Open access • Journal Article • DOI:10.1086/261888

Decomposing Learning by Doing in New Plants — Source link

Byong-Hyong Bahk, Michael Gort

Published on: 01 Aug 1993 - Journal of Political Economy (The University of Chicago Press)

Topics: Physical capital, Individual capital, Human capital, Means of production and Learning-by-doing (economics)

This research program of the Center for Economic Studies produces a wide range of theoretical and empirical economic analyses that serve to improve the statistical programs of the U.S. Bureau of the Census. Many of these analyses take the form of research papers. The purpose of the Discussion Papers is to circulate intermediate and final results of this research among interested readers within and outside the Census Bureau. The opinions and conclusions expressed in the papers are those of the authors and do not necessarily represent those of the U.S. Bureau of the Census. All papers are screened to ensure that they do not disclose confidential information. Persons who wish to obtain a copy of the paper, submit comments about the paper, or obtain general information about the series should contact Sang V. Nguyen, Editor, Discussion Papers, Center for Economic Studies, Room 1587, FB 3, U.S. Bureau of the Census, Washington, DC 20233-6300, (301-763-2065).

DECOMPOSING LEARNING BY DOING IN NEW PLANTS

By

Byong-Hyong Bahk
Dong-A University
Korea

and

Michael Gort
State University of New York
Buffalo

CES 92-16 December 1992

Abstract

The paper examines learning by doing in the context of a production function in which the other arguments are labor, human capital, physical capital, and vintage as a proxy for embodied technical change in physical capital. Learning is further decomposed into organization learning, capital learning, and manual task learning.

The model is tested with time series and cross section data for various samples of up to 2,150 plants over a 14 year period.

Keywords: Learning-by-doing, Technical Change, Productivity

The study was carried out with assistance from the ASA/NSF/Census Fellowship Program. The authors are, of course, solely responsible for the conclusions and methods of analysis used.

This paper attempts to decompose learning by doing (hereafter LBD) into its principal elements: organization learning, capital learning, and manual task learning. We focus on firm-specific LBD and assess its magnitude in the context of a production function that permits us to distinguish the effects of such learning from the accumulation of labor, general (as distinct from firm specific) human capital, physical capital, and embodied technical change. We then examine the time interval over which the several elements of firm specific LBD continue to accumulate.

At the empirical level, we focus on new plants and their histories following birth. As will be shown later, learning has a finite time dimension beyond which increments to learning approach zero. We do not, however, focus on inter-plant spillovers of learning within the same firm. The latter is an important extension that, hopefully, later studies will consider.

Since learning by doing has no generally accepted definition, it is useful to start with a taxonomy. We distinguish two forms of accumulation of knowledge and skills. One form consists of accumulation that requires an investment through such means as purchases (hiring) of human capital, training programs, and expenditures on research and development. The second is accumulation as a by-product (or joint product) of production of goods and services and represents what we call LBD.

Killingsworth (1982), among others, argued that LBD is truly costless only when working time is fixed and additional experience cannot be acquired by sacrificing leisure. However, the costs of LBD are quite different from those of knowledge and human capital acquired in other ways. To the extent that the costs of LBD are lower than those associated with knowledge acquired in other ways, older firms have an advantage relative to new entrants.

A second distinction that we make is between LBD that can be appropriated by its producers and industry-wide or economy-wide LBD. And within the set that permits appropriation, there is the further question of by whom? As Becker (1964) has shown, the returns to general human capital, however acquired, should generally be captured by the employee, and hence, reflected in the wage rate. Thus LBD the returns to which are not captured by labor (hereafter LBDF) is usually associated with firm-specific LBD. The latter enters into what we call the firm's stock of organizational capital.

Still a further distinction can be made between LBDF associated with production process improvements and with product innovations, or improvements in product quality. However, the distinction can be overdrawn since production process improvements frequently go hand in hand with product quality changes. And even more important, product quality improvements with no change in nominal costs raise productivity (at least if it is correctly measured) in much the same way as reductions in costs with no change whether such change manifests itself in production process or in product improvements.

1. Modeling Firm-Specific Learning by Doing (LBDF)

Starting with Wright's (1936) study of the airframe industry, LBD has most often been examined in the context of a progress function defining the change in average costs over time. Other studies in this general vein were Alchian (1950) for aircraft, Montgomery (1943) for shipbuilding, Hirsch (1952) and Baloff (1966) for machine manufacturing, Preston and Keachie (1964) for radar equipment, and Lieberman (1984) for chemical products. Alternatively, LBD can be viewed as a productivity enhancing factor in a conventional production function. The latter approach was first taken by Rapping (1965) and Sheshinski (167). In modeling LBDF, we take the latter approach; but this still leaves us two options. Namely, LBDF can be modeled as a separate argument in a production function, or alternatively, as simply a shift parameter. Within the context of an empirically testable model, the choice between the two depends upon whether meaningful measures, or proxies, exist for changes in the accumulated stock of knowledge and skills.

Let us start with a simple production function as in Equation (1) below:

$$Y_t = F(L_t, K_t, X_t) \tag{1}$$

where Y refers to output, L to labor input, K to capital input, X to the stock of knowledge, and t to the relevant time period. We have implicitly assumed that X can be measured or proxied by some variable that gauges cumulated experience. Thus,

$$X_t = h(S_t)$$

where h' > 0, and experience in production at time t, $S_t = E_{t-1} y_J$, that is cumulated gross output from the birth of the organization to t-1, the beginning of the production period. Of course, LBD need not continue indefinitely. After a time, net learning may decline to zero.

