# THE INFLUENCE OF RESEARCH AND EDUCATION ON CES PRODUCTION RELATIONS

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## *Introduction*

THIS PAPER describes an experiment intended to reduce one part of the simultaneous equation bias usually encountered in the statistical estimation of production relationships. In the earliest, classic discussion of the simultaneity problem in production functions, by Marschak and Andrews,[1] changes in technology and differences in efficiency among the firms or industries were left among the random disturbances. In a more recent encounter with the problem, Irving Hoch [2] accounted for the differences in efficiency among agricultural units and the change in productivity over time by fitting individual time and firm intercepts in a generalized regression technique derived from the analysis of covariance.

As in our earlier paper,[3] we hypothesize that the "fundamental" variables, research and education, are influential in explaining inter- and intra-industry differences in efficiency. In this experiment, these variables are incorporated into the production function and their influ-

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[1] J. Marschak and W. H. Andrews, "Random Simultaneous Equations and the Theory of Production," *Econometrica,* 1944.

[2] I. Hoch, "Estimation of Production Function Parameters Combining Time-Series and Cross-Section Data," *Econometrica,* 1962, p. 34.

[3] "Fundamental Variables in a Generalized System of Production," presented at Econometric Society meetings, Copenhagen, July 1963.

ence on labor productivity is measured in a pooled time series and cross-section set of observations for a limited group of manufacturing industries in the United States during the 1950s.

We develop a production model which generalizes previous attempts in two respects: first, it does not assume that the elasticity of substitution between labor and capital is equal to any specific constant, as, e.g., in the Cobb-Douglas production function; second, the model permits the fundamental variables to influence all parameters in the system, not simply those that have a neutral effect on technology. In unconstrained form, the model is capable of measuring the influence of the fundamental variables on output, productivity, labor demand, and capital demand, as well as measuring the elasticity of substitution.

The paper is organized as follows. A labor productivity equation is derived from the constant-elasticity-of-substitution (CES) production function in the next section. The parameters in the equation are identified, and the effects of their changes are noted. Most of the section is devoted to the specification of the fundamental variables in the CES labor productivity equation, and to a discussion of their influence on the parameters of the CES production function.

The variables and the data are described in the third section. Ten manufacturing industries in the United States, for the period 1950–60, constitute the basic set of observations. The following variables are specified: real corporate gross product, labor, capacity utilization, the wage rate, product price, education, and research—all at the industry level. An extensive discussion of education and research is warranted by virtue of the paucity of data and their intractability. In particular, it was necessary to devise a new procedure to *quantify* the interindustry flow of knowledge from research that affects productivity. This required an application of the 1958 input-output table that was prepared by the Office of Business Economics.

The fourth section discusses the estimation procedures. It is mainly concerned with an application of covariance analysis to our productivity equation in the context of pooled time series and cross-section observations.

Finally, the empirical results are given in the fifth section in two parts: the first shows the results obtained from pooling all industry data and not explicitly introducing the research variable; and the second part contains the results of the complete model.

A principal, though tentative, conclusion that emerges from our empirical investigation can be anticipated here. It derives from the disparate estimates of the labor productivity equation in the durable and nondurable industries: Education and research have a relatively larger impact on productivity in the group of durable goods industries than they do on labor productivity in the nondurable group. In order to rationalize this pattern we note that the industries in the durable group are more closely linked in an interindustry trading nexus than those in the nondurable group; the diffusion of the results of education and research is therefore more effective in durables than among the nondurable industries.

## *The Model*

The constant-elasticity-of-substitution model of production forms the framework for the analysis. Since its properties have been explored in detail elsewhere, only a summary is given here. We write the production function of the two-factor case as follows:

$$X_0 = \gamma[kX_1^{-\alpha} + (1 - k)X_2^{-\alpha}]^{-v/\alpha} \tag{1}$$

where $X_0$ is gross output, $X_1$ represents the services of labor, and $X_2$ denotes the services of capital as measured by net capital stock. The parameters of the function require more discussion.[4]

### THE PARAMETERS

$\gamma$ denotes the efficiency of a technology. Given the primary factors of production—labor and capital—and given the other characteristics of a technology, the efficiency characteristic determines the output that results. Changes in $\gamma$ are neutral, i.e., they alter the relationship of the combined factor inputs to output but do not affect the marginal rate of substitution between labor and capital for given labor-capital ratios.

$v$ is a homogeneity parameter, representing the degree of returns to scale. For $v \gtreqless 1$, there are economies of scale, constant returns, and diseconomies of scale, respectively. Changes in $v$ have a neutral effect.

$k$ is a capital intensity parameter. Degrees of capital intensity are reflected in the size of labor-capital ratios for given relative factor prices.

[4] A complete exposition of the function is given in M. Brown, *On the Theory and Measurement of Technological Change*, Cambridge, Eng., 1965, Chaps. 2, 4.

Thus, the larger is $k$, the larger is the labor-capital ratio for all values of the ratio of labor and capital prices. A change in $k$ will have a nonneutral effect; an increase in the value of $k$ is laborsaving, in the sense that the marginal rate of substitution of labor for capital rises at each labor-capital ratio. However, an increase in $k$ augments the rate of growth of output only if the supply of capital is increasing relatively faster than the supply of labor.

$\alpha$ is a function of the elasticity of substitution between labor and capital; specifically, $\alpha = 1/\sigma - 1$. The elasticity of substitution measures the rate at which the marginal product of capital rises relative to the marginal product of labor as labor is substituted for capital. It can also be thought of as measuring the rate at which the marginal product of labor rises as the real wage rate rises. We know that if a change in technology generates an increase in the elasticity of substitution, there is a nonneutral effect: the increase in $\sigma$ is laborsaving if the growth of capital exceeds the growth of labor. Moreover, changes in the elasticity of substitution due to technological progress are directly related to changes in the growth of output.[5]

THE PRODUCTIVITY EQUATION

We now want to specify the labor productivity relation in terms of the CES production function. We can start by considering the marginal productivity of labor derived from (1):

$$(2) \qquad \delta X_0/\delta X_1 = h_0' X_0^{1+\alpha/v} X_1^{-1/\sigma}, \text{ where } h_0' = (1 - k)v\gamma^{-\alpha/v}.$$

The capital intensity affects the marginal productivity by way of the $k$ parameter and the elasticity of substitution. A crucial assumption here is the independence of the empirical substitution relationship from the stock of capital.

Equating (2) to the deflated wage rate, $P_1/P$, and expressing the result in terms of the labor productivity index, $X_0/X_1$, we have

$$(3) \quad X_0/X_1 = h_0^*(P_1/P)^\sigma X_0^r, \text{ where } r = 1 - \sigma + \frac{\sigma - 1}{v}, \text{ and } h_0^* = (h_0')^{-\sigma}.$$

The output term, $X_0$, brings returns to scale and variations in capacity utilization into the relationship. Clearly, when $v = 1$, that is, when there

[5] The proofs of the propositions that involve changes in the parameters of the CES production function are given in *loc. cit.*

are constant returns to scale, then $r = 0$, and variations in output have no effect on the productivity of labor. In the empirical tests, the output term on the right of (3) has been replaced by a capacity utilization index, denoted by $S$, so that we have

$$X_0/X_1 = h_0^*(P_1/P)^\sigma S^a, \tag{4}$$

where $a$ is a parameter. One final adjustment should be noted before introducing the fundamental variables into the labor productivity equation. In (4) the real wage rate is assumed to influence output per unit of labor in the given period. But that assumption rests upon a dubious and unnecessary assumption that the observed data reflect equilibrium situations. The possibility that labor productivity is not in instantaneous equilibrium at the given real wage rate can be handled realistically by allowing the effects of changes in the wage rate to be spread over time. This requires that we write the deflated wage variable in distributed lag form. In this case, a Fisher distributed lag is specified.[6] It is written as $\rho'_{\eta,t-\delta}$, where $\eta$ is the number of wage terms in the distributed lag expression and $\delta$ is the order of the lag. For example,

$$\rho'_{3,t-2} = [(P_1/P)_t^3(P_1/P)_{t-1}^2(P_1/P)_{t-2}]^{1/6}.$$

The labor productivity estimating form is now given by

$$X_0/X_1 = h_0^*(\rho'_{j,t-\delta})^\sigma S^a. \tag{5}$$

It should be noted that (5) is linear in logarithms and can be easily estimated by standard regression techniques.

We still have the problem of specifying the fundamental variables in the labor productivity equation. And, we want to accomplish this in such a way that the resulting econometric testing form is a simple one, in this case, one that is linear in logarithms. Data constraints are so severe, as we shall see below, that a simple form is required. Now suppose that our production function is the generalized CES function:

$$X_0 = \gamma[k_1X_1^{-\alpha} + k_2X_2^{-\alpha} + k_3X_3^{-\alpha} + k_4X_4^{-\alpha}]^{-v/\alpha}, \tag{6}$$

where $X_3$ is an educational attainments variable, $X_4$ represents the services of research and development, and the $k$'s are intensity coefficients.

[6] The choice of the Fisher lag scheme in this setting is discussed in M. Brown and H. Wachtel, *The Share of Corporate Profits in the Postwar Period,* U.S. Department of Commerce Staff Working Paper No. 11, April 1965, pp. 66 ff.

Equation (6) is the first type of generalization proposed by H. Uzawa.[7] It assumes, *inter alia,* that the elasticities of substitution between all pairs of variables are the same. Now, taking the marginal product of labor from (6) gives us (2), as the reader can verify. This, of course, does not contain the fundamental variables in a simple manner, and hence we cannot accomplish our objectives by specifying the production function as in (6).

Consider another generalized CES function (also proposed by Uzawa):

$$(7) \qquad X_0 = \gamma[k_1X_1^{-\alpha_1} + k_2X_2^{-\alpha_1}]^{-v_1/\alpha_1}[k_3X_3^{-\alpha_2} + k_4X_4^{-\alpha_2}]^{-v_2/\alpha_2},$$

where $\alpha_1$ is the partial elasticity of substitution between $X_1$ and $X_2$, and $\alpha_2$ is the partial elasticity of substitution between $X_3$ and $X_4$; the other parameters are interpreted as above, with the modification that $v_1 + v_2 = v$. In this particular form of the generalized function, the ease of substitution between the fundamental variables is allowed to differ from the partial elasticity of substitution between labor and capital, which seems to be more reasonable than the assumption in (6). However, the elasticity of substitution between labor and education, say, is taken to be unity, an assumption that is subject to serious question. In any event, the marginal product of labor from (7) yields (2), and we have still failed to specify a productivity equation which includes research and education in a simple manner (as defined above).

Arguing as we did in the previous Brown-Conrad paper that the parameters of the production function are influenced by variations in the fundamental variables, we can return to (1) and specify the following:

$$(8) \qquad \gamma = \gamma(X_3, X_4) = \gamma_0X_3^{\gamma_1}X_4^{\gamma_2},$$

$$(9) \qquad k = k(X_3, X_4) = k_0X_3^{k_1}X_4^{k_2},$$

$$(10) \qquad \alpha = \alpha(X_3, X_4) = \alpha_0X_3^{\alpha_1}X_4^{\alpha_2},$$

$$(11) \qquad v = v(X_3, X_4) = v_0X_3^{v_1}X_4^{v_2}.$$

By inspection, it is seen that if we assume $\alpha_1 = \alpha_2 = 0$, then the substitution of (8)–(11) into (5) yields precisely what we are striving for:

[7] "Production Functions with Constant Elasticities of Substitution," *Review of Economic Studies,* October 1962, pp. 291–99.

a labor productivity form which both contains the fundamental variables and is linear in logarithms. Before specifying the relationship formally, however, we wish to indicate the directions of the effects of the fundamental variables on the parameters of the CES production function. In other words, what signs should be expected on the parameters in (8)–(11)?

