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A Study of Standard Setting and Productivity Measurements using Learning Curves

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A STUDY OF STANDARD SETTING
AND PRODUCTIVITY MEASUREMENTS
USING LEARNING CURVES

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CHAPTER I

INTRODUCTION

BACKGROUND OF THE PROBLEM

Standards can provide both management and rank and file workers a measurement device to evaluate performance. As such, standard setting may help identify specific performance objectives for a firm. Various methods have been utilized to establish worker performance standards. One such strategy is to project work performance using learning curves.[1] Thus, standard setting based on learning curves may aid management and the accountant in establishing, reporting, and evaluating worker performance in a manufacturing environment.

The concept of learning curve (LC) analysis is used in the literature in manufacturing progress functions,[2] technological progress functions,[3] progress curves,[4] cost-quantity relationships,[5] experience

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[1]D. R. Towill and U. Kaloo. "Productivity Drift in Extended Learning Curves, Omega, Vol. 6, No. 4, 1978, pp. 295-304.

[2]Werner Z. Hirsch. "Manufacturing Progress Functions," Review of Economics and Statistics, Vol. 34, No. 2, May 1952, pp. 143-55.

[3]D. Sahal. "Reformulation of the Technological Progress Function," Technological Forecasting, Vol. 8, 1975, pp. 75-90.

[4]Armen Alchian. "Reliability of progress Curve In Airframe Production," Econometrica, Vol. 31, No. 4, October 1963, pp. 679-93.

[5]R. Cole. "Increasing Utilization of the Cost-Quantity Relationship in Manufacturing," Journal of Industrial Engineering, Vol. 9, No. 3, May-June 1958, pp. 73-80.

curves,[6] production acceleration curves,[7] manufacturing improvement curves,[8] and learning by doing.[9] Conceptually, all of the technical uses are essentially identical.

Learning curve theory was first used in the production process in 1922[10] as a budgeting tool to establish performance standards. Once established, standards were then used to evaluate employee productivity and to minimize and control costs. LC theory is based on the premise that workers become more proficient at specific tasks by performing them repeatedly. LC theory suggests that throughout the production period, average overall performance will be increased by a constant fixed percentage as production increases. The rate of improvement will be greater for operations requiring higher proportions of assembly time than for those involving greater proportions of automated machine time. Thus, employee productivity should increase over time according to the general formula:[11]

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[6]R. A. Lloyd. " 'Experience Curve' Analysis," Applied Economics, Vol. 11, No. 2, June 1979, pp. 221-34.

[7]Stanford Research Institute, Development of Production Acceleration Curves for Airframes, 1949.

[8]Paul F. Williams. "The Application of Manufacturing Improvement Curves in Multi-Product Industries," Journal of Industrial Engineering, Vol. 12, March-April 1961, pp. 108-12.

[9]Kenenth J. Arrow. "The Economic Implications of Learning by Doing," Review of Economics Studies, Vol. 29, No. 80, June 1962, pp. 155-73.

[10]T. P. Wright, "Factors Affecting the Cost of Airplanes," Journal of the Aeronautical Sciences, Vol. 3, No. 4, February 1936, p. 128.

[11]A. B. Berghell. Production Engineering In The Aircraft Industry. (New York: McGraw-Hill Book Company, Inc., 1944), pp. 166-98.

OBJECTIVES OF THE STUDY

The purpose of this study is to examine LC theory when used as a performance measure to (1) evaluate the time frame over which the derived LC will shift, (2) identify some of the factors affecting LC variation over time, and (3) offer suggestions to management for determining the time frame of LC variation and for specifying some significant factors affecting LC variation over time. Some insights concerning employee performance groupings (above average, average, and below average) may be obtained by determining significant factors such as demographic, economic, or psychological factors which are common to employee groups. Factors common to employee groups may have significant impact on the hiring and retention process in the firm if these factors can be used to predict worker groupings at hiring dates.

The specific objectives of this study are listed as follows:

(1) To provide evidence to determine the extent to which production worker performance has changed over time.

(2) To provide broad guidelines and recommendations for production-type industries concerning performance evaluation of employees during training.

(3) To find evidence that standards and environmental factors for production workers can be linked and to provide information to the firm for hiring, budgeting, and planning purposes.

(4) To provide the basis for further research associated with identifying variables related to improving worker performance.

JUSTIFICATION OF THE STUDY

It is generally perceived that employee performance, based on LC theory, increases at a constant rate over time. However, Towill and Kaloo's study provided evidence that performance of employees based on LC theory changes over time for steady state production.[13] The results of their study may be applicable to the training period as well. The current study may provide evidence that production performance of employees is not equal for different groups of employees over different time periods. Employee performance may change over time at a rate which would indicate a need for periodic updating of LC based performance standards more frequently than is generally perceived. Thus, the contribution of the research should provide additional evidence for the need, or lack thereof, of developing more dynamic standard setting and review practices.

Identifying factors affecting desired levels of performance may facilitate management's screening and hiring process with regard to specific characteristics of prospective production workers. The difficulty associated with identifying even a naive explanative or predictive model concerning potential changes in performance levels offers management a challenge.

Greater awareness of these issues, along with tools that enable management to forecast future performance levels, may increase utilization of a firm's human resources. The accounting function of establishing, reporting, and evaluating information concerning the budgeting and

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[13]Op. cit. Towill and Kaloo, pp. 295-304.

planning process may provide a useful information center for gathering and evaluating worker performance data.

DEFINITIONS

Specific definitions will be used for this study. They are:

(1) Learning curve standard. As noted above, many production processes may be adapted to a LC measurement. A learning curve standard may be defined as a predetermined desired performance level which is based on LC theory and developed by management to measure and evaluate performance of production workers. A learning curve standard may be developed from time and motion studies, past performance records of employees, or *a priori* managerial expectations.

(2) Efficiency or performance ratings. The efficiency or performance rating for each observation will be calculated using the following formula:

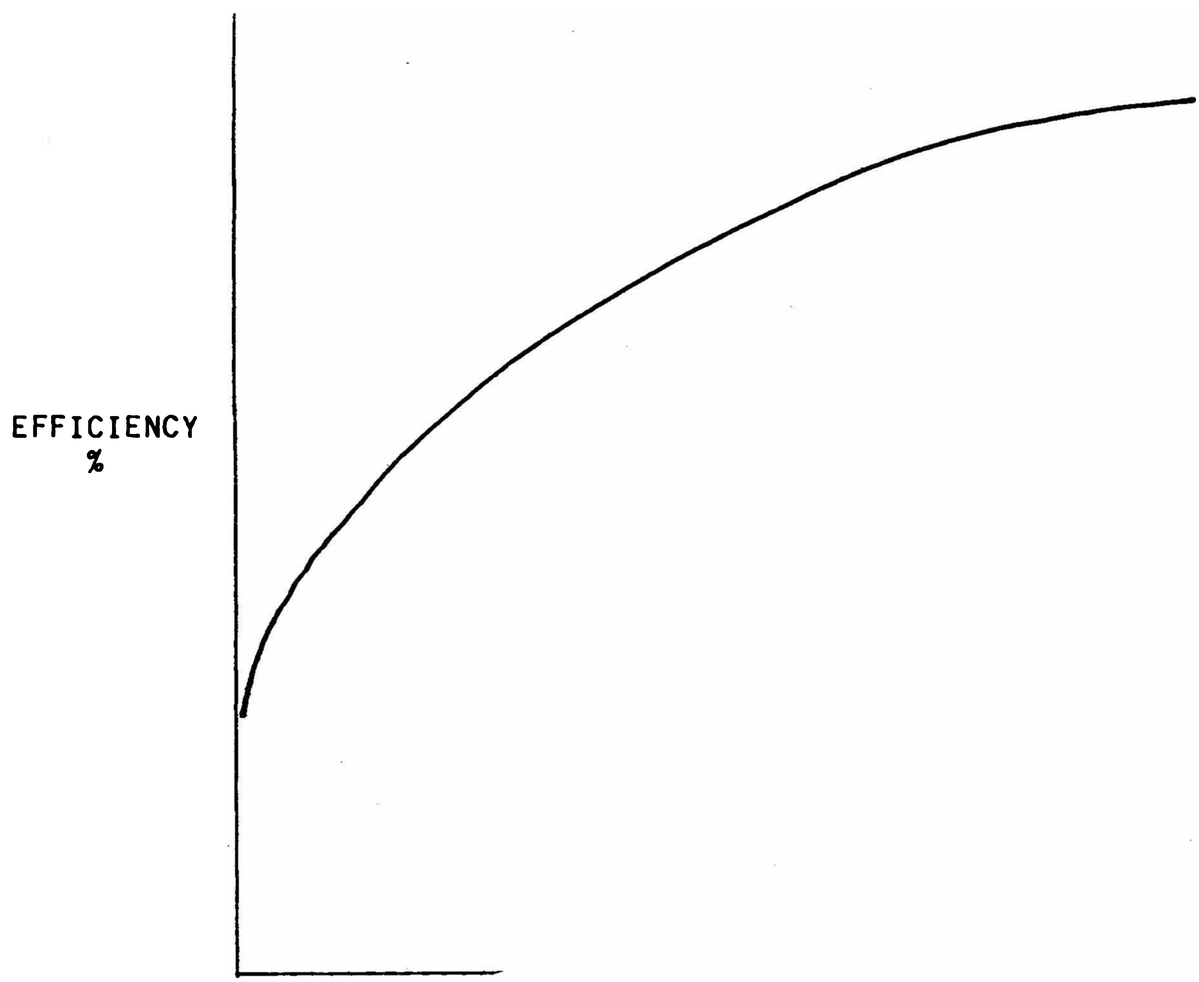
$$\text{Efficiency or Performance Rating (\%)} = \frac{\sum \text{Actual Time Units to Complete a Job}}{\sum \text{Standard Time Units to Complete a Job}} \qquad (1.2)$$

Whereas the general LC described in Formula 1.1 is negatively sloped and generally describes the reduction of man-hours or production costs as production continues, Formula 1.2 refers to a performance measure. As such, the LC exponent from Formula 1.1 becomes positive and the LC formula measures efficiency or performance ratings rather than cost reduction as when the LC exponent is negative. For this study, the efficiency or performance rating percentage is based on Formula 1.2 and appears as an upward sloping curvilinear line as shown in Figure 1.1 on normal graph paper and is a positively sloped straight line on log/log graph paper, as depicted in Figure 1.2.

(3) Average employee efficiency or performance. Average employee efficiency or performance is the combined aggregate efficiency or performance ratings during training for a group of employees over a specified training period (i.e. days, weeks, months). Average Employee efficiency or performance will be calculated for each employee according to the format:

FIGURE 1.1

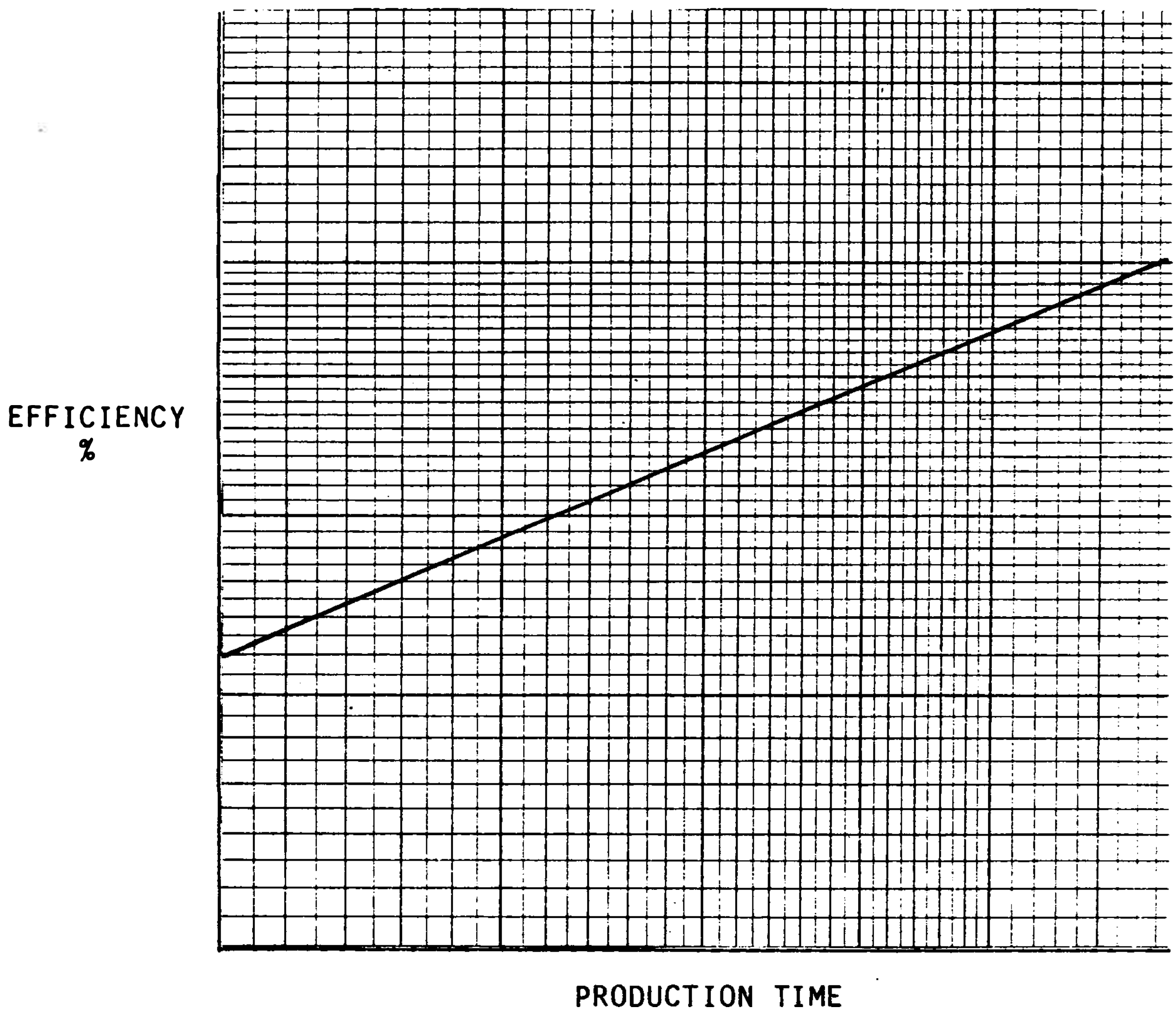
CURVILINEAR EFFICIENCY
LEARNING CURVE



LC using formula Y =

FIGURE 1.2

LINEAR EFFICIENCY LEARNING CURVE



LC using formula $Y = aX^b$ on log/log graph paper

$$
\begin{matrix}
Y_{1,1} & , & Y_{2,1} & \cdots\cdots & , & Y_{i,1} & & \bar{Y}_1 \\
Y_{1,2} & , & Y_{2,2} & \cdots\cdots & , & Y_{i,2} & & \bar{Y}_2 \\
\vdots & & \vdots & & & \vdots & = & \vdots \\
Y_{1,j} & , & Y_{2,j} & \cdots\cdots & , & Y_{i,j} & & \bar{Y}_j
\end{matrix}
$$

(4) Production factors. Production factors are all factors within the factory environment which affect worker performance such as management policy, union requirements, temperature, lighting, general working conditions, etc.

(5) Environmental factors. Environmental factors are those factors that affect worker performance, other than production factors such as manual dexterity, personality factors, hygienic factors, demographic factors, economic factors, etc.

(6) Management. Management includes managers within the firm from accounting, production, marketing, and/or finance areas of the firm.

STATEMENT OF THE HYPOTHESES

Two general hypotheses are tested in this study. The first hypothesis attempts to identify if differences between standard performance and average production worker performance exist over time. Hypothesis one (H1) is stated as follows:

$H1_o$) Learning curve standard performance equals average employee performance over time.

$H1_a$) Learning curve standard performance does not equal average employee performance over time.

Sub-hypotheses may be developed from H1 to test for differences between groups of employees over different time periods. These tests will allow the researcher to test for: (1) differences between employee groups and (2) differences between an employee group and a learning curve standard. The sub-hypotheses are stated as follows:

$H1_{o1}$) Average employee performance for one group equals average employee performance for another group.

$H1_{a1}$) Average employee performance for one group does not equal average employee performance for another group.

$H1_{o2}$) Conditional hypothesis that average employee performance for two groups (from $H1_{01}$) equals the learning curve standard.

$H1_{a2}$) Average employee performance for two groups does not equal the learning curve standard.

$H1_{o3}$) Average employee performance (combined groups from $H1_{01}$) equals the learning curve standard.

$H1_{a3}$) Average employee performance does not equal the learning curve standard.

Identification of non-production factors affecting standard performance or average producion worker performance is stated in the second hypothesis (H2).

$H2_{o}$) Production factors, as compared with environmental factors, are the only identifiable factors which affect differences in average employee performance.

$H2_{a}$) Production factors, as compared with environmental factors, are not the only identifiable factors which affect differences in average employee performance.

METHODOLOGY

In order to test whether standard performance is equal to average employee performance over time (H1), regression analysis will be used. If standard performance and average employee performance are not equal, one may conclude that production worker performance does not follow an established standard over time. Further, assuming that a production process has remained the same over a specific time period, the change in productivity may be a result of environmental factors. This would indicate that standards should be reviewed periodically and perhaps revised.

Testing whether environmental characteristics affect worker performance will be accomplished using discriminant analysis. Discriminant analysis will be used to identify environmental characteristics which affect production worker groups. Production worker groupings may explain some of the environmental factors influencing production worker performance.

LIMITATIONS OF THE STUDY

Analysis of non-production factors to predict employee groupings such as above average, average, or below average groups for production workers may prove to be expensive and time consuming in practice. Hence, implementation of such analysis will depend largely on a cost-benefit decision by prospective users. If long term benefits exceed the costs involved, a decision should be made to adopt some type of pre-selection and evaluation program for employees. If costs exceed benefits for an employee pre-selection and evaluation program, such analysis should not be used.

An acceptable employee hiring percentage, with respect to choosing those employees capable of meeting or surpassing standard performance levels, will also depend on the continuity of the production process. Industries that experience periodic technological changes in production or industries that employ workers based on fluctuating demand and production schedules may have little need for this type of analysis.

The results from this study may have limited applicability to workers in industries or firms not included in the study or for those firms not possessing similar worker characteristics. Generalized applications to similar firms within like industries may be made but may have decreased applicability to other industries, particularly those industries which do not have a production-oriented work force.

Finally, the psychological and sociological impact on performance of production workers will not be examined in this study. Intuitively, one can accept the premise that psychological and sociological factors affect worker performance. The degree of importance has been debated and is beyond the scope of this study.

DESIGN OF THE STUDY

The design of this study will include a historical review of standard setting practices using LC theory. Chapter II will include a contemporary review of the related literature. First, a general review of the theory of LC analysis with respect to the production environment and standard setting practice will be presented. Secondly, a learning curve concept will be discussed with respect to the measurement and evaluation of performance and its applicability to the standard setting process. Finally environmental factors will be introduced for the potential influence which they may have on worker performance.

The methodology for the study will be discussed in Chapter III. The findings of the study including the results of comparisons between existing performance standards and actual performance results and an examination of environmental factors which may help segregate employee groups on the basis of worker performance will be presented in Chapter IV.

Finally, data from Chapter IV will be reviewed in Chapter V in order to make suggestions concerning the evaluation of worker efficiency as well as to suggest recommendations that may be applicable in similar industrial settings. Suggestions for future research will be offered as well.

CHAPTER II

REVIEW OF RELATED LITERATURE

INTRODUCTION

Standard setting, based on learning curve (LC) theory, is an important element of the budgeting process and may influence productivity levels within a firm. Setting standards or goals helps to identify specific performance and cost objectives for a firm.

According to the National Association of Accountants, standard costs developed for use in the factory to control costs, while budgeting developed as a tool for financial planning of the business.[14] Stedry concluded that budgets emphasize financial aspects, while standards are used as part of a cost control system within the factory environment.[15] Both standard setting and budgeting involve management's philosophy of cost control. Specification of standards in a production setting typically assists management in its task of forecasting worker performance and budgeting production costs.

Budgeting and standard setting include establishing, reporting, and evaluating performance. Kohler defined a standard as a "desired

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[14]"A Reexamination of Standard Costs," N.A.C.A. Bulletin, Vol. 29, Section 3 (Research series No. 11), February 1, 1948, p. 697.

[15]Andrew C. Stedry. Budget Control and Cost Behavior (Englewood Cliffs, N.J.: Prentice-Hall, Inc., 1960), pp. 8-9.

attainment; a performance goal; a model".[16] Stedry's view of a budget "carries with it the connotation of a 'goal' or 'desired attainment' which is also noted in Kohler's definition of a standard." Stedry concluded that "'budgeted performance' and 'standard performance' differ only in name if they are both goals or desired attainments."[17] Thus, budgets and standards, based on LC theory, may be interpreted as tools to establish, report, and evaluate worker performance in a manufacturing environment.

Williams asserted that LC theory may be used for different purposes within a firm. According to Williams, the most important reasons for using LC theory are:

1. Prediction of manufacturing performance may be made systematically, consistently, and objectively.
2. Estimates average costs of start-up and follow-up quantities for production purposes.
3. The graphic technique is simple to use.
4. The LC may be used for setting standards to aid management in the evaluation process.
5. Estimation of costs may be made more accurately.[18]

Thus, application of LC theory results in budgets, targets, or standards being useful as a tool to establish, report, and evaluate worker performance in a manufacturing environment.

