factor that may have favored a competitor of Lockheed's, McDonnell Douglas, is its shared production line between the DC-10 (a commercial product) and the KC-10 military tanker (Harris Jr, 1981c). Thus, the DC-10 had a larger experience base from which to learn and improve than the L-1011. McDonnell Douglas could transfer knowledge from the KC-10 tanker to the DC-10 and thereby reduce the unit cost of production of the DC-10. Further, production of the DC-10 was not characterized by the "roller coaster" production that characterized production of the L-1011 ("TriStar's trail," 1980).

In addition to these factors that seemed to disadvantage Lockheed in particular, other conditions hurt all firms producing wide-body jets. Deregulation (Harris Jr, 1981c) and high fuel prices (Harris Jr, 1981b) favored smaller aircraft. The market for wide-body jets, such as the L-1011, was not as large as had been anticipated.

The classic model that assumes that knowledge is cumulative is too simplistic to capture the dynamics of organizational learning in firms such as Lockheed. The L-1011 is regarded as a technological—but not a financial—success (Harris Jr, 1981a). The L-1011 data are more consistent with a model that assumes knowledge depreciation than with one that assumes knowledge persistence.

Subsequent empirical work by Benkard (2000) confirmed that depreciation occurred in the L-1011 production program. Using newly available data he obtained from Lockheed, Benkard demonstrated very convincingly that organizational forgetting explained the upturn in labor requirements observed in the Lockheed data. Given the large losses Lockheed sustained on the L-1011 program, averaging more than $15 million per year over the decade ending in 1980 ("TriStar's trail," 1980), improved strategies for estimating learning rates are clearly of great importance.

The 3-year delay Boeing experienced in launching its 787 Dreamliner is reminiscent of Lockheed's problems with the L-1011 TriStar. Boeing began assembly of the 787 in 2007 and planned the first delivery for mid 2008. Many problems arose that caused the first delivery to be delayed over 3 years (Kesmodel & Michaels, 2011). Boeing outsourced many of the Dreamliner's components. When assembly began at Boeing's plant, mechanics discovered boxes from suppliers with thousands of parts that should have been installed by the suppliers. Machinists went on strike for 2 months in 2008. Boeing discovered a structural flaw in 2009 that delayed test flights. In 2010, Boeing identified problems with Rolls-Royce engines and experienced a fire on a test flight, which required an emergency landing. After spending billions correcting problems in its supply chain and compensating customers for delivery delays, Boeing finally delivered its first Dreamliner in September 2011.

Boeing has been able to produce about two jets a month. It aims to increase production to ten aircraft a month by 2013. Analysts predict that Boeing will reach its ten-a-month target a year late and that Boeing will lose money on the first 1,000 Dreamliners (Kesmodel & Michaels, 2011). Thus, similar to Lockheed's L-1011, analysts argue that Boeings' Dreamliner will not be profitable for many years.

3.4 Empirical Evidence

3.4.1 The Shipyard Study

Our first empirical study of knowledge depreciation was based on data from the construction of the Liberty Ship during World War II (Fisher, 1949). We learned about these data from Rapping's (1965) study, in which he found evidence of learning in the shipyards. Rapping's study provided particularly compelling evidence of learning because he controlled for important factors such as economies of scale and technological progress associated with the passage of time in his analysis. Rapping found significant evidence of learning when these important additional factors were taken into account.

The Liberty Ship production program is particularly attractive for studying organizational learning and forgetting. The Liberty Ship was built in 16 different shipyards in the USA.[1] Each of the yards producing the Liberty Ship began production during 1941 or 1942. The yards were new yards, the Emergency Shipyards, constructed under the authority of the US Maritime Commission. A central agency was responsible for purchasing raw materials and equipment, approving each yard's layout and technology, and supervising its construction (Lane, 1951). A standard design was adopted and produced with minor variation in all of the yards (Lane, 1951). The overwhelming majority of workers employed in the Emergency Shipyards had no prior experience in shipbuilding (Fisher, 1949). The yards constructed a very large number (almost 3,000) of Liberty Ships. On average, 2 months were required to build each Liberty Ship.

Thus, the Liberty Ship production program is ideally suited for studying organizational learning, forgetting and transfer (See Chap. 6 for a discussion of the transfer results). Many ships were produced from homogeneous raw materials in different organizations by workers without prior industry experience. These features of the

[1] In our analysis, data from 13 of the 16 yards that produced Liberty Ships were used because data on one or more variables were missing for the other yards.

Table 3.2 Variables used in the shipyard study

Symbol	Variable
t	Calendar time in months; $t=1$ in January, 1941
q_{it}	Tonnage (in thousands) produced in yard i in month t
H_{it}	Labor hours (in hundreds) in yard i in month t
W_{it}	Shipways used in yard i in month t
$Q_{it} = \sum_{s=0}^{t} q_{is}$	Cumulative experience in yard i through month t
$A_t = \sum_{i=1}^{13} Q_{it}$	Aggregate cumulative experience through month t
K_{it}	Knowledge acquired in yard i through month t
$AK_t = \sum_{i=1}^{13} K_{it}$	Aggregate knowledge acquired through month t
S_i	Month production started in yard i
Hire_{it}	Number of new hires per hundred employees in yard i in month t
Sep_{it}	Number of departures per hundred employees in yard i in month t

Liberty Ship production program control naturally for many important factors, such as prior experience of workers, which are difficult to control for statistically in many production environments. Further, the shipyards began production at different times, produced at very different scales of operation, and experienced different rates of labor turnover. Thus, there was variance on important factors that allowed us to examine whether knowledge depreciated and whether it transferred. We also explored the role of labor turnover in the acquisition and depreciation of knowledge. The following section describes in depth the method we used to assess whether knowledge depreciated. Readers less interested in the details of the estimation might wish to skip to the results or discussion sections.

3.4.1.1 Method and Sources of Data

Our general approach was to estimate production functions in which output produced in a given period depended on the inputs of labor, capital, organizational experience, and other variables. Variables used in our analysis of the shipyards data and the symbols used to designate them are listed in Table 3.2.