### THE INFLUENCE OF THE FUNDAMENTAL VARIABLES ON THE CES PARAMETERS

It is difficult to see how the $\gamma_i$ ($i = 1, 2, 3$) could be anything but positive. That is, an increase in education and research should raise the productivity of each variable input in a neutral sense. A number of recent studies on the Cobb-Douglas function support this assertion.

As we pointed out earlier, an increase in $k$, the capital intensity parameter, is laborsaving in any event but will augment output only if the relative supply of capital is increasing. The effect of research on $k$, then, depends upon the success of research in reducing relative factor scarcity. If the innovational activity is directed toward saving labor, and if it is effective, then $k_2 > 0$. If long-term unit capital rents are increasing relative to wages, then $k_2$ may be negative when research has succeeded in reducing the relative scarcity. This argument rests upon a model of research activity in which the stock of technical information is reoriented by shifts in the composition and reductions in the service life of knowledge aimed at economizing in the face of different relative factor scarcities. In the present paper, the relationship between the service life of information and the long-run relative scarcities is avoided by treating $X_4$ as a flow rather than a stock. This involves some misspecification, however.

With respect to education, there should be a positive relation between that variable and the capital intensity of a technology. For if $k$ rises, then a laborsaving technological change has occurred; and if education is doing its job well, then a labor force with a given stock of education and a given stock of facilities on which to operate should be more productive than a labor force with a smaller stock of educational attainments, *cet. par.* Hence a rise in $X_3$ should be laborsaving, and $k_1$ should be positive.

We note that the homogeneous functional form for $k$ is a misspecification, since it is constrained in the interval, $0 < k < 1$. A form incorporating an asymptote for each of the fundamental variables would have been more appropriate. However, being interested only in the directions of the effects, it is unnecessary to pursue this here.

Although we are assuming that $\sigma$ is constant in this paper, it may be useful to make a few remarks about the possible effects of the fundamental variables on the elasticity of substitution. Research directed toward reductions in factor scarcities should also be oriented toward making factor substitutions relatively easier. However, to the extent that innovation and education have the effect of increasing specialization, the elasticity of substitution may be reduced: A given machine may require a given complement of specific skills. One more anomaly follows from this suggestion: If increasing specialization means that more highly trained people achieve larger outputs with given stocks of equipment, then increasing education raises the elasticity of substitution. Obviously, more work is required on these questions.

To the extent that research and education increase the complexity of production processes, requiring control over increasingly larger amounts of resources for economical operations, there is a positive relation between the fundamental variables and the homogeneity parameter, $\nu$. Hence: $\nu_1, \nu_2 > 0$.

## THE ADJUSTED PRODUCTIVITY EQUATION

The discussion of the relationships between the fundamental variables and the characteristics of the technology in a CES production system has raised many more problems of measurement than we are prepared to handle in the present paper. In order for us to make contact with the central issue of the relationship between the fundamental variables and productivity, it is necessary to treat the former set of relationships in a highly simplified manner. Thus, since it is known that the $h_0{}^*$ term in the labor productivity form, (5), is a conglomerate of parameters, each of which is a function of the fundamental variables, then $h_0{}^*$ must be a function of the fundamental variables, and can be specified as

$$h_0{}^* = h_0 X_3{}^{h_1} X_4{}^{h_2}. \tag{12}$$

This specification treats the relationships between the fundamental variables and the technology as a package, a procedure which has the considerable advantage of permitting direct estimates of the influence of the fundamental variables on productivity. For, combining (12) and (5) yields:

$$(13) \qquad X_0/X_1 = h_0 X_3^{h_1} X_4^{h_2} (\rho'_{\eta,\, t-\delta})^{\sigma} S^{a},$$

which is linear in the logarithms and is relatively simple to estimate. The fundamental variables in (13) are expected to be directly related to labor productivity.

To sum up, labor productivity in (13) depends upon the following factors: the long-term substitution of capital for labor, as reflected by the lagged product-deflated wage rate; the utilization of capacity; the educational attainments of the work force; and the knowledge resulting from research and development activity. The form permits the fundamental variables to reflect the neutral as well as nonneutral characteristics of the technology within a constant-elasticity-of-substitution framework.

We now turn to a description of the procedures used to estimate (13).

## *The Variables and the Data*

A basic set of data for ten industries is used in the present study. Although some of the series are available for longer periods, a reasonably matched set of data can only be developed for the period 1950–60. For the most part the data conform to the United States national income accounting system. The industries are given in the following table with their SIC codes.

| *Industry* | *SIC Code* |
|---|---|
| Food and kindred products | 20 |
| Textile mill products plus apparel | 22 |
| Paper and allied products | 26 |
| Chemicals and allied products | 28 |
| Stone, clay, and glass products | 32 |
| Primary metal industries | 33 |
| Fabricated metal products, including ordnance and accessories | 34 |
| Machinery, except electrical | 35 |
| Electrical machinery | 36 |
| Automobiles and automobile equipment plus other transportation equipment | 371 |

All major series are on an establishment basis. With the exception of the basic education data, all refer to the corporate sector in each industry.

REAL CORPORATE GROSS PRODUCT AT FACTOR COST FOR INDUSTRY $j$, $X_{0,j}$

This is obtained by summing profits (net of depreciation but including the inventory valuation adjustment), interest, employee compensation (wages and salaries plus supplements), and capital consumption allowance (depreciation plus accidental damage, and capital outlays charged to current expense).[8] By excluding such nonfactor costs as indirect business taxes, the corporate gross product series is conceptually closer to a factor cost than a market cost measure. The current-dollar corporate gross product series are deflated, using specific two-digit industry deflators developed in the National Economics Division of the Office of Business Economics.

As measured here, the corporate real gross product variable reflects advances in technology that result in reductions in costs; however, those reflected in new products, or in improvements in existing products which do not affect costs, are not included in the gross product series. To the extent that research inputs are directed toward new-product development, which is considerable, the estimated contribution of research will be biased downward in our model.

THE SERVICES OF LABOR, $X_{1,j}$

This is measured by the total annual man-hours worked in industry $j$, which is obtained by combining the total employed and an average hours series. The series for total employed is the same as that used by the National Income Division of the Office of Business Economics, which is based upon data compiled by the Bureau of Employment Security.[9] The industry series on production hours is from the Bureau of the Census.[10] The average hours series refers to production hours worked,

[8] The conceptual and methodological framework for developing a corporate gross product series by industry of origin is patterned after that used by the National Economics Division of the Office of Business Economics. See Martin L. Marimont, "GNP by Major Industries," *Survey of Current Business*, October 1962, pp. 13–18; and "GNP by Major Industries," Office of Business Economics, unpublished.

[9] *Employment and Wages*, U.S. Department of Labor, Bureau of Employment Security.

[10] *Annual Survey of Manufacturers*.

but the employment series includes both production and nonproduction workers. It is assumed that nonproduction workers work approximately the same hours as production workers.

### THE WAGE RATE, $P_{1,j}$

The variable which measures the price of labor in equation (13) is derived by taking the ratio of employee compensation to total man-hours worked, $X_{1,j}$. Compensation of employees includes the sum of wages and salaries, plus such supplements to wages and salaries as employer contributions to social insurance funds, private pensions, health, and welfare funds. The source of the data is the Bureau of Employment Security. To obtain the product deflated wage rate, $P_{1,j}$ is divided by $P_j$, which is the same deflator that is used to obtain the constant-dollar corporate gross product series. The resulting deflated wage measure for each industry approximates the weighted average hourly product deflated wage in the industry, the weights being the total hours worked in each occupation.

It should be mentioned that the derivation of the hourly wage rate requires that employee compensation be divided by total man-hours worked, which is the same variable that forms the denominator in the labor productivity ratio. This does not introduce spurious correlation, however, since the productivity relationship is specified in terms of ratios; specifically, it relates labor productivity to the average wage rate.[11]

The distributed lag in the real wage rate was specified, as noted above, to reflect the long-run influences on productivity.[12] Due to data constraints, the order of the lags that were selected are typically low; for the most part, they are of order two and three. This limitation can be easily remedied, if necessary, as data points accumulate.

### THE CAPACITY UTILIZATION INDEX, $S_j$

Two measures of capacity utilization were constructed at the industry level. One was patterned after the Wharton School methods; and the

[11] E. Kuh and J. R. Meyer, "Correlation and Regression Estimates When the Data Are Ratios," *Econometrica,* October 1955.

[12] The particular Fisher lag used in the present study was selected by criteria developed and presented in an earlier monograph: Brown and Wachtel, *op. cit.,* pp. 72–73.

other makes use of a method developed by Daniel Creamer.[13] The Wharton School measure requires that trend lines be constructed through output peaks which represent potential output series; the ratio of actual to potential output forms the measure of capacity utilization. The Creamer method uses a minimum capital-output ratio as a capacity benchmark, and then specifies the ratio of benchmark minimum capital-output ratio to each annual capital-output ratio as the measure of utilization. In the present applications, both methods are modified in certain respects which are detailed in the data appendix to the Brown-Wachtel study. The two utilization series are quite different for most industries. The criteria used to select the index for the productivity relationships are discussed also in the Brown-Wachtel study. Suffice it to say here that the construction of two indexes and the selection of the one which performed in a superior manner was motivated by a desire to reduce the specification error inherent in capacity utilization variables.

The specification of the output variable in the capacity utilization measures raises again the possibility of spurious correlation. Yet, recognizing this deficiency, we decided to use them in the present study in lieu of an acceptable alternative. Clearly, additional work is required on the problem of specifying the capacity utilization variable.

EDUCATION, $X_{3,j}$

The education variable is a measure of the average attainment of formal education in the employed work force of each industry over the sample period. Measured simply in years per worker, it is an average measure of the stock of educational capital embodied or objectified in the employees of the industry.

The basic data from which the variable was constructed were taken from the 1/1000 household sample, 1960 Census tape, and the 1950 Census, PE1-C, "Occupation by Industry," Table 2, and "Occupational Characteristics," Table 10.

The key figure in the computation, the median years of education in the industries in 1960, was obtained by aggregating over the medians of the detailed (297 individual titles) occupations within each industry. There is considerable variation in the years of education within single

[13] The methods are described in *Measures of Productive Capacity,* Report of the Subcommittee on Economic Statistics, Joint Economic Committee, 87th Cong., 2d Sess., 1962.

occupations, depending upon the industry, and for that reason it was decided to construct the industry estimates from the complete education-by-occupation-by-industry block of data.

Since comparable data were not available for 1950, however, the rate of change within each industry had to be computed from the medians for each of the occupations, given without regard to industry. For each industry in 1950 and 1960, the number of employees in each occupational category was multiplied by the median years of school completed for that occupation, to give a "stock" of education for the occupation in that industry. The stock figures were then aggregated for the two groups for which annual employment data were available—production workers and nonproduction workers—for each industry.

A set of median-stock-of-education series was then computed, using the decade trends for each industry's production and nonproduction workers separately and the annual employment proportions for the two groups. Finally, the year-to-year proportional changes from that series were applied to the 1960 detailed industry and education stock figure. The resulting education series is in units of average years of education per worker, unweighted by income differentials. The improvement in the "quality" of labor brought about by education is taken to be directly proportional to median school years completed.