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[16] E. L. Kohler. A Dictionary For Accountants. (Englewood Cliffs, N.J.: Prentice-Hall, Inc., 1970), p. 400.

[17] Op. cit., Stedry.

[18] Op. cit., Williams." pp. 108-9.

LEARNING CURVE THEORY

T. P. Wright is credited with the development of LC theory from his observations of aircraft assembly. He described his findings in a paper presented in 1936 to the Aircraft Operations Session of the Industrial Aeronautical Sciences Fourth Annual Meeting. Wright discovered that aircraft production costs generally decreased over time as indicated in Figure 2.1, page 16.[19] Recent studies have reexamined the concept developed by Wright.[20]

Wright's paper introduced the notion that the ratio of labor to raw material will vary as the quantity of aircraft produced varies. An inherent assumption of this notion is that a given task can be accelerated through repetitive procedures performed by workers. Also, it should be recognized that the procedures performed by workers must remain relatively unchanged in order to be compared with one another over time.[21]

Wright determined that cost reductions existed within the framework discussed above concerning labor, material, and overhead costs. Each of these elements was supported by the following factors:

Labor

- Proficiency of workers over time improved from practice.
- As the quantity of production increases, worker frustration due to process changes is lessened.

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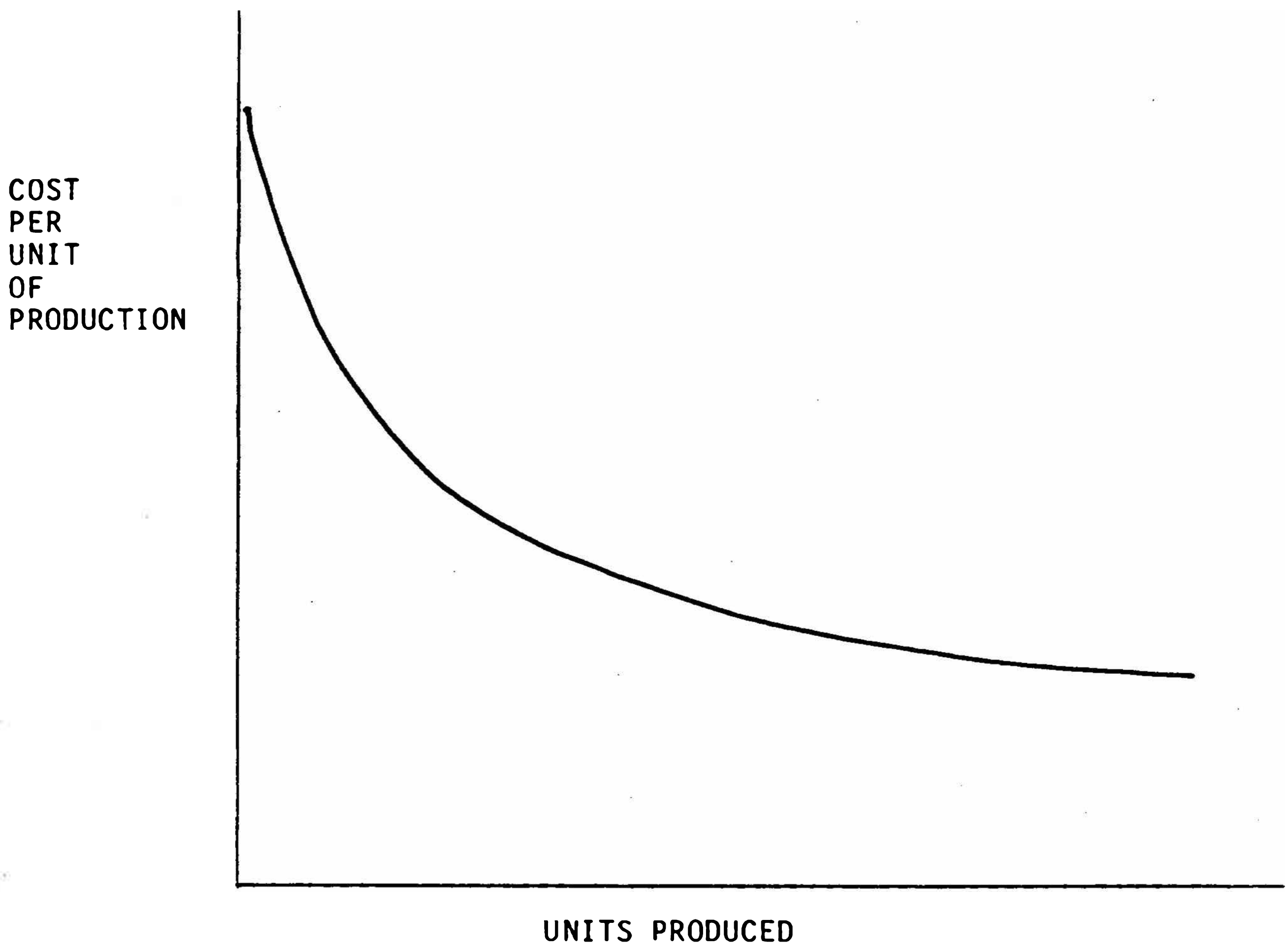
[19] Op. cit., Wright. pp. 122-28.

[20] See Alchian [1978], and Morse [1972].

[21] Ibid., pp. 122-23.

FIGURE 2.1

LABOR PRODUCTION COSTS



(Source: T. P. Wright, "Factors Affecting the Cost of Airplanes," Journal of the Aeronautical Sciences, Vol. 3, No. 4, February 1936, p. 122.)

- For large production orders, greater amounts of specialized tooling can be utilized to facilitate economies of labor.

- The use of specialized tooling will facilitate the use of less skilled labor.

Material

- Costs decrease generally as quantity increases because of greater efficiency of workers, better matching of metal patterns to the sheets received from suppliers, and the prospect of receiving purchase discounts for larger orders.

Overhead

- The amount of overhead will vary, within a relevant range with quantity. As quantity of production increases, the amount of overhead will decrease from a range of one hundred percent of direct labor to as low as sixty percent.[22]

Wright developed a single LC which included all production costs of labor, material, and overhead. Conditions affecting output such as labor turnover, re-tooling, new set ups, and order modifications were factored into the LC in order to properly estimate orders.[23]

Wright also introduced the notion that a LC could be useful in other industries. His analysis of costs between the aircraft industry and the automobile industry demonstrates generalizations of production increases and cost reduction, and the LC phenomenon.[24]

The use of LC theory to estimate and forecast production variables (costs, output, efficiency) has predominantly employed the general formula:[25]

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[22]Ibid., pp. 124-26

[23]Ibid.

[24]Ibid.

[25]The formula $y = aX^{-b}$ is used throughout most learning curve formula derivations. See chapter twelve, A. B. Berghell, Production Engineering in the Aircraft Industry. New York: McGraw-Hill Book Company, Inc., 1944, for a detailed analysis of LC derivations.

$$Y = aX^{-b} \tag{2.1}$$

where:

Y = production predictor (estimated required labor units, costs units or efficiency percentages)

X = production quantity (units of product or time)

a,b = parameter values

The production predictor (Y) has been represented as direct labor hours required for production of a specified unit[26], a factor of cost variation[27], annual plant capacity[28], productivity[29], or efficiency.[30] Frank Andress generalized that the Y variable could measure cumulative average units, specific units, or total units with only small adjustments made in the general formula.[31] Generally, Y may be defined as a cost element, unit output element, or efficiency measure pertaining to labor, materials, or overhead.

The X variable has usually been described as a quantity in units. Typically, a reference to completed units of a product or a period of

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[26]Bruce F. Baird. "Note On Confussion Surrounding Learning Curve," Production and Inventory Management, April 1966, Vol. 7, p. 7.

[27]Op. cit., Wright. p. 124.

[28]Paul L. Joskow and George A. Rozanski. "The Effects of Learning By Doing On Nuclear Plant Operating Reliability," The Review of Economics and Statistics, Vol. 61, No. 2, May 1979, pp. 161-68.

[29]D. R. Towill and U. Kaloo. "Productivity Drift in Extended Learning Curve," Omega, Vol. 6, No. 4, 1978, p. 297.

[30]Op. cit., Berghell. p. 183-84.

[31]Frank J. Andress. "The Learning Curve As A Production Tool," Harvard Business Review, January-February 1954, pp. 88-89.

time (i.e. months or years) has been utilized as the basis for applying the LC formula.

The parameter value (a) has also been represented by different measurements. It may represent the number of direct labor hours to build the first unit[32], or a measure of efficiency of an initial unit of production.[33]

The (b) parameter value generally determines the measure of the rate of reduction for the LC.[34] The exponent (b) will usually be negative, resulting in a constant reduction in labor as production is increased.[35] In fact, the exponent explains the ratio of labor and machine input in the production process. In general, the trend between the ratio of labor and machine input has been:

75% labor, 25% machine	80% learning curve
50% labor, 50% machine	85% learning curve
25% labor, 75% machine	90% learning curve[36]

The implications of these ratios demonstrate a greater influence of LC theory for high labor input production environments and a lesser influence in those production processes which are more automated. However,

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[32]Ibid.

[33]Op. cit., Berghell.

[34]Op. cit., Baird. p. 71.

[35]If the slope of the LC is 100% then the exponent will not be negative. An example of this might occur in an automated operation requiring no labor input and would therefore negate any opportunity for learning to occur.

[36]Raymond B. Jordan. "Learning How To Use The Learning Curve," N.A.A. Bulletin, January 1958, p. 27.

it is important to note that effects of the LC are present even in such highly automated industries as nuclear energy[37] and petroleum refining.[38] Baird described the effects of the LC:

> The essence of the concept for, say an 80% curve is that every time cumulative production is doubled the average direct labor time per unit is diminished by 20%. Direct labor time for the second unit is 80% of direct labor time for the first unit, the fourth unit requires 80% as much as the second unit, and so on.[39]

Baird also noted the differences which exist for calculation of average hours per unit of output. The most common assumption for determining the learning base "asserts that average unit time required by direct labor to perform an operation decreases by a constant percentage whenever the total quantity produced is doubled." Table 2.1, columns 3, 4, and 5 illustrate the effect of an 80 percent decrease in average time required to complete a production lot. A second assumption may be made which considers the "cumulative average time per unit as the basis for the measurement of progress" which is illustrated in columns 6, 7, and 8 of Table 2.1. The difference between the average unit hours per lot (columns 3 and 6) and the average hours per unit (columns 5 and 8) can be explained by the difference in the assumption that the learning base is calculated from average hours per unit as opposed to cumulative

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[37]Op. cit., Joskow and Rozanski. p. 165.

[38]Winfred B. Hirschman. "Profit From The Learning Curve," Harvard Business Review, January 1964, pp. 129-34.

[39]Op. cit., Baird. p. 72.

TABLE 2.1

COMPUTATION OF AVERAGE HOURS PER UNIT OF
OUTPUT USING DIFFERENT DEFINITIONS OF THE LEARNING BASE

PRODUCTION QUANTITY		AVERAGE UNIT TIME LEARNING BASE			CUMULATIVE AVERAGE TIME LEARNING BASE		
Production Quantity			Cumulative hours			Cumulative hours	
Per lot	Cumulative	Average unit hours per lot	Total	Average Per unit	Average unit hours per lot	Total	Average per unit
1	1	1000.0	1000	1000.0	1000.0	1000	1000.0
1	2	800.0	1800	900.0	600.0	1600	800.0
2	4	640.0	3080	770.0	480.0	2560	640.0
4	8	512.0	5128	641.0	456.0	4096	512.0
8	16	409.6	8404	625.3	307.2	6554	409.6
16	32	327.7	13648	426.5	245.8	10486	327.7
32	64	262.1	22.35	344.3	196.6	16744	262.1
64	128	209.7	35456	277.0	157.1	26829	209.7
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)

General Assumptions of Table 2.1:

(A) The first unit produced requires 1000 direct labor hours, i.e., $Y_1 = 1000$
(B) An 80% learning curve applies, i.e., $b = -0.322$.

(Source: Bruce F. Baird, "Note On The Confusion Surrounding Learning Curve," Production and Inventory Management, April 1966, Vol. 7, pp. 71.)

average hours per unit.[40] Thus, it is apparent that significant differences may exist for comparative analysis of different LC applications unless the computation of the learning base is consistently specified. It is also apparent that comparisons between different firms will be relevant only in those instances where the LC base is common.

Another consideration affecting comparative analysis of applied LC theory is the "learning" characteristic to be measured. An analysis of costs or reduction of man-hours will generally yield a negatively sloped curve as shown in Figures 2.2 and 2.3.[41] Figure 2.2 depicts the LC plotted on a normal graph, while Figure 2.3 is plotted on logarithmic graph. It is noted that the learning curve (plotted on Figures 2.2 and 2.3) may be utilized as a curvilinear line or a straight line to explain and predict cost behavior.

On the other hand, the general LC described above also may be used to measure productivity or employee performance.[42] Figures 2.4 and 2.5 refer to the LC as it is related to productivity or performance efficiency of employees. For this purpose, the LC is positively sloped and appears as an upward sloping curvilinear line on normal graph paper as shown in Figure 2.4 and is a positively sloped straight line on logarithmic graph paper as depicted in Figure 2.5. Thus, it is apparent

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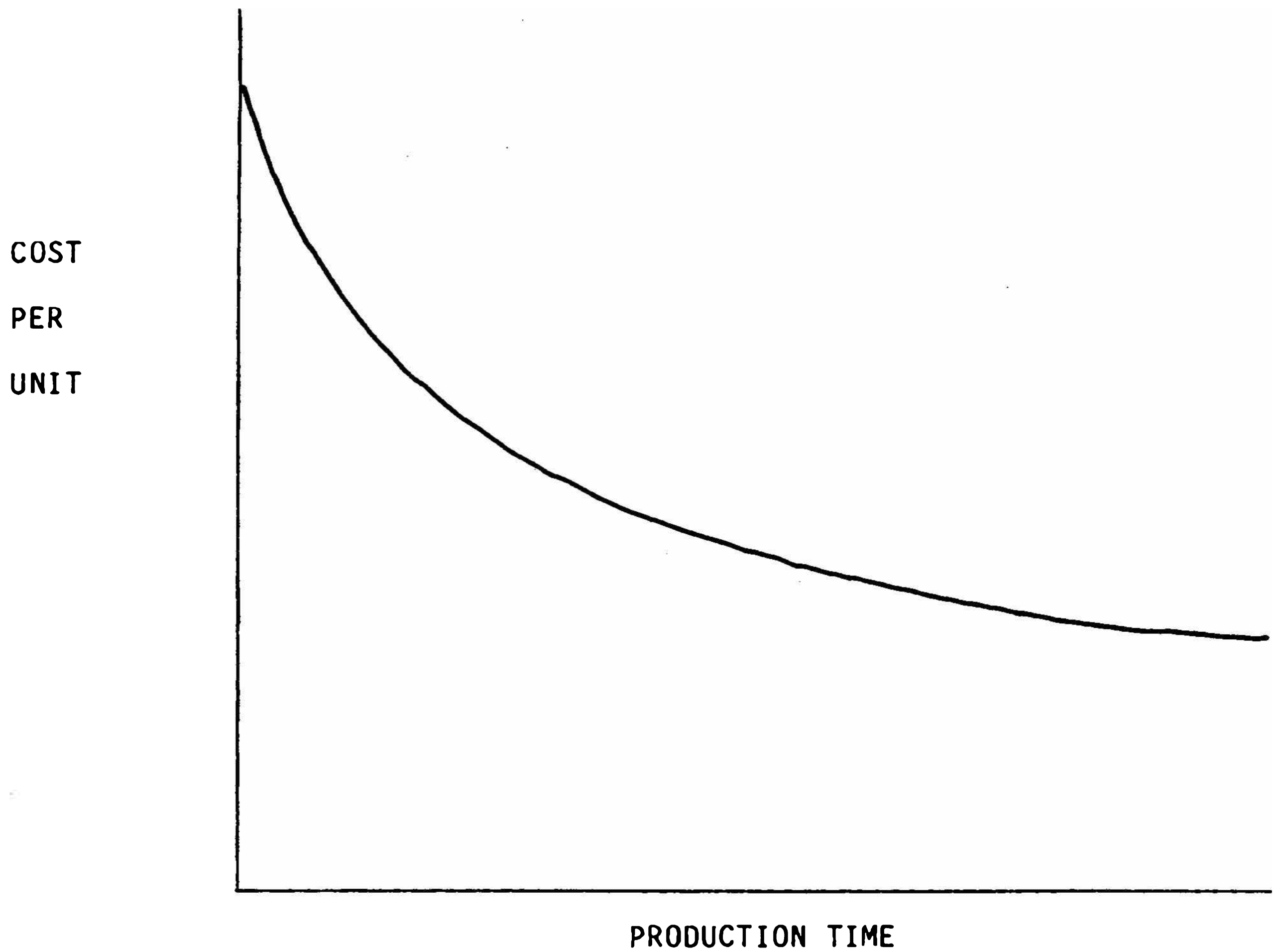
[40]Ibid.

[41]Harold Asher. Project Rand: Cost-Quantity Relationships In The Airframe Industry. (Santa Monica, California: The Rand Corporation, 1956), pp. 1-2.

[42]Glenn M. Brewer. The Learning Curve In The Airframe Industry. (Wright-Patterson Air Force Base, Ohio: School of Systems and Logistics, Air Force Institute of Technology), pp. 11-16.

FIGURE 2.2

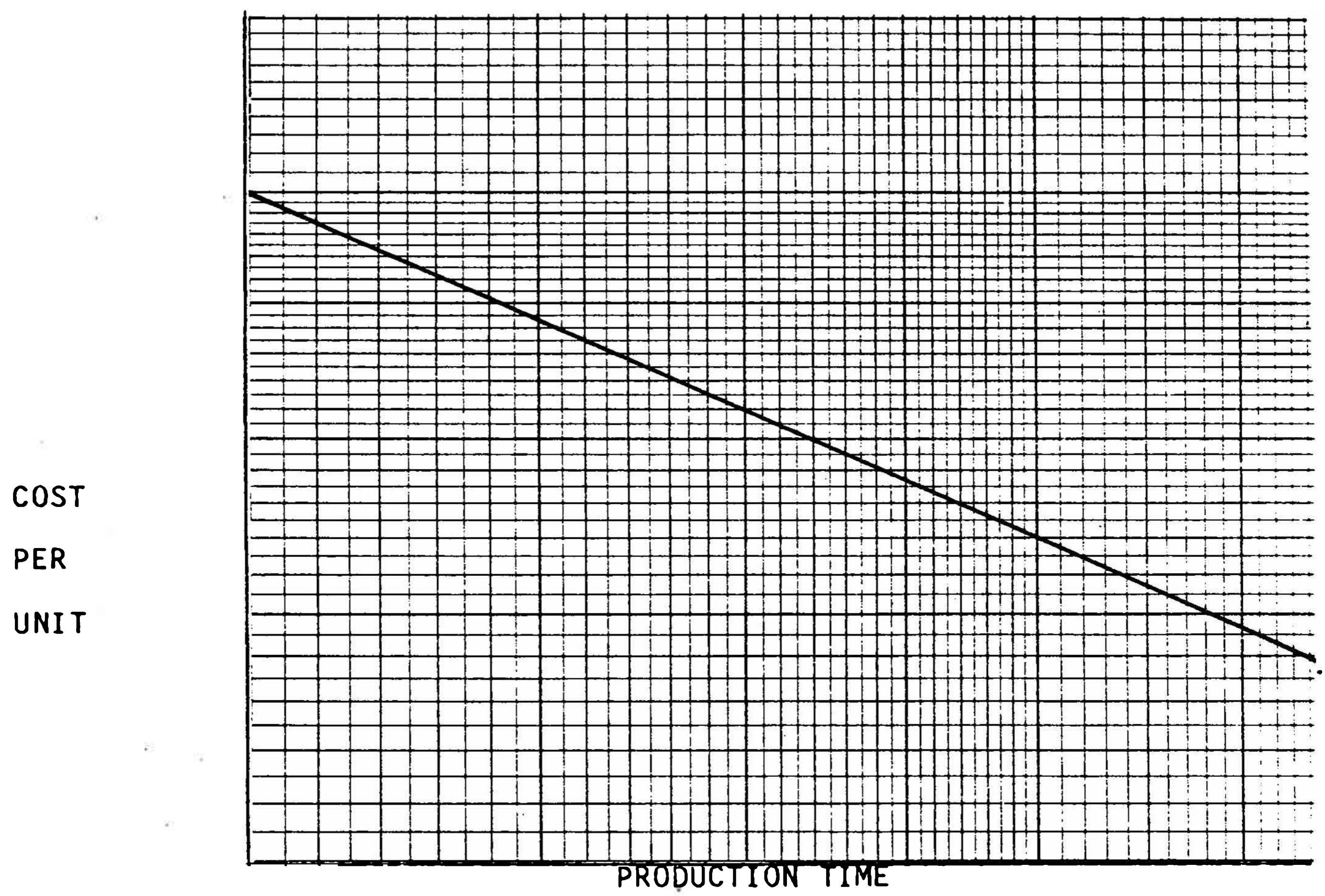
NEGATIVELY SLOPED CURVILINEAR LEARNING CURVE



Learning Curve Formula ($Y = aX^{-b}$) on normal graph paper.