Our primary dependent variable was tonnage of ships produced per month. Tonnage produced per month refers to the weight of all vessels or portions of vessels produced during a month. Womer (1984) demonstrated that inappropriate inferences can be drawn from empirical analyses of learning if the measure of output is based on units finished in a given month, and the period of production exceeds a month. This problem did not arise in our analysis of the shipyard data because our output measure was the tonnage actually constructed in a given month.

Independent variables included measures of labor and capital inputs. Following Rapping (1965), shipways in use was our measure of capital inputs. Shipways are the structures upon which the ships were built.

We estimated models in which output in a given period depended on the inputs of labor (labor hours), capital (shipways), experience and other variables. Specifically, we estimated production functions of the following form:

$$\ln q_{it} = a_0 + \sum_{i=2}^{13} a_i D_i + \alpha \ln H_{it} + \beta \ln W_{it} + \gamma \ln K_{it-1} + \delta' Z_{it} + u_{it} \tag{3.1}$$

where

$$K_{it} = \lambda K_{it-1} + q_{it} \tag{3.2}$$

and

$$u_{it} = \rho_1 u_{it-1} + \rho_2 u_{it-2} + \rho_3 u_{it-3} + \varepsilon_{it}. \tag{3.3}$$

As noted previously, Womer (1979) emphasized the importance of integrating the neoclassical production function approach and analyses of learning by doing. Because the Liberty Ship data were from several organizations that differed significantly in their scale of operation, we were able to integrate the production function approach and learning by doing. By controlling for inputs of labor and capital, we were able to separate increases in productivity due to learning from increases in productivity due to increasing exploitation of economies of scale. In addition, we controlled for calendar time in order to separate the effect of technical progress associated with the passage of time in the general environment from productivity improvements associated with increasing experience at a particular shipyard. The vector Z_{it} in Eq. (3.1) varies from regression to regression and represents these other variables that could influence productivity.

Because our empirical analysis of knowledge depreciation is a new contribution, an explanation of how we measured depreciation is developed. Our approach to measuring depreciation is formalized in Eq. (3.2). Variable K_{it} is the stock of experience accumulated by yard i at date t. Equation (3.2) allows for the possibility that the stock depreciates over time by including the parameter lambda, λ. Lambda is estimated through a scanning procedure for maximum likelihood estimation (Dhrymes, 1966; Goldfeld & Quandt, 1972). If λ is estimated to be one, the accumulated stock of knowledge is simply equal to lagged cumulative output, the classic measure of experience. If λ is estimated to be less than one, however, there is evidence of depreciation because output from the distant past receives less weight than recent output.

As an example of the implications of estimates of lambda, consider a case where lambda is estimated to be 0.90. If the estimate of lambda (0.90) is substituted into Eq. (3.2), output from the previous period would be weighted by 0.90, output from the period before that would be weighted by 0.81 ($\lambda^2=0.90^2$), output from the period before that would be weighted by 0.73 ($\lambda^3=0.90^3$), and so on. Thus, if lambda is estimated to be less than one, output from the distant past receives progressively less weight than recent output in predicting current productivity. Further, as lambda becomes smaller, output from the distant past receives even less weight. Thus, the smaller lambda is, the less knowledge is retained, and the more depreciation of knowledge occurs.

Our measure of knowledge computed from Eq. (3.2) is substituted as a predictor variable into Eq. (3.1).[2] As Eq. (3.1) indicates, knowledge acquired through the end of the preceding month, K_{it-1}, appears in the production function for month t. Thus, past but not current output appears on the right-hand side of Eq. (3.1). The coefficient on gamma (γ) in Eq. (3.1) indicates whether organizational learning occurred. If gamma is significantly different from zero, organizational performance changed as a function of experience. Thus, organizational learning occurred; the organization acquired knowledge. If the lambda (λ) in Eq. (3.2) is significantly less than one, depreciation occurred. The knowledge acquired from recent experience is a more significant predictor of current performance than knowledge acquired from experience in the more distant past.

We controlled for unmeasured yard-specific factors that could affect the productivity of the yards. In Eq. (3.1), the D_i are "dummy" variables for each shipyard. These dummy variables are included to capture unmeasured yard-specific factors such as land that could affect production and are relatively constant through time.

The error u_{it} is assumed to be serially correlated as shown in Eq. (3.3).[3] The serial correlation coefficients are assumed to be the same across all shipyards. The choice of a third-order autoregressive error was based on our analysis of the data. Third-order serial correlation coefficients all reached at least the .05 level of significance. This is not surprising because production of a ship required an average of 2 months, and longer periods were required early in the operation of the yards.[4]

3.4.1.2 Results

Our findings concerning whether knowledge depreciated in the shipyards are presented in Table 3.3. Results obtained from estimating five different models of current production are shown in Table 3.3. The dependent variable in all of these models

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[2] Data on output were available from the beginning of production in each yard, but observations on other variables typically were unavailable until the yard had been operating for a month or more. Hence, the first month of production never appears in our sample. Consequently, K_{it-1} is always greater than zero and ln K_{it-1} is always defined.

[3] The error term ε_{it} in Eq. (2.3) is assumed to be serially uncorrelated and uncorrelated (in large samples) with all variables other than u_{it} on the right-hand side of Eq. (2.1). Furthermore, the ε_{it} are assumed to be uncorrelated across shipyards.

[4] Benkard (2000) provided a more general treatment of the error structure in his analysis of knowledge depreciation.

Table 3.3 Results concerning the persistence of knowledge from the shipyard study

	(1)	(2)	(3)	(4)	(5)
Constant	−3.91	−3.74	−3.85	−3.83	−3.52
	(12.72)	(9.73)	(11.75)	(11.87)	(10.95)
Labor hours	0.16	0.18	0.16	0.15	0.14
($\ln H_{it}$)	(5.14)	(5.18)	(4.60)	(4.38)	(4.09)
Shipways	1.15	1.08	1.15	1.13	1.12
($\ln W_{it-1}$)	(21.83)	(21.02)	(21.77)	(21.84)	(19.38)
Knowledge	0.65		0.71	0.71	0.67
($\ln K_{it-1}$)	(31.42)		(9.54)	(17.82)	(29.96)
λ	0.75[a]		0.75[a]	0.85	0.70[a]
Cumulative output		0.44	−0.04		
($\ln Q_{it-1}$)		(15.74)	(0.72)		
Calendar time				−0.01	
(t)				(3.33)	
New hires					0.003
($\ln \text{Hire}_{it}$)					(0.22)
Separations					−0.019
($\ln \text{Sep}_{it}$)					(1.09)
R^2	0.9911	0.9900	0.9912	0.9912	0.905
$\ln L$	379.047	358.254	379.321	380.463	375.680
N	337	337	337	337	327