Alternatively, learning may simply depend on time as assumed by Fellner (1969)[1] in which case, within our framework of firm specific learning, the relevant measure would be time elapsed from the birth of the organization. And still another alternative is that X depends on both S_t and time from birth[2] though, as an empirical matter, the high collinearity between the two variables would render it difficult to identify the separate effects of each.

Assume that L and K are each measured in equivalent efficiency units -- that is, they are adjusted appropriately for input augmenting technical change. Assume further, as is plausible, that in a modern economy blueprint technology is widely diffused and the best blueprint technology can, therefore, be purchased by all firms. It then follows within a strictly cross section framework, that LBDF is the sole source of disembodied technical advance. We deem it to be disembodied in that it is reflected in neither the labor nor the capital inputs but rather explains differences across firms or plants in the productivity of the same levels and types of inputs.

If, however, the data refer to time series, sources of disembodied technical advance other than LBDF need to be considered. In that event, the

---

[1] A similar view is implied by Oi (1967) who associates progress functions with intertemporal substitution in which costs are reduced by later delivery.

[2] A model with both experience and time was considered by Sheshinski (1967), though with learning not limited to the firm-specific type and, hence, time not measured by terms of the organization's life.

production function is still left with a multiplicative productivity term A(t) as in equation (3) below. This term captures the residual rate of output augmentation over time that arises from industry-wide or economy-wide learning by doing.

The discussion with respect to labor and capital inputs has thus far followed the conventional approach of defining the inputs in equivalent efficiency units. But an alternative-and one that we adopt in this paper is to introduce separate arguments in the production function for embodied input augmenting technical change. For labor, we assume that its quality, or the human capital associated with labor, is measured by the wage rate. In short, the quality adjusted labor input is measured by the wage bill and the latter can be decomposed into pure labor (number of employees) and human capital (the average wage). This is discussed further below. For physical capital, as also explained below, the index of quality is the average vintage of the capital stock. Thus using a Cobb-Douglas specification for the relation of inputs and output we have, within a time series and cross section framework:

$$Y_{it} = A(t)G(V_{it}, X_{it})\ L_{it}^{\$_1}\ W_{it}^{\$_w}\ K_{it}^{\$_k} \qquad (3)$$

where Y is output, V is the average vintage of the gross stock of physical capital, X the index of firm specific knowledge, L is pure labor, W is human capital, K physical capital and the subscripts i and t refer, respectively, to the plant or firm and the relevant time interval.

The productivity shift term A(@ is the residual after all embodied technical advance in both labor and physical capital has been accounted for, as well as firm-specific learning. Conceptually, it is meant to capture industry-wide or economy-wide LBD, but only after knowledge that is uniquely associated with a given vintage of physical capital or level of labor skills has been captured by V and W. One cannot separate the effects of knowledge accumulation from those of the special attributes of the inputs with which such knowledge is uniquely related. Such separation would be empty of observable phenomena since the same variables would always capture the concurrent effects of both. Thus

A(@ captures only the symmetrical effects of knowledge across all vintages of physical capital and all levels of human skills. In a world in which general, as distinct from firm specific information on technology is widely diffused, we are unlikely to observe cross sectional variations in the implementation of general knowledge except to the extent that such implementation depends uniquely on this attributes of the specific inputs employed by each firm or plant. A(@ is, therefore, specified with time as its argument (that is, without variables with relevance for cross sectional variations).

We assume that average wages reflect the human capital associated with the labor input. This, in turn, is based on the assumption that plants generally face a common labor market and that variations in average wages at a point in time, therefore, mainly measure differences in skills rather than differences in the prices of identical classes of labor. Empirically, this assumption is supported in Gort, Sapra, and Bahk (1990) and Gort, Bahk and Wall (1991). These studies indicate the following for large samples of the U.S. manufacturing plants: 1) the variations in average wages for plants in the same industry are far larger than could be attributed to unionization or to historical accident, 2) across industries, there is no consistent inter-regional variation in average wages and 3) within industries, the variation in average wages was larger for new than for old plants. The third observation is viewed as especially decisive since new plants have considerable choice in location and could therefore adapt to large regional variations in wages.

While intertemporal variations in real wages also reflect changes in human capital associated with labor, factors other than labor quality enter into historical changes in real wages. However, for our time series and cross section analysis, the average wage is still an acceptable though less precise proxy for human capital inasmuch as, for the time interval on which our empirical analysis is based, cross sectional variations were clearly dominant.

The capital stock variable in Equation (3) stands for a vector of past gross investment streams. If each successive vintage of investment is more productive than the last, we can take due account of the effect of vintage by measuring the average vintage of the stock. Accordingly, Equation (3) assumes the following relationship at any point in time:

$$Y_t = g(K_{tv}e^{kv}, L_t, W_t, X_t)$$

where K is the sum of gross investments of various vintages, v is the weighted average vintage of the stock, with weights based on the investment of each vintage relative to K, and k measures productivity enhancement from the embodied effects of vintage.

Within a cross section context, the model requires no modification if we assume that each successive vintage of investment is more productive than the last not only because of obsolescence of older investment but also because of physical decay. But within a time series, or time series and cross section framework, investment of the <u>same</u> vintage must be associated with differing amounts of physical decay, at different points in time. Our model is based on the assumption that maintenance outlays offset the adverse output effects of physical decay leaving only obsolescence (embodied technical change) to be accounted for in the estimates. This assumption is, at best, only an approximation of reality. However, an ability to derive stable measurable coefficients for vintage, using time series and cross section data, may be viewed as support for the above assumption.

Equation (3) defines the role of LBDF without reference to the specific processes that bring it about. A first step in understanding how it takes place is to decompose aggregate LBDF into its principal components. More specifically, which of the various inputs rise in productivity as learning takes place? How rapid are the rises and for how long do they continue? To examine these questions, we need to know the impact of learning on the coefficients of each of the inputs, that is, labor, human capital, and physical capital.

