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BEHIND THE LEARNING CURVE: A SKETCH OF THE LEARNING PROCESS*

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This exploratory paper sketches some of the behavioral processes that give rise to the learning curve. Using data from two manufacturing departments in an electronic equipment company, we construct a model of productivity improvement as a function of cumulative output and two managerial variables—engineering changes and workforce training. Exploration of this model highlights the complex relationship between first-order and second-order learning.
(PRODUCTIVITY; LEARNING; LEARNING CURVE; MANUFACTURING; ENGINEERING CHANGES; TRAINING)

The apparent regularity of cost reductions captured in the concept of the learning curve (and the related concepts of experience curve and progress function) has given rise to an abundant but frustrating literature. The study reported here makes a step toward remedying the central problem identified by many commentators: the fact that the simple form of these functions linking productivity and cumulative experience only reflects the result of learning but does not clarify the complex process that gives rise to its approximate regularity (see, for example, Dutton and Thomas 1982).

Most learning curve studies have focused on better specifying the aggregate learning effect, primarily concentrating on the selection of proxies for experience. Cumulative output was privileged in the original formulations by Wright (1936) and by many later studies. Arrow (1962) and Sheshinski (1967) examine cumulative investment as an alternative to cumulative output. Alchian (1959) and Hirschleifer (1962) distinguish between rate of output and scheduled volume of output. Cooper and Charnes (1954), Rapping (1965), Sheshinski (1967), Fellner (1969), David (1970), Stobaugh and Townsend (1975) discuss time as an alternative or complement to cumulative output. Some attention has also been paid the functional form of the learning curve, with studies concentrating on the presence of plateaus (Carr 1946; Asher 1956; Conway and Schultz 1959; Baloff 1966, 1971); the so-called Stanford-B effect (Garg and Milliman 1961), and the possibility of a cubic form (Carlson 1973).

These modelling problems should not, however, obscure a fundamental fact: across plants, a wide range in learning rates is found, even where products and scale are similar (Alchian 1959). This variation has not been the subject of much systematic analysis. Stobaugh and Townsend (1975) comment on the fact that the costs of "standardized" petrochemical products fall faster than those of nonstandardized ones; Hirsch (1952, 1956) notes differences in learning rates between machining and assembly; Asher (1956) notes differences between new and old aircraft. But these differences are noted only in ex post observations and have not been the focus of analysis.

If we are interested not only in describing but also in explaining such differences, the literature thins out even further. Several studies follow Arrow (1962) in focusing attention on the role of equipment changes (Sheshinski 1967; Searle and Goody 1945). Hollander (1965) studied the different impact of major and minor technical changes. But only a few studies have paid attention to indirect labor, while most focus exclusively on direct

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labor (Andress 1954; Hartley 1965; Hirshmann 1964) despite the work by Baloff (1966) and Hirsch (1952, 1956) showing learning effects in capital-intensive operations.

The proposition underlying this paper is that progress in research has been impeded by lack of a behavioral model of the learning process. Precursors to our approach include Levy (1965) who suggests a breakdown of behavioral factors of learning into planned, exogenous, and autonomous. Dutton and Thomas (1982) expand on this framework by cross-tabulating the exogenous/endogenous distinction with the induced/autonomous and the random/deterministic distinctions. But with very few exceptions indeed, these behavioral distinctions have not been incorporated into learning models:

- Conway and Schulz (1959) offer an impressive list of preproduction and during-production factors that can affect learning performance,[1] but these are never included in their model.
- Hollander (1965) offers a rich account of productivity changes at DuPont's rayon plants, but does not attempt to formulate a model;
- Baloff (1970) mentions factors such as technical support and labor motivation and shows cases where the learning rate seems to have been affected by these factors; but he does not incorporate these into the model;
- Hayes and Wheelwright (1984), expanding on the insights of Hirschmann (1964), suggest a set of factors that encourage and impede learning at an individual and a group level, but offer no empirical analysis.

One exception to this research strategy is the previously noted study by Levy (1965), which explicitly includes direct labor training variables in a model. We shall build on this starting point by exploring two managerial variables that may contribute to learning.

Our learning process will focus on the different roles played, on the one hand, by what is variously called informal, behavioral, tacit, single-loop, autonomous or first-order learning—as captured by the traditional experience variables—and on the other hand by more formal, cognitive, explicit, double-loop, induced or second-order learning—as captured in two key managerial variables (see Fiol and Lyles 1985 for discussion of these parallel distinctions). Relative to Dutton and Thomas's (1982) distinctions, we shall thus focus on the autonomous/induced dimension. (We ignore their exogenous/endogenous and random/deterministic distinctions because our unit of analysis offers little variation in these dimensions.)

The approach taken in this paper is to exploit some of the data commonly available at the plant level in order to sketch a plausible causal model of the learning process. Our methodological premise is that, given our almost total ignorance of this learning process, an in-depth case study can help us with the first research step—hypothesis formulation and model building. Our case-study approach trades generalizability for the richness of approximately one hundred interviews at all levels of an organization, for the opportunity to observe the learning and production processes in action, and for the possibility of exploring patterns in the quantitative data through dialogue with the managers responsible for these operations.