Note: Unstandardized coefficients are reported, with associated t-statistics shown in parentheses. $Ln L$ is the natural logarithm of the likelihood function. Reprinted by permission from L. Argote, S L. Beckman and D. Epple, The persistence and transfer of learning in industrial settings, *Management Science*, Volume *36*, Number 2, (February, 1990). Copyright 1990, The Institute of Management Sciences (currently INFORMS), 7240 Parkway Drive, Suite 300, Hanover, MD 21076 USA

[a]Significantly different from one ($p < .0001$)

is the logarithm of current production; the predictor variables for each model vary from column to column. The models were estimated by maximum likelihood. The coefficients of the yard-specific dummy variables are not of particular interest and are therefore not reported. A joint test of the null hypothesis that there were no yard-specific effects was rejected at a high significance level ($p<.001$), so important yard-specific effects were present. Yard-specific dummy variables were included in all analyses shown in Table 3.3.

Estimation was done using the following search procedure. Values of lambda, λ, in the interval [0,1] were chosen. With lambda fixed, the remaining parameters were estimated by standard procedures for estimating regression models with autocorrelated errors. Hence, for each chosen value of lambda the remaining parameters were estimated. We began with a search over values of lambda at increments of 0.05 in the interval [0, 1] to identify the subinterval in which the function reached a maximum and then located the maximum by searching that subinterval at increments of lambda of 0.01. The maximum likelihood estimates for the overall model were the value of lambda and the values of the associated coefficients that yielded the largest value of the likelihood function. This procedure is equivalent to nonlinear search procedures that vary all parameters simultaneously, but is computationally easier to implement.

The maximum likelihood estimate of the depreciation parameter, lambda, for the model shown in Column 1 of Table 3.3 was 0.75. The estimation procedure did not yield a standard error for lambda. The standard errors of the remaining coefficients were computed treating lambda as a known parameter. This could result in some understatement of the standard errors of the coefficients and a corresponding overstatement of the t-statistics. Therefore, all conclusions regarding significance of alternative measures of learning were based on likelihood ratio tests. Using the distribution of the likelihood ratio, we determined that a 93% confidence interval for lambda was approximately (0.65, 0.85). Thus, the hypothesis of no depreciation ($\lambda=1.0$) was very strongly rejected by these data. Hence, the classic measure, cumulative output, significantly overstated the persistence of knowledge. Depreciation of knowledge was found to occur in this production environment.

These results indicate a rapid rate of depreciation. As noted previously, the results were obtained from monthly data. A value of $\lambda=0.75$ implies that, from a stock of knowledge available at the beginning of a year, only 3.2% ($\lambda^{12}=0.75^{12}$) would remain 1 year later. Thus, if the stock of knowledge is not replenished by continuing production, it depreciates rapidly.

Third-order serial correlation coefficients all reached at least the 0.05 level of significance. Estimates of the other parameters were not sensitive to the order of serial correlation. For example, with either first- or second-order autocorrelation, the maximum likelihood estimate of lambda for the model in Column 1 of Table 3.3 was 0.80. Because autocorrelation coefficients up to third-order were significant, we adopted the third-order specification for the remaining analyses.

We investigated alternative models to see if a specification of the learning process that allowed for depreciation was more satisfying than one that did not. Column 2 of Table 3.3 is identical to Column 1 except that Column 2 included the classic cumulative output measure whereas Column 1 included the knowledge variable that allows for depreciation. The log of the likelihood function in Column 1 was significantly greater than the log of the likelihood function in Column 2, $\chi^2=41.59$, $df=1$, $p<.0001$. The contrast of Columns 1 and 2 provides further evidence that learning depreciated and that our knowledge variable was a better measure than the conventional one, cumulative output.

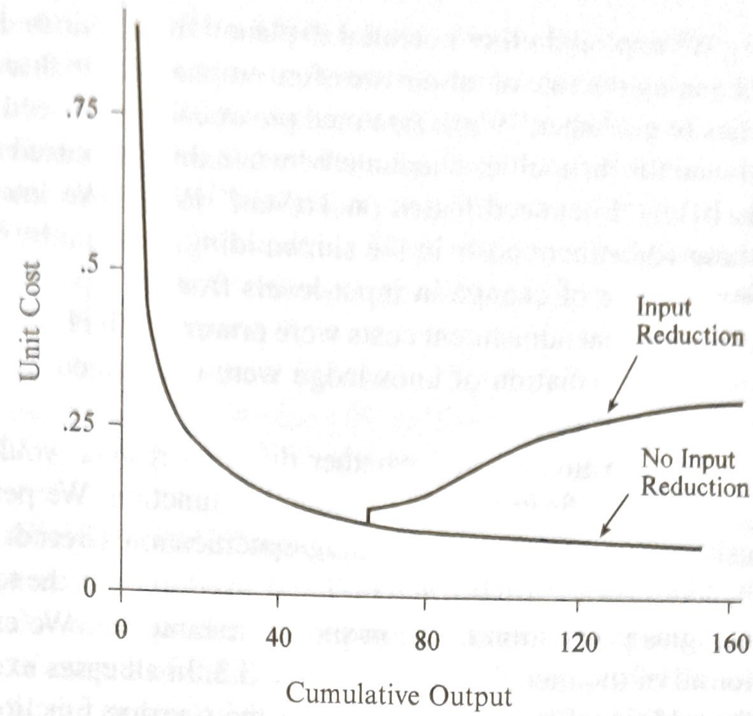
Results presented in Column 3 of Table 3.3 show the effect of including the conventional measure, cumulative output, and our knowledge variable in the same model. When cumulative output is included, the value of lambda that maximized the likelihood function was 0.75, as in Column 1. The conventional measure, cumulative output, had a small and statistically insignificant coefficient, whereas the knowledge variable was highly significant in this model. This is further evidence that the knowledge variable that allows for depreciation is better than the conventional measure, cumulative output.