The change in coefficients could be examined with respect to experience proxied by cumulated output, or simply, by time elapsed from the birth of an organization. The latter lends itself more readily to predictive hypotheses about the shifts in the productivity of each input (examined at a later point). We, therefore, specify Equation (5) below with learning leading to time dependent input augmentation. Once again using a Cobb-Douglas specification and assuming A(@ is irrelevant since the model is estimated for a series of cross sections for individual years, we have

$$Y_t = H(V_t) L_t^{\$_l+8_l t} W_t^{\$_w+8t} K_t^{\$_k+8_k t} \tag{5}$$

where the $'s are the input coefficients independent of learning and the 8's are the shifts in the coefficients from time dependent input augmentation arising from firm specific learning. Thus, the effects of all LBDF are assumed to be captured by the time dependent shifts in the input coefficients. Time is measured here from the birth of the organization.

Before proceeding to empirical work, we stress that our definition of LBDF differs from the concept of learning by doing used by most authors. We focus on learning that is proprietary to the firm and is transferable only through the sale of the firm (or its relevant subdivision e.g. the plant). In this, our approach is similar to that of Rosen (1972). Not only is industry-wide LBD excluded, but also all learning that is vested in the employee and, therefore, supposedly reflected in the input of human capital. And even in Equation (3), where we allow for industry-wide LBD, we define it as independent of changes in the inputs of the production function. That is, the effects of increases in knowledge associated with the quantity of human capital used, or with the embodied technical change of physical capital, are excluded from the definition of LBD.

We now turn to empirical analysis. Equation (3) is tested in Section 2, while Equation (5) is tested in Section 4.

2. Measuring the Effects of Learning By Doing

The empirical analysis in this section is carried out with time series and cross section data for 15 individual industries and, also, for all observations for the same 15 industries pooled. To test the robustness of the results based on pooled data, we then proceed with a larger sample of 41 industries. The broader sample of industries included those with too few plants to carry out the analysis at the industry level.

All analysis using production functions involves some aggregation; there are few single product plants. Moreover, all plants are aggregates of separate processes involving a variety of machines. The choice of level of aggregation involves a balancing of considerations. The advantage of analysis with plants within 4-digit SIC industries is the greater homogeneity of production relations within than across industries. Offsetting this advantage for pooled data is the increase in sample size--a factor of considerable importance given the unbalanced nature of the panels. Plants were born at various points in time and hence endowed with time-dependent attributes not fully accounted for by the explanatory variables. Moreover, the product structures of plants vary within individual industries.

Apart from technical statistical considerations, it is also important to determine if meaningful averages can be estimated for broad aggregates of plants with respect to such variables as learning by doing and the vintage effects of physical capital. The results below indicate that they can. Obviously such averages are not intended for use as point estimates in projecting input requirements for particular production processes.

Still another issue, implicit in Equation (3) and later in Equation (6), is that the quality of labor (human capital) and the quality of physical capital (vintage) are treated symmetrically as separate variables. We view this unconventional approach as an important step in decomposing what otherwise tend to be black boxes. One will recall that it was customary at one time to view labor and capital as homogeneous jellies. When the practice shifted to expressing each in supposedly homogeneous efficiency units, a variety of adjustments were made to the labor and capital variables. These, however, made it impossible to separate out the distinct impacts on output of the assumed adjustments versus the variables in original unadjusted form.

The method we use introduces average vintage of physical capital as a technology index, and the effect of vintage on output is <u>estimated</u> rather than <u>assumed</u> as is the case with customary measures of capital net of depreciation. The role of human capital is introduced in a way symmetrical with that of the technology index and may be viewed as the level of human knowledge that is combined with raw labor (employees) and with physical capital. Submerging the variable in a single index of labor input merely reduces the available information.

We next test Equation (3) in its empirical specification:

$$\log Y_{it} = \$1 + \$2 \log L_{it} + \$_3 \log W_{it} + \$_4 \log K_{it}$$
$$+ \$_5 \log X_{it} = \$_6 V_{it} + \$_7 t + U_{it} \qquad (6)$$

where Y is output measured by shipments, L is pure labor measured by number of employees, W is human capital measured by the average wage rate, K is the gross stock of physical capital, V is the weighted average vintage of the capital stock with ascending values for more recent vintage and permits us to use gross rather than net capital since it supposedly captures the differing service terms of older and newer capital goods, X is the index of accumulated experience (measured alternatively by variables S and S_1 defined later), and t is chronological time in years. The subscript 1 refers to the plant.

While Equation (6) uses shipments as a measure of output, later regressions substitute value added with substantially similar though slightly weaker results--a fact that we attribute to measurement errors associated with materials inputs in deriving value added. An option in using shipments as a dependent variable is to introduce material inputs on the right side of the equation. However, such inputs are so large a fraction of shipments that the introduction of this variable, at least in the context of cross section data where differences in scale are very large, dominates the regressions and tends to obscure other relationships.

The appendix discusses data construction as well as the choice of samples of industries, and the criteria for selecting the sample of plants within the industries. We first present the results for pooled data for 15 industries (Table 1). We then proceed to examine the results for each of the 15 industries separately (Table 2). Finally, we show the results for pooled data for 41 industries.

Table 1 presents the results of Equation (6) for a set of fifteen manufacturing industries, for pooled time series and cross section data in the fourteen year period 1973-86. The sample consisted of 1281 plants born in 1973 or later, but plants born in 1983 or later were excluded since the interval was judged too short to capture learning effects for these plants. The sample was not a balanced one over time. Thus there were 7,064 observations in the time series and cross section pool for the fourteen years. A new plant was deemed new if there was no record for it prior to 1972. The circumstances that lead to this include (as discussed in the appendix) the transfer of old assets to new users.