RESEARCH AND DEVELOPMENT, $X_{4,j}$

The problem of finding an empirical specification for research and development that would fit the fundamental variable in the model and at the same time match the other variables dimensionally was one of the most difficult tasks of this study. (We are far from satisfied with the measures upon which we settled.) The model calls for an estimate of the knowledge that results from research activity, in the form that affects measured labor productivity. That is, since we use a productivity measure based upon national income concepts, which is therefore downward biased to the extent that technological changes are reflected in new products and new distribution systems, etc., the measure of research and development should have been confined, if possible, to cost-reducing activities.

Two upward biases can be identified in the research data we found available. The first, directly related to what has been said above, arises from the fact that much research activity in American industry is directed to the development of new products and is therefore not relevant to the explanation of labor productivity which is defined in gross product terms.[14] The second comes from the shift from unreported, unorganized research to organized and explicitly budgeted activities. However, in view of the short period covered in this study, this would be of negligible importance.

On the other side, there are downward biases in the data. Many innovations occur in the form of organizational knowledge—for example, as improved work-flow layouts. These result in productivity increases, but are not likely to be based on measured research and development activity. But this is of minor importance compared to the downward bias in the published series, attributable to the international and interindustry nature of technological knowledge. Obviously, the total flow of technological information which can be utilized by a given industry is in no way limited to what is produced within the industry's research facilities.

There is a kind of temptation offered by the fact that we can balance the biases in terms of direction, even though we are otherwise almost totally ignorant of their quantitative effects. Without pretending that we can cancel them off against one another, we do assume that increments of technological knowledge are proportional to the resources used for industrial research and development.

A second major, maybe heroic, assumption underlies the identification of each industry's research level. The second assumption is addressed to the part of innovational activity that is relevant to an industry's productivity but is not conducted in the industry itself. The activity in question may be carried out in those sectors that supply the given industry with structures, equipment, and materials. Improved processes and products in supplying industries will have cost-reducing effects among their customer industries. It is natural, in this light, to search for an interindustry measure of the flow of knowledge, corresponding to the diffusion or reverberations of technological improvements through the economy, which a number of writers have examined before. The basic data will be described first and then the input-output procedure will be outlined.

The industry data on research and development expenditures are pro-

[14] See Nestor Terleckyj, *Research and Development, Its Growth and Composition,* National Industrial Conference Board, 1963, p. 54.

vided by the National Science Foundation. From 1952 to 1956 the Bureau of Labor Statistics developed the data for the NSF, and from 1956 to the present the Bureau of Census has been responsible for the compilation. Differences between the two series are due to different industry classifications, differences in reporting, variations in responses from the same reporting entity, and different sampling and estimating methods. These discrepancies have not deterred several investigators—including the present authors—from attempting to link the two sets of time series. Putting the two together allows us to test the model on industry observations drawn from the period 1952–60.

Attempting to mitigate the unreliability of the basic research and development data, several forms of the variable were constructed and tested. A third-order Fisher lag in real research expenditures and the unlagged real expenditure series were both tried. In addition, a research intensity variable was prepared by averaging the real gross product–real research expenditure ratios for 1952 and 1960 for each industry. From these averages, dummy variables were constructed which had the effect of grouping the industry observations into three sets according to their relative research commitments. None of these specifications provided a satisfactory measure of the relevant cost-reducing inputs of research and development. Finally, an interindustry research variable was constructed in the following manner.

For each industry in the data sample an interindustry research weight was estimated, reflecting the cost-reducing possibilities carried by the major intermediate flows of goods in 1958. From the column of inputs into each industry, purchases (from manufacturing industries) that exceeded 1.2 per cent of the column total were recorded. Then, the ratio of the recorded flow to the delivering industry's output was listed, and these proportions were then applied to the delivering industries' research and development expenditures. A similar division was made of the receiving industry's own research expenditure and the two—the direct expenditure and the indirect sum of expenditures—were summed to give the industry weight. An illustration, from the computation for food and kindred products, is given in Table 1. The interindustry flows are taken from the 1958 Input-Output Study.[15]

[15] M. R. Goldman, M. L. Marimont, and B. N. Vaccara, "The Interindustry Structure of the United States," *Survey of Current Business,* November 1964, pp. 10–29 (the SCB numbers in the table are those used in the article). An alternative proposed by Mr. Terleckyj—to include as the "own-expenditure" contribution

TABLE 1

*Interindustry Research Weight for Food and Kindred Products (SCB 14)*

| | | |
|---|---|---|
| (1) | Purchases by SCB 14 from: SCB 39 – Metal containers | $23.88 mill. |
| | SCB 25 – Paperboard containers | 13.81 mill. |
| (2) | Proportion of delivering industry outputs: SCB 39 | 72.80% |
| | SCB 25 | 24.20% |
| (3) | Delivering industry's research expenditures: SCB 39 | $13 mill. |
| | SCB 25 | $11 mill. |
| (4) | Proportions applied to Food, (2) × (3): SCB 39 | 9.46 |
| | SCB 25 | 2.66 |
| | | 12.12 |
| (5) | Receiving industry's research expenditure | $83 mill. |
| (6) | Receiving industry's delivery to itself, proportion: | 16.20% |
| (7) | Proportion of (5) applied to Food: | $13.45 mill. |
| (8) | Interindustry research weight, (4) + (7): | 25.57 |

The next step involved the construction of a time series of research expenditures to which the interindustry weights could be applied. Again, a data constraint presented itself, for reasonably reliable research expenditure data by industry extend only back to 1952. This is inadequate for the time series analysis, since it is well recognized that research expenditures are related to productivity with a lag, and the available industry research data is of insufficient length to permit a lag specification and still have a minimally acceptable number of degrees of freedom. In addition, the length or order of the lag is difficult to specify. The first problem was treated by assuming that the trend in the growth of knowledge in each industry is proportional to the trend in the non-

*all* of the industry's research expenditure, instead of the internal deliveries only—involves considerable double-counting and inflation in some sectors. We tried it in the procedure used for the Table 3 estimates, with the following results: The coefficients on education were rendered completely insignificant in both groups, though $R^2$ was improved in the nondurables. When the symmetrical procedure (see our Reply to the Comment below) was used, there was no significant difference between the results with the two research variants.

farm private domestic sector, which permitted us to use total industry research and development expenditure data covering the period 1921–60, derived by Nestor Terleckyj,[16] but adjusted to exclude government and farm expenditures.[17] The final series were deflated by a cost-of-research index developed by Ellis A. Johnson and Helen S. Milton.[18]

The determination of the distributed lag in research expenditures was accomplished by trial and error: i.e., we experimented with various lag structures and orders and selected the one that performed in a superior manner. This gave us an inverted-V, fifteen-year Fisher lag which has the impacts of each annual, real expenditure on research and development increase at the rate of 20 per cent up to the fifth year and decrease by 20 per cent annually thereafter to the fifteenth year.[19] The application of the interindustry weights to the time series variable provided us with a research variable that has two important characteristics: a lag in the impact of real research and development expenditures, and interindustry differences that reflect the diffusion of technological knowledge among industries. We discuss this further below.

### *Estimation Procedures and the Analysis of Covariance*

The logic of the technological progress relationship, the econometric specification derived from the CES function, and practical constraints imposed by the multicollinearity in our short time series require that we turn to pooled data in order to estimate the elasticities attached to research and education. Reasonably sufficient evidence is available for the estimation of the elasticity of substitution, $\sigma$, and the short-run capacity utilization effect, $a$, in the individual industries. But the fundamental variables in time series present us with serious statistical and conceptual problems. First, the series for research and education move closely together, and the short-run variations, especially for education, are dominated by strong trends. Since World War II, especially, there have been upward pressures on both series due largely to government

[16] *Op. cit.*, p. 39.

[17] Brown and Conrad, *op. cit.*

[18] "A Proposed Cost-of-Research Index," Operations Research Office, Johns Hopkins University, Staff Paper ORO-SP-142, February 1961.

[19] The justification for specifying the fifth year as the year of major impact is derived from a McGraw-Hill survey reported by Terleckyj, *op. cit.*, p. 55n. The fifteen-year service life assumption emerged from experiments in which different service lives were specified; the one we selected performed best.

support of a national policy for technological change and the continuing high level of activity. The resulting high correlation makes it extremely difficult to distinguish between the influences of the two variables or to estimate their parameters with much precision.

Secondly, it is difficult to conceive of the technological progress function (13) as representing the structure within which short-run choices are made among the alternatives facing an individual decision maker (whether the unit is a firm or establishment or even, stretching several points, an industry). Short-run variation in the production-worker-overhead–worker ratio is feasible, of course, and in most industries would cause the education index to vary. But that variation is more likely to be based upon exogenous cyclical swings in production levels than upon a real substitution decision. Changes in the amount of education "embodied" in the labor force reflect relatively long-run decisions rather than responses to short-term fluctuation in the relative price of formal training. Over a short period of time, then, we should expect levels of education to vary much more *among* industries than within single-industry time series.

There is more obvious evidence of year-to-year variation in expenditures on research and development. Research budgets, though they have been increasing at an increasing rate during the postwar years, tend to be tied, in the short run, to lagged gross profit levels, for reasons of capital supply, and to movements in relative factor prices, in a Hicksian or neoclassical response to cost pressures.[20] But, given the lags between (1) industrial research outlays, (2) innovational results, if any, and (3) subsequent embodiment in equipment or organizational change, we should not expect the appropriate evidence for innovational influence to show up in the short-run covariation between industrial development expenditures and an index of productivity change. Again, however, differences in the level and trend of the fundamental variables among industries, indicating differences in innovational activity, can be expected to vary with the long-run trends in productivity.

Given these constraints, we decided to use pooled time series and cross-section data in order to test the hypothesis that the fundamental variables affect the parameters of the CES production function. When

[20] See E. Mansfield, "Industrial Research and Development Expenditures: Determinants, Prospects, and Relations to Size of Firm and Inventive Output," *Journal of Political Economy*, August 1964, on the first reason, and Brown and Conrad, *op. cit.*, on the second.

the time and industry data were pooled, there was a sufficient number of observations for the test and considerably enriched variation to justify some hope of precision. But from the outset, it was obvious that the industries were heterogeneous in their productivity relationship and that some extraneous estimating procedures would be needed. Actually, two alternative statistical specifications of equation (13) were tried in a regression procedure derived from the analysis of covariance by S. S. Wilks. The difference between the two forms is in the method used to adjust labor productivity for the effects of short-run capacity utilization and for the substitution of capital for labor.

In the unconstrained model, derived directly from equation (13), the effects of the fundamental variables, the short-run capacity utilization variable, and the long-run factor substitution variable are estimated over the whole set of observations. Productivity is to be explained by all four variables; and estimates of the parameters, fitted by the usual regression procedures (under the usual assumptions), are undifferentiated as to industry.

In the "constrained" model, the factor price and cycle effects on productivity are accounted for by individual time series analyses. The productivity variable is then adjusted for these effects and the residual variation is explained by the fundamental variables in a time series of manufacturing cross sections. Consider the new variable,

$$z_{jt} = \log (X_0/X_1)_{j,t} - \hat{\sigma}_j \log \rho'_{j,\eta,t-\delta} - \hat{a}_j \log S_{jt} \tag{14}$$

where the $\hat{\sigma}_j$ and $\hat{a}_j$ coefficients have been extraneously estimated from single-industry data.[21]

[21] See Brown and Wachtel, *op. cit.*, for the procedure that was used to fit the industry coefficients. There is some asymmetry in the "constrained" model, in that the productivity variable is adjusted for factor price and cycle effects, but the explanatory variables are not.