In Column 4, calendar time was introduced to capture the possibility that technical change associated with the passage of time rather than learning in the shipyards was responsible for productivity improvements in shipbuilding. The negative coefficient for the time variable indicated that the mere passage of time did not explain the productivity gains. When the more general translog specification of the production function (Berndt & Christensen, 1973) was used, the coefficient of the calendar time variable was smaller in magnitude and statistically insignificant. Thus, there was no evidence that the shipyards became more productive simply as a function of the passage of time.

What are the implications of depreciation for future productivity? Figure 3.1 depicts results from a simulation to illustrate the effect of depreciation on unit costs. In this simulation, input levels were held constant at the sample mean for the first 13 months of operation of a shipyard. As can be seen from Fig. 3.1, during this period, unit costs declined at a decreasing rate. The levels of inputs were halved in month 14 and held constant thereafter. The reduction in input caused an immediate increase in unit costs, indicated by the vertical line at the date of the reduction. This jump in unit costs at the vertical line was due to scale economies. The subsequent increase in unit costs was due to the depreciation of knowledge. The reduction in inputs led to a reduction in output which in turn reduced the knowledge variable, K. Gains in knowledge from current production were not sufficient to offset the losses in knowledge from depreciation of the previous period's stock. Thus, depreciation of knowledge led to an increase in the unit cost of production.

Why did knowledge depreciate? One very plausible cause for knowledge depreciation was personnel turnover. If knowledge were embedded in individuals and those individuals were "separated" or departed, their turnover might hurt organizational performance. Therefore, we investigated the role of labor turnover in the productivity gains. Labor turnover was included in the model shown in Column 5 of Table 3.3. The rate of new hires and the rate of departures were included as explanatory variables. This model shown in Column 5 has fewer observations than previous runs because of missing data for the rates of hires and departures. Hence, the likelihood function value for this equation cannot be compared to those for other equations in Table 3.3. As can be seen from Column 5, these variables together did not

Fig. 3.1 The relationship between unit costs and cumulative output when inputs are reduced to half their initial levels. *Note*: Reprinted by permission from L. Argote, S L. Beckman and D. Epple, The persistence and transfer of learning in industrial settings, *Management Science*, Volume 36, Number 2, (February, 1990). Copyright 1990, The Institute of Management Sciences (currently INFORMS), 7240 Parkway Drive, Suite 300, Hanover, MD 21076 USA



contribute significantly to explaining changes in productivity. Additional analyses revealed that neither variable made a significant contribution when included separately. The estimate of the depreciation parameter in Column 5, $\lambda=0.70$, indicates that knowledge depreciated rapidly, even after the effects of labor movement were taken into account.

Conditions at the shipyards could have buffered them from the effects of turnover. A war was on—jobs were designed to be low in skill requirements so that inexperienced workers could be brought up to speed very quickly. Therefore, there was tremendous emphasis on standardization and formalization (Lane, 1951). Improvements made in one part of the yard were quickly codified and transmitted to others.

In summary, the results presented in Table 3.3 indicate that organizational learning occurred: productivity improved markedly as the organizations gained experience in production. As discussed in Chap. 1, learning curves are often characterized in terms of a progress ratio, *p*. The progress ratio describes what happens to unit costs with each doubling of cumulative output. The parameter, *b*, in Eq. (1.1) is related to the progress ratio, *p*, by the expression $p=2^{-b}$. The progress ratio derived from the estimate of *b* in Column 2 of Table 3.3 is $2^{-44}\%$. This is a remarkable rate of productivity. With each doubling of the cumulative number of ships produced, the unit cost of production declined to 74% of its former value. This rapid rate of productivity growth is generally consistent with other analyses of productivity in the Liberty Ship production program (Searle & Gody, 1945).

The results shown in Table 3.3 also indicate that learning did not persist—knowledge acquired through production depreciated rapidly. With the exception of the model that included calendar time, estimates of lambda, the depreciation parameter, were all significantly less than one. When the model with calendar time was estimated using the more general translog specification, the depreciation parameter was significantly less than one.

We explored other potential explanations of our findings. For example, costs of changing the rate of output are often emphasized in discussions of production activities (e.g., Asher, 1956). As noted previously, Lockheed executives frequently mentioned the difficulties encountered when they increased the rate of production of the L-1011 ("Lockheed losses on TriStar," 1980). We investigated the importance of these adjustment costs in the shipbuilding program by including variables measuring the rate of change in input levels from one period to the next. While there is evidence that adjustment costs were present in the Liberty Ship program, our results on the depreciation of knowledge were unchanged by the inclusion of the adjustment-cost variables.

We also investigated whether different results would be obtained with a more general specification of the production function. We performed additional analyses using the more general translog specification (Berndt & Christensen, 1973) that includes $(\ln H)^2$, $(\ln W)^2$ and $\ln H \ln W$ in addition to the terms appearing in the Cobb–Douglas production function shown in Table 3.3. We estimated the translog model for all of the models shown in Table 3.3. In all cases except Column 2 of Table 3.3, the additional terms introduced for the translog function were significant ($p<.05$). Estimates of lambda, the depreciation parameter, in these alternative models ranged from 0.62 to 0.80 and were all significantly less than one. Thus, the results with the more general translog model reinforced the results on knowledge depreciation.

We also allowed for the possibility that the rate of learning slowed down or leveled off. Cumulative output is the conventional measure of experience. Using cumulative output in logarithmic form, as in Eq. (1.2), implies that unit costs converge to zero as cumulative output increases. It may be that cumulative output is the correct measure but that unit costs converge to a positive number rather than to zero. To investigate whether the rate of learning levels off, we estimated Cobb–Douglas and translog production functions with both $\ln K$ and $(\ln K)^2$ as predictors. This quadratic function, evaluated at values of K less than the value at which the function reaches a minimum, approximates a function with a positive asymptote—even with no depreciation of learning. The maximum likelihood estimate of lambda was significantly less than one when knowledge was included as a quadratic function, providing further evidence that knowledge acquired through learning by doing depreciated.