The data come from an intensive study of the comparative performance of eight departments of an electronic equipment firm, which, in order to preserve its anonymity, we shall call "Hi-Tech." These departments, located in the U.S., Europe, and Asia, produce between them the four major components of a computer peripheral device. We have collected data on the first three years of the life of Hi-Tech's new generation product. This study focuses on two departments in the U.S. facility, where production began somewhat earlier than overseas.

[1] Preproduction factors: tooling, equipment and tool selection, product design, methods, state of the art, magnitude of the design effort, shop organization. During-production factors: tooling changes, methods changes, design changes, management, volume change, quality improvements, incentive pay, operator learning.

TABLE 1

Annual Output (in '000s Units)

	1979	1980	1981	1982
B	0.8	14	53	273
C	0	0.2	1.7	17.5

TABLE 2

Approximate Input Shares (December 1982)

	B	*C*
Direct Labor	10	12
Indirect Labor	30	14
Materials	10	62
Capital	35	7
Inventory	5	5
Total	100%	100%

In § 1, we present a brief sketch of the manufacturing process. Section 2 describes the two basic kinds of learning models: first, the traditional learning curve, and second, a new type of model that we propose in order to incorporate managerial variables related to the acquisition of process knowledge. In § 3, we detail the sources and construction of variables. Section 4 compares the standard learning curve model with the learning process models of the two departments. Section 5 proposes an expansion and refinement of our learning process model, and § 6 concludes with some suggestions for future research.

Two principal conclusions can be drawn for our analysis. First, and contrary to a common preconception, the learning effect can be just as strong in very capital-intensive operations as in labor- or materials-intensive operations. Second, our case data suggest that learning processes may be quite dissimilar across departments. Future research into the anatomy of the learning process will need to focus on the differences across types of departments in the internal structure of the learning process, in particular the relationship between first-order and second-order elements of learning.

1. The Context

Respect for the company's anonymity demands that our description of the product—a computer peripheral device—and its manufacturing process be very stylized. We focus on two departments, *B* and *C*.[2]

The period under study is the ramp-up period. This can be seen in the data on output presented in Table 1. Indeed, Hi-Tech experienced a large order backlog throughout this period.

We will define input variables in the next section, but Table 2 introduces some key characteristics of the departments under study. This table highlights some important features of these two departments:

- Machinery and equipment assets per direct and indirect worker are relatively low in *C*, which is primarily an assembly operation with sophisticated testing machines. Assets per worker are much higher in *B*, which is a much more automated machining and coating operation.

[2] Adler (1990) discusses the performance of all four departments in the U.S. plant as well as the performance of several departments in two overseas plants.

• Purchased materials account for only about 10% of the *B* area total manufacturing costs, but about two-thirds of *C* costs (these figures exclude inputs from upstream in-plant departments).

• Some indication of the "knowledge-intensive" nature of the operations is reflected in the fact that indirect personnel associated with the daily manufacturing operations (primarily manufacturing engineers and technicians) account for well over half the total manufacturing personnel costs in both departments, even three years after startup.

2. Two Models of Learning

We review here the two learning models we shall use: first, the conventional "catch-all" model with one explanatory variable, "experience"; second, our learning process model which attempts to explicate some of the variables underlying improvement.

2.1. *The Learning Curve Model*

We shall test first the applicability to Hi-Tech of the classic learning curve model in which productivity (to be defined in § 3.3) is an exponential function of experience.

The two principal candidate expressions of experience are cumulative output and time. Previous research (Adler 1990) leads us to focus on cumulative output as the operationalization better suited to our sites. To avoid spurious correlation between cumulative volume and the measure of output used in the numerator of our productivity ratio, equation (1) specifies the use of the previous period's cumulative experience as the appropriate measure of the experience-base available for this month's activity:

$$\ln \mathrm{PDTY}_t = a_1 + b_1 \cdot \ln \mathrm{CVOL}_{t-1} + e_t, \qquad \text{where} \tag{1}$$

PDTY = productivity,
ln = natural logarithm,
CVOL = cumulative output to date,
e = error term,
t = month.

2.2. *The Learning Process Model*

The learning process model we explore is premised on the notion that a significant part of the effect of experience on productivity captured in the learning curve model might be due to the influence of identifiable managerial actions. It should be possible to identify at least some of the things an organization learns to do better in order to move along a learning curve.

Our learning process model begins with the relationship between experience and the generation of data driven by that experience. This data is processed in the organization to create new understanding (knowledge) of the design and the production process.

Some of this new knowledge fuels productivity directly, via experiential learning-by-doing, or first-order learning. This is learning based on repetition and on the associated incremental development of expertise. This learning makes direct workers and other contributors more effective in executing the tasks assigned to them.