Professors Malinvaud and Griliches have noted that if the explanatory variables are uncorrelated with $\rho'$ and $S$, then the coefficients should not be biased, though the standard errors may be underestimated. Two additional experiments have since been tried: (1) using a pooled residual procedure to get round the problem of insufficient significance in the regressions of the individual-industry education and research variables on $\rho'$ and $s$; and (2) a completely symmetrical procedure. In the first experiment, there was improvement in the $t$ ratios and $R^2$ (corrected) for the durables group, with some exaggeration of the difference between the coefficients; in the nondurables, the $t$ ratios were reduced and the $R^2$ (corrected) much reduced, with no essential change in the magnitudes. In the second, fully symmetrical case, there was very little change in the durables statistics, but the significance on the nondurables research variable was obliterated, along with the $R^2$ (corrected). The estimates, and an intuitive argument for preferring the original procedure, will be found in our Reply.

Almost from the first appearance of a production function fitted across industry data, it has been argued that no economic meaning can be attached to a regression surface fitted to industry points in a three-dimensional—value added, labor, capital—space. Industries are not decision-making units, allocating homogeneous resource inputs under equivalent profit-maximizing conditions. Secondly, as technological conditions and the composition of aggregate value added both change, it is unlikely that industries will retain their relative positions on the production surface; the fitted elasticities in the production function will then be unstable, however stable the component (micro-) relationships might be. In the present case, the first problem, with respect to the homogeneity of inputs, is partially met. The education variable is defined so as to give considerable comparability among industries; research and development activity is unfortunately more specific to the individual sectors. The second difficulty is more effectively met in our data, however; relative research intensities and educational attainments remain stable among the industries in our sample over the period under examination.

In addition to the specific short-run industry production parameters, it is expected that there will be other omitted variables which differ among industries, but which may or may not differ over time. The manufacturing industries present a basically heterogeneous sample. The fitted time series elasticities, then, which define the response of output per unit of labor to the quality of that labor and to the research expenditures within single industries, may vary significantly from sector to sector. We argued earlier, however, that the technological progress relationships are not to be defined meaningfully in terms of short-run variations: the economic significance of heterogeneity among the time series regression coefficients is therefore limited and much less compelling with respect to the estimation of our model than the formal tallies of heterogeneity in the $F$ tests would imply. The important short-term microrelationships do enter the econometric model explicitly: individual capacity utilization and elasticity of substitution terms are entered with each observed point in the array. After the short-run adjustments have been made, it is assumed that the remaining variation is similar from industry to industry, when the fundamental variables have been entered, *except for a constant.* Following Hoch, we experimented with the use of individual-industry intercepts to pick up the differences with respect to omitted influences which are peculiar to each industry and independent of the included variables. The effectiveness of these procedures and the plausibility of these arguments can be considered again when we present the covariance results.

The analysis of covariance enters the present study in the estimation of the regression coefficients as well as in the testing of the model, first, for stability over time, and then, for homogeneity among the industries. Kendall [22] pointed out the relationship between variance analysis and regression analysis, following Fisher and Wilks. Then he extended the discussion to the analysis of covariance. The testing procedure, derived from Kendall and Mood, has been described in an econometric time series and cross-section setting by Kuh.[23]

Let us consider the simplest version of the problem at hand. We are trying to estimate the response of adjusted output per unit of labor ($z$) to the logarithm of inputs of education in the labor force ($x_3$). The observations in given slices of time across industries will yield the following moments:

$$(15)\qquad \sum_{jt}(z_{jt}-z_{..})(x_{3,jt}-x_{3,..}) = \sum_{jt}(z_{jt}-z_{.t})(x_{3,jt}-x_{3,.t}) + \sum_{t}(z_{.t}-z_{..})(x_{3,.t}-x_{3,..})$$

from which the pooled regression coefficient

$$\hat{h}_1 = \frac{\Sigma(z_{jt}-z_{..})(x_{3,jt}-x_{3,..})}{\Sigma(x_{3,jt}-x_{3,..})^2}$$

may be derived. The sum of squares of the deviations from the pooled regression equation may then be partitioned as follows:

$$(16)\qquad \sum_{jt}(z_{jt}-h_t-h_1x_{3,jt}) = \sum_{jt}(z_{jt}-\hat{h}_t-\hat{h}_1x_{3,jt})^2, + \sum_{jt}(h_1-h_1)^2(z_{jt}-\bar{z}_{.t})^2 + J\sum_{t}(\bar{z}_{.t}-\hat{h}_t-h_1\bar{x}_{3,.t})^2$$

where $h_t$ is a single constant, which will be replaced in the final estimates by the individual-industry constants, and $J$ is the number of industries in the cross section.

[22] M. G. Kendall, *The Advanced Theory of Statistics,* London, 1951, II, 237.

[23] E. Kuh, *Capital Stock Growth: A Micro-economic Approach,* 1963, Chaps. 5 and 6.

From the pooled data and the moments defined in (15), it is possible to estimate the constant of regression and the coefficient on $x_3$, by ordinary least squares, under the assumption that the effect of time is not significant. Then, by taking deviations from the cross-section or cell means, we can estimate individual regressions for the annual cross sections, which are needed to test the pooled estimates for stability over time. Finally, we may use the analysis of covariance to fit individual-industry intercepts.

For each cross section, the residual sum of squares may be written as follows:

$$(17)\quad \sum_j (z_{jt} - h_t - h_{1,t}x_{3,jt})^2 = \sum_j (z_{jt} - \hat{h}_t - \hat{h}_{1,t}z_{jt})^2 + (\hat{h}_{1,t} - h_{1.t})^2 \sum_j (x_{3,jt} - \bar{x}_{3,.t})^2 + J(\bar{z}_{.t} - h_t - \hat{h}_{1,t}x_{3,.t})$$

The sum of these residuals (reduced by appropriate degrees of freedom) over the span of years for which we have cross sections, becomes the denominator in the over-all test for heterogeneity. The numerator is the difference between the residual variation from the pooled regression and the total of the sums of squares just defined, i.e., $\sum_t \sum_j (z_{jt} - h_t - h_{1,t}x_{3,jt})^2$. That is, the $F$-test numerator measures the variation from the ordinary least squares regression not taken into account already by the unrestricted cross-section regressions.

Should the test indicate that there is no significant heterogeneity among the time slices (as it did) we are justified in concluding that the pooling over time is a legitimate procedure. Either time is not directly associated with the dependent variable or, more likely, we have corrected or allowed for the short-run differences in the relation of interest by introducing the index of capacity utilization and the "neoclassical" deflated wage effect. There is, in particular, no reason to introduce individual *time* constants, nor to attempt to estimate individual slopes for each cross section.

An analogous set of tests can be made in the time series direction, to test for heterogeneity among industries. As the second over-all test (across the industry series) indicated considerable departure from homogeneity, we were faced with the possibility that the heterogeneity might be due to the regression coefficients or, if the slopes are equal, due to heterogeneous intercepts. Kuh, following Mood, turns the test question first to the linearity of the regression coefficients and then, conditionally, to the homogeneity of the intercepts. In the present case, the over-all $F$-test in the industry time series direction indicated extreme heterogeneity. Visual inspection left no doubt as to the possible equality or linearity of the slopes. But, since we do not consider the progress function to be a short-run relationship over time, we concluded that no serious weight could be given to the single-industry slopes in these short time series, whatever the $F$-test might have shown. It followed, then, that the time series $F$-test result should not prohibit pooling in the adjusted productivity relation and need not be taken to indicate that individual slopes on the fundamental variables should be fitted within the pooled data. What remained, however, was the possibility that the residual variation might be considerably reduced if the differences among industries—apart from the short-run cyclical and substitution effects—were allowed to enter in the form of individual industry constants.

Returning to the pooled moment matrix, $\sum_{jt} (z_{jt} - z_{..})(x_{3,jt} - x_{3,..})$, individual dummy variables were introduced into the data set in the following form:

$$X_{bj} = \begin{cases} 1 \text{ for each observation on industry } j \\ 0 \text{ for each observation on industries not } \text{-}j \end{cases}$$

The coefficients of each $x_j$ in the regression are estimates of the differences due to unspecified variation in the "industry" variate. The "correction," then, for industry $j$, is [24]

$$h_j = (z_j - \bar{z}_{..}) - \hat{\beta}_3(\bar{x}_{3,j} - \bar{x}_{3,..}). \tag{18}$$

## *Empirical Results*

### ALL INDUSTRIES POOLED, NO EXPLICIT RESEARCH EFFECT

We begin with the hypothesis that productivity in each industry is influenced in a systematic manner by variations in the long-run real wage rate, by shifts in the degree of capacity utilization, and by changes in educational attainments—all peculiar to the given industry. The first two forces are permitted to affect productivity uniquely in each industry, whereas the effect of the education variable, though differing from

[24] I. Hoch, *op. cit.*, p. 40.

industry to industry, is represented by a single parameter fitted across all industries (the research and development variable in (13) will be added subsequently). The statistical specification of the model can be represented symbolically by

$$(19)\quad z_{j,t} = (x_{0,j,t} - x_{1,j,t}) - \hat{\sigma}_j \rho_{\eta,t-\delta} - \hat{a}_j s_{j,t} = h_0 + h_1 x_{3,j,t} + u_{j,t}.$$

Logarithms are denoted by lower-case letters and by omitting the prime on $\rho$, which is the Fisher distributed lag in the deflated wage rate; the $u_{j,t}$ is a stochastic term interpreted in the error-in-equation sense. The extraneous estimates of the elasticities of substitution, $\hat{\sigma}_j$, and the capacity utilization coefficient, $\hat{a}_j$, were derived previously on an industry-by-industry basis from the same set of data used in the present study.[25] Consequently, the estimating form (19) recognizes explicitly the heterogeneity of the industries with respect to the cyclical and factor price variables. The effect of education is represented by $h_1$, which in the present form is common to all industries.

For pooled data (eight industries and eight years), the least squares estimate is

$$(20)\quad z_{j,t} = -1.639 + \underset{(4.127)}{1.923}\, x_{3,j,t} \qquad \bar{R}^2 = .190.$$

The number in parenthesis is the $t$ ratio for the estimate of $b$. Even though the coefficient on education is highly significant and has the correct sign, the variable explains less than 20 per cent of the increase in productivity. In other words, the education attainments variable cannot, by itself, explain a major part of the inter- and intra-industry variation in productivity after adjustments have been made for the effects of shifts in factor substitution and capacity utilization.

Not only is (20) inadequate in its explanatory power, but as may be seen in Table 2, the residual disturbances appear not to be independently distributed with constant variance. The time-slice cross-section standard errors give a clear impression of upward drift.

The implication of this heteroscedasticity is that we have omitted a systematic variable (or variables) which can account for more of the variation in adjusted productivity through time, as well as the differences in adjusted productivity among the industries. It will be seen that a

[25] See Brown and Wachtel, *op. cit.*

TABLE 2

*Standard Errors of Estimate of Cross-Section Estimates of Equation (20)*

| Year | Standard Errors of Estimate (Unbiased) |
|---|---|
| 1953 | .1464 |
| 1954 | .1525 |
| 1955 | .1460 |
| 1956 | .1588 |
| 1957 | .1613 |
| 1958 | .1651 |
| 1959 | .1582 |
| 1960 | .1695 |

proper specification of the research variable can explain much of the remaining variance.