We performed additional analyses to deal with the possibility that there might be simultaneity in the choice of inputs and outputs. This simultaneity might occur, for example, if shipyards that were less productive scheduled more labor hours. To deal with this issue, we estimated several of the models shown in Table 3.3 using the nonlinear two-stage least-squares procedure of Amemiya (1974). As instruments, we used current and lagged values of real wages, shipyard dummy variables, time and time squared, lagged endogenous variables (output, shipways, labor hours), and current and lagged exogenous variables. The results from the nonlinear two-stage least-squares procedure were virtually identical to those obtained using ordinary least squares (see Table 3.3).

The results consistently exhibit evidence of economies of scale in shipbuilding. For example, the results in Column 1 of Table 3.3 indicate that an increase in hours and shipways of one percent would result in a 1.31% increase in output, other things constant. The results indicate that an increase in shipways would result in a more than proportionate increase in output, other things constant. When measures of labor hours and shipways were included in the models, the knowledge variable, K, was highly significant and the estimate of lambda, λ, that best fits the data was significantly less than one. Thus, the results shown in Table 3.3 indicate that when input effects and economies-of-scale effects are controlled for, strong evidence of learning and knowledge depreciation remain.

3.4.1.3 An Application

My colleagues and I used publicly available data to apply our findings on organizational learning and knowledge depreciation to Lockheed's production of the L-1011 (Argote et al., 1990). Table 3.1 displays the yearly production of the L-1011. As Table 3.1 indicates, the rate of output of the L-1011 varied enormously over time. For a wide range of values of the depreciation parameter, Lockheed's production rates imply that the knowledge variable for the L-1011 peaked in late 1974 or early 1975 and then declined. A high level of the knowledge variable would be associated with low production costs.

Examining reports of Lockheed's cost data, we found that they were consistent with our hypothesis of depreciation. Lockheed reported in 1975 that production costs were less than the price at which each plane was sold ($20 million). Thus, production costs were low during the period when the knowledge variable was high. As can be seen from Table 3.1, cuts in production occurred in late 1975. Costs rose to exceed price and appeared to remain above price for the rest of the production program. In 1982, the L-1011 sold for between $29 and $35 million (converted to 1975 dollars for comparison with the earlier period). Thus, the unit cost of production was less than $20 million in real terms in 1975 when the knowledge variable was at its highest but greater than $29 million in real terms in 1982. These data are consistent with the hypothesis that depreciation occurred at Lockheed.

Benkard (2000) obtained detailed data from Lockheed on the production of the L-1011. Benkard demonstrated very convincingly that depreciation occurred in the L-1011 production program. Indeed, the attractiveness of the model including depreciation is that it explains both the first half of production, which is consistent with the classic learning curve model, and the last half of production, in which costs rose rather than receded with increasing experience.

Benkard (2000) also investigated whether knowledge transferred completely between two different versions of the L-1011 produced by Lockheed. Although there was significant transfer across the two models, it was incomplete. That is, the second model benefited from some—but not all—of the production experience acquired on the first model. Evidence of depreciation remained—even when one allowed for incomplete knowledge transfer across the two models. This finding is very important because it suggests that the depreciation results are not due to product changes that render previous knowledge obsolete. Evidence of depreciation remained strong when incomplete knowledge transfer across the different models of the product was taken into account.

When we presented our results on depreciation along with follow-up work in aerospace, automotive and service industries to managers, the results seemed to strike a chord with them. Indeed, one manager referred to our results as documenting a phenomenon he fervently believed in and called "industrial amnesia."

3.4.1.4 Discussion of Causes of Knowledge Depreciation

What causes industrial amnesia? That is, why might knowledge depreciate? Knowledge could decay because products or processes change and thereby render old knowledge obsolete. The incomplete transfer of knowledge observed across the two models of the L-1011 by Benkard (2000) could reflect this obsolescence. Some of the knowledge acquired on the first model may not have been relevant for the second. The depreciation observed in the Lockheed case, however, was not due solely to this obsolescence. Evidence for depreciation remained strong even when incomplete transfer of knowledge across the models was taken into account. Future research aimed at assessing depreciation would benefit from allowing for incomplete transfer across models, if different models are manufactured. This would enable one to determine if depreciation occurred, while allowing for the possibility that knowledge acquired on one model might not be relevant for another.

Knowledge could also decay because organizational records are lost or become difficult to access. This phenomenon occurred at Steinway piano company. When the firm decided to put a discontinued piano back into production, Steinway discovered that it did not have any records or blueprints at its New York facility about how to produce the piano (Lenehan, 1982). Similarly, almost all of the information collected and stored before 1979 by Landsat, an earth surveillance program, is no longer accessible: the data were recorded by equipment that no longer exists or cannot be operated, and the magnetic images have "bled" over time (Marshal, 1989).

In a similar vein, the editors who restored the "Star Wars" trilogy discovered that the original prints of the film had seriously decayed (Morgenstern, 1997). The colors seemed wrong; the print looked faded. Although "Star Wars" had originally been shot on four different varieties of film stock, all of the varieties were subject to fading and various color shifts. Attempts had been made to preserve the completed negative of "Star Wars" on a pair of "protective masters." The preservation effort, however, was not successful. The negative was not cleaned properly before it was copied. The results of the copy attempt were never inspected. According to Morgenstern (1997), this problem is not unique to "Star Wars" but rather characterizes many films made as recently as the 1980s: "Many of our most cherished modern movies...are already in deep decay and could be lost to theatrical audiences forever" (p. A16). These examples illustrate that organizational knowledge can exhibit decay: having knowledge at one point in time does not guarantee that the organization will have it in the future.

Another possible cause of knowledge depreciation is member turnover. Organizational members can leave and take their knowledge with them. Turnover not only deprives the organization of the knowledge and skills of the departing member, turnover also disrupts the performance of members who were interdependent with the departing member and had developed relationship-specific assets. In a study of ambulance companies, David and Brachet (2011) found evidence of organizational forgetting. Further, the researchers distinguished the effect of member turnover from the effect of skill decay of individual members caused by inactivity or task interference. Results indicated that the contribution of member turnover to organizational forgetting was about twice the effect of skill decay. Studies of the effect of turnover on organizational learning and forgetting are discussed in Chap. 4, on organizational memory.