The data for Table 1 (and later for Table 2 and 3) were, of course, predominantly cross sectional. While a panel could have a maximum of 14 years, the average length of a panel was only between six and seven years. Hence, while some serial correlation is still possible, its effect is unlikely to have been large. With short panels and a highly unbalanced sample, a D-W statistic would not yield a clear indication of the role of serial correlation and, hence, is not presented.

For results based largely on cross section data, the values of R^2 were very high and all the input coefficients were associated with high t-values. Most coefficients appeared to be quite stable across alternative specifications. The high r^2 values may, however, arise in part from the large differences in plant size in the sample. The key results of Table 1 may be summarized as follows:

1) The residual time trend in equation (ii) in the table indicates a productivity growth of two percent per year. But when due account is taken, through the vintage variable, of the effects of embodied technical change of capital (as in equation (1)), all evidence of a positive residual trend

disappears. Within the context of our analysis, this has an unequivocal meaning. Industry-wide learning by doing--that is, industry-wide increases in the stock of knowledge--affect output only insofar as they are uniquely related to embodied technical change of physical capital (and, perhaps, though not tested, to increases in human capital).

2) In contrast, firm specific learning by doing showed a significant effect on output in all five equations in Table 1. When LBDF was proxied by number of years from birth of the plant, equation (v) indicates about a one percent rise in output per year. When proxied by cumulative output, a one percent change in the latter variable is associated with roughly a three one-

Table 1

Production Relations for 15 Industries,
Pooled Time Series and Cross Section Data,
1973–86[1]

(Dependent Variable = Shipments, n = 7,064, t-values below each coefficient)

Equation	Intercept	L	W	K	V	T	S	S_1	P	Adj.R^2
i	1.55	.612	.690	.286	.035	−.011	.037			.813
	19.4	83.6	25.7	33.8	6.6	−2.1	13.8			
ii	1.58	.629	.704	.275		.020	.028			.812
	19.8	88.7	26.3	33.0		7.2	12.0			
iii	1.53	.620	.693	.284	.025		.034			.813
	19.3	87.3	25.9	33.8	9.6		15.0			
iv	1.53	.634	.694	.254	.027			.079		.819
	18.9	93.5	26.5	30.5	10.3			22.1		
v	1.53	.634	.691	.307	.025				.012	.807
	19.0	88.0	25.5	36.4	9.1				4.3	

Source: Based on U.S. Bureau of the Census, LRD database.

[1] The data relate to pooled time series and cross section observations for 1281 plants with varying birth years in 1973 or later. L = number of employees, W = average wage rate, K = gross stock of capital, V = average vintage of physical capital, S = cumulated gross output since birth, S_1 = cumulated gross output since birth divided by average number of employees (average of last 3 years for each plant), P = number of years plant has been in operation since birth, and the dependent variable is shipments.

hundredths of a percent change in output. This, however, rises to almost eight one-hundredths of a percent when cumulative output is measured in a more meaningful way, namely, as cumulative output per unit of labor input. By standardizing cumulative output in this way, we avoid the possibility that the variable simply captures plant scale.

3) Embodied technical change of capital, as measured by average vintage, is associated with between 2.5 and 3.5 percent change in output for each one-year change in average vintage.

4) The elasticity of output with respect to "pure" labor was roughly the same as that with respect to human capital. The similar coefficients for the two variables imply that the marginal products per dollar of expenditures are about the same for the two inputs--a results consistent with an optimal input allocation rule. However, this result does not hold for most of the individual industry estimates reported later.

The variables in Table 2 are defined in the same way as in Table 1 (the role of S_1 however was not estimated) and the composition of the sample is the same also except that it is broken down by industry. Two equations are estimated, one with a time trend and one without. For the latter, coefficients are shown only for the estimates which change more than imperceptibly as a result of the exclusion of a time trend. Thus, for example, none of the estimates for L, W, and K change meaningfully as a result of the introduction of a trend term. In contrast, the estimates of learning by doing (s) and particularly the technology index (V) are sensitive to the introduction of trend in more than half the industries.

With V out of the equation (not shown in the Table), there was a significant positive residual time trend for nine of the fifteen industries. But with the technology index in the equation, Table 2 shows only two cases of a statistically significant positive residual (industries 3573 and 3674) plus one case of a significant negative residual (2911). In effect, the average vintage of capital explains away the residual which, as previously noted, may be associated with industry-wide as distinct from firm or plant-specific learning.

Table 2

Production Relations for 15 Industries,
Time Series and Cross Section Data Pooled by Industry, 1973-86

Industry SIC	Intcept	L	W	K	V	t	S	R^2	df
2086	3.92	.336	.385	.350	.049	-.036	.019	.656	297
2421	2.15	6.31	.937	.122	-.003^x .016	.021	.020 .027	.807	932
2451	1.45	1.144	.995	-.061	-.016^x	.019^x	.000^x	.889	309
2653	1.95	.553	1.082	.168	-.004^x .011	.016^x	.006^x .011	.825	347
2752	1.51	.750	.664	.236	.040^x	-.039^x	.021	.945	423
2813	1.98	.556	.455	.366	.006^x -.012^x	-.022^x	.031 .024	.763	705
2851	0.89	.490	1.083	.353	.039^x	-.019^x	.022^x	.816	150
2911	-1.65	.799	2.089	.379	.059^x	-.176	.025^x	.810	170
3411	4.27	.844	.571	-.054^x	.012^x .018	.007^x	.045 .047	.773	464
3441	2.14	.836	.924	.014^x	.000^x .021	.023^x	.013^x .019	.856	303
3573	-0.18	.941	.531	.093	.101 .252	.164	.023 .050	.812	829
3585	2.23	.895	.507	.099	-.017^x .019^x	.037^x	.022 .031	.866	285
3662	2.52	.890	.532	.059	.026^x .014	-.013^x	.015 .012	.859	721
3674	2.01	.932	.437	.029^x	-.001^x .064	.069	.021^x .034	.820	367
3714	2.01	.848	1.004	.053	.013^x	-.015^x	.025	.848	489

Source: Based on U.S. Bureau of the Census, LRD database. Variables defined as in Table 1. The superscript x next to a coefficient signifies it was not significant at the .05 level.