FIGURE 2.3

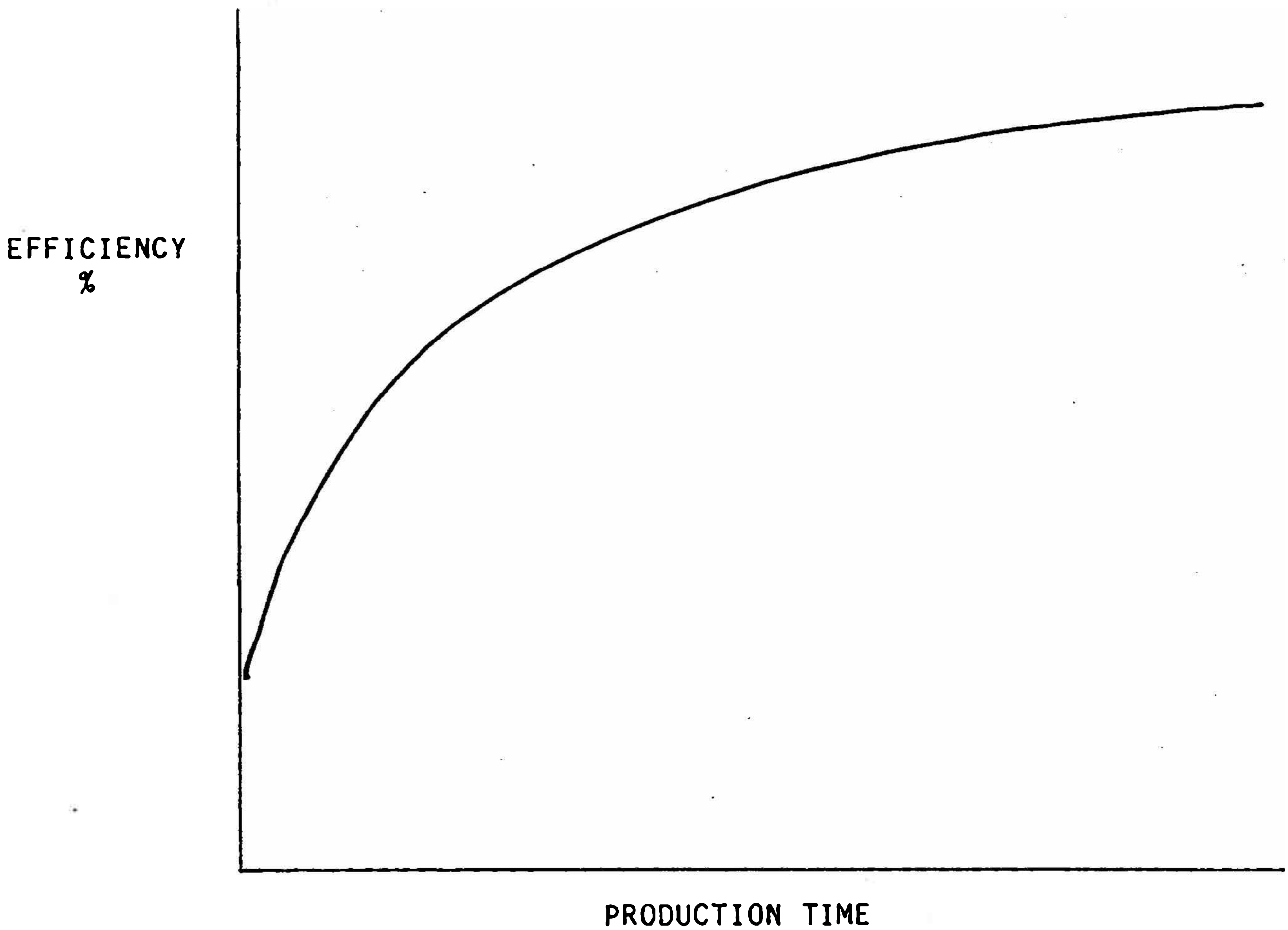
NEGATIVELY SLOPED LINEAR LEARNING CURVE



Learning Curve Formula ($Y = aX^{-b}$) on logarithmic paper.

FIGURE 2.4

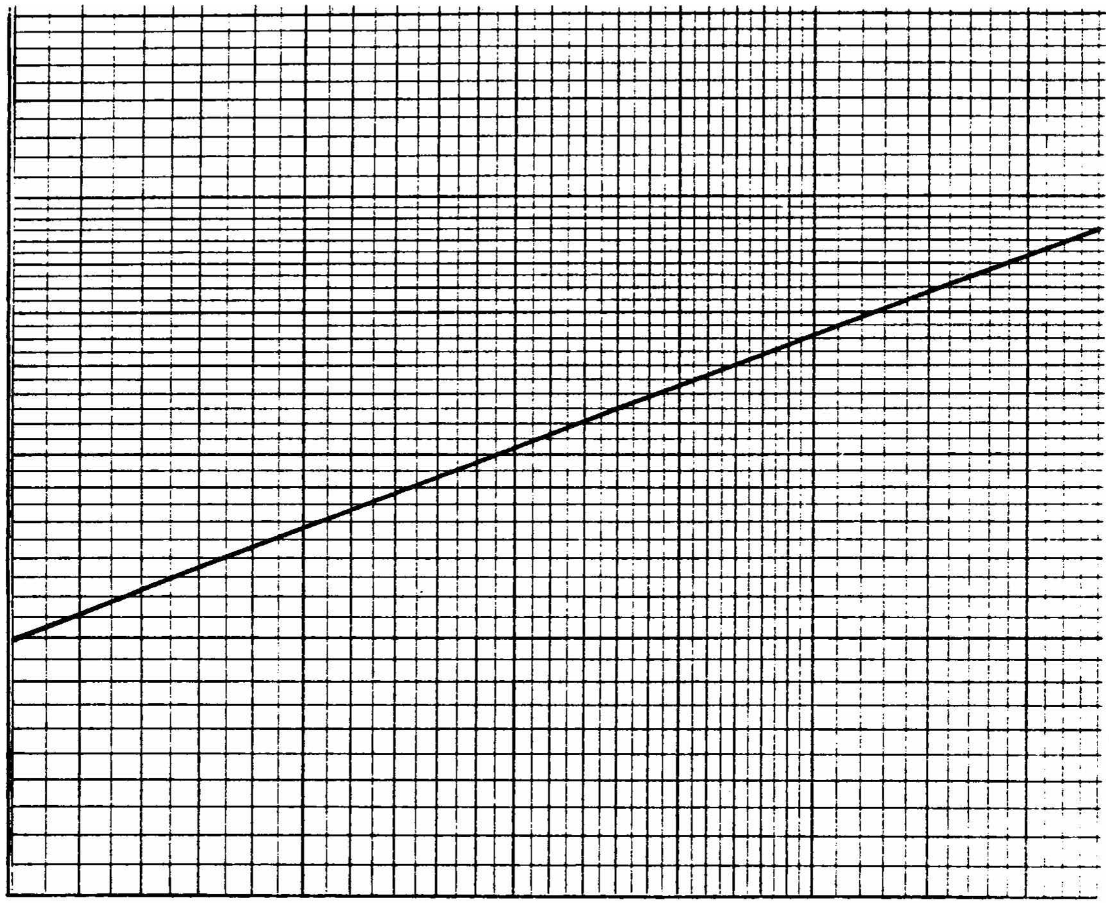
POSITIVELY SLOPED CURVILINEAR LEARNING CURVE



Learning Curve Formula ($Y = aX^{-b}$) on normal graph paper.

FIGURE 2.5

POSITIVELY SLOPED LINEAR LEARNING CURVE



Learning Curve Formula ($Y = aX^{-b}$) on logarithmic paper.

that either application of LC theory (i.e. negatively or positively sloped LC) may be used as a standard.

STANDARDS BASED ON LEARNING CURVES

A number of studies, other than in the aircraft industry, have been completed using LC theory as the principal tool for setting standards for production workers. Knowles and Bell developed standard learning curves to measure employee performance for new employees in an electric tool company. The standards were developed from an analysis of successful employee performance and used to evaluate new employees during initial training periods. The benefits to the electric tool company were a reduction of turnover and related costs, higher employee morale, and a training period of twenty-two days as compared to earlier training requirements of sixty to one hundred eighty days.[43]

Another study by Broadston examined the concept of using LC theory to establish variable time allowances for workers based upon improvement, rather than fixed time standards for the production of mechanical pencil mechanism assemblies. The variable time standard was developed to allow "high achievers" an opportunity to earn bonus pay in a wage incentive system. Broadston believed the incentives, based on LC theory, were possible solutions to five basic problems that he noted:

(1) Voluntary restriction of output.

(2) Desire not to antagonize fellow workers by competing with them.

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[43]Alvis R. Knowles and Lawrence F. Bell. "Learning Curves Will Tell You Who's Worth Training and Who Isn't," Factory Management and Maintenance, Vol. 108, No. 6, June, 1950, pp. 114-15.

(3) Loss of take home pay due to a job reassignment.

(4) Encouragement of mediocrity.

(5) Indirectly penalizing outstanding performance.[44]

Towill and Bevis used LC theory to establish a managerial control system with respect to a number of worker operations for watch assembly tasks. LC models for individual operators (also groups of operators) were compared with actual output of completed tasks during training to measure productivity, monitor training, revise time standards, and develop incentives. The managerial control system resulted in observed increases in productivity during the observation period.[45]

Concerning productivity measurement, Lloyd stated:

> There is no doubt that the slope of the [learning curve] is being used as some sort of index of industrial efficiency.[46]

Lloyd further stated that LC theory may serve four purposes:

(1) To compare the performance of the same manufacturing operation at different points in time,

(2) To compare manufacturing operations in two separate plants which ostensibly are producing the same, or very similar products,

(3) To use as an absolute measure of efficiency, and

(4) To disaggregate production costs into separate components.[47]

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[44]James A. Broadston. "Profit by Using Variable Time Allowances," Management Accounting, October 1968, pp. 26-28.

[45]E. R. Towill and F. W. Bevis. "Managerial Control Systems Based On Learning Curve Models," International Journal Production Research, Vol. 11, No. 3, 1972, pp. 219-38.

[46]R. A. Lloyd. "'Experience Curve Analysis," Applied Economics, Vol. 11, No. 2, June 1979, p. 222.

[47]Ibid., pp. 222-23.

Clearly, using LC theory to set standards (Lloyd's first and second purpose) may be useful in establishing and measuring worker performance. The third purpose might lead to normative statements concerning the slope of the curve. A description of such applications was not found in the literature. The final purpose for using LC theory will impact the budgeting and planning phase of operations.[48] However, better use of LC theory for establishing and measuring worker performance or for the firm's budgeting and planning phase may be made if other forces (other than those represented by the LC) are determined to affect worker productivity. These forces should be identified and evaluated if possible.

LEARNING CURVE CAUSAL FACTORS

The distinction between learning in the literal sense and learning based on a combination of other factors was first postulated by Frank Andress in 1954. Andress claimed that learning in the literal sense and learning based upon the combination of other factors do not always complement each other, but sometimes operate in an opposing manner. The LC, according to Andress, is:

> An empirical method for charting all the various forces which work on labor hour input than it is a truly scientific device.[49]

He hypothesized that learning in the literal sense was the predominant influence of the LC because of its consistent behavior in the production

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[48]Ibid.

[49]Frank J. Andress. "The Learning Curve As A Production Tool," Harvard Business Review, January-February 1954, p. 89.

process, whereas other factors tended to possess erratic behavior patterns.[50]

Furthermore, Baird asserted that the causal forces behind LC theory implied that individual learning was the key factor in the rate of reduction associated with labor output and increased production output. Baird stated that the increase in production output "is due, in general, to the entire organization and, in particular, to managerial decisions." Many factors may be responsible for increased production output. Some of these may be technological advancements, plant layout, scheduling and reductions in idle time, and scrap. Baird regarded the essential elements as a "combination of causes, operator learning [being] only one factor."[51]

An extreme example of the concept that other factors (in this case technological factors) affect performance was discovered by Joskow and Rozanski. The authors examined whether production based on LC theory shifted over time for nuclear plants. It was found that boiling water reactor nuclear plants, which had begun on or after April 1, 1975, performed significantly better than boiling water reactor nuclear plants established earlier. The results indicated that the LC continually shifted upward for nuclear plants utilizing boiling water reactors.[52] No mention of the factors attributable to this shift was given other

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[50]Ibid.

[51]Op. cit., Baird. p. 75.

[52]Paul L. Joskow and George A. Rozanski. "The Effects of Learning By Doing On Nuclear Plant Operating Reliability," The Review of Economics and Statistics, Vol. 61, No. 2, May 1979, pp. 161-66.

than the implied technological improvements responsible for more efficient plant operations.

In a summary report dealing with performance and productivity for employees within the federal government, a joint project team listed several causes of productivity improvement and decline. They divided the causes into three groups:

(1) Human factors.

(2) Management factors.

(3) Workload Factors.[53]

Human factors associated with productivity improvement were (a) increased efficiency of personnel, (b) acquisition of skilled personnel, and (c) job restructuring. Job restructuring was typically accomplished through job redesign. Increasing productivity using management factors was identified as (a) improvement through capital investment (typically computerization), (b) automation procedures simplification (paper work simplification), (c) organizational improvements (more efficient work assignment) and (d) work attitudes. An increase in productivity for workload factors was typically due to (a) workload increases (higher productivity), (b) workload stability (better planning and staffing), (c) workload predictability, (d) reduction in complexity (usually procedures simplification), and finally (e) reduction in quality (resulting from higher productivity due to downgraded quality requirements).[54]

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[53]Bernard Rosen, Thomas D. Morris, and Dwight Ink. Phase III-Summary Report: Measuring & Enhancing Productivity In The Federal Government, (United States Government: Office of Management and Budget and others, June 1973), pp. 26-31.

[54]Ibid.

On the other hand, human factors which caused the declining productivity were (a) high turnover, (b) loss of skilled employees, (c) drop in organization efficiency, and (d) an increase in nonproductive time for training. These factors were indicated as probably "associated with other causes for which management is responsible." Management factors affecting productivity decline were primarily due to (a) loss of productive effort while phasing in new facilities, (b) loss of productive effort during transition brought about by reorganization, (c) lags in adjusting personnel strength upward or downward during periods of workload change, (d) outmoded facilities, and (e) uneconomic contracting. The principal workload factors attributed to productivity decline include (a) more complex automatic data processing requirements (increased review procedures for paperwork), (b) rapid drop in military forces (impact was primarily in support and logistics areas), (c) increase in output complexity (i.e. health care upgraded requirements and quality increase), and (d) change in character of work (i.e. rebuilding stocks in military depot complexes as opposed to processing and shipping requisitions).[55]

In summary, the causal factors of LC theory may be more than individual learning ability. Production factors, which may have an impact upon standard setting and budgeting, may be listed as:

(1) Labor input.
    (a) proficiency of worker - combination of worker fatigue during early training stages and discovery of time-saving techniques as job tenure increases.[56]

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[55]Ibid.

[56]Op. cit., Hirsch. p. 146.

(b) fewer production interruptions.
(c) use of less skilled labor.[57]

(2) Material input.
(a) waste reduction.
(b) increased efficiency through more economic purchasing.
(c) reduction of material cost for larger orders.[58]
(d) shortages.[59]
(e) expeditious and reliable material receipts.[60]

(3) Overhead. (same characteristics as the base used for determining overhead).

(4) Management.
(a) production and labor scheduling in the flow of materials and labor into and within the plant.
(b) backward integration to steady and expedite the flow of materials, improvements in the coordination between engineering and manufacturing, and better production control technique can be instituted.[61]
(c) reduction of idle time.[62]

(5) Engineering department.
(a) more economical methods of reducing production time through redesign of assembly, plant, and equipment.[63]
(b) redesign of special tools.
(c) technological advancements.
(d) reduction of scrap through efficient utilization of materials.[64]

(6) Quality control improvement through coordinated actions between management, engineering, and labor.

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[57]Op. cit., Wright. p. 124-25.

[58]Ibid.

[59]E. Cochran. "New Concepts of the Learning Curve," Journal of Industrial Engineering, Vol. 11, No. 4, July-August 1960, p. 320.

[60]Op. cit., Hirsh. p. 147.

[61]Ibid., p. 146.

[62]Op. cit., Alchian. p. 75.

[63]Op. cit., Hirsch. p. 146.

[64]Op. cit., Alchian. p. 75.

All of the production factors listed contribute to some degree, to the production and performance levels for each worker. Generally, these factors have also been attributed to be causal factors with regard to overall productivity of a firm. Other factors such as environmental factors outside of the production environment may also impact worker performance. Although not directly under control of management, environmental factors may offer insight, with respect to budgeting and standard setting, in the evaluation process.

ENVIRONMENTAL FACTORS

Some of the environmental factors that may influence worker performance include hygienic, personality, economic, and demographic factors.

HYGIENIC FACTORS.

Waters and Waters found that factors within an industrial setting, such as Herzberg's hygiene factors (supervision, salary, interpersonal relations, working conditions), appear to have little positive effect toward motivation and higher performance levels of employees.[65] In fact, these factors, if significant, were not readily identifiable and affected job dissatisfaction more than job satisfaction.[66] Schwab, et al. were unsuccessful in an attempt to duplicate Herzberg's

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[65]L. K. Waters and Carrie Wherry Waters. "An Empirical Test of Five Versions of the Two-Factor Theory of Job Satisfaction," Organizational Behavior and Human Performance, No. 1, February 1972, pp. 18-24.

[66]Nathan A. King. "Clarification and Evaluation of the Two-Factor Theory of Job Satisfaction," Psychological Bulletin, Vol. 74, No. 1, July 1970, p. 18.

Methodology.[67] Thus, identification and replication of the effects of hygienic factors may not be significantly or easily duplicated. However, Herzberg does cite the results of an impressive number and diversity of replications of his original study which supported his position that motivators, such as achievement, recognition, work itself, responsibility, and advancement, rather than hygienic factors, are factors that affect worker performance. This notion presupposes that employees have received an adequate amount of hygienic reinforcement to allow the motivating factors to influence worker productivity. This idea is analagous to Maslow's upper level hierarchy of self-actualization. Herzberg's theory did much to clarify differences between satisfaction and motivation, the former being necessary in order to have positively motivated employees and the latter being necessary to achieve higher performance levels from employees.[68] An attempt to measure variation in employee satisfaction (hygienic factors) is beyond the scope of this study.

PERSONALITY FACTORS.

Motivation factors, a subset of personality, may influence worker performance along with other personality factors. Much of the research about predicting job success is related to measurement of motivation. The results from comparing job success and personality testing have met

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[67]Donald P. Schwab, H. William DeVitt, and Larry L. Cummings. "A Test of the Adequacy of the Two-Factor Theory As A Predictor of Self-Report Performance Effects," Personnel Psychology, Vol. 24, Summer 1971, pp. 293-303.

[68]Frederick Herzberg. Work and the Nature of Man. Cleveland: The World Publishing Company, 1966, pp. 71-129.

with little success. Specifically, personality factors have not proven to be good predictors of job success. However, some evidence based on raw score distributions from a Guilford-Zimmerman Temperament Survey has revealed "useful differences" when comparing job success, but not at significant levels.[69]

A study by Ghiselli and Barthos found that personality

> inventories have proved to be effective for some occupations in which factors would appear to be of minimal importance (e.g., clerks, trades, and crafts) and ineffective

for supervisors and foremen.[70] Perhaps production line worker performance may be predicted from personality testing, but Ghiselli and Barthos did warn that personality tests were not easily substituted from one work environment to another and that implementation of personality testing within a specific environment must be made with caution.[71]

ECONOMIC FACTORS.

Some of the economic factors which affect worker performance may be local unemployment levels, levels of economic activity, or perceived or actual pending factory orders for a firm. A search for supportive studies relating economic factors with employee performance yielded very little significant evidence. However, the Porter and Lawler Motivation

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[69]R. Hedberg and B. Baxter. "A Second Look at Personality Test Validation," Personnel Psychology, Vol. 10, 1957, pp. 157-60.

[70]E. E. Ghiselli and R. P. Barthos, "The Validity of Personality Inventories in the Selection of Employees," Journal of Applied Psychology, Vol. 37, No. 1, February 1953, pp. 18-20.

[71]Ibid.

Model has implications which may be useful in identifying economic factors and worker performance relationships.[72]

Porter and Lawler pointed out that effort does not directly lead to performance but that perceived reward determines satisfaction and subsequent performance.[73] From this point of view, perceived reward may vary with changing economic conditions. Rewards may be perceived higher during periods of high unemployment and lower for periods during low unemployment levels. The analogy will be the same for inflationary versus recessionary periods, perceived or actual pending factory orders, and perhaps other economic factors.

DEMOGRAPHIC FACTORS

Demography is, "the statistical study of human populations, especially with reference to site and density, distribution and vital statistics."[74] Demographic factors may be described as "an examination of different statistical measures of characteristics of a group of people."[75] In a survey of twenty-one studies, Schuh reported at least one significant factor relating

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[72]Lyman W. Porter and Edward E. Lawler, III. Managerial Attitudes and Performance. (Homewood, Illinois: Richard D. Irwin, Inc.), 1968, pp. 159-84.

[73]Ibid.

[74]Webster's New Collegiate Dictionary. Springfield, Massachusetts: G. & C. Merriam Company, 1980, p. 299.