But some of the learning created by production experience is second-order—learning that transforms the goals of the process by explicit managerial or engineering action to change the technology, the equipment, the processes or the human capital in ways that augment capabilities. (On the distinction between first-order and second-order types of learning see Dutton and Thomas 1982 and Fiol and Lyles 1985.) Specifically, we will focus on two types of learning activities: changing the product design through engineering changes and building human capital through training:

(a) *Engineering Changes* (ECs). We know that approximately one quarter of the ECs for the product under analysis at Hi-Tech were motivated by design errors. Some of these errors would be uncovered in production through testing, while other design changes might reasonably be expected to be made under the impetus of market experience. The bulk of the ECs, however, were not motivated by design errors, but instead by ease-of-manufacture and cost-reduction concerns. These changes are primarily prompted by production experience. So we might expect part of the experience effect captured in the learning curve to reflect deliberate engineering changes.

(b) *Training*. Training of "direct" personnel (nonsupervisory, shop-floor personnel) should be a second conduit for learning. The investment of training time should lead to some improvement in worker performance, and thus, productivity. So part of the experience effect should be due to training.

This leads us to the learning process model diagrammed in Figure 1. Using this model, this paper attempts to "get behind" the learning curve to understand how much of the experience effect can be explained in terms of the two basic kinds of learning. Our learning process model is thus a simple framework in which we investigate the extent to which the observed general relationship between cumulative volume and experience is accounted for by a distinct second-order path of deliberate managerial/engineering action.

The preceding description of the two managerial learning process variables indicates that each of them is linked to the more traditional source of learning—the learning-by-doing, "autonomous" accumulation of understanding and expertise. The second managerial variable, training, is moreover linked to ECs. Training should be a conduit for engineering change activity's effect on productivity, since engineering changes often necessitate time out from the directly productive to familiarize personnel with the new specifications and their production requirements. In fact, our data allocates the training time that is directly attributed to ECs to the Engineering Change variable itself, and the

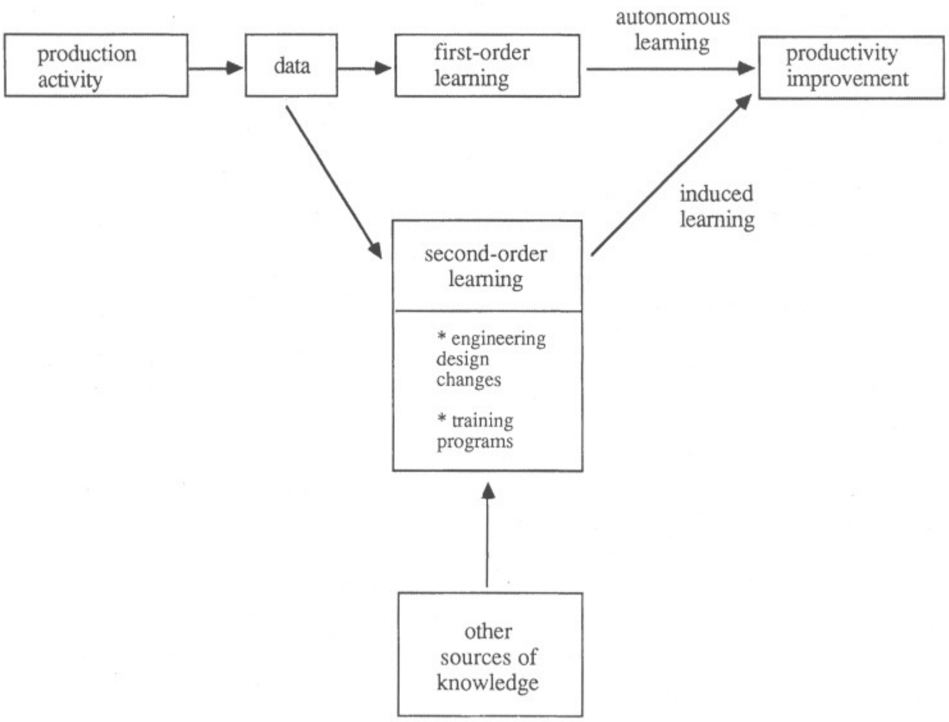

FIGURE 1. The Learning Process Model.

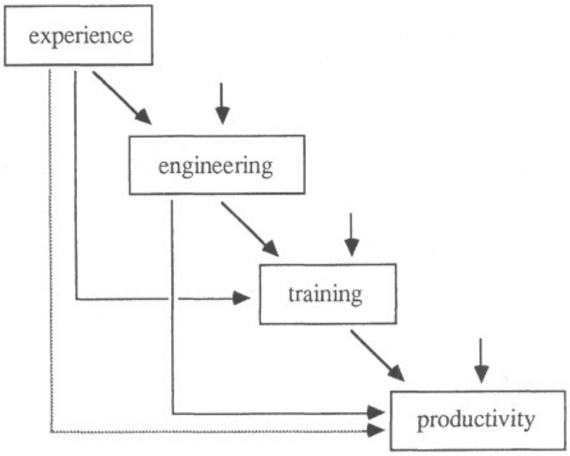

FIGURE 2. A Recursive Learning Process Model.

training variable we shall use in net of this EC-motivated training; but there may be some spill-over into training activity only indirectly linked to ECs.