Table 3

Production Relations for 41 Industries,
Pooled Time Series and Cross Section Data
1973-86[1]

(t-value below coefficients)

Dependent Variable	Equation	Intercept	L	W	K	V	S_1	S^k	Adj.R^2
Shipments n=13,055									
	vi	1.76	.671	.591	.260	.023	.080		.791
		30.9	112.3	31.7	40.6	11.5	29.5		
	vii	1.67	.592	.580	.339	.021		.149	.796
		29.5	99.5	31.4	56.0	10.8		34.2	
Value Added n=13,064									
	viii	.78	.695	.734	.219	.034	.039		.739
		12.1	103.3	34.9	30.3	15.4	12.7		
	ix	.76	.663	.730	.254	.032		.051	.738
		11.8	97.7	34.6	36.8	14.6		10.1	

Source: Based on U.S. Bureau of the Census, LRD database.

[1] The data related to pooled time series and cross section observations for 2150 plants with varying birth years in 1973 and alter. The dependent variables are shipments or value added. S_k = cumulated gross output divided by 1982 book value of gross physical capital, S_1 = cumulated gross output divided by 1982 number of employees, and all other variables are as defined for Table 1.

Deleting the time trend for industries where its collinearity with S and V obscures the underlying relationship, leaves us with eleven out of fifteen industries that show statistically significant positive learning by doing. In sum, the industry results confirm those with pooled data except that the coefficients for the key inputs now show considerable variability.

Table 3 presents a test of substantially the same model but with plants in a broader set of 41 industries (for composition of sample of industries see Appendix Table A). Moreover, it shows the effect of alternatively measuring output by value added versus shipments. The two dependent variables yield very similar results but the fit is better with shipments as the proxy for output. The estimates of coefficients are, on the whole, quite similar for the 41 and 15 industry samples. Table 3 also shows the effect of measuring LBDF by cumulative output per unit of capital versus per unit of labor. The coefficient is somewhat higher for the latter version. Statistical criteria above, however, are insufficient for choosing between the two proxies for LBDF. The principal conclusion to be drawn from Table 3 is that the results support, and hence, reinforce the conclusions drawn from Table 1.[3] we believe a more plausible explanation lies in the measurement errors associated with value added alluded to earlier.

3. Decomposing LBDF

We have thus far examined the overall effects of LBDF, but to understand the process requires that it be decomposed into the elements that produce it. We start with a three-way classification of a) labor learning, b) capital learning, and c) organization learning.

We will be shown, an additional advantage of this decomposition is that it helps identify the rate of decline in learning. Equation (6) implies a constant rate of learning by doing. This is permissible as a rough approximation for the

[3] As a note on the estimation of overall LBDF, preliminary experiments with alternatives to a Cobb-Douglas specification were conducted. Both the CES and translog production functions yielded inferior results in these experiments.

plants in our sample, decomposition permits an assessment of the rate of decline in learning as a plant matures.

a) Labor learning

In the LBD literature, labor learning is most often associated with the learning of manual and semi-manual tasks. Workers' skills in specific tasks are enhanced through experience. Jobs become routinized through repetition and workers better adjusted to the jobs. Hirsch (1952, 1956) and Hartley (19650 found that the importance of this type of learning is greater in labor intensive production processes. Baloff (1969), however, concluded that even for machine-intensive processes labor learning is important but is reflected in the integrated adaptation of various types of labor (e.g. direct labor, indirect labor, technical personnel) rather than in the independent learning of specific tasks. Baloff's implied concept of learning borders on our concept of organization learning, discussed below.

Within our analytic framework, the acquisition of general skills through experience would be captured through our variable for human capital. Consequently, it is only firm-specific skills that are relevant. Within the above context, this refers to routinization of tasks, and to adaptation to the tasks that are peculiar to individual plants or firms. *A priori*, the time interval over which such gains in productivity are likely to continue must be short relative to gains from organization learning.

b) Capital learning

This refers to the increases in knowledge about the characteristics of given physical capital. It encompasses engineering information that accumulates through experience on the tolerances to which parts are machined, on the use of special tools and devices, and on improvements in plant lay-out and the routing and handling of materials. As operation continues, information also accumulates on the true capacity of equipment, on required maintenance, on how to avoid breakdowns and malfunctions or minimize their effects, and on complementarities or interactions among capital inputs added at different points in time. There is no a priori basis for speculating about the interval over which gains in productivity from capital learning are likely to continue.

c) Organization learning

The concept of organization learning and its role in producing organizational capital did not creep into the literature of economics proper until the early 1980's.[4] It has an older history, however, in industrial engineering. Conway and Schultz (1959) stressed that the manufacturing progress function is essentially a managerial adaptation involving largely the changing of tasks for individuals.

The principal elements of organization learning may be summarized as follows:

(1) The machine of individuals and tasks based on knowledge derived from experience of the capacities and limitations of employees. Another aspect of the same process is the screening of personnel from external sources to assure the matching of individuals and tasks.