[75]Gerald Zaltman and Melanie Wallendorf. Consumer Behavior-Basic Findings and Management Implications. (New York: John Wiley & Sons, 1979), pp. 48-49.

demographic variables and employee tenure in all but two studies.[76]

Kirchner and Dunnette found a significant relationship between personal (demographic) traits and long tenured female employees and replicated the test with similar results a year later.[77] In another study by Wernimont, positive predictive results were found to exist for office personnel but the predictive ability of the test deteriorated over time. The results of this study suggested that the test be reweighted after three to five years in order to retain its predictive characteristics.[78]

In a study of turnover for an optical manufacturer, Tiffin, Parker, and Haberstat found a positive relationship in performance for employees who were older, heavier, and/or had more dependents. They found a negative relationship for performance of employees who had more education and who were tall.[79]

Several studies have examined the relationship between demographic factors and job tenure. However, there appears to be little published work concerning the relationship of demographic factors and employee performance.

Demographic factors may be selected in two ways. First, factors may be identified from previous research or from underlying factors from the

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[76]A. J. Schuh. "The Predictability of Employee Tenure: A Review of the Literature, "Personnel Psychology, Vol. 20, 1967, pp. 140-1.

[77]W. K. Kirchner and M. D. Dunnette. "Applying the Weighted Application Blank Technique to a Variety of Office Jobs," Journal of Applied Psychology, Vol. 41, No. 4, 1957, pp. 206-7.

[78]P. F. Wernimont. "Re-Evaluation of Weighted Application Blank for Office Personnel," Journal of Applied Psychology, Vol. 46, No. 6, December 1962, pp. 417-19.

[79]J. Tiffin, B. T. Parker and R. W. Habersat. "The Analysis of Personnel Data in Relation to Turnover on a Factory Job," Journal of Applied Psychology, Vol. 31, No. 5, October 1947, p. 616.

theoretical model from previous research. Using factors in a model which have previous statistical significance may prove easier to justify. The second alternative involves extending the researcher's knowledge and intuitive selection of factors for a model. Selection of factors, without prior statistical support, is made on an a priori basis, but should be justified on experience criteria.

Famularo reviewed sample personnel applications[80] in order to determine common demographic factors which may influence performance of factory employees. Factors identified are listed in Table 2.2, pages 40 and 41.

Many of the factors included in Table 2.2 have been statistically identified as being related to employee tenure.[81] It seems reasonable to postulate that a relationship between these factors and employee performance exists. Additional demographic factors, which are not supported in literature, have been included in Table 2.2. These factors may enhance the ability of a study to develop a measure of description and potential predictive power concerning production employee tenure or performance. Production factors, and possibly environmental factors, influence worker performance.

In the next chapter, a methodology for determining if worker performance changes over time will be presented. Selected environmental factors, which may influence worker performance, will also be discussed.

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[80]Joseph Famularo. Handbook of Modern Personnel Administrators. (New York: McGraw-Hill Book Company, 1972,) Ch. 77; pp. 4-16. Interviews were also conducted with employees from The Classified Section-The Personnel Agency and with Snelling and Snelling Personnel Consultants for supportive information.

[81]Op. cit., Schuh, pp. 133-52.

TABLE 2.2

DEMOGRAPHIC FACTORS AND POSSIBLE EFFECTS ON EMPLOYEE PERFORMANCE

Factor	Rationale of the Factor
Age when starting work	Rate of learning for younger workers is higher than for older workers.*
Educational level attained	Higher education levels and performance for highly repetitive tasks have an inverse relationship.*
Number of years in local area	Longevity in the area has a stabilizing effect on workers' self esteem.
Commuting distance to job	Commuting distance affects job performance as more or less susceptibility to change in economic factors relating to transportation, travel time, fatigue etc.
Marital status	Married workers perform at higher efficiency levels.*
Number of dependents	Workers have more incentive as size of family becomes larger.*
Relatives employed at this work place	The employment of relatives in the same workplace has a positive effect on job performance.*

TABLE 2.2 continued on next page

TABLE 2.2 (Continued)

DEMOGRAPHIC FACTORS AND POSSIBLE EFFECTS
ON EMPLOYEE PERFORMANCE

Factor	Explanation of the Factor
Own home	Higher self-esteem of owning one's home has a positive effect on job performance.
Residence with relatives	Living with relatives has an adverse effect on performance.
Length of preceding job	A positive relation between length of previous employment and potential performance for the current job exists.
Immediate preceding job classification	Related experience has a positive relationship with current performance.
Reason for leaving last job	Job dissatisfaction will affect performance.
Weight vs. height ratio	Extreme ratios (small or large) are related to poor performance.*
Flexible attitude for working different shifts	An expressed willingness to work all shifts is positively related to performance.

*Significant statistical results linking these factors and job tenure have been verified from other studies. [See Schuh (1967), Kirchner and Dunnett (1957), Wernimont (1962), and Tiffin, Parker and Habersat (1947)].

CHAPTER III

RESEARCH METHODOLOGY

INTRODUCTION

Learning Curve (LC) analysis has been used to establish performance standards in industries such as aircraft[82], computers[83], producing oil for refineries[84], nuclear plant operations[85], machine labor[86], clerical operations[87], and others.[88] Performance data, based on LC theory, will be compared with standard performance to determine if differences exist over time. Furthermore, environmental factors will be examined to determine the effects, if any, that they have on worker performance.

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[82]K. Hartley. "The Learning Curve and Its Applications to the Aircraft Industry," Journal of Industrial Economics, Vol. 13, No. 2, March 1965, pp. 122.

[83]W. J. Abernathy and K. Wayne. "Limits of the Learning Curve," Harvard Business Review, September-October 1974, p. 116.

[84]Winfred B. Hirschman. "Profit From the Learning Curve," Harvard Business Review, January-February 1964, p. 131.

[85]Paul L. Joskow and George A. Rozanski. "The Effects of Learning by Doing on Nuclear Plant Operating Reliability," The Review of Economics and Statistics, Vol. 61, No. 2, May 1979, p. 161.

[86]Werner Z. Hirsch. "Manufacturing Progress Functions," Review of Economics and Statistics, Vol. 34, May 1952, p. 154.

[87]M. D. Kilbridge. "Predetermined Learning Curves for Clerical Operations," Journal of Industrial Engineering, Vol. 10, No. 3, May-June 1959, p. 203.

[88]See, for example, E. Cochran. "New Concepts of the Learning Curve," Journal of Industrial Engineering, Vol. 11, No. 4, July-August 1960, p. 326.

As stated in Chapter I, the differences between average production worker performance and standard performance will be identified and tested. Based on the LC theory discussed in Chapter II, the hypothesis (H1) is:

$H1_o$) Learning curve standard performance equals average employee performance over time.

$H1_a$) Learning curve standard performance does not equal average employee performance over time.

Sub-hypotheses may be developed from H1 to test for specific differences between groups. These hypotheses are stated as follows:

$H1_{o1}$) Average employee performance for one group equals average employee performance for another group.

$H1_{a1}$) Average employee performance for one group does not equal average employee performance for another group.

$H1_{o2}$) Conditional hypothesis that average employee performance for two groups (from $H1_{01}$) equals the learning curve standard.

$H1_{a2}$) Average employee performance for two groups does not equal the learning curve standard.

$H1_{o3}$) Average employee performance (combined groups from $H1_{01}$) equals the learning curve standard.

$H1_{a3}$) Average employee performance does not equal the learning curve standard.

The research methodology used to test the first hypothesis (H1) will be discussed in this chapter.

Additionally, a second hypothesis will be tested. Hypothesis H2 will be tested in an attempt to identify factors which affect differences between standard performance and average production worker performance. H2 is:

$H2_o$) Production factors, as compared with environmental factors, are the only identifiable factors which affect differences in average employee performance.

$H2_a$) Production factors, as compared with environmental factors, are not the only identifiable factors which affect differences in average employee performance.

In developing a test method for the second hypothesis (H2), a method for grouping employee performance will be defined in order to categorize employees into groups.

Further, environmental factors, other than production factors, which may affect employee performance will be identified. These factors will be included in the test of H2. Finally, a description of the experimental group and a discussion of measurement errors will follow.

RESEARCH DESIGN OF H1

A comparison between average employee performance and standard performance will provide information concerning the nature of differences, if any, which exist. A linear model approach, developed by Chow, will be used in testing H1.[89] Procedures used for this test, as well as subsequent testing, will primarily be taken from Neter and Wasserman[90] and implemented using the Statistical Analysis System (SAS) software package.[91]

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[89]Gregory C. Chow. "Tests of Equality Between Sets of Coefficients in Two Linear Regressions," Econometrica, Vol. 28, No. 3, July 1960, pp. 591-92.

[90]John Neter and William Wasserman. Applied Linear Statistical Models. (Homewood, Illinois: Richard D. Irwin, Inc., 1974), pp. 160-5.

[91]Anthony J. Barr et al. SAS User's Guide--1979 Edition. (Raleigh, N.C.: SAS Institute, Inc., 1979), pp. 237-63.

TESTING TWO REGRESSION LINES

GENERAL LINEAR TEST APPROACH. A general test of a linear statistical model will be used to test H1 since it is completely general and may be used to test two linear, curvilinear, or multiple regression functions. The general linear test also may be extended to test the equality of more than two linear, curvilinear, or multiple regression functions.[92]

A full general linear model (F) for testing whether two regression lines are identical can be determined by fitting two separate regression lines for each of the data groups using the general equation:[93]

$$Y = \alpha + \beta X + \varepsilon \tag{3.1}$$

where:

Y = production performance

X = period of time of first performing work

α = parameter value (percentage value of the first unit)

β = parameter value representing the average unit reduction between cumulative production and period of time of training

ε = error terms

The full general linear model is computed using the method of least squares to obtain the error sum of squares [SSE (F)]. The error sum of squares for the full model [SSE (F)] "indicates the variation of the Y's around the regression lines."[94] Next, a general linear model

[92] Op. cit., Neter and Wasserman.

[93] Ibid.

[94] Ibid.

is computed to obtain the error sum of squares for the reduced model [SSE (R)]. A reduced model "implies fitting one regression line to the combined data for the groups."[95]

Testing H1, the equality of two regression lines, can be made thus:

(1) fit the full model and obtain the error sum of squares SSE(F) = $SSE_1 + SSE_2$, (error sum of squares for group 1 and group 2),

(2) obtain the error sum of squares for the reduced model SSE(R) (error sum of squares for both groups), and

(3) calculate the F*. F* is calculated as:

$$F^* = \frac{SSE(R) - SSE(F)}{2} \div \frac{SSE(F)}{n_1 + n_2 - 4} \qquad (3.2)$$

where $SSE(R)$ = error sum of squares for the reduced model

$SSE(F) = SSE_1 + SSE_2$

n_1, n_2 = number of observations for groups.

Determining whether two regression lines are identical will be tested by calculating an F*-statistic. The decision rule will be:[96]

If $F^* \leq F(1-\alpha\ ;\ n_1 + n_2 - 4)$ do not reject $H1_0$;

If $F^* > F(1-\alpha\ ;\ n_1 + n_2 - 4)$ reject $H1_0$ and conclude that standard performance does not equal employee performance over time.

The general linear test discussed above will be used to determine if average employee performance, based on LC theory, is different for groups of employees. $H1_{01}$ will be tested to determine if two groups are different. If the groups in $H1_{01}$ are significantly different, $H1_{02}$ will be tested to determine if either, or both, of the groups are significantly different from a learning curve standard.

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[95] Ibid.

[96] Ibid.

If the groups are not determined to be significantly different (unable to reject $H1_{01}$) then data from the groups may be pooled.[97] The pooled data will be used to test $H1_{03}$ to determine if the learning curve standard equals the pooled or combined average employee performance.

<u>ASSUMPTIONS REGARDING LINEAR REGRESSION ANALYSIS</u>. When a regression model, such as equation 3.1 is used to test the equality of two linear, curvilinear, or multiple regression functions, it is appropriate to examine the aptness of the model. Aptness of the model may be determined using residual analysis by examining the assumptions regarding linear regression analysis. Violation of the assumptions (constant error variances, independence of residuals, and normality of error terms) may bias the results of linear regression and lead to incorrect application and interpretational inferences.[98] The tests that will be used in this study to identify possible violations of the assumptions noted above are discussed in Appendix 1.

<u>PROCEDURAL METHODOLOGY FOR TESTING H1</u>. Testing H1 will be accomplished using a general test of a linear statistical model. The procedures for performing the general test in this study are stated as follows:

1) Test data regarding assumptions of linear regression.
   a) Assumption of constant error variances.
   b) Assumption of independence of residuals.

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[97]Ibid.

[98]Ibid. pp. 97-99.

c) Assumption of normality of error terms or residuals.

2) Transform data to correct for violations in (1).

3) Perform F-test between regression lines to test H1.

EVALUATING THE RESULTS OF TESTING H1. If H1 is not rejected, then standard performance equals average employee performance over time. If H1 is not rejected, the implications of the hypothesized differences between standards and average employee performance over time will impact the standard setting and reviewing process.

The test of H2 will emphasize the relationship between average performance of employees and non-production factors which influence performance over time. However, the results from testing H1 will not lessen the implications concerning performance and environmental factors to be tested in the second part of this study. In fact, if the null hypothesis cannot be rejected for H1, an indication of stable performance levels compared to established standards will indicate a need to identify factors, other than production factors, which may affect performance of factory workers.

If H1 is rejected, that is, performance does not prove to be equal to the established standard, a new standard using average actual performance will be constructed which is a representative standard of current employee productivity. Thus, it will be assumed that worker performance continues on the same function of a learning curve (Equation 1.1):

$$Y = aX^b \tag{3.3}$$

where: Y = production efficiency

X = production period from time of first performing work, but with different parameters a and b.

In order to derive new a and b estimates, a linearized logarithmic function of average employee performance will be calculated by:

$$\log Y' = \log a' + b \log X' \tag{3.4}$$

The production periods (X), along with average employee performance values (Y), will be transformed into log (base 10) values and then log Y' will be regressed on log X', resulting in the regression equation (3.1):

$$Y = a + b X$$

$$Y = \log Y'$$

$$X = \log X'$$

$$a = \log a'$$

$$b = b$$

New values for a and b will be calculated. By holding the upper limit of X constant at some specified time period, a new learning curve will be derived from average employee performance data using Equation 3.3. A new standard, representing observed average employee performance data, will be calculated.

If H1 is rejected, a significant impact concerning standard setting and the reviewing process may exist, perhaps indicating a need for timely review and revision of established standards. Subsequently, a test of H2 will emphasize (1) differences between employees which may reflect changing performance levels and (2) the relationship between average performance of employees and non-production factors which influence performance over time.

RESEARCH DESIGN OF H2

In testing H2, several environmental factors, other than production factors, which affect worker performance must first be identified. This study will examine environmental factors which may influence the behavior or the performance of individual workers. The discussion which follows identifies and includes selected measurable factors in the research design. Second, performance of employees will be grouped or divided according to average performance over time. Finally, the specific methodology for this part of the study will be presented to develop a classification model concerning production employees.

The purpose for testing H2, as previously stated, is to identify environmental factors which affect average employee performance. For review, the second null hypothesis is restated:

$H2_0$) Production factors, as compared with environmental factors, are the only identifiable factors which affect differences in average employee performance over time.

$H2_a$) Production factors, as compared with environmental factors, are not the only identifiable factors which affect differences in average employee performance.

There are two steps which must be taken before testing H2. First, environmental factors will be selected as independent variables. Environmental factors selected will be those factors which may be used by management in evaluating and selecting factory workers and/or worker applicants. Second, factory worker performance is typically based on some measure of actual performance compared with management's desired or standard level of performance. Since this study is concerned with groupings or divisions related to employee performance, a method will be presented to divide employees into groups. These groupings will form the dependent variables for the study.

After the independent and dependent variables are selected, all values for each employee will be collected. H2 will be tested using a multiple discriminant analysis procedure. Multiple discriminant analysis is a statistical technique designed to identify differences between two or more groupings (dependent variable) with respect to several variables (independent variables or discriminatory variables). The equation for multiple discriminant analysis is based on a linear combination as follows:[99]

$$Z = W_1 X_1 + W_2 X_2 + W_3 X_3 + \dots + W_n X_n \tag{3.5}$$

where : Z = the discriminant score

W = discriminant weight

X = the independent variables.

Hair, et al. stated that discriminant analysis is particularly well suited for "understanding group differences or in correctly classifying statistical units into groups or classes." The authors further asserted that discriminant analysis is useful as a profile analysis or an analytical predictive technique.[100] As such, the objectives for using discriminant analysis include:

1) Testing whether significant differences exist between the mean predictor-variable profiles of groups.

2) Determining which variables account most for intergroup differences in mean profiles.[101]

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[99]Hair, Joseph F., Jr., et al. Multivariate Analysis--Data Analysis with Readings (Tulsa, Oklahoma: Petroleum Publishing Company, 1979), p. 85.

[100]Ibid. p. 90.

[101]Paul F. Green and Donald S. Tull. Research For Marketing Decisions. (Englewood Cliffs, New Jersey: Prentice-Hall, Inc., 1978), p. 383.

The following sections will present an examination and selection of environmental factors (independent variables), performance groupings (selection and division of the dependent variable), and a general method for testing the equality of group means using multiple discriminant analysis.

SELECTION OF INDEPENDENT VARIABLES

Selecting independent variables from the environmental factors (hygienic, personality, economic, and demographic), which were discussed in Chapter II, will be made on the basis of accessibility. Information that is easily obtained and readily defined, such as information from personnel applications, will provide a basis for selecting independent variables for use in this study. Other inputs, such as personality profiles of employees, may be more difficult to obtain since specialists are usually required to gather this type of data.

The study will be more meaningful if data from all four areas can be obtained. Pragmatic limitations, as stated above, within factory environments may pose some difficulty for gathering such data. For example, factory workers may be unwilling to participate in personality testing or in answering personal questions. Furthermore, management may be reluctant to allow employees to be tested or observed because of possible interference with normal routines.

R. A. Fisher proposed a linear discriminant function to classify objects into mutually exclusive groups. He pointed out an analogy beween discriminant analysis and regression analysis.[102] Lachenbruch found that estimators of the regression coefficients are proportional to the estimators of the discriminant coefficients.[103] Thus, the analogy for using dichotomous variables in regression analysis is very similar to that of discriminant analysis and, as such, dichotomous variables will be selected so as not to violate regression or discriminant analysis procedures.

Independent variables (X_1, X_2, ..., X_n), in multivariate analysis, utilize the relationship between two or more quantitative variables so that a response variable (Y) may be predicted. This study will utilize two types of data. They are interval and nominal scaled data. Interval data allow "meaningful statements about the differences separating objects."[104] However, as in an example using the measurement of fahrenheit or centigrade temperature, one cannot directly compare one measurement with the other.[105] On the other hand, nominal data only allow labeling of observations. Nothing may be concluded from an examination of ordinal scaled data other than existing differences between one observation and another. For example, a person may be employed or unemployed. It is apparent that a difference exists between the two classifications. It is not apparent how different one classification is

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[102] R. A. Fisher. "The Use of Multiple Measurement in Taxonomic Problems," Annals of Eugenics, Vol. 7, 1936, pp. 179-88.

[103] Peter A. Lachenbruch. Discriminant Analysis, (New York: Hafner, 1975), pp. 1-20.

[104] Op. cit., Green and Tull, p. 167.

[105] Ibid.

from the other.[106] Interval scaled data is ideally suited for use in multivariate analysis, whereas nominal scaled data must be transformed before it can be used in multivariate analysis.

A method typically used to transform nominal scaled data is through the use of indicator or "dummy" variables. If the nominal scaled variable, sex, is a dichotomy, then a zero, one (0, 1) scale may be used to describe the dichotomy (i.e., 0 = male, and 1 = female may be used). If the nominal scaled variable is not a dichotomy, but has more than two possible responses, then 0, 1 scales for each class minus one (k-1), will be used. If all classes (k) of a variable are coded 0, 1, then the sum of the columns for that class in the matrix will be equal and the result will be a condition of linear dependency.[107] Specification and coding of actual variables for this study will be selected from the possible factors affecting employee performance discussed in Chapter II. The description and listing of the actual indicator variables to be used will be presented in a subsequent section of this chapter.

Next, an analysis of the "nature and significance of the relations between independent variables and the dependent variable" will be made with respect to multicollinearity and multiple correlation. Multicollinearity exists when variables are correlated among themselves. Cochran concluded that any negative correlation and extremely high positive correlation among variables improved the discriminant classification

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[106] Ibid. pp. 165-6.

[107] Op. cit., Neter and Wasserman, pp. 297-99.

procedure.[108] Eisenbeis stated that multicollinearity is:

> An irrelevant concern in discriminant analysis except where the correlations are such it is no no longer possible to invert the dispersion matrices.[109]

Pinches stated that correlation among variables appears to be a significant problem; but, he also noted that the literature fails to provide support for this position. Pinches also noted that:

> A large number of [positively but correlated] variables .... may cause the probability of misclassification to increase.[110]

The effect of multicollinearity may affect the classification results of the discriminant model and will be evaluated in the context that the effects of multicollinearity will be reduced unless negative correlation exists.

Multiple correlation is a statistical technique used to make conditional inferences on one variable against all other variables in a model. A test for multiple correlation will allow the researcher "to make conditional inferences on one variable when the other variables have given values."[111] These methods will now be discussed.

TEST FOR MULTICOLLINEARITY. After potential predictor variables are selected, a correlation matrix using the Pearson product-moment method

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[108]W. G. Cochran. "On the Performance of the Linear Discriminant Function," Technometrics, Vol. 6, May 1964, pp. 179-90.

[109]Robert A. Eisenbeis. "Pitfalls In the Application of Discriminant Analysis In Business, Finance, and Economics," The Journal of Finance, Vol. 32, No. 3 June 1977, p. 883.