Figure 1 can thus be operationalized in the form of the cascade shown in Figure 2. The linkage and ordering of the two managerial variables in this cascade depends on variable construction, and in the general case, it is open to debate. The main question this model was designed to help investigate does not, however, hinge on this ordering; we are primarily concerned to differentiate between the two sources of the learning curve's characterization of the effect of experience on productivity: first-order learning, which appears in the path model of Figure 2 as a direct effect of experience on productivity indicated by the dotted path, and second-order learning, which is captured in all the other paths leading from the head to the tail of the cascade. The learning curve model's estimate of the experience effect combines both the direct and indirect effects; we shall attempt to disentangle them.

3. Sources and Variables

Our data comes from company sources, primarily Cost Accounting and Industrial Engineering reports. This section first outlines our use of the cost reports to construct productivity measures: the first three subsections cover outputs, inputs and total productivity. (For more detail and discussion of these measurement issues, see Adler 1987.) The next subsections review the definitions of the learning variables: first experience, then the two variables that we hypothesize are the specific elements of second-order learning.

3.1. *Outputs*

The measure of output quantity is straightforward, since monthly cost reports gave us physical quantities produced in the month, and since in each of these two departments, there was only one product that we can assume homogeneous.[3]

3.2. *Inputs*

The inputs we consider in our total productivity framework include direct and indirect labor, materials, capital, and inventory. We wanted to include all the principal inputs,

[3] Three factors brought the benefits of an inventory adjustment well below the costs: finished goods are immediately charged to the next downstream department; the cost reports only include material actually used in that month's output; and work-in-process inventory turned out to be relatively small.

since across departments and over time the different factors accounted for very different shares, and we sought a synthetic indicator of overall efficiency in resource use.

We defined input quantities as follows:

• *Direct Labor*. The monthly headcount of direct personnel in each department was available from Industrial Engineering records.

• *Indirect Labor*. A full-time equivalent headcount was estimated and interpolated from the Manufacturing Engineering department expenses charged to each department annually.

• *Purchased Materials*. The sum of purchases and interplant transfers (net of the Materials function's overhead burden) taken from monthly cost accounting reports gave the dollar value of the materials incorporated into the output claimed that month. A materials quantity series was derived from these data by deflation, using a company-supplied price index.

• *Capital*. These data are derived from Industrial Engineering reports on the potential output (in units per day, or "daily going rate") of the department's machines working three shifts per day under optimal technical conditions. The annual data were interpolated.[4]

• *Inventory*. This series was derived from the monthly accounting data on work-in-process and materials inventory. To focus on efficiency rather than financial performance, it was important to deflate the value of inventory so as to correct for the rapidly falling unit costs of many of the inventoried components. We therefore valued this inventory at Cost Engineering's estimate of projected minimum unit cost of these components.

These input quantities were weighted so we could form an aggregate:

• *Direct and Indirect Labor*. We used the end-of-period sum of wages and benefits to generate a distinct total employment cost for each department and each category.

• *Materials*. The materials measure needed no weighting since it was already in deflated monetary units.

• *Capital*. The appropriate weight for the capital input is a total cost of capital. Consistent with the engineering approach to measuring capital input quantity, we used the Kendrick-Creamer approach to estimating this weight, calculating the cost of a unit of capital (capacity) by adding the return *of* capital (depreciation) to the return *on* capital (its opportunity cost). For the former, we derived a depreciation schedule from company documents. For the latter, we used a real cost of financial capital of 7%, reflecting the long-run average inflation-corrected cost of a typical mix of debt and equity (Kaplan 1985). We ignored real estate costs on the principle that manufacturing managers are not responsible for their locations in high or low land-value areas.

• *Inventory*. This was valued at a 10% annual cost.[5] A fixed-weight system was adopted, where the base period was the most recent month (after checking that it was not an abnormal month). This way, start-up costs and the indivisibilities of early, small-scale operations would not cloud the results over the whole period.

3.3. *Total Productivity*

We adopted an elementary, additive model in preference to any more complex model. In this approach, we follow the American Productivity Center's example and such practically-oriented researchers as Kendrick and Creamer (1965), Craig and Harris (1973), and Sumanth (1984). The additive model has the overwhelming advantage of giving a

[4] Facilities, as distinct from machinery and equipment, were reflected in the weight, not in the quantity, of the capital input.

[5] We did test our subsequent analyses of performance for sensitivity to the capital and inventory cost rates: the analysis proved very insensitive. Our choice of a fixed-base pricing procedure minimized that potential impact of these costs, as did the large share of total costs accounted for by materials and indirect labor (see Table 2).

productivity measure that is intuitively understandable as the inverse of an inflation-corrected unit cost.