(ii) Accumulation of interdependent knowledge about production possessed by members of a team and not portable by any one member of the team.

(iii) The development of interactions among employees an example of which might be knowing whom to ask for help when problems arise.

(iv) Managerial learning reflected in improved scheduling and coordination among departments and in the selection of external suppliers of services or products.

Perhaps related to learning, though more appropriately classified as simply the accumulation of organizational capital, is the possible development of loyalty to the employer and the consequent motivational effects on productivity.

By its nature, organization learning is likely to accumulate much more slowly than other forms of firm-specific learning, though hard evidence on this is not available.

[4] Prescott and Vissher (1980), Tower (1981), and Gort, Grabowski, and McGuckin (1985).

4. Empirical Estimates of the Components of LBDF

Our estimates of the magnitude and duration of various types of learning are based on the empirical implementation of Equation (5). Specifically, we estimate Equation (8) for each successive year following the birth of plants.

$$\log Y_{it} = \$_1 = \$_2 \log L_{it} = \$_3 \log W_{it} = \$_4 \log K_{it} = u_{it} \qquad (7)$$

where, as before, Y refers to output, L, W, and K, respectively, to labor, human capital, and physical capital inputs. The subscript t, however, refers not (as before) to a point in chronological time but to the amount of time elapsed from the birth of the plant, and i refers to the plant. Learning is thus captured by the shifts in the $'s across successive t's. Each successive regression, however, is estimated with plants of the same age (that is, with the same t's). For reasons given below, V does not appear in the equation and, since the $'s are estimated for each cross section separately, A(@ is excluded by definition.

In order to exclude the possibility that shifts in coefficients were the consequence of changes in sample composition over time, Equation (7) was estimated for successive years for identical plants. The larger, therefore, the number of such successive estimates the smaller the available sample. Thus for eight estimates, the maximum available sample for 15 industries was 399 plants. For 10 estimates, it was reduced to 237 plants, and for successive estimates exceeding 10 it was too small for reliable conclusions. While the years in which the plants in the sample were born varied, the range was quite narrow. Since the data set encompassed the period 1973-86, an identical sample for 10 consecutive estimates required that no plant in the sample be born before 1973 or after 1977, and a large proportion had to be born no more than a year apart. As a result, the variation in vintage was not sufficient to estimate a meaningful coefficient for V and the variable was omitted from Equation (7).

Table 4 shows the results for the 399 and 237 plant samples (that is, for eight and ten consecutive years). Output is proxied by shipments. Value added as a proxy for output yielded similar but much weaker results. Since the 10-year period is more revealing than the shorter interval, we focus on the former.

However, the results shown for the 8-year interval area, generally, quite similar.

From the standpoint of the three types of learning discussed earlier, capital, labor, and organization, capital learning is distinguishable from the other two in that it is reflected mainly in the productivity of the capital input. Similarly, labor learning as defined earlier, should be mainly reflected in the productivity of the labor input though, for reasons noted later, our data are not suitable for capturing the effects of this variable. But organization learning is reflected in <u>both</u> the productivity of "pure" labor and of human capital. The varying shifts in the productivity of the two inputs, therefore, yield information on whether organization learning is labor saving or human capital saving rather than on the type of learning that takes place.

The principal conclusions to be drawn from Table 4 follow:

1) The R^2 values steadily rise as one moves from the first to the tenth year after birth. Thus the consistency across plants of the relation between inputs and output rises with learning but the time required to approach the production frontier varies across plants.

2) Capital learning continues until the 5th or 6th year after the birth of a plant. Indeed, in the first year of a plant there is almost no measurable effect of variations in capital on output. The latter result probably arises less from unequal rates of capital learning across plants than from the fact that capital goods are not installed in balanced systems initially. Thus, at first, the productivity of capital varies greatly across plants.

3) The results an on organization learning are far less clear. <u>A priori</u>, organization learning should be reflected in both the coefficients of "pure" labor and of human capital. The effect on the former is, however, far more consistent. The coefficients for the first two years are misleading because of the unstable effect of capital on output. But starting with the third year, there does appear to be a steady rise in the elasticity of output with respect to labor input that continues through at least the tenth year after birth of the

plant.

4) The effect of organization learning on the elasticity of output with respect to human capital is much more erratic. Once again ignoring the first two years because of the unstable, and hence distorting, effect of the physical capital input, a pattern is however observable with the help of a three-year moving average. The coefficients centered on the fourth through the ninth year are, respectively, as follows: .749, .763, .826, .973, .990, .964.

In sum, there appears to be a rise from the fourth to the eighth year, measured in this way.

5) Annual data are insufficient to identify the effects of learning or manual tasks. Moreover, the variables we used do not effectively distinguish between organization and manual learning. We assumed the observed learning reflected in the coefficients of the two labor inputs was of the organization type of *a priori* grounds related to its duration.

6) In sum, it is clear that productivity continues to rise for a considerable period of years after the birth of a plant.

5. Conclusions

We approach the problem of assessing the effects of learning by doing by focusing on firm or plant-specific learning. We do so in the context of a production function in which the other arguments are labor, human capital, physical capital, and vintage as a proxy for embodied technical change in physical capital. Firm or plant specific learning is proxied, alternatively, by cumulative output per employee (or per unit of physical capital) and by time elapsed since the organization's birth. Learning is conceptually decomposed into organization learning, capital learning, and labor or manual task learning although the last cannot be measured with our data. In contrast to firm or plant specific learning, industry-wide learning is captured simply by a time dependent shift parameter.