[110]George E. Pinches. "Classification Results and Multiple Discriminant Analysis," School of Business, Uuiversity of Kansas Working Paper Series, No. 116, September 1978, p. 19.

[111]Ibid., p. 249.

will be computed in order to discover possible effects of multicollinearity among the variables.[112] A correlation matrix will allow judgements concerning the nature of the relations between the variables. R. A. Fisher noted the analogy between discriminant anlaysis and regression analysis[113] and, as such, the discussion of possible negative effects of multicollinearity will be discussed in the context of regression analysis. Neter and Wasserman state an important conclusion concerning the negative effects of multicollinearity:

> When independent variables are correlated, the .... coefficient of any independent variable depends on which other independent variables are included in the model. Thus, a .... coefficient does not reflect any inherent effect of the particular independent variable on the dependent variable but only a marginal or partial effect, given whatever other correlated independent variables included in the model.[114]

Neter and Wasserman further commented that multicollinearity causes two key problems in model building. First, the addition or deletion of an independent variable will change the coefficients and second, estimated coefficients for individual variables may not be statistically significant but display a statistical relation between the dependent variable and a set of independent variables. Furthermore, the authors state:

> Some or all independent variables correlated among themselves does not, in general, inhibit our ability to obtain a good fit nor does it tend to affect inferences about mean responses or predictions of new observations.[115]

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[112]Op. cit., Barr and others, pp. 173-75.

[113]Op. cit. Fisher.

[114]Op. cit., Neter and Wasserman, p. 252.

[115]Ibid., pp. 339-47.

If high levels of multicollinearity exist between variables the classification results of the discriminant model may be reduced. Thus, some procedure should be selected to reduce the effects of high multicolinearity among variables.

One method for reducing multicollinearity between variables would be to delete one or more of the independent variables exhibiting high levels of correlation. However, a shortcoming exists when a variable(s) is deleted from the model. The effects of the deleted variable(s) is unknown and the coefficients of the variables left in the model are affected by the variable(s) that is no longer in the model.[116] Thus, misspecification of the model may result.

A second method for reducing the effects of multicollinearity in a model is to use factor analysis (usually the principal components method). One of the purposes of factor analysis is for data reduction and summarization. Interest is centered on relationships of entire sets of variables in order to derive "a smaller set of linear composites that preserve most of the information in the original set." The major purpose of factor analysis is the "search and test of constructs assumed to underlie manifest variables." Inferred measures may be identified from highly correlated variables.[117]

Factor analysis does have certain inherent weaknesses. First, some of the information content for the original set of variables is lost

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[116] Ibid.

[117] Op. cit., Green and Tull. pp. 418-419.

when a smaller number of hypothetical variables are substituted.[118] Second, at least interval level measurement is necessary to use "correlation or covariance matrices as the basic input to factor analysis."[119] Finally, it is not appropriate to use factor analysis when dichotomous variables are used. Kim and Mueller state:

> Each variable is assumed to be a weighted sum of at least two underlying factors (one common and one unique). Even if these underlying factors have two values, ..., the resulting values in the observed variable must contain at least four different values, which clearly is inconsistent with a dichotomous variable.[120]

However, dichotomous data may be used with a purely heuristic set of criteria, as long as "the underlying correlations among variables are believed to be moderate--less than .6 or .7."[121]

Factor analysis, using the method of principal components analysis, will be applied in order to determine if the data can be reduced or summarized. This method is only one technique for identifing and extracting components or factors. Principal components factor analysis procedures possess an advantage over less structured factor analytic procedures in that "unique, reproducible results" may be obtained.[122]

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[118] S. S. Stevens. "On the Theory of Scales of Measurement," Science, Vol. 103, No. 2684, June 1946, p. 678.

[119] Jae-On Kim and Charles W. Mueller, Factor Analysis: Statistical Methods and Practical Issue (Beverly Hills: Sage Publications, Inc., 1978), pp. 73-75.

[120] Ibid.

[121] Ibid.

[122] Op. cit., Green and Tull, pp. 429-30.

Green and Tull discuss the principal components method thus:

> The objective is to portray a set of associated variables in terms of a set of orthogonal (mutually uncorrelated) linear combinations of those variables. The linear combinations are chosen so that each set of component scores accounts for a decreasing proportion of the total variance in the original variables subject to being orthogonal with previously extracted components.[123]

The authors further state that the component scores (weights) are unique in that:

> These particular sets of weights yield unstandardized component (i.e., factor) scores whose variance is maximal, subject to each set of component scores being uncorrelated with previously obtained component scores. ... that is, no other set of weights could lead to a column of component scores with higher variance [for a specific problem][124]

Furthermore, when a component accounts for very little of the variance in an original set of data, the component may be omitted, with very little information being lost.[125]

<u>TEST FOR MULTIPLE CORRELATION</u>. Multivariate correlation is a method to study relationships between variables. Suppose one wishes to obtain multiple correlation between X_1, X_2, ..., X_n variables. A multiple correlation statistic (F^*) for X_1 may be computed by first computing R^2 using the formula:[126]

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[123]Ibid.

[124]Ibid.

[125]Ibid.

[126]Op. cit., Neter and Wasserman, pp. 408-9.

$$R^2_{1.23\ldots n} = \frac{SSR\ (X_2, X_3, \ldots, X_n)}{SSTO\ (X_1)} \qquad (3.6)$$

where:

$R^2_{1.23\ldots n}$ = coefficient of multiple determination for X_1 when other variables are fixed at given values.

SSE = regression sum of the square error.

SSR = regression sum of squares (SSTO-SSE) when X_1 is regressed on the other variables.

SSTO = regression total sum of squares.

The estimated coefficient of multiple correlation is the positive square root of $R_{1.23\ldots n}$.[127] Subsequently, values for all independent variables may be calculated, one by one, using the above procedure. The analysis of multiple correlation may be interpreted by measuring:

> How much smaller, relatively, is the variability in the conditional distributions of [X_1], when the other variables are fixed at given values, than is the variability in the marginal distribution of [X_1].[128]

In essence, the variance may be reduced for highly correlated variables but not reduced in variables displaying low correlation values.

Testing the coefficients of multiple correlation can then be made using the formula:[129]

$$F^* = \frac{R^2_{1.23\ldots n}}{1 - R^2_{1.23\ldots n}} \cdot \frac{n - q - 1}{q} \qquad (3.7)$$

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[127]Ibid.

[128]Ibid.

[129]Ibid.

where: q = number of predictor variables.

The decision rule for control of the Type I error risk is:

If $F^* \leq F(1 - \alpha; q, n - q - 1)$, conclude the coefficient = 0

If $F^* > F(1 - \alpha; q, n - q - 1)$, conclude the coefficient $\neq 0$.[130]

The test for multiple correlation allows the researcher to make an important conclusion. A measure of independence (small level of correlation) between each variable and all other variables will be obtained. This is important since multiple correlation will detect correlation between one variable and groups of variables, thereby allowing the researcher to determine whether different variables are closely associated.

After the tests for multicollinearity and multiple correlation have been made, it will be necessary to determine whether a transformation, such as the iterative method, will be required or whether the results of these tests are within a range which will not adversely affect the analysis. Accepting less than desired results may be a limiting factor for the study. The next section will discuss the method for selecting the classification variable of the study.

SELECTION OF CLASSIFICATION VARIABLES

Typically, multivariate models with interval scaled data use the regression technique. Alternatively, discriminant analysis utilizes dichotomous data. However, it is appropriate to use interval scaled

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[130] Ibid.

data as a categorical dependent variable in some circumstances.[131] An appropriate circumstance exists when classifications of specific characteristics of performance for a group are the attributes of interest as opposed to the prediction criterion used in regression analysis. It should be noted, however, that the classification of interval scaled data into dichotomous variables, as demonstrated by some researchers,[132] is not universally accepted.[133]

In order to test H2, average employee performance will be compiled and employees will be divided according to overall performance. Usually employee performance over time is not consistent with respect to being always above average or below average. Therefore, divisions will be made on the basis of overall rankings for each employee examined. Three employee groups will be selected, based on performance. Employee performance in the upper third will be considered above average for the group. Employee performance in the middle and bottom third will be classified average and below average respectively.

Attributes common to one or two groups may provide descriptive characteristics for purposes of predicting future levels of performance. Three groups have been selected on the basis that management will want to identify and hire as many prospective above average production

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[131] Op. cit., Hair, et al. pp. 92-93.

[132] Some of the studies of this nature are by Walter (1959), Haslem and Longbrade (1971), Klemsky and Petty (1973), Norgaard and Norgaard (1974), and Shick and Veebrugge (1975).

[133] Eisenbeis (1977) and Pinches (1978) assert that valuable informational content of the model is wasted when reclassification of interval scaled data is utilized.

workers as possible. After hiring as many above average applicants as possible, management will then hire average applicants. An objective of hiring above average employees first, average employees next, and not hiring below average performers should provide a satisfactory structure for this study.

Choosing three groups instead of two, four, or more, is based on the authors preceived needs of management. While an individual in the above average group may consistently perform better than another employee in the same group; this individual difference should not be significant. The important point is that they are both in the same group with respect to overall performance and this grouping scheme should provide adequate discrimination among employee groups for most purposes. For the purpose of this study, three groups will be selected.

Once groups have been defined, they will be ranked according to groupings or divisions using indicator variables. The divisions will be specified thus:

Above Average Group = 2

Average Group = 1

Below Average Group = 0

In order to classify employees into groups, each employee's efficiency rating will be gathered for all work periods during training. Each employee's training work period will be classified as above average, average, or below average performance with respect to comparisons with other employee efficiency ratings during the same training work period. Classifications of above average, average, and below average for each training work period will be made by taking the maximum and minimum efficiency rating and dividing the overall efficiency rating into three equal parts. Each employee will then be classified into one of three groups for each training work period and percentages will be calculated based on the number of classifications in each group compared with the total reported classifications.

Finally, each employee will be grouped into an overall grouping of above average, average, or below average based on the largest percentage value for the entire training period. Now that the method for selecting the dependent and independent variables has been discussed, the methodological use of discriminant analysis for this study will be presented.

DISCRIMINANT ANALYSIS

Multiple discriminant anlaysis is a method used to identify a classification model for two or more classification groups. According to Hair et al., the classification model (Equation 3.5),

$$Z = W_1 X_1 + W_2 X_2 + W_3 X_3 + \ldots + W_n X_n$$

is well suited for testing H2 when the independent variables (X_n) and dependent variable (Z) have been specified correctly (i.e. independent variables are not correlated, multiple correlation does not exist, or factor analysis has been used to correct for either simple or multiple correlation effects and the dependent variable has been specified into groups).[134] The principal reason for using multiple discriminant analysis in this study is the categorical nature of the dependent variable (i.e. above average, average, and below average groupings). When the

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[134]Op. cit., Hair et al., pp. 85-6.

dependent variable consists of interval data, regression analysis may be more appropriate, or when more than one dependent variable exists, canonical correlation methods may be more appropriate.

As noted earlier, discriminant analysis is designed to identify differences between two or more groupings. Hair et al. describe the analytic differences between two or more groupings as:

> Discriminant analysis involves deriving the linear combination of the (two or more) independent variables that will discriminate between the *a priori* defined groups. This is achieved by the statistical decision rule of maximizing the between-group variance relative to the within-group variance--this relationship is expressed as the ratio of the between-group to within-group variance.[135]

The result of "deriving the linear combination" of the independent variables is equation 3.5. Eisenbeis and Avery discuss the underlying assumptions and purposes of discriminant analysis. They state:

> Discriminant analysis encompasses both predictive and inferential multivariate statistical techniques. It deals with a specific class of statistical problems focusing on the analysis of groups of populations and/or data sets. In general, the underlying assumptions of discriminant analysis are that (1) the groups being investigated are discrete and identifiable, (2) each observation in each group can be described by a set of measurements on m characteristics or variables, and (3) these m variables are assumed to have a multivariate normal distribution in each population. The [objectives] of discriminant analysis are (1) to test for mean group differences and to describe the overlaps among groups and (2) to construct classification schemes based upon the set of m variables in order to assign previously unclassified observations to the appropriate groups.[136]

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[135] Ibid.

[136] Robert A. Eisenbeis and Robert B. Avery, *Discriminant Analysis and Classification Procedures: Theory and Applications*, (Lexington, Mass.: D.C. Heath and Company), p. 1.

Much like Eisenbeis, Klecka lists the same two purposes of discriminant analysis but describes the first purpose as primarily interpretational. He asks, is the model

> Is the model able to "discriminate" between the groups on the basis of some set of characteristics, how well do they discriminate, and which characteristics are the most powerful discriminators?"[137]

Furthermore, Klecka describes the second purpose as one of classification of one or more mathematical equations. He states:

> These equations, called "discriminant functions," combine the group characteristics in a way that will allow one to identify the group which a case most closely resembles.[138]

The calculated "discriminant functions" can be used to compare past data and "indicate" a higher probability of one occurrence over another occurrence.[139]

TEST FOR GROUP MEAN DIFFERENCES. The first objective in discriminant analysis is to test for mean group differences from *a priori* defined groups. This procedure is accomplished by testing for statistical significance of the discriminant function, which is described as "a generalized measure of the distance between the groups centroids."[140] Hair, et al. further described the procedure as comparing the distribution of group discriminant scores, which results in good (poor)

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[137]William R. Klecka. *Discriminant Analysis*. (Beverly Hills: Sage Publications, Inc., 1980), pp. 8-9.

[138]Ibid.

[139]Ibid.

[140]Op. cit., Hair et al., p. 86.

seperation if the overlap in the distributions is small (large).[141]

The test for significant difference between group means is calculated from "a variability measure known as 'Mahalanobis squared distance'" and is based on an F ratio.[142] Green and Tull describe the Mahalanobis squared distance as:

> Like ordinary (Euclidean) squared distance that is computed between two centroids in a space with correlated axes and different measurement units.[143]

Two important assumptions exist when testing for group mean differences. They are:

1) Multivariate normality of the distributions.

2) Unknown (but equal) dispersion and covariance structures for the groups.[144]

Multivariate normality is an important assumption when using discriminant analysis procedures. If multivariate normality does not exist, Klecka points out an important consideration, concerning our second objective, that of classification of the discriminant function. He asserts that classification, based on the probability of group membership, will be biased if multivariate normality does not exist. Furthermore:

> If the distribution deos not not meet this assumption, the calculated probabilities will be inaccurate. It may turn out, for example, that the probabilities for some groups will be exaggerated while the probabilities for

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[141]Ibid.

[142]Op. cit., Green and Tull, pp. 394.

[143]Ibid.

[144]Ibid., pp. 86-87.

> other groups will be underestimated. Consequently, this procedure will not be optimal, in the sense of minimizing the number of misclassifications.[145]

The second assumption is that the group dispersion (variance-covariance) matrices are equal across all groups. A test of homogeneity of within covariance matrices, using a SAS-DISCRIM procedure, will be used.[146] The procedure calculates a test chi-square value and the decision rule is stated:

> H_o) Test chi-square value is distributed approximately as chi-square.
>
> H_a) Test chi-square value is not distributed approximately as chi-square.

If the null hypothesis cannot be rejected, it will be concluded that the population matrices are equal and that linear classification procedures are appropriate. Should the null hypothesis be rejected, it will be concluded that the population dispersion matrices are unequal and that quadratic classification procedures are appropriate.[147] According to Pinches, quadratic classification procedures should only be used for those cases:

> Where the test for the equality of the dispersion matrices presents overwhelming evidence of non-homogeneity in the population.[148]

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[145]Ibid.

[146]Op. cit., Barr et al. pp. 183-90.

[147]Ethel S. Gilbert. "The Effect of Unequal Variance-Covariance Matrices on Fisher's Linear Discriminant Function," Biometrics, Vol. 25, September 1969, pp. 505-15.

[148]Op. Cit. Pinches, pp. 36-38.

It would appear to be appropriate to use linear classification procedures for the present study, assuming that dichotomous variables will, in fact, be used, which indicates a condition where multivariate normality will not exist. This conclusion is based on discussion from three different studies. Lachenbruch, Sneeringer, and Reno found that deviation from multivariate normality influenced quadratic discriminant results more unfavorably than linear discriminant results.[149] Moore has shown that quadratic classification rules seldom outperform linear discriminant results.[150] Finally, Lachenbruch comments:

> Although in theory this [quadratic procedure] is a fine procedure, it is not robust to nonnormality, particularly if the distribution has longer tails than the normal.[151]

It is apparent that this study, by using dichotomous variables, will use variables which are not multivariate normal and perhaps do not have equal dispersion and covariance structures for the groups, leading to possible improper classification results. It is possible to obtain significant differences between centroids and still develop a poor classification model. Furthermore, the classification model may perform

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[149] Peter A. Lachenbruch, Cherly Sneeringer, and Lawrence T. Reno, "Robustness of the Linear and Quadratic Discriminant Function to Certain Types of Non-Normality," Communications in Statistics, Vol. 1, No. 1, 1973, pp. 39-56.

[150] Dan H. Moore, II. "Evaluation of Five Discriminant Procedures for Binary Variables," Journal of the American Statistical Association, Vol. 68, June 1973, pp. 399-404.

[151] Op. cit., Lachenbruch.

more poorly than a random classification process.[152] This effect must be recognized as a possible limitation of the study.

If one or more of the assumptions of significant differences between centroids exist, this will indicate a possible justification for developing the classification analysis. In his discussion concerning violations of discriminant analysis assumptions, Klecka states:

> For the researcher whose main interest is in a mathematical model which can predict well or serve as a reasonable description of the real world, the best guide is the percentage of correct classifications. If this percentage is high, the violation of assumptions was not very harmful. Efforts to improve the data or use alternative formulas can give only marginal improvements. When the percentage of correct classifications is low, however, we cannot tell whether this is due to violating the assumptions or using weak discriminating variables.[153]

Should the test of significance for group centroids indicate further analysis, a classification procedure will be initiated.

CLASSIFICATION PROCEDURE. The purpose of the classification procedure is to validate the model. Once a determination has been made concerning the necessity of a classification procedure and once it is determined whether linear or quadratic rules will be used, a computer program such as the SAS-STEPDISC procedure or a Biomedical Computer Programs (BMD) procedure will be utilized. Other computer programs, such as the

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[152]Op. cit., Hair, et al., p. 97.

[153]Op. cit., Klecka, p. 62.

Statistical Package for the Social Sciences (SPSS), SAS-STEPWISE and the BMD, have equivalent procedures which yield similiar results. Pinches evaluated these discriminant packages and evaluated the SAS-STEPWISE package as being least effective.[154]

Subsequent to Pinches analysis, the SAS-STEPDISC package was released by Barr, et al. and now performs essentially the same procedures as SPSS and BMD. Pinches asserted "that judicious use of one or two programs will often allow the researcher to satisfactorily (and properly) complete studies."[155]

Once the method for deriving the classification process has been made, a method for deriving a discriminant function will be selected. Two common methods are: (1) the simultaneous method, which considers all independent variables in the model and (2) the stepwise method, (either forward selection, backward selection, or stepwise selection) which enters independent variables "into the discriminant function one at a time on the basis of their discriminating power."[156] A simultaneous method is more thorough, but a stepwise procedure will be utilized for this study as the level of improvement in a classified classification process using the simultaneous method usually does not improve the significance of the discriminant model.

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[154]Op. cit., Pinches, pp. 49-51.

[155]Ibid.

[156]Op. cit., Hair, et al., pp. 92-96.

Classification validation. Generally, three methods are used to validate the classification model. They are (1) the resubstitution method, (2) the holdout or split sample method, and (3) the Lachenbruch U or jackknife method.

First, the resubstition method requires the reclassification of the same data on which the discriminant analysis and classification rules are derived. This method provides results which are biased downward and implies that the model performs better than it actually does.[157]

Second, the holdout or split sample method requires that the original sample be divided into two (not necessarily equal) parts. The discriminant model is calculated on one set of data and evaluated on the other set of data. This method usually requires large sample sizes.[158]

For large samples, a SAS-STEPDISC procedure will be used. SAS-STEPDISC procedures (forward selection, backward selection, and stepwise selection) are based on one of two selection criteria to be chosen by the researcher. The two choices are based on:

1) The significance level of an F test from an analysis of covariance where the variables already chosen act as covariates and the variable under consideration is the dependent variable.

2) The squared correlation for predicting the variable under consideration, controlling for the effects of the variables already selected for the model.[159]

Forward selection for STEPDISC computes a sequence of equations, one for each of the independent variables, and first selects the "best one-

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[157]Op. cit. Pinches, pp. 29-30.

[158]Ibid.

[159]Barr, Anthony and others. SAS User's Guide--79.5 Edition. (Raleigh, North Carolina: SAS Institute, Inc., 1980), pp. 12.1-12.3.

variable model, based on one of the selection criteria listed above. After the "best" one variable model that produces the highest F* or squared partial correlation is selected, another variable which will add the greatest increase to one of the two test statistics is added to the model. Each of the remaining variables is compared to each of the variables in the model to determine if the test statistic can be increased until the "best" two variable model is selected. Comparisons are made until the "best" 1, 2, 3, ..., n variable models have been selected.[160]

Backward elimination is a similar procedure, except the process is reversed. All variables are entered into the model, and subsequently a variable which adds the least F* or squared partial correlation is removed from the model. The procedure is repeated in reverse fashion from forward selection until no more variables can be removed from the model.[161]

A stepwise procedure, which identifies all possible variables for entering and leaving the model, at all steps, will not be used if the number of independent variables for the study exceeds fifteen. This procedure is not within practical computer time requirements when a model has a large number of variables.