A question we examined in follow-up work was whether the departure of certain key people would affect organizational performance. Perhaps the departure of exceptional performers would affect organizational outcomes. Or perhaps the departure of gatekeepers (Allen, 1977) who bridge social networks or of individuals who occupy key positions in an organization's social network (Burt, 1992; Krackhardt & Hanson, 1993) would have more of an effect on organizational performance than the departure of individuals not occupying key structural positions (Shaw, Duffy, Johnson, & Lockhardt, 2005). Whether the effect of turnover on organizational learning and forgetting depends on who turns over is a focus of our second study of knowledge depreciation. This study is now described.

3.4.2 *The Automotive Study*

A major goal of our second study, which was conducted in the automotive industry, was to examine in more depth the role of labor turnover in the acquisition and depreciation of organizational knowledge. Although little empirical evidence existed about factors responsible for learning and depreciation in organizations, most discussions of organizational learning curves included individual learning as an important source of the gains in organizational productivity observed with increasing experience (Hayes & Wheelwright, 1984; Hirsch, 1952; Wright, 1936). Similarly, in their theoretical discussion of organizational learning, Walsh and Ungson (1991) pointed out that individuals can act as "retention facilities" for organizational memory. To the extent that knowledge acquired through learning by doing is embedded in individuals, their turnover would be harmful for organizational learning. Similarly, Huber (1991) and Simon (1991) suggested that turnover would be harmful for organizational memory.

3.4.2.1 Research on Consequences of Turnover

Although there has been a long tradition of research on predictors of turnover, research devoted to determining the consequences of turnover is more recent (Dalton

& Todor, 1979; Mobley, 1982; Mowday, Porter, & Steers, 1982; Staw, 1980). The automotive study analyzed whether the effect of turnover depended on who departed. Price (1977) suggested that the effect of turnover on organizational effectiveness depends on the performance levels of departing members. Similarly, Mowday et al. (1982) hypothesized that characteristics of individuals leaving the organization moderate the effect of turnover on organizational performance. Boudreau and Berger (1985) developed a multivariate decision-theoretic utility model for assessing the consequences of employee movement into and out of an organization.

Empirical studies of the performance levels of departing employees have yielded mixed results. Although Price (1977) concluded that leavers are relatively more often high-performing employees than those remaining in the organization, Dalton, Krackhardt, and Porter (1981), Dreher (1982), and Wells and Muchinsky (1985) all reported that the performance of employees who left an organization was significantly lower than the performance of those who remained. In their reviews of this literature, Jacovsky (1984) and McEvoy and Cascio (1987) concluded that turnover was higher among poor than among good performers. This relationship held for both voluntary and involuntary turnover but, of course, was stronger for involuntary turnover (McEvoy & Cascio, 1987).

Schwab (1991) suggested that whether it is the good or the poor performers who leave depends on several contingencies. Schwab (1991) found that the relationship between individual performance and turnover was positive for tenured faculty members and negative for untenured faculty. That is, for tenured faculty, higher performers were more likely to leave, whereas for untenured faculty the reverse was true. Schwab (1991) concluded that the relationship between individual performance and turnover depends on several contingencies, such as whether performance is externally visible, and whether there are external job opportunities. The mixed pattern of results on the relationship between individual performance and turnover suggests that it is difficult to predict a priori whether turnover is higher among good or among poor performers because the relationship depends on important contextual factors.

Nonetheless, whether it is the good or the bad performers who are leaving is likely to have important consequences for organizational outcomes. If it is the poor performers who are leaving an organization, we would not expect turnover to have a negative effect on organizational performance. Conversely, if it is the good performers who are departing, we would expect turnover to have a negative effect on performance. Thus, the performance of who is turning over should be taken into account when predicting the effect of turnover on organizational learning and productivity gains.

The automotive study examined empirically the role of turnover in organizational learning curves. We investigated whether the effect of turnover depended on the performance of those who departed. We also investigated the effect of movement of employees into the plant. Our expectation was that movement of employees into the plant at moderate levels would have a positive effect on productivity. March (1991) found a non-monotonic inverted-U relationship between the number of individuals moving into an organization and its performance in a simulation. New employees may bring new ideas and new skills and be more highly motivated than employees with longer tenure (Abelson & Baysinger, 1984; Mowday et al., 1982; Staw, 1980). At some point, however, the cost of integrating too many new employees becomes disruptive for organizational performance. Thus, we expected a non-monotonic inverted-U shaped relationship between movement of individuals into the plant and productivity gains.

3.4.2.2 Method and Sources of Data

We collected data from a North American truck plant (Argote, Epple, Rao, & Murphy, 1997). The workforce at the plant, which was unionized, numbered approximately 3,000. The technology at the plant was extremely advanced. We collected weekly data over a 2-year period from the start of production at the plant. Our data included measures of the number of trucks produced, total direct labor hours worked, number of shifts worked, and movement of employees into and out of the plant.

The turnover data were disaggregated according to the various reasons employees left the plant. Based on theoretical reasons, the effects of two types of turnover were investigated: turnover of high-performing employees who left the plant because they were promoted (promotion) and turnover of employees who were discharged for poor performance (discharge). A third turnover variable included all other reasons employees departed that were not a function of performance (e.g., retired, deceased, quit, laid off, and so on). We performed sensitivity analyses which disaggregated these other types of turnover and investigated their separate effects as well.

We took the same general approach to estimation described for the shipyards study. Our general approach was to estimate production functions. Because we analyzed data from only one plant and its physical facilities were relatively unchanged throughout the course of the study, there was no need to control for physical facilities.

The same approach to assessing depreciation was used for the automotive study as for the shipyards study. As in the previous study, if $\lambda = 1$, the accumulated stock of knowledge equaled cumulative output, the measure of experience in the conventional learning curve formulation. Thus, if $\lambda = 1$, there was no evidence of depreciation. If $\lambda < 1$, evidence of depreciation existed because past output received less weight than recent output in predicting current productivity.

3.4.2.3 Results

We first estimated the classic learning curve. In this analysis, the value of λ, the depreciation parameter, was constrained to equal one. Thus, this model is the conventional learning curve that assumes knowledge is cumulative and persists through time. The results from estimating this model provided strong evidence of learning at the automotive plant: production increased significantly with rising cumulative output. The progress ratio derived from the estimate of the learning rate in this study was 83%. Thus, each doubling of cumulative output at the plant led to a 17% reduction in unit cost. Results also indicated that there were constant returns to labor hours and that output went up proportionately with the number of shifts worked.