Our measure of total productivity is thus a simple ratio of total output to total input. ("Total" is traditionally distinguished from "total factor" productivity by the former's inclusion of materials.) It is calculated as follows:

$$\mathrm{PDTY}_t = \sum \frac{Q_i}{v^{j^d} \cdot X_j}, \qquad \text{where}$$

t = time period,
PDTY = total productivity,
Q_i = quantity of output i,
X_j = quantity of input j,
v^{j^d} = unit cost of input j at base-period d (a constant) and where the base period d is the last period under study.

3.4. *Experience*

As already indicated, we will use the most standard measure of experience, cumulative output volume (CVOL): cost reports always indicate cumulative volume to date. And as previously indicated, we shall use the lagged form to avoid spurious correlation.

3.5. *Managerial Variables*

The learning process variables are drawn from a variety of company sources:

- *Cumulative Engineering Activity* (*CENG*). This is measured as the cumulative number of hours officially spent by direct personnel in activities associated with product design changes, either running experiments or learning new specifications. (We would have liked to also analyze the number of ECs, but these data were irretrievable.) Our data does not include changes to process specifications unless they were directly associated with some product change.
- *Cumulative Training Activity* (*CTRN*). Here we use the cumulative number of hours spent in training by direct personnel. This is training activity *not* directly attributable to ECs. This training is all on-the-job and conducted principally by co-workers doubling-up on a work post. (Very little is done away from the work-station.)

Summary statistics for these variables are presented in the Appendix.

4. Results

Table 3 summarizes the results of both the learning curve and the learning process model.[6] Autocorrelation was corrected in every case using the maximum likelihood AR(1) model as specified in the AQD statistical package (Schlaifer 1981).[7]

[6] Following the suggestions of Alchian (1959), Hirschleifer (1962) and an anonymous referee, we tested for an independent effect of output rate; we found only a weak (positive) effect in both learning curve and learning process models in B and no statistically significant effect in either model in C.

[7] The theoretical importance of autocorrelation was pointed out by Montgomery and Day (1985) (see also McDonald 1987). Their criticisms raise a fundamental question regarding the value of the learning curve results obtained in almost all previous research (Hirsch 1952 is one of the rare exceptions). If the production process contains more than one step and these steps are characterized by different learning rates, the total cost will not be accurately predicted by an average, since as experience accumulates, the total cost will tend to be dominated by the step with the slowest learning rate. Since virtually any real production process is composed of more than one step—and how would we know when we have identified the "fundamental particles" of learning?—the objection is a fundamental one. Unfortunately, with our data, there is not much we can do to remedy it, except to control for its consequences. Specifically, positive autocorrelation would be created by such a misspecification. Autocorrelation produces unbiased but inefficient estimates and tends to understate standard errors. We shall therefore rely on estimates corrected for autocorrelation.

TABLE 3

Summary Results

(natural coefficients; standard errors in parentheses; * signifies $P \leq 0.02$ two-tail)

		ln $CVOL_{t-1}$	ln CENG	ln $CENG_{t-1}$	ln CTRN	ln $CTRN_{t-1}$	ρ	R^2	DF
B Department Models:									
*B*1	ln PDTY	0.5078*					0.22	0.8715	33
		(0.0432)							
*B*2	ln CENG	0.7760*					0.98	0.9973	33
		(0.0468)							
*B*3	ln CTRN	0.0069	0.9260*				0.98	0.9995	32
		(0.06394)	(0.0774)						
*B*4	ln PDTY	0.9483*	−2.300*		1.668*		−0.09	0.9014	31
		(0.2196)	(0.697)		(0.697)				
*B*5	ln PDTY	0.7455*		−2.046*		1.732*	−0.07	0.9049	30
		(0.1972)		(0.703)		(0.753)			
C Department Models:									
*C*1	ln PDTY	0.5032*					0.56	0.9571	29
		(0.0424)							
*C*2	ln CENG	0.4458*					1.0	0.9922	29
		(0.0756)							
*C*3	ln CTRN	0.1440*	0.6673*				0.82	0.9988	28
		(0.0383)	(0.0726)						
*C*4	ln PDTY	0.9771*	1.824*		−2.866*		0.18	0.9660	27
		(0.1541)	(0.562)		(0.796)				
*C*5	ln PDTY	0.8556*		1.860*		−2.605*	0.22	0.9705	26
		(0.1344)		(0.504)		(0.682)			

With but one exception (experience in the *B* department training equation), all these coefficients are significant at 2% (2-tail) level, and a very high proportion of the variance is captured. While the latter is not surprising for time-series data, the former enhances our confidence.

4.1. *Simple Learning Curve Model*

The coefficients in model *B*1 and *C*1 show a "learning rate" of some 71% in both cases. This is relatively fast, and at the faster end of the spectrum of results found by previous learning curve studies (Dutton and Thomas 1982). Comparison of the coefficients in model *B*1 and *C*1 reflects in an interesting manner on the long-standing debate over the intensity of the learning phenomenon in machine-intensive operations (Baloff 1966; Hirsch 1952, 1956): the learning coefficients are indistinguishable across the *B* and *C* operations. These results contradict the assumption—especially widespread among practitioners—that machine processes are slower learners.[8] This assumption reflects a common but idealized view of the production process, a view in which humans are the only source of errors and are therefore the main locus of improvement.