The STEPDISC procedure computes the squared partial correlation, F*, and the probability level of F* for each variable considered for entry or removal. It also prints variables chosen for the model, variables selected to be entered or deleted from the model, Wilks' lambda,

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[160] Ibid.

[161] Ibid.

illai's trace, and the average squared canonical correlation (ASCC).
ne authors state:

> The ASCC is Pillai's trace divided by the number of groups less one, and will be close to one if all groups are well separated and if all or most directions in the discriminant space show good separation for at least two groups. Wilks' lambda will be close to zero if any two groups are well separated.[162]

A level of statistical significance, such as an alpha level of .05, ill be chosen to assess a level of significance. Hair, et al. asserts nat unless a function is significant at or beyond the .05 level, there :

> Little likelihood that the function will classify more accurately (that is, with fewer misclassifications) than would be expected by randomly classifying individuals into groups.[163]

ne third method used to validate the classification model is the achenbruch U or jackknife method. Pinches states:

> The essence of this procedure is to omit each observation sequentially, calculate classification rules based on the remaining N-1 observations, and then reclassify the omitted observation.[164]

ne Lachenbruch U or jackknife method is generally robust for an extreme umber of variables and extreme number of observations.[165] Thus, this ethod will be used in the study if a large sample is not available.

If a large sample is not available for the study, a BMD-Stepwise scriminant Analysis Jackknife procedure will be used. The procedure

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[162] Ibid.

[163] Ibid.

[164] Op. cit., Pinches, pp. 29-30.

[165] Ibid.

calculates the same Wilks' lambda and F* as the SAS-STEPDISC procedure.[166] The advantage of using the BMD procedure for a small sample is that the jackknife procedure eliminates each of the remaining observations. The results of the jackknife procedure depict classification accuracy based on analysis of the entire sample, without the introduction of bias being present in the discriminant function.[167] Should an observation be used to derive the discriminant function as well as the prediction or classification matrix, the observation will naturally introduce bias into the results by influencing both derivation and verification of the model.

Classification assumptions. Additional assumptions, other than multivariate normality and equalty of dispersions, also have a significant impact upon the classification evaluation procedure. These assumptions concerning classification accuracies are:

1) Equal costs of misclassification.
2) Equal *a priori* group probabilities.[168]
3) Respective sample sizes for the k groups have been determined.[169]

The assumption concerning equal costs of misclassification implies that it is no more costly to misclassify individual observations

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[166] W. J. Dixon and M. B. Brown, ed. BMDP-79: Biomedical Computer Programs P-Series. (Los Angeles: University of California Press, 1979) pp. 717-18.

[167] Ibid. p. 730.

[168] Ibid.

[169] Op,cit., Pinches, p. 7.

belonging to the above average, average, or below average groups.[170] This assumption may not be true in that the cost of misclassifying an observation from one group may be more costly than misclassifying an observation from another group (i.e. misclassifying a below average employee as an above average employee and vice versa). However, the actual costs of misclassifying observations are difficult, if not impossible, to measure.

Equal _a priori_ group probabilities means that each observation in a model has an equal probability of belonging to each of the groups in the model. It is probable that misclassification of different members in a model may affect the final classification results. Furthermore, the percentage of making correct classifications should be greater when using discriminant analysis than making correct classifications due to chance.[171]

Some models, by design, may have a relatively high probability of correct classification due to chance. For example, a sample containing 100 observations and a dichotomous dependent variable designed to choose descriptive characteristics concerning sports car owners may include eighty non-sports car owners and only twenty sports car owners. In this instance, random selection from the sample would result in an eighty percent probability that a random choice would be a non-sports car owner. A discriminant model would not be appropriate unless it could improve on the random choice probability.

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[170]Ibid.

[171]Op. cit. Hair, et al., p. 103.

Pinches discussed the last assumption concerning sample size and the outcome of a potential study. He stated that there are definite relationships between sample size and achieved results for a study as well as with classification results. In general, results of discriminant analysis are improved as sample size increases and as the number of variables in the model increase if the sample size is sufficiently large or increasing.[172]

PROCEDURAL METHODOLOGY FOR TESTING H2. Testing H2 will be accomplished using discriminant analysis procedures. The steps in testing H2 are stated as follows:

1) Review data regarding assumptions when testing for group mean differences.
    a) Assumption of multivariate normality.
    b) Assumption of equal dispersion and covariance structures for the groups.
2) Test for group mean differences.
3) Derive the classification matrix.
4) Test results regarding assumptions of the classification Accuracy.
    a) Assumption of equal costs of misclassification.
    b) Assumption of equal *a priori* group probabilities.
    c) Assumption of sample sizes of the k groups have been determined.

EVALUATING THE RESULTS OF TESTING H2. Should a significant difference between group centroids be found and significant classification results

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[172]Op. cit. Pinches, p. 7.

exist, then H2 will be rejected. The results would indicate that environmental factors do help explain average employee performance over time. If H2 is rejected, based on the analysis of the study, then an indication for evaluating environmental factors for prospective employees will be supported. The results will have an impact on the budgeting and planning activity for the firm in that future performance classification predictions may be made for current as well as future employees. On the other hand, should it not be possible to reject H2, evidence will then exist which indicates that environmental factors examined in the study have little effect on performance. The method for gathering data for the study is presented in the next section.

DATA COLLECTION

Data will be collected from a firm which employs factory workers in assembly type production. Performance data during training will be collected and compiled in order to compare actual performance with existing standards. Furthermore, a firm will be chosen which determines standards by using learning curve theory. As mentioned earlier, many industries use learning curve theory to establish standards and subsequently evaluate performance. The primary objective in collecting data for this study from a single firm is to collect comparable performance information for employees during the training stage of employment. A secondary objective is to collect data which may be compared from one company to another or to gather employee data over a substantial period of time from a single company.

EXPERIMENTAL GROUP

An experimental group will be selected and data will be collected and coded to conform with the definitions listed in Chapter I. The data will be coded and verified in order to minimize or eliminate measurement errors caused by the researcher. Little may be done to prevent clerical performance measurement errors by company personnel except to evaluate the internal control methods being used. Personal information concerning employee environmental factors will be gathered either through personal interviews, personnel applications, or from written survey instruments, and then the data will be organized and coded.

Average efficiency or performance ratings will be computed for each level of training according to the format:

$$\begin{matrix} Y_{1,1} & Y_{2,1} & \cdots\cdots & Y_{i,1} \\ Y_{1,2} & Y_{2,2} & \cdots\cdots & Y_{i,2} \\ \vdots & \vdots & & \vdots \\ Y_{1,j} & Y_{2,j} & \cdots\cdots & Y_{i,j} \end{matrix} \quad = \quad \begin{matrix} \overline{Y}_1 \\ \overline{Y}_2 \\ \vdots \\ \overline{Y}_i \end{matrix} \qquad (3.8)$$

where:

$Y_{i,j}$ = efficiency rating for time period (i) and employee (j)
$\overline{Y}_i$ = average employee efficiency rating for time period (i).

Average employee efficiency ratings for each time period will be compared with standard or expected performance levels to test H1. The procedures for testing H1, will be utilized as discussed earlier in this chapter.

The data will be organized for testing H2 and coded for use with discriminant analysis. Groupings will be identified from data generated from (3.11):

$$\begin{matrix} \overline{Y}_1 \\ \overline{Y}_2 \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ \overline{Y}_i \end{matrix} \quad = \quad Z_k \qquad (3.9)$$

where:

Z_k = Discriminant group k.

Therefore, the discriminant model will be coded from the data gathered from personal interviews, personnel applications, or from written survey instruments and the discriminant groups from formula 3.9. The discriminant model is stated:

$$Z_k = \begin{matrix} W_1X_{1,1} & W_2X_{2,1} \cdots\cdots & WmXm,_1 \\ W_1X_{1,2} & W_2X_{2,2} \cdots\cdots & WmXm,_2 \\ \cdot & \cdot & \\ \cdot & \cdot & \\ \cdot & \cdot & \\ \cdot & & \\ W_1X_{1,n} & W_2X_{2,n} \cdots\cdots & WmXm,n \end{matrix} \qquad (3.10)$$

where:

Wm = Discriminant weight for variable m
Xm = Independent variable m
n = Observations.

The discriminant model will be derived and H2 will be tested using the steps discussed in the previous section of this chapter.

MEASUREMENT ERRORS

A possible delimitation exists that when a researcher gathers data, errors may prevail. Errors in the data may be caused by incorrect recording of performance by employees or supervisors, clerical mistakes, or recording mistakes by the researcher. However, the researcher has little or no control over the first two sources of error. The researcher is responsible for the last source of error. Every effort

(Equation 3.3) requires that the error term be independent of the independent variable. This is not the case when the error term includes measurement error. Neter and Wasserman state:

> Great difficulties are encountered in developing unbiased estimators when there are measurement errors in [the independent variable].[174]

Once it is determined that measurement errors will not be a delimiiting factor for the study, the hypotheses will be tested.

Hypothesis one (H_1) will be tested using a test between two regression lines. The second hypothesis will be tested using discriminant analysis procedures. Results obtained from these tests will be presented in Chapter IV. In addition, a description of the data to be used for this study will discussed.

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[174]Ibid.

CHAPTER IV

RESULTS AND ANALYSIS OF STATISTICAL TESTS

THE SAMPLE

EXPERIMENTAL GROUP

The sample selected for study is taken from a company that produces large quantities of business forms for government and private business clients. The manufacturing process requires several intermediate steps. Upon completion of each step of the process, another department receives the partially completed order and performs the next required step. This process is repeated until the order has been completed.

Characteristics of the specific firm from which the data are taken make this firm uniquely appropriate and representative for the study since the production processes have remained virtually unchanged over the test period. Plant layout, machinery, and formal management objectives are, essentially, the same and have existed in substantially the same manner for the past twelve years. Further, the production environment of the sample firm is representative of worker tasks of other production environments which also have assembly manufacturing processes.

PRODUCTION PROCESS

The production process is divided into steps. Standard time units for completing each step have been developed and are an integral part of the evaluation process for each employee. The number of standard time units allowable for each step on a given order is based upon the complexity and size of the order. Standard time units are determined by industrial engineers using, essentially, time and motion observations.

MONTHLY EFFICIENCY RATING

Once a production step is completed, the actual time required by the employee to complete the production step is compared to the standard time units allowed and a monthly efficiency rating is determined. The monthly efficiency rating, derived from Formula 1.2, from Chapter I, is calculated as follows:

$$\text{Monthly Efficiency Rating} = \frac{\sum \text{Actual Time Units Required to Complete all Jobs for the Month}}{\sum \text{Standard Time Units Required to Complete All Jobs for the Month}} \tag{4.1}$$

Thus, the monthly efficiency rating, as a percentage, is based on standard time allowed compared to actual time required for each job. Monthly efficiency ratings are then compared to monthly learning curve standards to evaluate current performance. Employees who consistently operate at high (five percent above the learning curve standard) production performance levels are recommended for merit raises. Those employees who do not perform at their expected performance ratings do not receive an increase in wage until they achieve the expected monthly learning curve standard.

MONTHLY LEARNING CURVE STANDARD (LCS)

Formula 1.1, from Chapter I, was used in 1967 to establish the monthly learning curve standard for training new employees. The monthly learning curve is thirty-two months in length, and new employees' monthly efficiency ratings are expected to improve according to the schedule listed in Table 4.1.

TABLE 4.1

EMPLOYEE TRAINING STANDARDS OF FIRM PROVIDING DATA

Month of Training	Monthly Learning Curve Standard (Percent)	Month of Training	Monthly Learning Curve Standard (Percent)
1	60%	17	91%
2	65	18	92
3	70	19	93
4	75	20	93
5	78	21	94
6	80	22	94
7	82	23	95
8	84	24	96
9	85	25	96
10	86	26	97
11	87	27	97
12	88	28	98
13	89	29	98
14	90	30	99
15	90	31	99
16	91	32	100

STUDY GROUP

The group selected for this study is employed in the Press Department. The study involves a total of ninety workers hired over a twelve-year period. Press Department production performance records for twelve years were used as the data base.

During the period studied, the Press Department used the learning curve established in 1967 to evaluate employee production performance. As indicated in Table 4.1, productivity of new pressmen is expected to increase to one hundred percent of the standard over the thirty-two month learning period.

Data were obtained from press efficiency ratings from actual performance. Performance records for the Press Department employees were matched with their expected monthly learning curve standard for each specific training segment level. Actual monthly efficiency ratings, based on the same levels of training in months, were totaled for all employees. Monthly efficiency ratings for each level of training, one for each of the thirty-two months, were calculated for comparison with expected monthly learning curve standards. Performance evaluations at monthly intervals of training were made for all employees based upon this data.

While collecting the monthly efficiency data, it was determined that employees were hired over the twelve-year period, for the most part, in two distinct time periods. Thus, it was possible to divide the study group into two employee groups and test not only for differences between standard employee performance and average employee performance, but also test for differences in average employee performance between groups as well. As such, employee group one (E1) encompassed the years 1968 through 1973 while employee group two (E2) encompassed the years 1974 through 1979. The two groups were selected on the basis of employee hirings over the twelve year period subsequent to setting the LCS. A total of 48 of 49 new employees for E1 were hired during the years 1967-1970. A similar hiring sequence occurred for E2 during the years 1977-1979. During this period, 37 of 41 employees were hired. The groups resulted from shift expansions of the firm rather than new hirings because of layoffs or other labor related problems.

DATA DESCRIPTION

The data obtained were compiled and grouped into the following categories:

(1) Average monthly efficiency ratings (AMER). A twelve year data

set which includes all employee efficiency ratings for the thirty-two months of training. Efficiency ratings for all workers in the Press Department were matched with their respective month of training (months one through thirty-two) and an arithmetic mean for all employees for that month was computed as:

$$\begin{matrix} Y_{1,1} & Y_{2,1} & \cdots & Y_{32,1} \\ Y_{1,2} & Y_{2,2} & \cdots & Y_{32,2} \\ \vdots & \vdots & & \vdots \\ Y_{1,90} & Y_{2,90} & \cdots & Y_{32,90} \end{matrix} \quad = \quad \begin{matrix} \overline{Y}_1 \\ \overline{Y}_2 \\ \vdots \\ \overline{Y}_{90} \end{matrix} \qquad (4.2)$$

where: $Y_{i,j}$ = monthly efficiency rating for month (i) and employee (j)

$\overline{Y}_{1 \ldots 90}$ = total average monthly efficiency ratings.

(2) Demographic data. Selected demographic factors for each employee in the Press Department were obtained from personnel records. Specific demographic factors (DEM) for this study are listed in summary form in Table 4.2, page 88. Justification for their selection was discussed in Chapter II.

(3) Economic factors. While economic factors may significantly influence performance of employees, the nature of this study would seem to preclude using economic factors in the analysis. Specifically, the study examined employee performance during the training period and, as such, employees were not trained at the same point in time and did not share common economic conditions. For example, some employees were hired and trained in 1968 and others were hired and trained in other years. However, the economic stability of this business suggests that

TABLE 4.2

DEMOGRAPHIC FACTORS FOR THE STUDY

Factor	Variable Name*
1. Age when starting work	DEM 1
2. Marital status: Married	DEM 2
Single	DEM 3
3. Number of dependents	DEM 4
4. Educational level attained	DEM 5
5. Own home	DEM 6
6. Relatives employed at this work place	DEM 7
7. Length of preceding job	DEM 8
8. Flexible attitude for working different shifts	DEM 9-11
9. Number of years in local area	DEM 12
10. Commuting distance to job	DEM 13
11. Residence with relatives	DEM 14
12. Immediate preceding job classification	DEM 15-19
13. Reason for leaving last job	DEM 20-24
14. Weight vs. height ratio	DEM 25

*Specific coding for each variable will be described in a later section of this chapter.

economic factors facing the firm relative to employee training may have been constant.

The economic condition of each individual within the firm, i.e., his personal economic position, is likely to have a greater influence on productivity. However, identification of such factors is beyond the scope of this study.

(4) Personality factors. Personality factors may affect worker performance, but, to date, little evidence has been given to support this notion in the literature. Thus, personality factors will also not be examined in this study. The following sections will present the results obtained from testing the hypotheses for this study.

TEST OF EQUALITY OF REGRESSION LINES--RESULTS

In order to test that standard performance (LCS) equals average employee performance, the functions first are linearized by transforming the respective monthly efficiency rating averages into log (base 10) values. The curvilinear LC formula will then have the same characteristics of a straight line and a general linear test approach can be used in testing H1.[175] H1 is now restated conditionally to test for significant difference between the two groups as:

$H1_{01}$) Average employment performance for the employee group hired in the years 1968-73 equals average employee performance for the employee group hired in the years 1974-79.

$H1_{a1}$) Average employee performance for the employee group hired in the years 1968-73 does not equal average employee performance for the employee group hired in the years 1974-79.

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[175] Op. cit., Neter and Wasserman. pp. 160-5.

If $H1_{01}$ is rejected, then an additional test will be made using the hypothesis:

$H1_{02}$) Average employee performance for the employee group hired in the year 1968-73 equals average employee performance for the employee group hired in the years 1974-79 and equals the learning curve standard.

$H1_{a2}$) Average employee performance for the employee group hired in the years 1968-73 does not equal average employee performance for the employee group hired in the years 1974-79 and does not equal the learning curve standard.

Should $H1_{01}$ not be rejected, then the data E1 and E2 will be merged and the following hypothesis will be tested:

$H1_{03}$) Average employee performance (combined groups 1968-79) equals the learning curve standard.

$H1_{a3}$) Average employee performance does not equal the learning curve standard.

However, prior to testing the hypotheses, tests of assumptions regarding the data are made.

TESTS OF ASSUMPTIONS REGARDING H1

Using the tests discussed in Appendix 1, it was determined:

1) The variance of the errors terms is constant.
2) The error variances for the group of employees hired in 1968-73 equals the average employee performance for the employee group hired in the years 1974-79
3) Autocorrelation existed in the data and independence of the residuals was obtained using an iterative method.
4) The error terms are normally distributed.

RESULTS OF TESTING H1

A test of equality between E1 and E2 was made to determine if the employee groups were significantly different. The results from TABLE 4.3 indicated that the first subhypothesis of H1 ($H1_{01}$) could not be rejected; therefore, the two groups were not different. The second subhypothesis, $H1_{02}$, was conditional upon rejecting $H1_{01}$ and not tested, since E1 and E2 were concluded not to be different and the data from E1 and E2 would be combined in order to test that the learning curve standard was different from average employee performance.

Next, $H1_{03}$ was tested and the null hypothesis rejected on the basis of $F^* = 31.54 > F = 3.15$ as indicated by the results in TABLE 4.3. Thus, the average monthly efficiency regression line (average employee performance) is not equal to the standard performance regression line (LCS) based on the learning curve.

The results suggest that workers are not experiencing the same learning curve as workers in the past. In an effort to determine a new performance standard, calculation of a new learning curve is suggested.

TABLE 4.3

RESULTS OF TEST FOR EQUALITY OF REGRESSION LINES

Hypothesis	F* (see note 1)	F-table Value (note 2)	Hypothesis Outcome
$H1_{01}$	-5.8949	3.15	Fail to reject
$H1_{02}$	N/A (note 3)	N/A	N/A
$H1_{03}$	31.5	3.15	Rejected

NOTE 1: F* was calculated using formula 3.2 from CHAPTER 2. See Appendix 2 for computations.

NOTE 2: $F(1-\alpha ; 2, n_1 + n_2 - 4) = F(.95; 2, 56) = 3.15$.

NOTE 3: Calculation is not applicable because of result from $H1_{01}$.

Assuming that worker performance continues on the same function of a learning curve (Formula 1.1), the function was linearized in order to derive new a and b parameters:

$$\log Y' = \log a' + b \log X'. \tag{4.3}$$

The periods (X) and the efficiency performance values (Y) were then transformed into log (base 10) values, and then log Y' was regressed on log X', resulting in a regression equation:

$$Y' = a + b\,X' \tag{4.4}$$

where:

$$\begin{aligned} Y' &= \log Y' \\ X' &= \log X' \\ a &= \log a' \\ b &= b \end{aligned}$$

New values were calculated for a and b (TABLE 4.4). By holding X constant for the training period, a new learning curve was formulated. TABLE 4.5, page 93 lists the new standard efficiency ratings in comparison to standard efficiency ratings established in 1967. FIGURE 4.1, page 94 illustrates the different standards (from 1967 and present) and average performance over time.