Before turning to the research variable, however, it is necessary to test the pooled estimate of equation (20), in the light of the suggested heteroscedasticity. The covariance analysis test described in the previous section was applied to the time slices. The result, as shown by the analysis of covariance for over-all homogeneity in cross-sections of equation (20), below does not permit the rejection of the homogeneity hypothesis:

| *Variance Ratio* | *Degrees of Freedom* Numerator | Denominator | *Approximate Significance Points on Null Hypothesis* |
|---|---|---|---|
| .44 | 14 | 48 | $F_{.05} = 1.90$ |

Conclusion: Over-all homogeneity hypothesis definitely accepted.

In spite of the appearance of a trend in the relationship among the industries, the conclusion of over-all homogeneity among the regression coefficients is definitely acceptable. The relationships did not vary significantly over time and the pooling of cross sections is justified. In the previous section we presented the economic reasons for not accepting a time series covariance test on the present body of data. Thus, for the moment, we accept the assumptions that permit pooling through time and across industries.

Let us return to (20) and hypothesize that the large residual variation is attributable mainly to *inter*industry differences that are not associated with different levels of educational attainments. If the remaining, unexplained variance can be identified with industry-linked, but otherwise unspecified, variables, then (19) should be specified with dummy variables as described at the end of the last section: A value of 1 is assigned to the first industry and zeros for the others, the next dummy assumes a value of 1 for the second industry and zeros for the others, and so on. Their inclusion in (19) yields:

$$(21) \qquad z_{j,t} = -.193 + \underset{(2.043)}{.507}\; x_{3,j,t} + \text{industry dummies} \qquad \bar{R}^2 = .990$$

(It is unnecessary to list the regression parameters on the dummy variables, since the point we wish to make does not require their quantitative examination. All but one of the coefficients on the dummy variables is significant.) The importance of (21) is that the inclusion of the dummies reduces the coefficient on education, though it is still significant at the .05 level, and exhausts nearly all of the residual variation produced by (20). Hence, the industry constants, which represent differences in level, are effective in accounting for the residual variation in the productivity equation after we have allowed for the effects of educational attainments. We can infer at this point that if research and development are relevant at all, their relevance must be in explaining these interindustry differences in adjusted productivity.

Before introducing the research variable into the model, we present the unconstrained analogue of (20); from equation (13):

$$(22) \quad (x_0 - x_1)_{j,t} = -.475 + \underset{(3.728)}{.432}\; \rho_{j,t-\delta} + \underset{(1.492)}{.297}\; s + \underset{(3.918)}{.877}\; x_{3,j,t}$$

$$\bar{R}^2 = .313$$

This regression cannot easily be interpreted as a structural estimate, since we are not justified in assuming slope homogeneity among industries with respect to the relative wage expression and capacity utilization. Having said that, we are encouraged to note that the signs are intuitively correct and that the two main parameter estimates are highly significant. But the coefficients on the wage rate expression and on the education variable are smaller than those in (20): The average of the elasticities of substitution used in the constrained productivity relation is .780, while that fitted in (22) is .432; and the coefficient on education in (20) is more than twice that obtained in the unconstrained regression. These are not stunning differences if we take into consideration the data deficiencies. But the direction of the difference between the elasticity of substitution estimates is surprising, since we should expect the estimate on the unconstrained productivity relation to be larger than the average of the estimates used in the constrained relation to the extent that the former embodies a cross-section effect.[26] It appears that the time series estimates of $\sigma$, adjusted for disequilibrium effects by the Fisher lag scheme, are longer-run estimates of the elasticity of substitution than the combined cross-section and time series estimate. Although this is ancillary to the principal problem under discussion, it has important consequences for the interpretation of time series and cross-section estimates.

EXPLICIT EDUCATION AND RESEARCH EFFECTS,
SUBGROUPS OF INDUSTRIES

In the preceding subsection we introduced the education attainments variable into the adjusted productivity equation and drew the conclusion that the research effect, if it is present at all, would manifest itself primarily in interindustry differences in adjusted productivity. This has the implication that the time profile of the research variable is of ancillary importance to the specification in terms of varying industry intensities.

In order to obtain reasonable estimates of both the research and the education elasticities in the adjusted productivity equation, it is necessary to focus on subgroups of industries within our total pooled sample, since the estimates with every research variable we specified were unacceptable when fitted in the total pooled sample. As we shall see below, the subgrouping of industries, though forced upon us, in the sense that we did not initially expect to disaggregate, has the serendipitous consequence of permitting us to offer some very interesting propositions.

A host of criteria for subgrouping industries was considered; we finally selected the durability of the final product as the grouping criterion, since this is relatively independent of the model. The selection of such a broad categorizing principle has the further advantage of allocating a sufficient number of industries in each subgroup to provide the estimates with some probability content. Following the Bureau of

[26] See Kuh, *op. cit.*, pp 182–83.

Census definitions, the sample was divided into subgroups: durable and nondurable industries. However, smaller groups were also used in certain experiments in order to assure that our principal conclusion is not conditional upon an arbitrary grouping. In many respects, the chemical industry is an uncongenial member of the nondurable group: it has a relatively high concentration ratio; more important, the coincidence of high mean $\rho$ and extreme research expenditures yields an essentially spurious correlation between those variables within the nondurable data set (see footnote 29, below).

The specification of the adjusted productivity equation in the present experiments is

$$z_{j,t} = h_0 + h_1 x_{3,j,t} + h_2 x_{4,j,t} + u_{j,t}, \tag{23}$$

where $h_1$ and $h_2$, the effects of education and research, respectively, are common to each industry in the subgroup, and $u_{j,t}$ denotes that the model is subject to error. It is useful to recall at this point that the research variable, $x_{4,\,j,\,t}$, is represented by a fifteen-year inverted V distributed lag in real research and development expenditures with weights assigned to each industry according to the inflow of research from its supplying industries, including the industry itself; the proportions being taken from the supplying industries' input-output rows and from the own-industry diagonal cell. Estimates of the two subgroups are contained in Table 3.

TABLE 3

*Estimates of Adjusted Productivity Equation (23) for Selected Durable and Nondurable Goods Industries, 1950-60*

| | Education $x_3$ | Research $x_4$ | Constant | $\bar{R}^2$ | Degrees of Freedom |
|---|---|---|---|---|---|
| Durable goods: | | | | | |
| Fabricated metals, machinery, | 1.236 | 0.300 | −1.892 | .844 | 41 |
| primary metals, automobiles | <u>1.585</u> | <u>5.432</u> | | | |
| Nondurable goods: | | | | | |
| Food, chemicals, paper, | 0.182 | 0.200 | −0.358 | .580 | 41 |
| textiles | <u>2.905</u> | <u>7.033</u> | | | |

As before, the numbers in parentheses in Table 3 represent the $t$ ratios for the respective coefficients. Except for the estimate of the education coefficient in the durable goods equation, which is significant only at the .15 level, the parameter estimates are highly significant, as are the coefficients of determination. Moreover, the coefficients bear intuitively correct signs, and the $\bar{R}^2$'s are quite respectable for pooled data, although a not inconsiderable amount of variation remains unexplained. However, the estimates are acceptable in providing orders of magnitude of the effects of the fundamental variables.

The most striking aspects of these results is the relative magnitude of the effects of the fundamental variables in the durable and nondurable groups. The sum of the elasticities (the coefficients are elasticities, since the estimating equation is homogeneous of degree, $h_1 + h_2$) in durable goods is 1.536, whereas it is 0.382 in the nondurable industry regression. In view of the shortcomings of the data and analysis, we do not feel justified in asserting that economies of scale to the fundamental variables were present in the durable goods industries while diseconomies existed in the other group. All we can say is that a given percentage increase in education and research in both sets of industries produces a substantially larger percentage increase in the adjusted productivity of durable goods than in the other set. Although there is some variation in the estimated elasticities when different groupings are specified, in general the same result emerges; e.g., the sum of the elasticities is significantly lower for chemicals and textiles, treated as a group, than the sum for fabricated metals, machinery, and primary metals, when those three industries are pooled. We conclude that this represents a persistent pattern in our data and that it is not an arbitrary artifact of our grouping procedure.[27]

How can we explain this pattern? Why do the fundamental variables tend to have larger elasticities in durable goods industries than in nondurable goods industries? The following consideration makes a considerable amount of sense to us, but nevertheless is offered in a tentative manner.

Suppose we have two groups of industries; in one group the industries are strongly coupled to each other, and in the other, they are less strongly coupled. Coupling strength is measurable by the size of the off-diagonal

[27] We did not run a covariance test to determine whether the estimates of the two groups differed from each other at a given significance level, since this is apparent by inspection.

elements in a matrix of input-output coefficients. For our present purposes there is no need to develop this further; suffice it to say that coupling strength represents the extent to which industries are "connected" to each other in a trading nexus. Now, the more strongly coupled are the industries in a group, *cet. par.*, the greater will be the percentage increase in productivity as a result of a given percentage change in the education and research in that group of industries.[28] For the stronger the coupling, the larger will be the *multiplier* of the fundamental variables, i.e., the research and education in one industry induce larger percentage increases in productivity in other industries in the group than if the coupling were weaker. Stated another way, the larger is the coupling, the more research and education will filter through the system to increase the time path of productivity in the highly coupled industries. Moreover, large diagonal coefficients work in the same direction, for the larger is the own research and education, the greater will be the impact on own measured productivity.

It is a straightforward matter now to rationalize the pattern of our results. We need only mention that our durable-nondurable goods distinction essentially conforms to a grouping of industries according to their degree of coupling: highly coupled industries in durables and less strongly coupled industries in nondurables.[29] Hence, the relatively large effect of the fundamental variables in the durable goods industries is probably attributable to the fact that they are more closely linked, and that the diffusion of the results of education and research is therefore more effective than among the industries in the nondurable category.[30]

When we turn to the relative sizes of the fundamental variables, we see that within the durables industries, the estimate of the education

[28] Analogous arguments have been put forward by R. M. Goodwin, "Dynamical Coupling with Especial Reference to Markets Having Production Lags," *Econometrica,* June 1947, pp. 181–204; in an international trade setting by M. Brown and R. Jones, "Economic Growth and the Theory of International Income Flows," *Econometrica,* 1962, p. 88; and to explain historical diffusion of technological change, in A. H. Conrad and J. R. Meyer, *The Economics of Slavery,* Chicago, 1965, Chap. 4, "Income Growth and Structural Change."

[29] By the coupling criterion, chemicals should have been included in the highly coupled group. When it is, the difference in the sums of elasticities of the fundamental variables between the two groups is augmented, thus lending support to our hypothesis. However, the estimates of the fundamental variables in the diminished nondurable group (food, paper, and textiles) have unacceptably high standard errors.

[30] The difference in degree of market imperfection between the two groups, raised in discussion by Mr. Weisbrod, is discussed briefly in our Reply to his Comment.

elasticity is four times as large as the research elasticity, whereas in the nondurables group the two elasticities are almost equal. Two explanations suggest themselves; both need further exploration. First, the education variable is specified as affecting only the own-industry's productivity. If it does have an interindustry effect, our failure to incorporate that effect into the model constitutes a misspecification and should, in particular, bias the elasticity estimate upward in direct relationship to the degree of coupling. Second, and perhaps more important, is the possibility that we are misspecifying by assuming that the two effects are additive. Some of the measured elasticity of response to education may in fact be due to the relationship between the two fundamental variables. Again, the degree of coupling would multiply the bias.