4.2. *Engineering Change Activity*

There are two kinds of factors we can imagine driving product engineering changes. First, engineering changes can be driven by process experience: we would expect that as

[8] Our results thus support the results of a rarely-cited study by the Department of Defense, Defense Contract Audit Agency (1970); in 182 learning curves sampled by the DCAA and for which they could distinguish assembly work from machine work, the proportion of the variance in progress rates explained by the single variable "% of assembly work in total" was a meager 2.9%.

plant personnel observe the production process and gather information on it, things would be learned about how to improve ease-of-manufacture, cost, or design specifications that prove unreliable. This would prompt engineering changes. Indeed, we know that at Hi-Tech some 50% of the product engineering changes on this product were motivated by manufacturability concerns, and that numerous design flaws were discovered in early manufacturing. Second, it is likely that some product engineering changes derive from market experience. One would expect that with technologically complex products, customer needs and product performance may not be fully revealed prior to the introduction of the product, and that as a consequence it may be necessary to make changes to the product design as customer experience accumulates.

Both of these variables, process experience and customer experience, are likely to be correlated with cumulative volume. The former's correlation might be quite high. The latter, however, involves much lengthier lags due to the time required for product distribution, implementation, failure and diagnosis (or alternatively, customer suggestion and adoption).

Models *B*2 and *C*2 support the hypothesis that engineering change activity depends to a considerable extent on production experience. Interestingly, there is a sizable difference in the magnitude of coefficients on experience in these two departments, and this difference suggests that the *B* department derives proportionately greater engineering learning than the *C* department for an equivalent increase in production experience. (Table 3 reports natural coefficients; the corresponding standardized betas are 1.065 in *B* and 0.837 in *C*.) Both departments' EC activity is very well accounted for by this simple model, as evidenced by their R^2; but production activity seems to have been a more fruitful source of knowledge in the *B* department.

Our fieldwork suggests one hypothesis concerning the origin of this difference: the engineering modifications made in the *C* department were more often motivated by producibility concerns, while in the *B* department, they were more oriented to product performance improvements. While the former tend to exhaust themselves as the process is debugged—lowering the coefficient on cumulative volume—the latter are renewed by insights by design and field engineers, and in a complex, innovative product such as this, the opportunities for product technology improvement were very considerable.

4.3. *Training*

The second major process variable is training. Training should be directly related to cumulative output: as the plant accumulates experience and learns about the process, it is likely that the things they learn involve readjustments of processes and procedures that will call for new training. We might also expect engineering changes to necessitate training efforts above and beyond the time specifically allocated to familiarization with the new product specifications.

Models *B*3 and *C*3 are very good predictors of training, as witnessed by their R^2. But the structure differs by department. In the *B* area, production experience plays no role, while engineering change activity is a strong driver of training activity. (It should be recalled that the training being captured in this variable does not include training that is a direct consequence of specification changes.) In the *C* area, by contrast, both production experience and engineering contribute to training. (Note that in neither area is a lagged engineering change variable significant.)

One possible reason for this difference lies in the departments' different capital-intensities. In the machine-gated *B* area, increases in output are much less dependent on hiring, and as a general rule hiring and the associated training are conducted on pre-established calendar. In the labor-gated *C* area, when engineering changes or procurement schedules allow for increases in output, hiring is accelerated, which in turn creates training needs. (Recall that Hi-Tech had a large order backlog throughout this period, so that the primary responsibility of the manufacturing managers was to ensure rapid ramp-up.)

4.4. *Process Model of Productivity*

Our initial notion was that cumulative volume's effect on productivity should in part be accounted for by variables reflecting second-order learning. While models *B*4 and *C*4 account for almost all the variance in productivity, they reveal a surprising result: compared to the simple learning curve models *B*1 and *C*1, experience turns out to have not a *less* powerful but an *even more* powerful effect on productivity once we include engineering and training. The partial correlation coefficients on CVOL suggest an extraordinarily fast "partialled" progress rate of some 51%; but we have no comparable data on other cases with which to compare this result.

The estimates explain the increase in the effect of experience as we go from the learning curve to the learning process models: in each department, one of the managerial variables has a strong negative effect on productivity, and since experience is in each case a strong determinant of this negatively-weighted variable, the learning curve model generates a coefficient for experience that simultaneously expresses its positive direct and negative indirect effects on productivity. The increase in the standard error of the experience estimate between the learning curve and the learning process models should make us cautious in interpreting the coefficients. Clearly there is some spurious collinearity in this model, which is normal for time-series analysis with their common-trend effects. But the increase in the standard errors is not so great as to deprive the estimate of statistical significance: the learning curve estimates of the experience effect (*B*1, *C*1) are at the very far lowest end of the confidence interval surrounding our learning process model's estimates of the experience effect (*B*4, *C*4). The fact that ρ drops between the first and the fourth equations in both departments supports our interpretation of the experience coefficient changes as model-driven rather than spurious, since ρ picks up the autocorrelation due to omitted variables.