TABLE 4.4

REGRESSION RESULTS FOR NEW STANDARDS

Coefficient	Value
log a	1.847
a	0.101
b	70.25
Y	70.25 $(X^{.101})$

The test of subhypothesis $H1_{03}$ resulted in the null hypothesis being rejected. The learning curve standard was not the same as average

TABLE 4.5

SCHEDULE OF EFFICIENCY STANDARDS
BASED ON LEARNING CURVES

Training Month	1967 Standard (%)	New Standard (%)
1	60	70.25
2	65	75.35
3	70	78.50
4	75	80.81
5	78	82.66
6	80	84.19
7	82	85.52
8	84	86.68
9	85	87.72
10	86	88.65
11	87	89.51
12	88	90.30
13	89	91.04
14	90	91.72
15	90	92.36
16	91	92.97
17	91	93.54
18	92	94.08
19	93	94.60
20	93	95.09
21	94	95.56
22	94	96.01
23	95	96.44
24	96	96.86
25	96	97.26
26	97	97.64
27	97	98.01
28	98	98.38
29	98	98.73
30	99	99.06
31	99	99.39
32	100	99.71

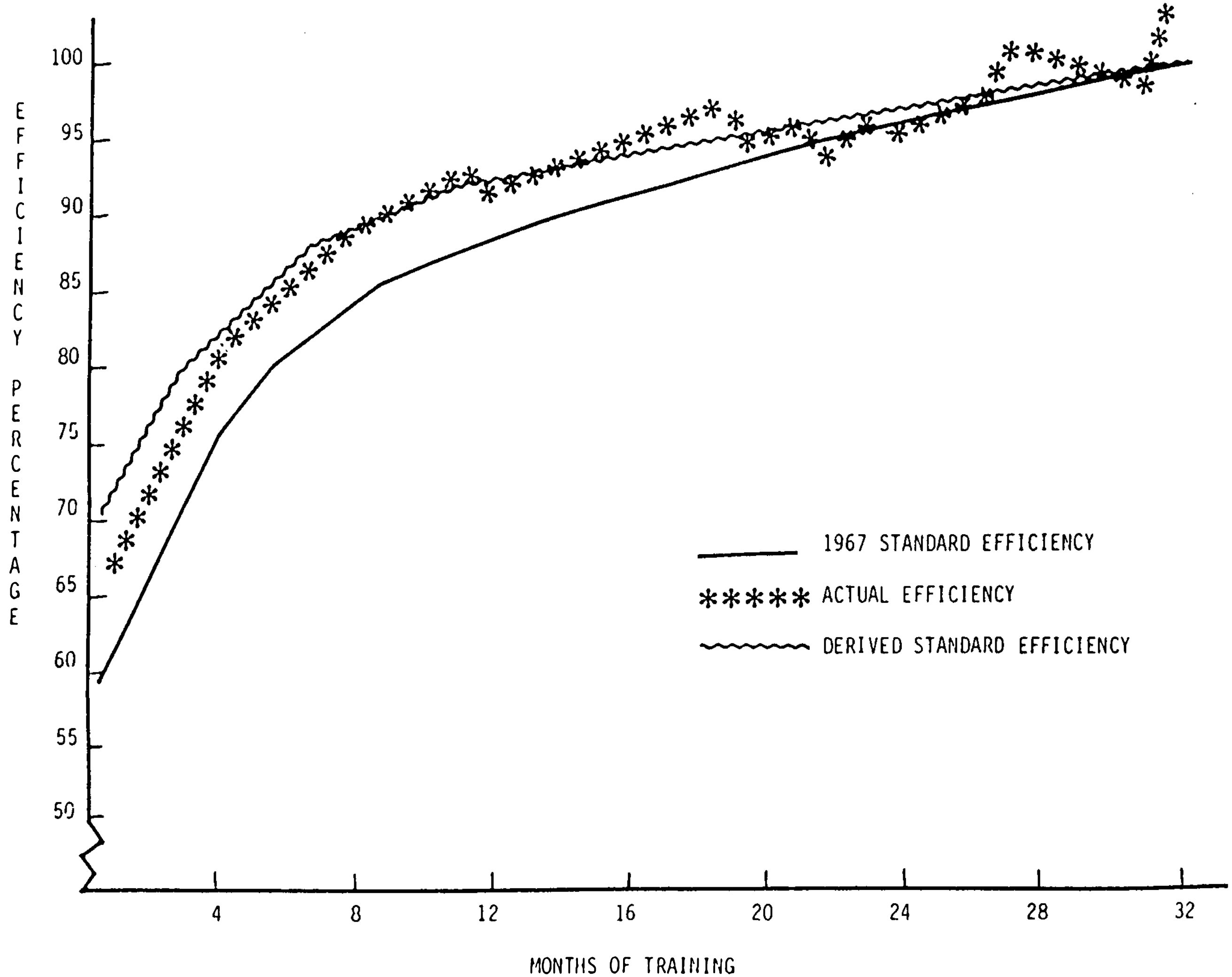

FIGURE 4.1
STANDARD, ACTUAL AND DERIVED PERFORMANCE

employee performance. This is further evident by examining Table 4.5, page 93 and Figure 4.1, page 94 in that average employee performance is higher during early training months than the 1967 standard indicates. The conclusion is that the new standard, calculated from average employee performance, represents current expected performance levels of employees.

TEST OF FACTORS AFFECTING EMPLOYEE PERFORMANCE--RESULTS

The selection process used for choosing factors (independent variables) and the results from subsequent tests for multicollinearity and multiple correlation between variables for the study will be presented in this section. Next, the classification variables are identified and selected for the study group. Finally, the results from testing H2 using discriminant analysis procedures are presented.

SELECTION OF THE INDEPENDENT VARIABLES

The independent variables selected from Table 4.2 were identified as either quantitative or qualitative variables. Quantitative variables were entered into the model at their stated values. Qualitative variables were coded as dichotomous or indicator variables. The variables for this study are defined, coded, and presented in Table 4.6, pages 96-97.

A possible limitation of the study is related to the measurement and classification of demographic characteristics for each employee. The measurement of demographic variables was made at the beginning of the training program. Subsequent classification of employees into groups was made using data collected over the entire training program.

TABLE 4.6

INDEPENDENT VARIABLES FOR
DISCRIMINANT ANALYSIS

VARIABLE NAME	VARIABLE DESCRIPTION
DEM 1	- Age of employee when starting work
DEM 2-3	- Marital Status
	DEM 2 = 1 if married 0 if otherwise
	DEM 3 = 1 if single 0 if otherwise
DEM 4	- Number of dependents
DEM 5	- Number of years in school
DEM 6	- Own home
	1 if own home 0 if otherwise
DEM 7	- Relatives employed at this plant
	1 if yes 0 if otherwise
DEM 8	- Length of preceding job in months
DEM 9-11	- Willingness to work different shifts before starting work (shift selections are not mutually exclusive)
	DEM 9 = 1 if employee is willing to work shift 1 0 if otherwise
	DEM 10= 1 if employee is willing to work shift 2 0 if otherwise
	DEM 11= 1 if employee is willing to work shift 3 0 if otherwise
DEM 12	- Number of years in local area
DEM 13	- Commuting distance to job

TABLE 4.6 (continued)

INDEPENDENT VARIABLES FOR
DISCRIMINANT ANALYSIS

VARIABLE NAME	VARIABLE DESCRIPTION
DEM 14	- Residence with relatives
	DEM 14= 1 if live with relatives 0 if otherwise
DEM 15-19	- Immediate preceding job type
	DEM 15= 1 if factory work (assembly) 0 if otherwise
	DEM 16= 1 if general labor 0 if otherwise
	DEM 17= 1 if farm related labor 0 if otherwise
	DEM 18= 1 if military service 0 if otherwise
	DEM 19= 1 if non-manual 0 if otherwise
DEM 20-24	- Reason given or reported for leaving last job
	DEM 20= 1 if dismissed (disciplinary action) 0 if otherwise
	DEM 21= 1 if laid off (other than disciplinary action) 0 if otherwise
	DEM 22= 1 if salary was too low 0 if otherwise
	DEM 23= 1 if advancement not likely 0 if otherwise
	DEM 24= 1 if still employed 0 if otherwise
DEM 25	- Weight vs. height ratio

Of the twenty-five pre-selected demographic variables, fourteen variables may change during the training period. These variables are listed in Table 4.7, page 99. If changes had occurred in a significant number of variables during the training period, the results may be biased. For example, if a demographic factor was in some way related to employee performance and that demographic factor changed during the training period, the predicted performance of that employee would change. The employee would have belonged to two performance groups during the test period but the classification, according to the study, would classify the individual into only one group. However, follow-up data concerning this limitation were not available.

TEST FOR MULTICOLLINEARITY. To examine the effects between the independent variables, correlation analysis and factor analysis were conducted. Pearson product-moment correlation analysis was conducted using a SAS procedure. This procedure indicated high correlation (-.94) between variable DEM 2 and DEM 3. Only two employees reported a status of being divorced or widowed, resulting in the high negative correlation coefficient. All other variables were correlated with coefficients less than .60.

Variable DEM 3 (single status) was deleted from the data set since DEM 2 (married status) indicates married versus single information for the study. Coded values of zero for DEM 2 indicate that the employee is single.

Variable DEM 20 (reason for leaving last job) was also deleted from the model, since no employees reported that they were dismissed from their last job as a result of disciplinary action. Finally, it was

TABLE 4.7

DEMOGRAPHIC FACTORS FOR EMPLOYEES
WHICH MAY CHANGE

Factor	Variable Name
1. Marital Status	DEM 2-3
2. Number of dependents	DEM 4
3. Educational level attained	DEM 5
4. Own home	DEM 6
5. Relatives employed at this work place	DEM 7
6. Length of preceding job	DEM 8
7. Flexible attitude for working different shifts	DEM 9-11
8. Number of years in local area	DEM 12
9. Commuting distance to job	DEM 13
10. Residence with relatives	DEM 14
11. Weight vs. height ratio	DEM 25

necessary to delete variable DEM 25 (height/weight ratio) because thirty-nine employees were not required to report either height or weight on the personnel applications used in the last five years.

FACTOR ANALYSIS. Next, a factor analysis procedure was used to determine if the remaining twenty-two variables could be reduced to a fewer number of factors for the study.

A SAS factor analysis procedure using the principal component axis method was conducted. Specifying a minimum eigen (or lambda) value of one resulted in nine factors being selected. However, the nine factors accounted for only seventy-two percent of the total variance and, as such, did not indicate a satisfactory reduction of the number of variables for the study.

Had the factors accounted for a significant portion of the total variance, the nine factors would have been summarized to explain specific characteristics of the factor analysis. For example, DEM 2 (married) and DEM 4 (number of children), with factor loadings of .96 and .74 respectively, loaded high on the first factor. This factor would be categorized as a family dependent factor and used in the analysis as a single variable rather than the input of two separate variables, DEM 2 and DEM 4. Variables DEM 2 and DEM 4 were the only multiple variables that had high loadings on any of the nine factors. Each of the remaining eight factors were associated (high loadings) with one variable per factor. Therefore, the factors contributed little in summarizing the data into a smaller number of variables.

A subsequent factor analysis specifying all possible factors (twenty-two) also resulted in high factor loadings for each variable to each factor in all but one case. As stated above, variables DEM 2 and DEM 4 loaded high on the first factor. These variables accounted mostly for the first factor having the highest portion of the explained total variance (15.5%). Factor 20 did not have any variable with a high (higher than .20) factor loading. All other factors listed high factor loadings ($\pm$ 0.80 or greater) associated with one specific variable.

The results obtained from the factor analysis procedure indicated that data reduction and summarization, a main objective of factor analysis, would not be beneficial. Therefore, the twenty-two variables were used and coded for the analysis.

TEST FOR MULTIPLE CORRELATION

In order to determine the relationship between each variable and all other variables, a test was conducted as discussed in Chapter 3. The results of this test are included in Table 4.8. Each variable had insignificant levels of correlation when compared to the remaining group of variables.

SELECTION OF THE CLASSIFICATION VARIABLE

Average monthly efficiency ratings (AMER) during training for each of the employees in the study were grouped from highest to lowest for each month of training. Of the ninety workers in the sample, seventeen employees had trained less than ten months. These workers were excluded from the study on the basis that they had not sufficiently participated in the training program to establish a tenured performance record.

Rankings of employees were based on average performance over the training period. Each month of training was examined separately and equal groupings (above average, average, below average) were made for

TABLE 4.8

RESULTS FROM TEST OF MULTIPLE CORRELATION

Variable	R^2 against all other variables	F* (note 1)	Independence between variables exists if F* < F (note 2)
DEM 1	0.6458	1.6575	YES
DEM 2	0.6125	1.4370	YES
DEM 4	0.7035	2.4134	YES
DEM 5	0.2431	0.2920	YES
DEM 6	0.5394	1.0646	YES
DEM 7	0.4050	0.6188	YES
DEM 8	0.4186	0.6545	YES
DEM 9	0.3151	0.4182	YES
DEM 10	0.2054	0.2350	YES
DEM 11	0.4234	0.6675	YES
DEM 12	0.4605	0.8536	YES
DEM 13	0.2893	0.3701	YES
DEM 14	0.5393	1.0642	YES
DEM 15	0.6999	2.1202	YES
DEM 16	0.8101	3.6592	YES
DEM 17	0.5844	1.2783	YES
DEM 18	0.8010	3.6592	YES
DEM 19	0.6676	1.8258	YES
DEM 21	0.4579	0.7679	YES
DEM 22	0.4447	0.7280	YES
DEM 23	0.4216	0.6626	YES
DEM 24	0.6488	1.6794	YES

Note 1: F* was calculated using Formula 3.11 from Chapter 3.

Note 2: $F(1-\alpha;\ q,\ n-q-1) = F(.95;\ 1,\ 20) = 4.31$

all employees involved with the monthly training period. Employees who performed in a specific group more often than the other two groups were classified into that specific group. Results of employee groupings are listed in Table 4.9. The discriminant analysis results are presented in the next section of this chapter.

TABLE 4.9

RESULTS FROM EMPLOYEE GROUPINGS

Classification	Number of employees in each group*
Above average	23
Average	24
Below average	26

*For employee performance ratings by month, see Appendix 3.

DISCRIMINANT ANALYSIS--RESULTS

Prior to deriving the discriminant function, a test of group mean differences was performed. A discriminant analysis jackknife procedure was used to validate the model. The jackknife procedure was used since only seventy-three observations were available for the study. The jackknife procedure is advantageous for discriminant analysis when an analysis has limited observations. This procedure may possess more power than other discriminant analysis procedures as no additional observations were available.[176]

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[176]Op., Pinches, pp. 29-30.

TEST FOR GROUP MEAN DIFFERENCES. As stated in Chapter III, group means should be significantly different for the discriminant function to be useful. In order to perform the test for group mean differences, a discriminant analysis procedure was performed and the test statistic lambda was obtained. A large value of lambda (0.94) for the complete model was obtained, which indicates little distinction between group means. Furthermore, the F-value of 2.098 was not significant at an alpha level of 0.10. Continuation of the analysis when group means are equal is usually not advisable and when such analysis is continued, a limitation for the study may exist.

TEST FOR EQUAL DISPERSION BETWEEN GROUPS. A SAS-STEPDISC procedure was used to test for equal dispersion between groups. The procedure also determines whether linear or quadratic classification procedures are to be used in the discriminant function. The test chi-square value of 97.04 was not significant at the 0.05 level. Therefore, linear classification procedures (a pooled covariance matrix) were used in the discriminant function. It was also concluded that the population matrices were equal indicating that equal dispersion between groups existed.

CLASSIFICATION RESULTS. An F-value of 2.74 (73 observations, 3 df, alpha level of 0.10) was specified for the first computer analysis. No variables were significant at a 0.10 level of significance. A second analysis, specifying an F-value to enter of 1.0, entered six variables into the model. These variables are presented in Table 4.10.

TABLE 4.10

RESULTS OF DISCRIMINANT ANALYSIS--
VARIABLES USED IN THE MODEL

Variable	F-statistic to remove	Group Means for Responses		
DEM 7	2.155	0.04	0.25	0.19
DEM 8	2.048	32.7	16.8	35.5
DEM 9	2.364	0.87	0.96	1.00
DEM 19	1.526	0.17	0.17	0.04
DEM 21	1.651	0.17	0.08	0.03
DEM 24	1.139	0.52	0.42	0.42
Required F-Value for significance 2.74 (alpha level of 0.10) Approximate F-statistic 1.686				

Although not significant at a 0.10 level, the variables with an F-statistic greater than 1.0 possessed general tendencies regarding group means. Table 4.10 also presents the group means for those variables with an F-statistic greater than 1.0. The group mean for DEM 7 (relatives employed at this plant) was very small for below average performers, indicating that workers with relatives already working at the plant tended to be average or above average workers. The variable DEM 8 (length of preceding job) indicated that below average and above average workers were previously employed longer than average workers. There was little difference between the group means for DEM 9 (willingness to work shift 1) except that a trend existed for workers indicating a willingness to work shift 1, with the mean response increasing from below average workers through above average workers.

Group means for the variable DEM 19 (prior job non-manual) indicated that above average performers were virtually employed in manual job types. A trend existed between the group means for workers being laid off from their previous job (DEM 21). More workers were previously laid off in the below average category with fewer workers being previously laid off in the average category and still fewer workers were previously laid off in the above average category. Finally, the variable DEM 24 (still employed when seeking employment at this plant) indicated that more workers performed at below average levels when interviewing and currently employed than did workers who were interviewing and currently unemployed.

A jackknifed classification matrix was obtained using the BMDP discriminant analysis procedure. The results are presented in Table 4.11.

The expected classification results based on a random selection of groups is only 33.3 percent. The results in Table 4.11 indicate an overall improvement of only 5.1%. Thus, classification of all three groups did not significantly improve those classifications based on random chance possibilities and validation of the model was not possible.

TABLE 4.11

RESULTS OF JACKKNIFED CLASSIFICATION MODEL

Group	Percent Correct	Number of cases classified into group		
		Below Average	Average	Above Average
Below average	43.5	10	6	7
Average	29.2	9	7	8
Above average	42.3	9	6	11
Total	38.4	28	19	26

RESULTS OF TESTING H2

In summary, a discriminant analysis model using three groups and twenty-five variables was designed to test that environmental factors affect differences in average employee performance. Tests of assumptions indicated that the variables were not highly correlated nor did any of the variables indicate high multiple correlation with other variables. Furthermore, an attempt to reduce the number of variables for the study, using factor analysis, did not succeed since all the variables, except for two, were associated with separate factors.

Next, tests for group mean differences and equal dispersion between groups were made indicating that equal dispersion between groups existed. However, the test for group mean differences indicated that the groups were not significantly different. It should be noted that when group means are equal a discriminant model will be unlikely to accurately separate (and thus classify) the groups. Therefore, the analysis did not allow H2 to be rejected and it was concluded that the factors for this study are not significantly related to average employee performance. Next, Chapter V will discuss the implications of the results presented in this chapter.

CHAPTER V

SUMMARY, CONCLUSIONS, RECOMMENDATIONS, AND SUGGESTIONS FOR FUTURE RESEARCH

SUMMARY

Performance standards encompass information characteristics which decay over time. Consequently, it is worthwhile to identify factors affecting information decay. In Chapter I, the objectives of this study were discussed. They are restated: (1) determine if production worker performance has changed over time, (2) provide broad guidelines and recommendations for production type industries concerning performance evaluation of employees during training, (3) find evidence that standards and environmental factors for production workers can be linked and provide information to the firm for budgeting and planning purposes, and (4) provide a basis for further research associated with identifying variables related to improving worker performance.

Two general hypotheses were used for the study. The first hypothesis was stated as follows:

> $H1_o$) Learning curve standard performance equals average employee performance over time.
>
> $H1_a$) Learning curve standard performance does not equal average employee performance over time.

Regression analysis was used to test the first hypothesis (H1), using three sub-hypotheses, to determine if actual average employee performance equaled standard performance over time. The sub-hypotheses were stated as follows:

$H1_{o1}$) Average employee performance for the employee group hired in the years 1968-73 equals average employee performance for the employee group hired in the years 1974-79.

$H1_{a1}$) Average employee performance for the employee group hired in the years 1968-73 does not equal average employee performance for the employee group hired in the years 1974-79.

$H1_{o2}$) Average employee performance for the employee group hired in the years 1968-73 equals average employee performance for the employee group hired in the years 1974-79 and equals the learning curve standard.

$H1_{a2}$) Average employee performance for the employee group hired in the years 1968-73 does not equal average employee performance for the employee group hired in the years 1974-79 and does not equal the learning curve standard.

$H1_{o3}$) Average employee performance (combined groups 1968-79) equals the learning curve standard.

$H1_{a3}$) Average employee performance does not equal the learning curve standard.

Specifically, $H1_{o1}$, was used to test for differences between two employee groups over a twelve year period and the results indicated that the null hypothesis could not be rejected. The results indicated that there was no significant difference between employee group one average performance and employee group two average performance. Sub-hypothesis ($H1_{o2}$) was not tested, as it was conditional upon $H1_{o1}$ being rejected. Thus, an alternate test of H1 ($H1_{o3}$) was tested and rejected at an a level of .05. It was concluded that a significant difference existed between the learning curve standard and average employee performance. A new LC was then derived, based on average employee efficiency data used in the study.

The second hypothesis used in the study was stated:

$H2_{o}$) Production factors, as compared with environmental factors, are the only identifiable factors which affect differences in average employee performance.

$H2_a$) Production factors, as compared with environmental factors, are not the only identifiable factors which affect differences in average employee performance.

A discriminant analysis procedure was used to test H2 for the study in an attempt to identify factors, other than production factors, which are related to employee performance. The study examined selected environmental factors in an attempt to identify factors which may be used to classify employee performance into groups of above average, average, or below average. Results from the discriminant analysis procedure did not allow H2 to be rejected.

The inability to reject H2 resulted because the centroids of the three groups were not significantly different. The discriminant analysis procedure was terminated; however, a classification matrix was constructed, and the application of the discriminant model resulted in an insignificant improvement over random chance of classifying employee performance.