The model is estimated with individual plant data for one sample of 15 industries, and another sample of 41 industries, using time series and cross section analysis both at the industry level (for the 15 industry sample) and pooled across industries. Industry-wide learning appears to be uniquely related to embodied technical change of physical capital. Once due account is taken of the latter variable, residual industry-wide learning disappears as a significant explanatory variable. In contrast, plant-specific learning remains important in all specifications of the model and for both samples of industries.

Based on cross sections for successive years for the 15 industry sample of plants, we find that organization learning appears to continue over a period of at least ten years following the birth of a plant. Capital learning continues for five or six years after birth. This means that new entrants incur costs that established organizations no longer face.

APPENDIX ON DATA CONSTRUCTION AND CHOICE OF SAMPLES

CAPITAL

For our measure of physical capital, we cumulated gross investment over each relevant interval (but lagged half a year). Investment was deflated by the implicit price deflator for capital expenditures in all manufacturing combined (the latter based on unpublished Bureau of Economic Analysis data).

To the cumulative total of gross capital expenditure we added the capitalized value of the changes in rentals of fixed assets.[5] For our sample of industries, the resulting addition was relatively small. Finally, for most plants there was some initial capital stock that anteceded the birth of the plants in the Census records. This stock had several origins: (a) from initial capital outlays preceding the recorded birth of the plant, (b) from the transfer of existing old assets to new activities following the recorded birth of the plant, (c) from the acquisition of old assets from other owner's in the year preceding the plant's recorded birth. We assumed that (a) and (c) accounted for most of this initial stock and the appropriate deflator for it, therefore, was the capital expenditure deflator for the year preceding the plant's birth. In short, we assumed that the assets were generally acquired at market prices prevailing just prior to the plant's birth.

LABOR AND HUMAN CAPITAL

Labor input for each plant was measured by the Census record for the plant's number of employees. An alternative measure, man-hours, was not used because it is available only for production workers. Our proxy for human capital, the average wage rate, was derived by dividing each plant's recorded wage bill by the number of employees. The average wage was deflated by the Consumer's Price Index to convert nominal to real wages.

---

[5] Rental payments for each plant are reported in our data base. The relevant change in value was capitalized by the average ratio of gross fixed assets to the sum of net income before taxes plus interest paid plus depreciation. In this way, estimates were made for aggregate manufacturing for 1972-86, as reported in U.S. Internal Revenue Service, Statistics of Income.

OUTPUT

Output was proxied alternatively by data for shipments and for value added, each deflated by an appropriate deflator for the relevant 4-digit industry.[6]

Shipments data ignore variations across plants in purchases from other plants--hence in the degree of vertical integration. On the other hand, value added is subject to statistical error in the measurement of cost of materials, and also errors arising from inconsistencies over time in the valuation of semi-finished and finished product inventories. The question of whether shipments or value added constitutes the better measure is an empirical one and the answer is likely to depend on the sample of industries considered.

COMPOSITION OF SAMPLE AND TIME PERIOD STUDIED

For our analysis, two sets of industries were selected, one comprising 41 manufacturing industries and a subset of 15 industries. For the larger set, we included all industries with at least 16 new plants that satisfied criteria noted below (excepting only NEC industries and several we did not consider to be primarily in manufacturing, e.g. publishing). For the subset of 15, we selected those from the 41 that were generally the largest in terms of number of plants to permit intra-industry analysis, but with selection also based partly on representation across the industrial spectrum.

Within these sets of industries, only plants that satisfied the following criteria were chosen: (a) a continuous history in the same industry from birth until 1986, (b) a primary industry specialization ratio of at least 50 percent. The latter criterion was introduced to give us some homogeneity of plants within industries. This gave us about 2,150 new plants for the 41 industries, and about 1,280 for the 15.

The period chosen for analysis, 1973-86, was determined by the time interval for which panel data were available.

---

[6] The deflators were drawn from unpublished data of the Bureau of Economic Analysis and consisted of implicit deflators at the 4-digit level.

Table 4

Production Relations for 15 Industries,
Cross Sections with Identical Samples for Eight and Ten Consecutive Years After Birth of Plant[1]

(t-values below coefficients)

Years after birth	Intercept		L		W		K		Adj R^2	
	8 years	10 years	8 years	10 years	8 years	10 years	8 years	10 years	8 years	10 years
1st Year	2.28 6.2	2.45 5.3	.770 21.3	.796 16.6	.966 8.0	.957 6.1	.049 1.7	.020 0.5	.662	.652
2nd Year	2.33 6.8	2.56 5.9	.575 15.4	.582 12.5	1.05 8.9	.985 6.4	.156 4.9	.150 3.7	.649	.655
3rd Year	2.84 6.9	2.75 5.8	.554 13.4	.553 12.1	.761 5.4	.859 5.3	.218 5.7	.210 5.2	.610	.676
4th Year	2.81 7.7	2.93 6.5	.544 15.0	.538 12.7	.711 5.6	.720 4.6	.253 7.3	.239 5.7	.692	.710
5th Year	2.54 7.5	2.86 7.3	.530 14.4	.546 12.8	.694 5.8	.669 4.7	.300 8.5	.261 6.2	.719	.744
6th Year	1.75 5.0	1.88 4.4	.588 16.6	.577 14.3	.853 7.0	.902 6.1	.300 8.7	.270 6.7	.756	.773
7th Year	1.56 4.6	1.87 5.3	.615 15.9	.587 14.5	.918 7.9	.907 7.7	.283 7.5	.262 6.5	.748	.792
8th Year	1.05 3.0	1.19 2.7	.647 18.8	.633 16.2	1.09 9.2	1.11 7.3	.265 7.8	.242 5.9	.787	.803
9th Year		1.61 3.7		.640 16.4		.954 6.1		.245 5.7		.810
10th Year		1.83 4.5		.654 16.5		.827 5.9		.259 6.1		.812

Source: Based on U.S. Bureau of the Census, LRD Data Base.