We then estimated a model that did not constrain the depreciation parameter to equal one. The value of λ, 0.989, obtained from estimating this model, was significantly less than one. In subsequent analyses, we also included time as an explanatory variable to investigate the extent to which technical progress associated with the passage of time was responsible for productivity gains. There was evidence that the plant became more productive as time passed. The experience variable remained highly significant when time was included as an explanatory variable. Further, the depreciation parameter was significantly less than one in this analysis that included the time variable. Indeed, the estimated value of the depreciation parameter was lower for this model than for the previous ones.

These results have interesting implications for organizational memory. The results suggest that there is a relatively permanent component to organizational memory as well as a more transitory component. The permanent component, which the time variable is picking up, could correspond to knowledge embedded in the organization's procedures and routines. This permanent or procedural component does not evidence depreciation. The more transitory component of organizational memory is reflected in the faster depreciation rate found in the model that accounts for the permanent component of organizational knowledge. This transitory component may be analogous to declarative knowledge, or knowledge of facts (Singley & Anderson, 1989). Cohen and Bacdayan (1994) extended the distinction between procedural and declarative knowledge made in analyses of individual cognition to the dyadic level of analysis. In an interesting laboratory study, Cohen and Bacdayan (1994) found that procedural knowledge exhibited less forgetting than declarative knowledge. Our results from the field suggest that there may be both a permanent and a transitory component to organizational memory.

Another major focus of the automotive study was analyzing the effect of personnel movement into the plant on productivity. We found an inverted-U relationship between the number of new hires moving into the plant and the plant's productivity. Further analyses revealed that the maximum of this function was reached at 38 persons per week. Thus, increases in the number of new hires moving into the plant up to approximately 38 persons (between 1 and 2% of the workforce) per week were associated with increases in productivity. Beyond that point, decreases in productivity were observed.

To investigate our hypothesis that the effect of turnover depended on the performance of the departing employees, additional analyses were performed in which the turnover variable was disaggregated as a function of the reason employees departed. In these analyses, the coefficient of the variable representing employees who were promoted out of the plant as a result of their good performance was negative and significant, as predicted. Thus, the turnover of these high-performing employees negatively affected the organization's productivity. The coefficient of the variable representing employees who were discharged for poor performance was positive, consistent with the expectation that their removal would improve organizational performance. The discharge variable, however, was not consistently significant. The variable representing other types of turnover did not approach significance.

Sensitivity analyses were performed in which the types of turnover included in the "other" category were disaggregated and their effects estimated, either separately or in combination with other types of turnover. With the exception of the "lay-off" variable, these other types of turnover were not significantly related to productivity. In a few analyses, the coefficient of the lay-off variable was negative and marginally significant. In a few regressions, the positive coefficient of the discharge variable was significant. These effects, however, were not consistently significant. Additional analyses were performed to investigate whether the rate of learning plateaued or slowed down over time. We investigated this possibility by including a quadratic term, the square of the knowledge variable. The coefficient of the square of the knowledge variable was extremely small in magnitude and did not approach statistical significance, suggesting that the rate of learning did not change in this production environment.

Because some product options may require more labor content than others, we also investigated the effect of product mix on productivity by including a variable representing different product options in the model. The coefficient of the product mix variable was small in magnitude and statistically insignificant. Including the product mix variable did not affect the coefficients of the other variables in the model.

The results obtained from these additional analyses reinforced our previous conclusions regarding learning, depreciation, and the role of turnover. The evidence for learning remained strong. The depreciation parameter was significantly less than one. Movement of new employees into the plant at moderate levels was consistently shown to help productivity. Turnover of high-performing employees due to promotions appeared to hurt the plant's productivity.

3.4.3 The Franchise Study

We also investigated whether knowledge depreciated in a study of fast food franchises (Darr, Argote, & Epple, 1995). Because our primary goal in the franchise study was to investigate the transfer of knowledge across the various stores, this study is described in depth in Chap. 6. We also investigated whether knowledge depreciated in the study because knowledge that depreciates rapidly can be difficult to transfer.

Our analyses of learning in the fast food franchises were based on weekly data. Estimates of the depreciation parameter obtained in the fast food study ranged from 0.80 to 0.83 (Darr et al., 1995). This is an incredibly rapid rate of depreciation. A value of the depreciation parameter equal to 0.83 implies that roughly one half ($\lambda^4 = 0.84^4$) of the stock of knowledge available at the beginning of a month would remain at the end of the month. From a stock of knowledge available at the beginning of a year, a very negligible amount ($\lambda^{52} = 0.84^{52}$) would remain 1 year later. Without continuing production to replenish the stock of knowledge, virtually all production knowledge would be lost by mid-year. The rate of depreciation found in the fast food study is the most rapid we have found.

3.4.4 *Other Analyses of Depreciation*

In addition to our work and that of Benkard (2000), several other studies have investigated knowledge depreciation. Thompson (2007) constructed a detailed data set about Liberty ship production from primary sources at the National Archives. Analyses of this data set, which included measures of product mix, resulted in more modest estimates of the rate of depreciation than we found. Further, Thompson (2007) found that labor turnover appeared to explain a significant amount of the depreciation. Kim and Seo (2009) analyzed the productivity of the shipyard that produced the largest number of Liberty ships. Based on a different model from ours that used the elapsed time between units to explain knowledge depreciation, Kim and Seo (2009) found rapid rates of depreciation similar to our estimates: only about three quarters of the knowledge available at the beginning of a month remained at its end. Thus, all three studies of the Liberty ship production program have found evidence of depreciation; the amount estimated is sensitive to model specification.

In a study of learning by and between firms in contractual relationships, Kellogg (2011) found significant evidence of knowledge depreciation. Further, Kellogg (2011) suggested that the depreciation was due to the loss of relationship-specific capital between firms.

A couple of studies contrasted the rate of depreciation for different types of experience. In an analysis of accident experience in coal mines, Madsen (2009) found that the effect of experience from major accidents in which lives were lost decayed at a slower rate than the effect of minor accident experience. Similarly, in a study of orbital launches, Madsen and Desai (2010) found that failure experience decayed more slowly than success experience.