CONCLUSIONS

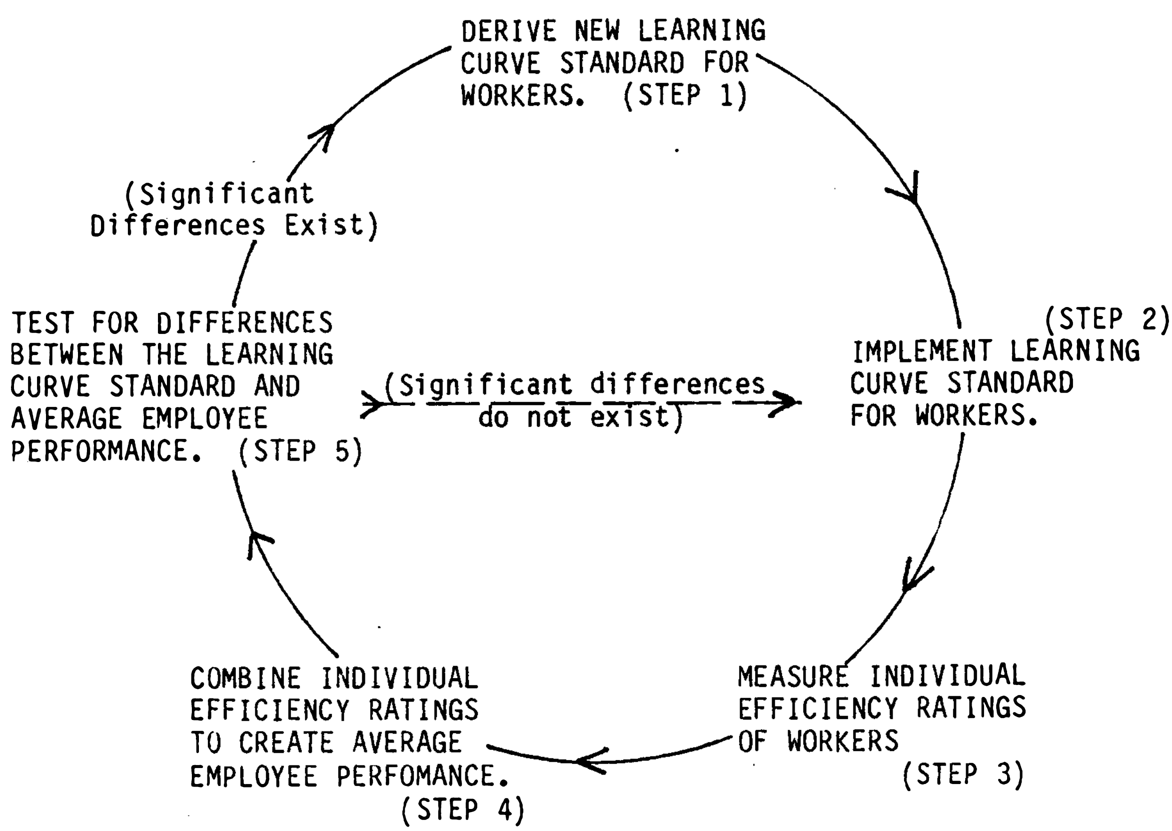
Rejecting $H1_{03}$ implies that workers were not subject to the same learning curve as workers were in the past, as standard performance used by the firm was derived from previous employee performance. Specifically, an examination of the performance data from Figure 4.1, page 94, showed that average employee efficiency is higher at the beginning of training and increases at approximately the same rate as with the 1967 standard. Furthermore, the average efficiency level of employees approaches the required level of one hundred percent much earlier than one would expect by references to the 1967 standard. The first objective of the study was accomplished, since it was determined that production worker performance had changed over time. The change in actual performance indicates that the calculation of a new standard is warranted on a periodic basis. The new derived standard efficiency curve depicted in Figure 4.1, p. 94, is based on the average employee efficiency data used for the test period and indicates that the learning curve standard be revised from the 1967 standard. For this firm, the learning curve standard should be revised at least every twelve years and perhaps more frequently.

As stated, it was found that the old learning curve no longer fits the current performance efficiency data. Furthermore, it can be generalized that over time the learning curve changes. Thus, performance guidelines (objective two for the study) based on learning curves are applicable. Thereby, a periodic review, such as the performance evaluation revision cycle based on learning curve standards and illustrated in Figure 5.1, will aid management in the budgeting and controlling function of the firm. Management should first gather performance or efficiency data from past production records and derive a learning curve standard for workers (Step 1). The learning curve standard may also be developed from time and motion studies or _a priori_ managerial or production expectations. Once learning curve standards are derived, management should implement them by establishing minimum performance criteria for workers (Step 2). Incentives also may be used to encourage workers to perform either at minimum acceptable or above average performance levels.

Once a learning curve standard curve has been implemented, worker performance measurements will be taken and efficiency ratings assigned

FIGURE 5.1

PERFORMANCE EVALUATION REVISION CYCLE
BASED ON LEARNING CURVE STANDARDS



to each individual worker (Step 3). The efficiency ratings will be used to evaluate promotions, merit increases, or disciplinary actions concerning individual workers. Next, individual efficiency ratings should be combined and an overall average employee performance will be determined (Step 4).

The last step in the cycle is to compare average employee performance and the learning curve standard using the procedures described in this study (Step 5). Should significant differences exist between the learning curve standard and average employee performance, the process should be performed again and a new learning curve standard should be derived for workers. If significant differences do not exist between the learning curve standard and average employee performance, it may be concluded that the learning curve standard is currently applicable. In this instance, the learning curve is reinstated (Step 2) for workers. A performance evaluation revision cycle based on learning curve standards will enable management to evaluate performance and insure that required standards are current.

The discriminant analysis procedure used to test H2 was an attempt to identify factors which could be used to explain the change in performance levels. Demographic factors, as identified in Table 4.2, page 88, were used to determine if factors, other than production related factors, would explain different performance levels for employees in the study. The discriminant function did not significantly improve the classification of employees in their respective groups better than random chance. It was determined that environmental variables identified from this firm's employment application form are not useful in explaining differences between above average, average and below average employee groups. Thus, the environmental variables used in the study are not unique to each of the employee groups in the discriminant model; therefore, it was concluded that the null hypothesis $H2_0$ could not be rejected and evidence was not obtained to relate standards and environmental factors for production workers. The study failed to accomplish the third objective of providing evidence that standards and environmental factors for production workers can be linked and provide information to the firm for budgeting and planning purposes. The fourth objective of the study (provide a basis for further research) is discussed in a later section of this chapter.

RECOMMENDATIONS

The results presented in the study show that management should be concerned with the need to test and update expected efficiency levels that have previously been established as part of the budgetary process. Periodic revision of performance standards may impact the firm in several ways:

(1) The nature and authority of a budget enable management to establish a measurement device to evaluate performance.

(2) Communication between management and workers will be enhanced.

(3) Weaknesses in the budgeting structure will be isolated by examining the outcome of efficiency variances for workers.

(4) The degree of attainability of future budget goals may be evaluated on the basis of past performance and past revisions.

Frequent revision of standards may be facilitated by identifying the causes of changing performance patterns. Production factors such as changes in training programs, hiring policies, attitudes (both management and line employees, and, perhaps, motivational levels of employees) may be identified. Other factors, such as the environmental factors discussed in this study, may not be as easily identified. Performance, which changes over time, may be related to some factor or factors other than production factors.

It was shown that other studies[182] have related environmental factors, such as demographic factors, to employee tenure. This study attempted to identify one or more variables from twenty-five preselected demographic factors taken from employment application forms which would classify employees into one of three groups. The results indicated that the factors obtained in this study do not aid management either for screening of prospective employees or for predicting future employee performance levels during training. The significant implications in this study for other firms are:

(1) Twenty-five demographic factors examined in the study do not aid management to classify employee performance during the training period.

(2) Twenty-five demographic factors examined in the study (obtained from personnel applications) in the hiring sequence do not enhance management's predictive ability concerning future employee performance.

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[182]See Schuh (1967), Dirchner and Dunnette (1957), Wernimont (1962), and Tiffin, Parner, and Habersat (1947).

Even though management may be unable to identify probable cause and effect for potential changes in performance levels based on demographic factors, it is important for management to be aware of potential changes in performance efficiency levels. A periodic review to verify current efficiency levels will improve management's use of learning curves in the performance function of planning and control. Production schedules, sales promotions, and the like can be budgeted more effectively when forecasted production is closer to actual production.

SUGGESTIONS FOR FUTURE RESEARCH

The results of this study lead to a number of additional research possibilities. First, an examination of changes in the demographic factors listed in Table 4.2, page 92, and how often they change for workers may allow for improved discrimination among groups. After adjustments for the changing factors are made, the discriminant model may correctly classify employees into groups, thereby providing an extension of the results of the present study.

Another research project could examine other factors such as hygienic, psychological, or economic factors in the same manner as the present study. If factors such as these affect employee performance, a subsequent study could identify the degree to which employee performance can be classified into groups. Such a study could encompass the evironmental and behavioral aspects associated with changes in performance of workers.

A corrollary study which examines the same issues of this research might be made which examines "steady state" performance of workers.

Factors other than production factors may affect performance after the training period is completed although these factors did not significantly affect performance during the training period.

Finally, a similar study using other industries may provide additional insight into changes in performance standards. Other industries may have employment characteristics which are more sensitive to demographic factors than those of the present study. Thus, other industry studies may provide support to the notion that factors outside of the factory environment will help to classify worker performance levels.

APPENDIX 1

ASSUMPTIONS REGARDING LINEAR REGRESSION ANALYSIS

The assumptions regarding linear regression analysis are:

1. Assumption of constant error variances.
2. Assumption of independence of residuals.
3. Assumption of normality of error terms or residuals.

When the assumptions regarding linear regression analysis are violated, the results of linear regression analysis may be biased and may lead to incorrect application and interpretational inferences.[183] Tests will be made in order to determine possible violations of the assumptions noted above. Thus, residual analysis will be used for examining the aptness of a model as well as for possible departures from the model (3.1).

Prior to testing H1, inferences concerning the data should be made. Initially, the normal error model given by equation 3.1 is:

$$Y = \alpha + \beta X + \varepsilon$$

where:

Y are the observed responses

α and β are parameters

X are unknown constants

ε error terms

If the unknown true errors are independent normal random variables, "the observed residuals should then reflect the properties assumed" for the unknown true error.[184]

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[183] Op. cit., Neter and Wasserman, pp. 97-99.

[184] Ibid. pp. 160-65.

<u>Test for constant error variance.</u> Determination of constant error variance may be examined two ways. First, a plot of residuals against the independent variable will tell the researcher whether the variance of the error terms is constant. Second, an insignificant correlation between error terms and the independent variable will indicate that the variance of the error terms is constant.

<u>Test for Equality of error variances.</u> The method discussed above for testing two regression lines requires that the error terms in the two independent regressions have equal variances.[185]

The equality of the error variances can be tested by the F-test where:

$$F^* = \frac{SSE_1}{n_1 - 2} \div \frac{SSE_2}{n_2 - 2} \qquad (A.1)$$

where: F^* = F-statistic

SSE_1 = error sum of squares for first group.

SSE_2 = error sum of squares for second group.

The decision rule is based on the alternatives:

$H_0)\ \sigma_1^2 = \sigma_2^2$

$H_0)\ \sigma_1^2 \neq \sigma_2^2$

If: $F(\alpha/2; n_1 - 1, n_2 - 1) \leq F^* \leq F(1 - \alpha/2; n_1 - 1, n_2 - 1)$, do not reject H_0 and conclude equal error variances for regression

[185]Ibid.

[186]Ibid.

lines. Otherwise, reject H_0 and conclude H_a.[186] If the error variances are not equal, then SSE will be biased for one group as compared with another group. A biased SSE for one group will increase the likelihood that the two regressions will be unequal.

Test of independence of residuals. Analysis of business and economics often involves time series data. It is common for time series data to have error terms which are correlated over time. When error terms are correlated over time and linear regression analysis is used a number of consequences may result. The consequences include:

1. The mean squared error (MSE) may seriously underestimate the variance of the error terms.
2. The confidence intervals and tests using the t and F distributions are no longer strictly applicable.[187]

A Durbin-Watson test for lack of randomness of the residuals will be performed. Since a test for equality between two regression lines is based on F* of Equation 3.4, the results will not be strictly applicable unless the error terms are uncorrelated. The formula to be used to determine the Durbin-Watson test is:

$$D = \frac{\sum_{t=2}^{n} (e_t - e_{t-1})^2}{\sum_{t=1}^{n} e_t^2} \qquad \text{(A.2)}$$

where: D = test statistic

e_t = observed residual for time period t.

n = number of observations.

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[187] Ibid. pp. 352-56.

The decision rule is stated:

H_0) $e_i = e_j$ and $i \neq j$.

H_a) $e_i \neq e_j$.

where: e = observed residual for observations i and j.

Upper and lower bounds for the test statistic are determined such that a test statistic outside the bounds will lead to a definite conclusion:

If $D > d_u$, fail to reject H_0 and conclude autocorrelation parameter is zero;

If $D < d_L$, reject H_0 and conclude autocorrelation exists (H_a);

If $d_L \leq D \leq d_u$, reject H_0 and conclude the test inconclusive.[188]

Should $D < d_L$, indicating that autocorrelation exists between residuals, then a procedure, such as the iterative method, or the first differences approach, will be initiated in an attempt to transform the data.[189]

Normality test. A modified Kolmogorov-Smirnov D-statistic will be calculated to test that the residual values are a random sample from a normal distribution. This test measures the absolute difference between all residual values and the assumed distribution. However, a Shapiro-Wilk method will be used if the sample is small as this test "offers good power against a large class of alternative hypotheses even with a small number of observations."[190]

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[188]Ibid.

[189]Ibid., pp. 361-66.

[190]Op. cit., Barr, p. 429

Neter and Wasserman discuss two reasons why the normality assumption for the error terms is necessary. First, "the error terms frequently represent the effects of many factors omitted explicitly from the model" and the consequent composite error term may bias inference of the model. Second, testing procedures based on an F-test are sensitive to "moderate departures" from the normality assumption. However, for large sample sizes, departures from normality have little influence on linear regression inferences.[191]

An important consideration when considering the assumption of normality is the possible presence of outliers. An outlier is a value which is outside the "normal range" of the data, i.e. an extreme value which may affect interpretational ability of a model. Residuals will be compared with an overall sample residual standard deviation so that a comparison may be made concerning outliers. It is difficult to say definitively at just what point a residual value becomes an outlier since it depends upon the relationship of the observation to the rest of the data and the use of the data. Any extreme observation (outlier) could have an adverse effect on a fitted line, and thus, lead to misspecification of the model. However, an outlier should not be discarded unless justification for not using the value is present.

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[191] Op. cit., Neter and Wasserman, pp. 47-8.

The presence of outliers can be identified using a method presented by Behnken and Draper (1972)[192], Tietjen, Moore and Bechman (1973),[193] Prescott (1975),[194] and Lund (1975).[195] Tietjen, et al. proposed a test procedure to identify a single outlier based on the test statistic.[196]

$$R^*_n = \max \left| e_i/s \right| \tag{A.3}$$

where R^*_n = standardized residual for n residuals.

e_i = ith residual.

s = standard deviation.

Equation 3.5 is used to obtain, "a test statistic for a single outlier in a simple linear regression."[197] Furthermore, Prescott stated:

> These results suggest that quite close approximations to these critical values could be obtained by assuming that the variances of the residuals are reasonably constant and using the average value of these variances in the development of the percentage points of the test statistic.[198]

Thus, the decision rule is stated:

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[192]Donald W. Behnken and Norman R. Draper. "Residuals and Their Variance Patterns," Technometrics, Vol. 14, No. 1, February 1972, pp. 101-11.

[193]G. L. Tietjen, R. H. Moore, and R. J. Beckman. "Testing for a Single Outlier In a Simple Linear Regression," Technometrics, Vol. 15, No. 4, December 1973, pp. 717-21.

[194]P. Prescott. "Approximate Test For Outliers In Linear Models," Technometrics, Vol. 17, No. 1, February 1975, pp. 129-32.

[195]Op. cit. Lund, pp. 473-76

[196]Op. cit., Tietjen, et.al.

[197]Ibid.

[198]Op. cit., Prescott. p. 130.

H_0) Standardized residuals are equal for n residuals.

H_a) Standardized residuals are not equal for n residuals. Therefore, should $R > R^*_n$[199], one may not reject H_0. While the test statistic is not exact, negligible differences existed when "many thousands" of sampling experiments were tested using simulation studies.[200] Once standardized residuals are calculated, if R^*_n is less than the R-table value of critical values for standardized residuals developed by Lund,[201] then one should conclude that no outlier exists in the data. Should $R < R^*_n$, then H_0 will be rejected and one should conclude that one or more outliers exist. The researcher must evaluate the outlier to determine that effect, if any, it will have on the data should it be retained or deleted for any subsequent analysis.

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[199]Op. cit., see Lund, pp. 474-75, for table values (R).

[200]Op. cit., Prescott.

[201]Op. cit., Lund.

APPENDIX 2

SUPPORTIVE COMPUTATIONS FOR TABLE 4.6

Regression output	SSE	n
GROUP ONE (E1)	0.0275	29
GROUP TWO (E2)	0.0240	29
Average Monthly efficiency rating (AMER)	0.0205	29
Standard efficiency rating (LCS)	0.0027	29
Full model for E1 and E2	0.0515	58
Reduced model for E1 and E2	0.0403	61
Full model for AMER and LCS	0.02323	58
Reduced model for AMER and LCS	0.0504	61

Test for $H1_{01}$:

$$F^* = \frac{SSE(R) - SSE(F)}{2} \div \frac{SSE(F)}{n_1 + n_2 - 4}$$

$$F^* = \frac{0.040256 - 0.0515}{2} \div \frac{0.0515}{58 - 4}$$

$$F^* = \frac{-0.005622}{0.000954} = -5.8949$$

Test for $H1_{03}$:

$$F^* = \frac{SSE(R) - SSE(F)}{2} \div \frac{SSE(F)}{n_1 + n_2 - 4}$$

$$F^* = \frac{0.050367 - 0.02323}{2} \div \frac{0.02323}{29 + 29 - 4}$$

$$F^* = \frac{0.013569}{0.00043} = 31.541068$$

APPENDIX 3

EMPLOYEE PERFORMANCE RATINGS DURING TRAINING

Employee Identification Number	Performance Rating			
	Months Above Average (%)	Months Average (%)	Months Below Average (%)	Overall Rating
10	37.9	24.2	37.9	2*
11	6.3	56.3	37.4	2
12	35.7	42.9	21.4	2
13	44.4	29.7	25.9	3
14	77.3	13.6	9.1	3
15	59.1	27.3	13.6	3
16	46.2	30.8	23.0	3
17	25.8	48.4	25.8	2
18	76.2	23.8	0.0	3
19	3.2	19.4	77.4	1
20	32.3	16.1	51.6	1
21	19.4	58.1	22.5	2
22	35.7	46.4	17.9	2
23	71.4	17.9	10.7	3
24	0.0	18.8	81.2	1
25	20.0	32.0	48.0	1
26	24.1	34.5	41.4	1
27	13.3	53.3	33.4	2
28	17.2	34.5	48.3	1
29	35.7	14.3	50.0	1
31	35.7	50.0	14.3	2
32	10.0	46.7	43.3	2
33	28.1	37.5	34.4	2
34	9.4	59.4	31.2	2
35	3.1	40.6	56.3	3
36	60.0	30.0	10.0	3
37	12.5	34.4	53.1	1
38	0.0	28.1	71.9	1
39	62.5	25.0	12.5	3
40	0.0	9.4	90.6	1
41	20.0	53.3	26.7	2
42	25.8	45.2	29.0	2
43	43.8	46.9	9.3	2
44	6.7	60.0	33.3	2
45	46.7	33.3	20.0	3
46	9.4	21.9	68.9	1
47	16.1	32.3	51.6	1

* Performance ratings were equal for above average and below average. The overall rating was classified as average ratings.

APPENDIX 3 (continued)

EMPLOYEE PERFORMANCE RATINGS
DURING TRAINING

Employee Identification Number	Performance Rating			
	Months Above Average (%)	Months Average (%)	Months Below Average (%)	Overall Rating
48	3.4	31.0	65.5	1
49	52.9	35.3	11.8	3
50	91.4	4.3	4.3	3
51	6.2	43.8	50.0	1
52	6.2	40.6	53.2	1
53	17.2	55.2	27.6	2
54	72.0	20.0	8.0	3
55	26.7	50.0	23.3	2
56	59.4	34.4	6.2	3
57	100.0	0.0	0.0	3
58	40.6	31.3	28.1	3
59	40.6	43.8	15.6	2
60	33.3	41.7	25.0	2
61	18.8	56.2	25.0	2
62	96.7	0.0	3.3	3
63	12.9	45.2	41.9	2
64	9.4	56.3	34.4	2
65	46.7	40.0	13.3	3
66	57.7	34.6	7.7	3
67	33.3	22.2	44.4	1
68	23.1	46.2	30.7	2
69	100.0	0.0	0.0	3
70	71.4	28.6	0.0	3
71	10.0	10.0	80.0	1
72	10.5	42.1	47.4	1
73	63.2	31.6	5.2	3
74	72.2	16.7	11.1	3
75	5.6	44.4	50.0	1
77	17.6	29.4	52.9	1
78	76.5	17.6	5.9	3
79	53.3	33.3	13.3	3
80	26.7	26.7	46.6	1
89	40.0	20.0	40.0	2*
95	12.0	28.0	60.0	1
97	22.7	36.4	40.9	1
99	67.7	19.4	12.9	3

*Performance ratings were equal for above average and below average. The overall rating was classified as average ratings.

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