[1] For the eight consecutive cross section, the sample consisted of 399 plants. For the ten consecutive cross sections, the sample consisted of 237 plants. Births occurred in 1973 or later. The terminal point was 1986. Observations for years represent events occurring a specified number of years after birth with nonidentical birth years for plants. The dependent variable is shipments and all other variables are as defined for Tables 1-3.

TABLE B

LIST OF 41 INDUSTRIES AND 15 INDUSTRY SUBSET

SIC Code		Industry Name	Number of New Plants in 1982
2011		Meatpacking Plants	
		25	
2013		Sausages and Other Prepared Meat Products	36
2016		Poultry Dressing Plants	26
2022		Cheese, Natural and Processed	16
2026		Fluid Milk	18
2037		Frozen Fruits and Vegetables	16
2051		Bread, Cake, Related Products	32
2065		Confectionery Products	21
2086	*	Bottled and Canned Soft Drinks	33
2328		Men's and Boys' Work Clothing	16
2421	*	Sawmills, Planing Mills, General	94
2436		Softwood Veneer and Plywood	17
2451	*	Mobile Homes	31
2512		Upholstered Household Furniture	21
2653	*	Corrugated, Solid Fiber Boxes	34
2655		Fiber Cans, Drums, Similar Products	17
2752	*	Commercial Printing, Lithographic	48
2813	*	Industrial Gases	68
2821		Plastics Materials and Resins	20
2834		Pharmaceutical Preparations	18
2851	*	Paints and Allied Products	16
2911	*	Petroleum Refining	18
3357		Nonferrous Wiredrawing, Insulating	22
3411	*	Metal Cans	50
3441	*	Fabricated Structural Metal	32
3443		Fabricated Platework, Boiler Shops	21
3494		Valves and Pipe Fittings	26
2523		Farm and Garden Machinery	26
3531		Construction Machinery	17
3533		Oilfield Machinery	39
3544		Special Dies, Tools, Jigs, etc.	20
3561		Pumps and Pumping Equipment	22
3573	*	Electronic Computing Equipment	96
3585	*	Refrigeration, Heating Equipment	35
3612		Transformers	16
3613		Switchgear, Switchboard Apparatus	22
3621		Motors and Generators	26
3662	*	Radio, TV Communication Equipment	76
3674	*	Semiconductors, Related Devices	43
3714	*	Motor Vehicle Parts, Accessories	48
3713		Ship Building and Repairing	21

*15 industry sample.

References

Alchian, A. "Reliability of Progress Curves in Airframe Production." Rand Corporation, Report 260-1, published in *Econometrica* 31 (1963): 679-93.

Baloff, N. "Startups in Machine-intensive Production Systems. *Journal of Industrial Engineering* 17 (1966): 25-32.

Becker, G. *Human Capital*. Columbia Univ. Press, 2nd ed., 1964.

Conway, R., and Schultz, A. "The Manufacturing Progress Function." *Journal of Industrial Engineering* 10 (1959): 39-53.

Fellner, W. "Specific Interpretations of Learning by Doing." *Journal of Economic Theory* 1 (1969): 199-40.

Gort, M.; Grabowski, H; and McGuckin, R.M. "Organizational Capital and the Choice Between Specialization and Diversification." *Managerial and Decision Economics* 6 (January 1985): 2-10.

Gort, M.; Sapra, S.; and Bahk, B.H. "Old Inputs, New Inputs, and Productivity." In U.S. Bureau of the Census, *1990 Census Research Conference* (1990).

Gort, M.; Bahk, B.H.; and Wall, R.A. "Decomposing Technical Change." Working paper (1991).

Hartley, K. "The Learning Curve and Its Application to the Aircraft Industry." *Journal of Industrial Economics* 13 (1965): 122-28.

Hirsch, W. "Firm Progress Rations." *Econometrica* 24 (1956): 136-43.

Hirsch, W. "Manufacturing Progress Functions." *Review of Economics and Statistics* 34 (1952): 143-55.

Killingsworth, M. "Learning by Doing and Investment in Training: Synthesis of Two Rival Models of the Life Cycles." *Review of Economic Studies* 49 (1982): 263-71.

Lieberman, M. "The Learning Curve and Pricing in the Chemical Processing Industries." *Rand Journal of Economics* 15 (1984): 213-28.

Montgomery, F. "Increased Productivity in the Construction of Liberty Vessels." *Monthly Labor Review* 14 (1943): 861-4.

Oi, W. "The Neoclassical Foundations of Progress Functions." *Economic Journal* 77 (1967): 579-94.

Prescott, E. and Visscher, M. "Organization Capital." *Journal of Political Economy* 88 (1980): 446-61.

Preston, L. and Keachie, E. "Cost Functions and Progress Functions: An Integration." *American Economic Review* 54 (1964): 100-7.

Rapping, L. "Learning and World War II Production Functions." *Review of Economics and Statistics* 47 (1965): 81-6.

Rosen, S. "Learning by Experience as Joint Production." *Quarterly Journal of Economics* 86 (1972): 366-82.

Sheshinski, E. "Tests of the Learning by Doing Hypothesis." *Review of Economics and Statistics* 49 (1967): 568-78.

Tomer, J. "Organizational Change, Organizational Capital and Economic Growth." *Eastern Economic Journal* 7 (1981): 1-14.

Wright, T. "Factors Affecting the Cost of Airplanes." *Journal of Aeronautical Sciences* 3 (1936): 122-8.