What are the marginal effects of the fundamental variables on adjusted productivity? These can be obtained from (23) and Table 3 by

$$\partial z_{i,t}/\partial x_{3,j,t} = \hat{h}_1(\bar{z}_{j,t}/\bar{x}_{3,j,t}) \tag{24}$$

$$\partial z_{j,t}/\partial x_{4,j,t} = \hat{h}_2(\bar{z}_{j,t}/\bar{x}_{3,j,t}), \tag{25}$$

where the bars indicate geometric means (since the arithmetic mean of a variable in logarithms is the geometric mean of the variable). The expressions (24) and (25) represent the marginal productivities of the fundamental variables—i.e., they are estimates of the marginal returns in terms of adjusted productivity change resulting from the change in education or research. They are evaluated for both sets of industries in Table 4.

TABLE 4

*Adjusted Marginal Productivities of Fundamental Variables in Two Groups of Industries*

| | Adjusted Marginal Productivities | |
|---|---|---|
| | Education | Research |
| Durable goods: | | |
| Fabricated metals, machinery, primary metals, automobiles | .197 | .053 |
| Nondurable goods: | | |
| Food, chemicals, paper, textiles | .046 | .009 |

If, as these estimates indicate, the marginal productivities of education and research in durables exceeded the marginal productivities of the respective variables in the nondurable group, then—overlooking the possibility of significant monopoly gains—it would appear that resources devoted to these activities were malallocated in the period under consideration. A preferable allocation would have had resources in these activities shifted to the durable group from the nondurable group.

From this and our discussion of the elasticities in Table 3, a Bohm-Bawerkian implication emerges: that inputs of education and research will have greater yields among industries with more roundabout linkages than in the less closely coupled, in this case nondurables, sectors. Our conclusion holds, a fortiori, if research and development efforts in the nondurables group may be more closely directed to new-product development and promotion than to cost reduction.

The reference to shifting of resources moves us to advise, as a final note, that a shift in the direction of more work along the lines developed in the present paper would yield substantial returns, especially if the framework we developed were confronted with superior data. It may then be possible to measure the effects of the fundamental variables in the unconstrained model, just as we have made a first attempt to do so with the constrained model.

## COMMENT

NESTOR E. TERLECKYJ, Bureau of the Budget

Brown and Conrad have constructed a model, built on a CES production function, which they propose for analysis of the relationship between productivity on the one hand, and education of the labor force and the amount of research and development activity on the other. They illustrate its use by applying it to a body of annual data for ten industries and ten years.

In my view, there are two particularly noteworthy features in the paper. One, of course, is the explicit treatment of education and research as variables affecting productivity, and the second is a novel specification of the R&D variable.

I will discuss first the results obtained within the framework which the authors set for themselves, then their framework itself, and finally the authors' specification of the R&D variable. The latter may well constitute a significant innovation, but probably for measuring the impact of outside R&D on an industry in addition to the industry's own R&D, and not as the authors use it to replace an industry's own research as a variable influencing its productivity.

## *The Authors' Results*

The authors work with a productivity equation in which the value added per man-hour—with adjustment for the real wage rate together with the elasticity of substitution and for capacity utilization—depends in the following manner on the years of schooling of the labor force and the amount of R&D conducted by the industry's suppliers: [1]

$$\frac{X_0}{X_1} \cdot \frac{1}{W^\sigma} \cdot \frac{1}{S^a} = h_0 X_3{}^{h_1} X_4{}^{h_2}$$

The constant, $h_0$, represents a conglomerate of the various parameters of the CES production function. This form is linear in the logarithms. One question I have about this equation, is that it may be subject to distortions in the case of industries whose suppliers conduct very little or no R&D ($X_4 = 0$).

At first, Brown and Conrad estimate the equation with the educational variable only. In their initial attempt with both education and R&D, the authors report that they were not able to get reasonable estimates of the coefficient for the R&D variable fitted across the board.

They looked for groupings of industries which would give them more "acceptable" estimates of this parameter. After some exploration they settled on the grouping of industries by the durability of the product. This did give them statistically significant and presumably economically acceptable estimates of the parameter. Their solution was one way of handling the situation. There is no reason why the authors should have pursued all the possible alternatives. However, in the light of their earlier approach with the education variable only, I am puzzled why they did not at this stage use dummy variables for industries, which perhaps would have given them one acceptable estimate for the R&D coefficient.

[1] $X_0$ is output value added; $X_1$—man-hours; $W$—the real wage rate, Fisher-lagged; $\sigma$—the elasticity of substitution; $S$—capacity index; $A$—a parameter; $X_3$—median years of schooling of employees; and $X_4$—the amount of R&D as defined.

The authors stress the differences in the estimated magnitudes of the regression coefficients for research and education variables between the durable and nondurable goods industries. I think that they overstate the case. Actually the coefficients are not that different from each other. For the research variable, they are quite similar, and one of the coefficients for the educational variable is not significant at the .05 level. Aside from the various possible questions regarding errors in the data and the use of the annual figures for estimating these long-run relationships (the R&D variable is lagged over fifteen years) a formal test would evidently show that the $2\sigma$ intervals for both pairs of coefficients would overlap.

### *The Authors' Approach*

I think the main limitation of the approach as finally [in estimating equation (23)] used by the authors, is that it does not lend itself well to analysis of changes in productivity over time, especially over longer periods, because it does not allow for a residual time trend, or change, in productivity. But it can be modified to serve that purpose, including some techniques explored by the authors elsewhere in the paper.

Essentially we are interested in explaining the unexplained residual in economic growth. Starting with the concept of inputs which include man-hours and services of the capital stock or some equivalent, and which leave a large residual, we add education and research (and maybe other variables), and reduce the residual. But we do not necessarily eliminate it completely. Also, the growth of output as conventionally measured is probably understated (in different degrees in different industries), and this bias is correlated with time (not necessarily in a simple manner). Therefore, it is important to have in the model an unexplained time residual in order better to estimate the effects of other factors.

For example, among the variables not included in the model there may be economies of scale at the plant or process level, and also economies of scale from the growth of industries which permit more efficient industrial specialization.

The data base is narrow. Given the authors' data and their final estimating form, the model is heavily oriented to the interindustry differences and not to changes over time.

The model also places a burden on the education and research variables as measured. For example, the authors argue for inclusion of R&D as a proxy variable for the flow of technologically relevant knowledge. I would prefer to view the flow of R&D expenditure as a form of capital investment. The organized and reported R&D probably cannot be stretched to cover all the technologically relevant knowledge but only a part of it.

Related to the data problem is a question of research strategy. While conceptually a CES formulation is preferable, it has at present a narrow data base and requires elaborate estimates (including those of elasticity of substitution) which are subject to errors. If CES estimates of productivity can be approximated by other procedures (e.g., using Cobb-Douglas functions or indexes of total factor productivity as developed by Kendrick), then a choice can be made between much more extensive coverage of real phenomena and the a priori preferable functional form.

Given a wider choice of data the approach of Brown and Conrad can be extended to cover longer periods. To be sure, some of the data, particularly those for research and development, are quite sketchy for earlier years, but the differences in the R&D level between industries have been very large (several orders of magnitudes), and the rates of growth in R&D have also been very high. Consequently, considerable lack of precision in the R&D estimates can be tolerated. Actually, I think that trading off the more precise but limited annual data covering a short period for perhaps less precise data for several periods [2] covering sufficient time for the underlying relationships to become manifest, is at least worth a try. Also the technique should allow for effects of factors not entered explicitly into the analysis. This could be done by various procedures allowing for separate equations (and/or intercepts) for the different periods and perhaps industries or sectors.

Brown and Conrad estimate large effects of education and R&D on adjusted productivity. A 1 per cent increase in the amount of research and development as measured is associated with a 0.2 or 0.3 per cent increase in the adjusted productivity. These estimates reflect primarily the interindustry variations.

I would like to cite here some of the estimates which I have obtained on an earlier occasion, relating research intensity to the rate of growth

[2] Or technological "epochs" as used by M. Brown and J. S. de Cani in "A Measure of Technological Employment," *Review of Economics and Statistics,* November 1963.

of industry productivity.[3] These estimates are also based on interindustry differences but cover a longer time period. Although the two formulations are not directly comparable, my estimates imply much smaller effects of R&D on productivity. These results also indicate the type of unexplained residuals associated with time periods that might be encountered in long-term analysis of the rate of growth in productivity.

Using Kendrick's data for nineteen two-digit manufacturing industries, I have calculated a number of regressions relating the average annual rate of growth in total factor productivity to the research intensity, defined as a ratio of research inputs to the total inputs. A measure of the amplitude of the cyclical fluctuations which these industries had experienced was also included in these equations. These in effect were cross-section regressions aimed at explaining the interindustry differences in the rate of productivity growth over the period 1919–1953, and two shorter subperiods. The results, shown in the tabulation below, suggests that a

| *Period* | *Constant* | Log (R&D)/I (research intensity) | *A* (measure of cyclical amplitude) | $R^2$ |
|---|---|---|---|---|
| 1919–53 | 0.74 | 0.69 | −0.06 | .55 |
| | | (4.85) | (1.82) | |
| 1919–37 | 2.49 | 0.77 | −0.12 | .30 |
| | | (2.84) | (1.97) | |
| 1948–53 | −2.96 | 1.26 | −0.05 | .28 |
| | | (2.95) | (0.44) | |

tenfold difference in the research intensity was associated with a difference of roughly one percentage point in the annual rate of growth of industry productivity.[4] There were large differences in the constant of the regression, depending on the period, implying large effects of other factors.

### *The Specification of the R&D Variable*

The novel treatment of the R&D variable introduced by the authors involves attributing the real R&D expenditures[5] as input not to the

[3] "Sources of Productivity Advance. A Pilot Study: Manufacturing Industries, 1899–1953," unpublished Ph.D. dissertation, Columbia University, 1960.

[4] The *t* values are in parentheses.

[5] Lagged over fifteen years. I am in perfect agreement with the authors regarding the lagging procedure.

industry which makes the outlays but to its customers (including itself) in proportion to purchases in the input-output matrix. This approach promises a possibility of measuring the benefits of R&D conducted elsewhere; however, this external effect should be counted in addition to the impact of own R&D on the industry's productivity, but not to replace the internal input, as was done by the authors.

The main reason why the authors undertake this adjustment is that in their view the research and development activities directed toward new or improved products do not find any reflection in the measured growth of output. While the output measures are probably biased, we have no evidence to assume that this bias is total. In fact, we do not even know whether the bias is more, or less, than one-half. Certainly, some of the new-product research finds its way into the value added in the form of higher profits and possibly higher wages. There is no need to assume a total bias. Eventually, the correct remedy should be to improve the output data rather than to eliminate new-product R&D from the input. We need more fundamental work on the "utility-oriented" measures of output. Noting this, of course, is not of much help in reviewing the present paper. Nevertheless, I think it is a valid point. Business-financed R&D, at least, is essentially no different from capital investment and, aside from possibly higher risk premiums, is decided upon by about the same set of considerations as any other investment. Consequently, the R&D expenditure should be treated similarly to fixed capital investment.