These results also highlight once again the different learning processes in the two departments: in the *B* area, engineering changes impede productivity, but training helps productivity, while in the *C* department the converse holds true.

(An alternative specification of our learning process model would use lagged forms of engineering and training alongside the lagged cumulative output term. Models *B*5 and *C*5 show that the basic pattern is unchanged. Including both contemporaneous and lagged terms of engineering and training leaves the contemporaneous terms statistically insignificant.)

Our field work suggests one hypothesis to explain the contrasting signs on engineering activity in the two departments. In the capital-intensive *B* area, the engineering changes were primarily motivated by product performance concerns. Their disruptive effect therefore dominates. In the *C* area, by contrast, proportionately more of the ECs were motivated by producibility concerns, and these ECs therefore "unblock" the process more than they disrupt it, with the net effect of improving productivity.

Our field work also suggests two hypotheses to explain the contrasting signs on training. First, the capital-intensity of the *B* area means that it is less disrupted by training efforts. Second, the manager of training programs for the site spoke with us before his resignation about his frustration with the "anarchy" prevailing in the training area—particularly, he explained, in the labor-intensive *C* department. We tested for lagged effects (going back up to three months) in an effort to detect a longer-term payoff to *C* area training, but found none.[9]

Table 3 suggests that the assessment of the influence of engineering and training on productivity should include consideration of the impact of ECs on training. In the *B*

[9] One might well argue that our analysis is bounded by the available data, and that productivity would have been even lower absent this training. We have little reason to doubt that; but our data suggest that given the organization's need for training, Hi-Tech managers would do well to explore the question of whether it could be managed in a way that disrupted productivity less.

area, ECs have a negative direct impact on productivity; but these ECs reflect product changes that drive training efforts which in turn have a strong positive influence on productivity. What is engineering's total impact on productivity? If we transform the natural coefficients into standardized betas, we can multiply CENG's effect on CTRN (beta = 0.9064) by TRN's effect on productivity (2.2315) and add this "indirect" effect of engineering on productivity (2.0226) to *B*4's "direct" effect of engineering on productivity (−3.0118) and we discover a negative total estimated effect of engineering activity on productivity (−0.9892). So the direct negative effect of engineering changes on *B* area productivity is somewhat mitigated by its training effects, but not entirely so. In the *C* area, by contrast, engineering changes look like a positive influence on productivity (in *C*4). But when we multiply out the corresponding betas, we discover that this positive effect (1.727) is outweighed by the fact that engineering activity drives training (beta = 0.7086) and training has a strong negative influence on productivity (−2.5549), creating a total indirect effect of engineering on productivity that is strongly negative ($0.7086X - 2.5549 = -1.8104$).

5. Discussion

Our initial intuition was that the managerial variables we have interjected between experience and productivity should account for some of the "explanatory power" of cumulative output in the simple learning curve model. This intuition was contradicted in Table 3: these other variables seem, on the contrary, to have masked the extent of cumulative output's explanatory power.

Our discussion has given us some understanding of how this paradoxical result arises:

- Second-order learning can disrupt as well as facilitate first-order learning: even a producibility-motivated engineering change may occasion temporary disruption before its beneficial effects are felt.
- A sizable proportion of second-order learning activity is prompted by problems that emerge in the course of the accumulation of production experience. Productivity is ul-