Rather than estimate the extent of knowledge depreciation using the method described here, several studies have used various discount factors which assume varying patterns of knowledge depreciation. These studies typically find evidence of some depreciation (e.g., see Ingram & Baum, 1997). An exception is Ingram and Simons (2002) who did not find evidence of depreciation in their analysis of kibbutz agriculture. Ingram and Simons suggested that the persistence of knowledge observed in kibbutzim may be due to the very stable and motivated membership of those organizations.

3.5 Depreciation Rates Vary

Because the extent to which knowledge depreciated varied across the contexts we have studied, these studies provide grist to develop hypotheses about factors affecting the rate of depreciation in organizations. By far the most rapid depreciation was found in the fast food study. One important way in which the fast food franchises differed from the other organizations we have studied is their low technological sophistication. An interesting hypothesis that is consistent with our results is that more technologically sophisticated organizations exhibit less depreciation than less technologically sophisticated ones. For high-technology organizations, much of their knowledge is embedded in their technology—in their layout, software, and hardware. Knowledge embedded in technology may be more resistant to depreciation than knowledge embedded in other repositories.

Another interesting hypothesis worthy of further investigation concerns the role of labor turnover in knowledge depreciation. The turnover in the fast food franchises was incredibly high: the turnover rate of employees was approximately 25% per month. The shipyards had an intermediate level of turnover, averaging approximately 10% per month. The turnover rate in the automotive plant was considerably less than this, averaging between 1% and 2% each month. Thus, we found the fastest depreciation in the organizations that experienced the highest turnover. These results suggest that the average turnover rate might affect the rate of depreciation. Further research is needed to understand the conditions under which knowledge depreciates in organizations and the factors affecting the rate of depreciation.

The following chapter develops these ideas further, introducing the concept of organizational memory and describing various "retention facilities" or "repositories" for organizational knowledge. The implications of where knowledge is embedded for its persistence over time and its transfer to other organizations are developed in Chaps. 4 and 6.

3.6 Implications for Practice

The results on knowledge depreciation have important implications for both operational and strategic decisions in organizations. On the operational side, depreciation has important ramifications for forecasting, planning, and scheduling. If knowledge depreciates, forecasts based on the conventional learning curve will systematically overestimate future productivity. The gap between an organization's actual and predicted productivity can cause major problems for the organization, including poor relations with customers and failure to make significant gains in market share. If the gap between actual and predicted productivity is high, the organization might never reach the point where its production program is profitable (e.g., see the Lockheed case). Thus, knowledge depreciation has important implications for operational decisions in firms.

Knowledge depreciation also has important implications for the strategic behavior of firms. If knowledge depreciates, recent output is a more important predictor of current productivity than cumulative output. Thus, knowledge depreciation lessens the benefits of having a large stock of accumulated knowledge. Under conditions of knowledge depreciation, a recent entrant to an industry would not be disadvantaged relative to firms with a large stock of cumulative output. Knowledge depreciation could explain in part how Korean semiconductor firms that started production in the 1980s, which was much later than their counterparts in the USA and Japan, achieved significant positions in world markets by the 1990s (Cho, Kim, & Rhee, 1998).

Several researchers have argued that forgetting can be functional in organizations (e.g., see Easterby-Smith & Lyles 2011). De Holan and Phillips (2004) identified four modes of organizational forgetting with two underlying dimensions (1) accidental versus purposeful; and (2) focusing on newly acquired versus previously embedded knowledge. Although accidental forgetting typically harms an organization's performance, De Holan and Phillips (2004) argued that purposeful forgetting can improve organizational performance. The latter form of forgetting has been referred to as "unlearning" (Hedberg, 1981; Nystrom & Starbuck, 1984).

By contrast, I would argue that unlearning is a form of learning: the organization learns that what worked in one context does not work in another. That is, the organization refines its understandings and elaborates its response repertoires to take into account various contingencies. Rather than purge the past, it is useful to retain it, while recognizing that past experience might not be appropriate for current conditions. How to retain knowledge in organizational memory is a challenging issue. It would not be efficient or even possible for all members of an organization to retain knowledge about what worked and what did not work under various conditions in the past. That knowledge, however, should be retained in repositories at the organizational level so that the organization avoids repeating mistakes from the past or reinventing solutions already developed. For example, Hargadon and Sutton (1997) showed how knowledge of prior designs retained in an organization's memory facilitated innovation. Organizational memory is discussed in the next chapter.

3.7 Conclusion

The results of the three studies described here provide evidence that knowledge acquired through learning by doing depreciates. Knowledge was found to depreciate in both the shipyards and the fast food franchises. There was also evidence that knowledge depreciated in the truck assembly plant, although the extent of depreciation was much slower than that observed in the shipyards or fast food franchise setting. Thus, the classic learning curve that assumes knowledge is cumulative overstates the persistence of organizational knowledge for these organizations. Results presented here suggest that recent experience is a more important predictor of current productivity than experience in the distant past.

The fastest rate of depreciation was found in the fast food franchises. Several important differences between these organizations and the other study settings were described that could explain the differences observed in their rates of knowledge depreciation. One key difference centered on the technological sophistication of the settings. Knowledge embedded in technology may be more resistant to depreciation than knowledge embedded in other repositories. Another key difference between the settings was the extent of labor turnover. High levels of turnover can make it very difficult for organizations to retain knowledge. We found evidence that turnover made a difference in the automotive plant, when who was turning over was taken into account. The departure of high-performing employees appeared to hurt the truck plant's productivity. When we presented the findings to managers at the plant, they provided an example of how individuals can make a difference even in these capital-intensive systems. The plant had been plagued by a persistent problem: the same defect (a thin scratch) appeared on all the trucks. Considerable energy was invested to isolate the source of the defect. Equipment was inspected; software was checked. It was ultimately discovered that the defect was caused by a disgruntled employee who used his watch to scratch the paint job on each truck! This example illustrates how individuals can affect organizational outcomes—even in highly capital-intensive industries.

Understanding whether knowledge depreciates is important for organizations. If depreciation occurs, failure to allow for it in forecasts of future productivity will lead to forecasts with large errors. This occurred at Lockheed. Lockheed's forecasts of future productivity systematically overshot their actual productivity by a significant amount. Lockheed lost billions of dollars on the L-1011 program, the last commercial aircraft Lockheed produced. Such overly optimistic forecasts may cause significant problems for organizations.

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