A few more technical points: While it provides a good starting point, the input-output matrix is a rather indiscriminate device to distribute R&D effects. It reflects all types of purchases. While the R&D conducted by suppliers of the intermediate materials too may influence productivity of the purchasing industry, its effect may be expected to be smaller than the effect of R&D conducted by suppliers of the industry's capital goods. Moreover, on the output side, the return to capital and profits enters into value added while the intermediate purchases do not. Also, the transformation carried out by the authors does not take into account R&D conducted outside of the manufacturing sector. Finally, there may also be a question about the use of the constant input-output weights taken from the 1958 matrix for the long periods, but I do not know how serious it may be.

Let me now state what I would consider a more complete treatment of R&D as a variable which affects output and productivity. I think it is very important to distinguish between the internal and the external R&D inputs. These two should enter as separate variables. One is a direct input and the other an external economy. Using the authors' notation, I would test the following productivity function

$$\frac{O}{I} = F(X_3, X_{4A}, X_{4B}; T)$$

with the productivity ratio as defined by the authors, or its empirically acceptable approximation estimated otherwise, and with time treated parametrically.

The first R&D variable, $X_{4A}$, would be the direct R&D undertaken by the industry in order to reduce unit cost or to develop new or better products, and should show up in properly measured real value added. If output measurement is deficient, it should be improved, but R&D undertaken by the industry is a valid investment input.[6] This, after some suitable time aggregation, I would consider direct input paid for by the sponsoring industry (possibly including the government-sponsored R&D done by the industry).

In addition to these internal inputs, I would consider external R&D inputs ($X_{4B}$). These, I would estimate as the authors estimated their $X_3$, but excluding the industry's own R&D part. This second variable would probably have a longer time lag. I would also like to test the hypothesis that the R&D conducted by the suppliers of capital goods has a different effect on productivity of an industry than the R&D done by the suppliers of intermediate goods.

In summary, I am inclined to see the principal contribution of the Brown and Conrad paper in the exploration of a series of techniques to deal with education and R&D as inputs, which the authors try, particularly the use of separate intercepts, and the specification for measuring the impact of outside R&D. The empirical results which the authors show, however, are to be considered of an exploratory nature, mainly because their time period is quite short and, consequently, the inter-industry variation is used to estimate time-process relationships. But

[6] Since the R&D data are reported on a company basis and all the other variables on an establishment basis, I would consider (for the more recent periods) making some use of the product line R&D data, published by the National Science Foundation, to obtain closer approximation to the establishment concept.

the paper does raise a number of meaningful questions which are subject to treatment by further research.

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The resurgence of interest in the sources of economic growth has led to investigation of a number of variables other than traditional labor (man-hours), and capital that might explain the "unexplained residual" in observed U.S. economic growth. Among the variables receiving particularly augmented attention have been education and research.

A number of researchers have attempted to explore the impact of rising educational attainments on labor productivity by examining the differential earnings experience of persons similar in several respects but differing in level of educational attainment (LEA). Then, differential earnings—perhaps adjusted downward for the hypothesized effects of ability differentials which are believed to be correlated positively with LEA—can be taken as an approximate measure of the effects of education on labor productivity. Presumably in this way the effects of education on the value of a worker's *marginal* productivity are measured—if there are reasonably competitive labor and output markets and if equilibrium is approximated in these markets.

While this line of investigation has merit, alternative approaches are also needed. Professors Brown and Conrad utilize an aggregate production function model that incorporates education and also research inputs. With respect to education, this approach, as distinguished from the incremental earnings approach I briefly sketched above proceeds directly to the production function to seek the influence of education embodied in the labor force. After all, if schooling does contribute to labor productivity, then the effects of additional schooling of the labor force should appear in real output figures, whether or not it appears in the labor earnings data that serve the incremental earnings approach. Thus, in principle the Brown-Conrad approach appears to be superior to the incremental earnings approach, although we do not have to choose either one *or* the other.

Some of the comments that follow about this most stimulating paper deal with the model employed and its assumptions; some deal with the statistical results and their interpretation; but most of the comments deal with the ways that variables are measured. In raising some preliminary questions about the model's assumptions I do not intend to imply that "realism" of assumptions is a necessary condition of a useful model. However, without much evidence regarding the predictive accuracy of the behavioral and technological relationships that the model assumes, reference to the accuracy of assumptions seems warranted.

## *The Model*

To begin with, the assumptions that perfect competition prevails in labor markets and in output markets, and that profit maximization is the goal of firms in each industry—assumptions implied by the hypothesized equalization of the marginal productivity of labor with the deflated wage rate (the ratio of factor price to output price)—must surely be subject to some eyebrow raising. Automobiles are one of the industries investigated: perfectly competitive? In addition, the degree of imperfection probably varies from industry to industry in both input and output markets, thus tending to affect differentially the input coefficients estimated for various industries. And since expenditures on research may well be related positively to the degree of monopoly power, a further bias is introduced.

In any event it is difficult to reconcile the perfect competition, profit maximization assumptions with the authors' statement of their principal conclusion—that the allocation of resources could have been improved had education and research resources been re-allocated from nondurable goods industries to durable goods industries during the 1950–60 decade. If perfect competition did prevail we would expect each resource to move until the values of its marginal product were equalized in all uses (and equalized with factor price). Why, then, would any misallocation remain? Although the authors did not take up this question, there appear to be three possible answers. (1) There might be differentials between durable goods and nondurable goods industries in the magnitudes of uncaptured real external benefits; (2) there might be differentials in extent of decreasing costs that tended to cause durable goods industries to operate at relatively suboptimal levels compared with nondurable goods industries; and (3) there might be differential lags in the adjustment process in the two types of industries.

These potential reasons for nonoptimalities are important; for, since there is no particular reason to believe that the interindustry distribution of externalities, or of decreasing costs, or of adjustment lags is very different today from what it was in 1950–60, the authors' conclusion that resources in education and research were misallocated in that decade suggests misallocation today. In short, Brown and Conrad are saying that a *systematic* tendency exists for relatively too little of these resources to flow into durable industries, and too much into nondurables.

Yet they offer no reason for believing that such a tendency exists. They do not argue that real externalities from education and research were and are generally more prominent in durable goods industries. Nor do they assert that durable goods industries have more generally decreasing costs than do nondurable goods industries. If they had, this would be a sufficient explanation for finding nonoptimal allocations—along traditional neoclassical lines. However, while this argument would suggest that the level of output should be expanded in these industries, it would not suggest that the level of any particular input, such as education or research, should be increased. There are obviously other means for inducing expansion in decreasing cost industries, and the presumption is still in favor of a lump-sum subsidy rather than a research or education subsidy.

If lags in adjustment to changing marginal value productivities of education and research varied systematically between durable and nondurable goods industries, this, too, would be a sufficient explanation for finding nonoptimalities, but neither is this argued by Brown and Conrad. In short, it is difficult to understand what economic theory underlies what seems to be their view that research and education are systematically underutilized in certain industries and overutilized in others.

There are a few other aspects of the model to which I would like to call brief attention.

1. Lags are assumed to exist in the process of adjustment to wage rate variation. However, the theoretical justification for the particular lag structure that is used is not clear, nor is it clear why adjustment lags, if they are relevant, should not also apply to the firm's employment of other inputs. Brown and Conrad note that labor productivity may not always be in instantaneous equilibrium at the given wage rate. Similarly, other productivities may not always be in equilibrium at their respective prices.

2. The model—or, at least, its current applied form—assumes implicitly that the levels of research and development expenditures and the (median) educational attainments of the labor force in each industry are

determined exogenously. Yet, the spirit of the decision-making process underlying the model—one of profit maximization—suggests that labor, capital, research, and education inputs should all be determined jointly. It seems that the authors' model which they select to estimate—namely, equation (13)—involves a questionable specification of economic behavior.

3. With regard to R&D, it is quite probably true, as the authors state, that the effect of R&D on labor productivity does depend upon the *stock* of knowledge; but since we know so little about the *durability* of productivity-increasing knowledge—or, in fact, about how to go about analyzing it—I can fully understand why they try to avoid estimating that stock. Thus they treat the relevant R&D measure as a current flow rather than as a stock. Yet one can only agree with their statement that "this involves some misspecification." And, unfortunately, one cannot avoid the issue, even if one can evade it by assuming, *implicitly,* that the stock is irrelevant.

4. One other aspect of the model merits particular emphasis, because it relates to some later remarks about the interpretation of the Brown-Conrad findings. Equation (3) and its subsequent description make it clear that the Brown-Conrad measure of "labor productivity" permits measured productivity to change *both* when a *shift* occurs in the production function for some commodity, *and* when a movement occurs *along* an unchanging production function that exhibits increasing returns—because of increasing returns to scale or increased capacity utilization. I shall suggest later that the use of a productivity measure that blends both kinds of effects may have led the authors to an unwarranted inference from their statistical findings.

5. Finally, it is worthwhile at least to raise the question of the appropriateness of a CES form of production function for every "industry"—no matter at what level of aggregation. Little attention to this question was given in the paper, although the empirical work implies that the authors feel the CES form is appropriate for the broadly conglomerate two-digit industries with which they dealt.

## *The Empirical Work*

Moving from the conceptual form of the model to its empirical counterpart we face particularly intriguing questions about the proposed measures of $X_{3,j}$ and $X_{4,j}$, the educational input and R&D input, respectively.

The education variable, $X_{3,j}$, is a weighted average of median years of formal schooling per employee in industry *j*. The assumption that the median amount of schooling is the best measure of educational inputs is open to question on a variety of grounds. For one thing, a mean—arithmetic or perhaps geometric—would give a more accurate picture of total educational inputs than does a median. It is true that data availability may dictate using medians; however, their use may introduce a bias.

In addition the use of only a measure of central tendency, with no measure of dispersion, implies that *all* years of schooling—whether the fourth year, eleventh, or nineteenth—are perfect substitutes in production—i.e., have equal marginal value productivities. Two industries in a single year, or one industry in two different years, with the same median years of schooling per worker have, according to Brown and Conrad, the same educational inputs, although one industry might have all workers at the median while the other had some very highly educated workers and some workers with very limited schooling. To imply, as the authors do, that these two situations are equivalent seems very questionable. In fact, such an assumption flies in the face of the findings of other research, that substantial variation exists in the earnings differentials associated with various incremental years of schooling.

In addition, the productivity of a given incremental year of schooling is probably different according to when the education was received, as measured by the age of the worker. The expansion of knowledge alone tends to make more recent schooling more valuable. If one considers some sort of *value* weights for educational inputs, as an alternative to the simple median years of schooling, one probably comes to share my skepticism about the latter measure. For example, if the authors had considered *cost* (expenditure) weights—as they did implicitly for research—they would have recognized the considerable increase in cost of a year's schooling as the level of schooling rises.

Even apart from these questions about the homogeneity of years of schooling, that is, even if the function relating output per worker to median years of schooling per worker were log-linear within each firm —indicating that any year of schooling embodied in a worker is equivalent to any other year embodied in that or another worker—it would not follow that the *same* linear functions would apply to all firms in all of the component industries of the broad, two-digit industry groupings the authors treat. But unless each of the firms in each industry does have a similar production function a finding that the coefficients of the education (or research) input differs considerably among industries tells us nothing about whether these inputs should, for greater efficiency, have been re-allocated *among* industries rather than *within* industries. However, such a recommendation is precisely what Brown and Conrad make. They write: "A preferable allocation would have had resources in [education and research] shifted . . ." *to* the industries with high coefficients and *from* those with lower coefficients.