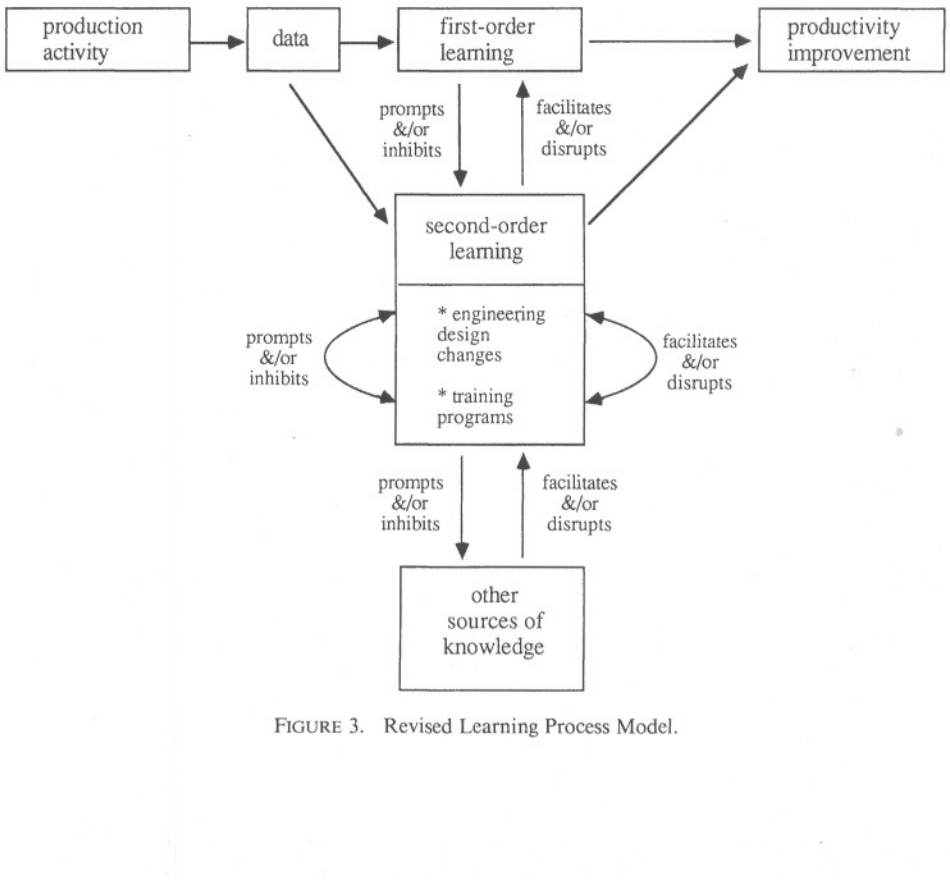

FIGURE 3. Revised Learning Process Model.

timately improved by these policy responses, but (a) productivity may have been even higher had the problem never manifested itself, and (b) this "reactive" form of second-order learning may also generate disruption.

• Whether independent or reactive, second-order learning initiatives in one domain can force changes in others (engineering changes often create training needs) with cascading disruption effects.

Revising our initial model, therefore, we might therefore propose a more complex learning process: see Figure 3.

This model adds to our initial learning process model some of the complexity revealed by our case study, by including arrows representing the way experience can prompt engineering or training, the way the two interact, and the way they in turn react on first-order learning. We have extended this reasoning to suggest, following Levitt and March (1988), that "competence traps" might inhibit second-order learning—for example, if rework becomes so efficient that it makes engineering changes (specifically, ECs designed to eliminate the quality problems at the origin of that rework) appear too disruptive. We have also added a link to a "third-order" learning box, which in a case such as ours might represent design-for-manufacturability (Whitney 1988) initiatives that are designed to eliminate the need for some of the ECs, but which might also disrupt a well-established EC routine.

6. Conclusion

This sketch of the learning process generates three principal conclusions. A first conclusion is that the total learning effect is just as strong in the capital-intensive *B* area as in the labor and materials-intensive *C* area. Contrary to the popular learning-curve wisdom, a machine-gated process permits considerable learning.

A second conclusion is that the learning process is internally complex. This complexity arises because, in order to respond to problems uncovered in the production process, actions are undertaken, some of which can have sizable, if perhaps temporary, negative effects on performance.

A third conclusion is that the relative roles of explicitly managed, second-order learning and of tacit, first-order learning vary very substantially across processes. The roles of the different modalities of second-order learning also vary across processes.

We have also identified some opportunities for future research. First, we have focused on two important managerial policy domains, but we have certainly not exhausted their analysis. Product engineering changes and direct labor training hours are perhaps reasonable proxies for the more explicit efforts at building production capabilities, but they have no obvious relation to the finer-grain components of production capability-building, such as equipment modifications and debugging. We need more detail on these policy variables.

Second, both the things the plant does to respond to problems uncovered by experience and the implementation of policy changes motivated by other considerations can, we have shown, be costly in their disruption of current capabilities. But we have not analyzed the longer term benefits: longer data series allowing for more systematic lag structure analysis would be a valuable next step.

Third, the presence of positive autocorrelation in many of our regressions suggests an inadequately specified model. The further disaggregation of the analysis down to discrete operations might be pursued.

If our analysis has served as encouragement for going beyond the simple learning curve model and its associated rules of thumb, it will have served its purpose.[10]

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Appendix

Descriptive statistics (minima, maxima, means, standard deviations, and zero-order correlations) for all the variables we use are presented in the following tables.

B Department

Variable	Min	Max	Mean	SD
ln PDTY	−2.2303	0.4125	−0.8386	0.81817
ln $CVOL_{t-1}$	11.3093	16.8666	14.5064	1.47025
ln CENG	13.9225	18.1195	16.5990	1.07137
ln CTRN	13.5145	17.5529	16.0858	1.09458

Correlations

	ln PDTY	ln $CVOL_{t-1}$	ln CENG
ln $CVOL_{t-1}$	0.9305		
ln CENG	0.9030	0.9905	
ln CTRN	0.9126	0.9909	0.9983

C Department

Variable	Min	Max	Mean	SD
ln PDTY	−2.7161	0.3041	−1.1261	0.9936
ln $CVOL_{t-1}$	11.6874	17.8798	14.8906	1.2007
ln CENG	15.7507	19.0059	17.6790	0.9405
ln CTRN	15.6092	18.6596	17.3944	0.8857

Correlations

	ln PDTY	ln $CVOL_{t-1}$	ln CENG
ln $CVOL_{t-1}$	0.9698		
ln CENG	0.9393	0.9735	
ln CTRN	0.9433	0.9855	0.9959

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