This noteworthy conclusion about efficient resource allocation is, according to the authors, an implication of the "main conclusion" of their empirical investigation. Yet, to repeat, for this conclusion to follow logically, a number of assumptions must be made. (1) It must be true that all years of schooling are perfect substitutes in production for all industries—i.e., all years of schooling have equal marginal value productivities; otherwise, it would be necessary to specify *which* years of schooling should have been shifted, and the Brown-Conrad model cannot specify this. (2) It must be true that all firms within the two-digit industrial classes must have approximately the same value of the marginal product (VMP) of education and VMP of research functions; otherwise internal shifts within industries might be preferable to shifts between industries. (3) It must be true—at least in the long run when the stock of education is a variable—that all years of schooling for workers in all industries must have the same cost of production; otherwise it would be wrong to reallocate resources in education so as to train more workers for the industries in which the VMP of a year of schooling is highest. However, the authors do not even mention the *cost* of producing educated people.

I turn now to the R&D variable, $X_{4,j}$. The measure of R&D proposed by the authors represents a most interesting and imaginative proxy for the flow of R&D effects between industries. It is quite clear that the research from which an industry benefits—in the sense that its average production costs are reduced—may bear little relationship to the research it performs. Therefore, Brown and Conrad sought to devise a research variable that would reflect this fact. Under certain conditions the measure they have produced—one which assumes that the benefits of research flow along with and in proportion to, the flow of industry sales to other industries—is appropriate and creative. This is the case, for example, when one industry performs research that it sells to another—either directly as research or advice, or indirectly, as when it sells goods in an improved form that makes the goods easier to handle or process. In such cases, which involve a change in the customer-industry's production function, the flow of transactions is a useful measure of the first industry's contribution to the customer-industry's labor productivity.

However, not all research expenditures have such effects in the customer industries. Some research is not effective at all; some research is not cost-reducing, but is, as Brown and Conrad recognize, quality-changing. Some research—such as that on improved processes—may be cost-reducing only for the supplying industry, having no effect whatsoever on costs in the customer industries. Thus, the authors have overstated when they assert that improved processes and products in supplying industries *will* have cost-reducing effects among their customer industries. There *may* be such effects, but there need not be. To the extent that less than 100 per cent of research expenditures is cost-reducing in customer industries, the Brown-Conrad method of allocating all research among industries in accordance with interindustry trading patterns allocates too much research expenditures to some industries and too little to others. The effect is to bias the industry research coefficients in some unspecified way. More study is needed of the degree to which research expenditures by one industry redound to the advantage of other industries with which it trades, or even of industries with which it does not trade. Yet, even if the Brown-Conrad research measure is not the last word, it is worthy of further consideration.[1]

A conceptual difficulty arises here in deciding what should be meant by the expression, "cost-reducing effects among customer industries." As the authors use the term "cost-reducing," they mean as noted previously, either that the production functions for customer industries shift outward, or that movement occurs along existing production functions that exhibit increasing returns—because of scale economies or excess

[1] It is interesting to note that what the authors term the "fundamental" variables, research and education, are not treated in parallel fashion. While each industry's research input is estimated to be net of its outflow of research embodied in sales to other industries, and gross of its inflow of research embodied in purchases from other industries, the education input is simply a function of each industry's own use of educated workers.

capacity. A potentially serious problem arises from their inclusion of the latter—movement along a production function—in their concept of "cost-reducing." To see why, consider the following two cases:

In case 1, industry A performs additional research, or employs better-educated workers, with the result that the production cost of the widgets that A sells to industry B falls. (I shall assume that the quality of widgets is unaffected.) In the first instance, labor productivity in industry A will rise, its production function having shifted. Productivity in industry B will also rise—provided that all of the following three conditions are met: (1) A must cut the price of widgets (which it may not do if competition is inadequate); (2) B must then proceed to cut the price of its output; and (3) the resulting expansion of B's output—assuming nonzero price elasticity—must bring either scale economies or use of excess capacity. If any of these three conditions fails to be met, productivity (as Brown and Conrad measure it) will not rise in industry B as a result of the measured rise in research or education inputs by A. Incidentally, as the authors measure research inputs (but for some unstated reason, not education inputs) the increased research expenditures by A would be partially allocated to industry B. Thus, if any of the three conditions just enumerated were not met, industry B would be shown by Brown and Conrad to have increased its research inputs but not its labor productivity.

Assume, however, that all three conditions are met, with the result that measured productivity in B, as well as in A, rises as a consequence of the initial increase in research by A. Note that in this case, productivity in A rises because of a *shifting* production function—although productivity might also be affected by a movement along the new function, if sales increased—but productivity in B rises only because of a movement along its original production function. Note also that depending on the price elasticity of demand for B's output, the expansion of B's output could bring a contraction in output in some other competing industry, C, with accompanying effects on its productivity.

Next, consider an alternative case in which A sells no output to other manufacturing industries like B, but sells only to retail stores or to the final-demand sector. As in the first case, real productivity in A would rise because of the production function shift. If we retain the assumption that industry A cuts its price, then, if price elasticity of demand is less than unity (in absolute value), consumers will spend less on A; and demand for products of some other industries—call them D—will rise correspondingly. Such an expansion of demand will bring increased productivity in D (as Brown and Conrad measure productivity) insofar as scale economies or unused capacity brings reduced unit costs even with a given production function. But recall that an expansion of output, rather than a shift in the production function, was also what brought the increased productivity in industry B in case 1.

In other words, a cost-reducing innovation in one industry can bring about a rise in average labor productivity in other industries if the industries are connected—whether via *trading* relationships or via *consumer budgets,* even when there are no real external effects. In the trading-connected industries, the productivity change in A may trigger a price reduction to B and, hence, a downward shift in B's marginal cost function, with a resulting expansion of output by B. Alternatively, in the budget-connected industries, the change in A may trigger a shift in demand for some other industry's output, and this, in conjunction with its declining cost curves, would tend to produce a falling price in B and a rising output. Thus, in both cases the result could be the same: falling price and rising output in some other industry as a consequence of the innovation in industry A. However, while the details of the Brown-Conrad computations are not in the paper, their estimation method seems to be one that would not treat these two cases—of budget-connected and trading-connected industries—as equivalent. As a result, while the estimated coefficients of the research and education variables in the Brown-Conrad model may well be greater in trading-connected industries, the appearance of a greater responsiveness of productivity to research and education in those industries may be an illusion.

As additional attention is devoted to this or related models, alternative specifications of the economy's behavior will, deservedly, receive hard study. At the moment we are hard-pressed to decide to what degree the author's operational model correctly portrays the responsiveness and adjustment opportunities of the economy—for to that extent the discovery of inequalities in marginal value productivities would indicate inefficiencies—and to what degree the model is incorrect in this regard, in which case the observed inequalities may be irrelevant. But this is a never-ending issue; it is no criticism of Brown and Conrad to suggest that they have not resolved it. Nonetheless, the boldness with which they conclude that educated workers and research inputs were malallocated in the 1950s suggests that they have greater confidence in their specification of the economy's behavior than many readers may have.

It seems to me, however, that the general aggregate production function approach to the understanding of the productivity effects of research and education is well worth pursuing. Additional study is particularly needed of the best measures of research and education inputs, and of the level of data aggregation that is most appropriate. Brown and Conrad should be congratulated, however, on their bold, imaginative, and thought-provoking effort. It should stimulate additional research on the contribution to output of education and research—two of the most rapidly expanding sectors of the economy.

ZVI GRILICHES

1. The stepwise procedure used by Brown and Conrad to estimate the coefficients of $E$ and $R$ (education and research) is inconsistent. The correct symmetrical procedure is to relate $Z$ (which is a residual from regressions of $y$ on $w$ and $t$) to the *residuals* of $E$ and $R$ from similar regressions on $w$ and $t$. As it stands, neither the coefficients nor the standard errors are correct (unless $E$ and $R$ are independent of $w$ and $t$). In particular, the standard errors are underestimated. In light of this it is doubtful that their finding of different coefficients for the durable and nondurable groups is in fact significant (on top of the obvious biases introduced by pretesting). These coefficients could be estimated by fitting the whole set of industries jointly, allowing the coefficients of $w$ and $t$ to differ between industries but imposing the same coefficients on $E$ and $R$. This procedure would be somewhat complicated, but it is entirely feasible.

2. It seems to me that the equation that Brown and Conrad finally estimate does not really depend much on the special assumed form for the production function. Thus, e.g., if $L$ (labor) is not measured correctly and quality of labor is a function of $E$, $E$ will enter the $Y/L = f(w)$ relation—where $Y$ denotes output—even though it does not affect the parameters of the production function directly. Thus their reduced form cannot be distinguished from one derived from a "pure embodiment" model. In addition, the coefficient of $E$ will be proportional to $(1 - \sigma)$ and hence will be small if $\sigma$ is close to unity. Thus, this may

not be a very powerful procedure for testing hypotheses about $E$. (A similar argument can be also developed with respect to $R$.)

3. Since on their hypothesis $E$ affects the distribution parameters, could not one test this more directly by looking at the relationship between factor shares and $E$?

REPLY by Brown and Conrad

The purpose of our paper was to report upon a series of experiments which was designed to test a way of treating the technological change "residual." Since our main interest was in the simple model we proposed, and in the possibility of estimating parameters for it, we accepted the data that were immediately available, excepting only our manipulation of the NSF research and development series in order to include some reflection of the interindustry flow of innovation. This being the case, we will not comment at length here upon the well-intentioned reminders that our data are faulty. There may well be bias in our results due to errors in our variables, but neither we nor our critics could assign a direction to the bias, and we felt it was sufficient to state our discomfort as clearly as possible.

Two problems with the data are worth some further comment, however, since both involve our handling of evidence, rather than its quality. Mr. Weisbrod complains that our use of a measure of central tendency for education, and an unweighted one at that, fails to reflect differences in the marginal value productivity over the range of years of schooling. We chose the simplest measure, first, because earnings differentials seem to us to reflect a great deal more than marginal productivity differentials, and second, because the *cost* of schooling probably contains a great many elements of consumption that are irrelevant to the productivity residual. Third, our own preliminary investigation of the relationship between the years of schooling and the earnings series, and Griliches' observations on the correlations among the quality-of-labor series derived with different weighting schemes, suggested that the increase in the quality of the data from more manipulation—with the additional load of assumptions—would be more apparent than real. Finally, the cost of education may have relevance for the remarks about reallocation of resources, but it can only have relevance for the estimation of the elasticity on education when it has been demonstrated that the increased cost of a specific year is directly related to the marginal increase in the quality of the graduated output. We have seen no convincing evidence on this question.

Both discussants suggest shortcomings in our interindustry research variable. It seems unnecessary to repeat that we are aware that not all research expenditures are cost-reducing in customer industries. With regard to Mr. Weisbrod's case 1, as long as A cuts the price of its deliveries to B, there will be an increase in labor productivity using our value-added measure of outputs, whether or not conditions (2) or (3) are met. The possible interindustry connection via consumer budgets—Mr. Weisbrod's second case—is an admitted oversight on our part. Over longer time periods than the one we had, the problem might have been encountered; in fact, the variations in industry mix were negligible in the period of our experiment. Since Hicks, in 1936, defined the role of the elasticity of product demand in factor demand relations, there have been no empirical applications (to our knowledge) outside of the zero-elasticity-of-substitution input-output case.

Mr. Terleckyj, especially, has suggested that the interindustry research and development variable might be constructed in other ways. We have tried one of the implied variations—attributing *all* of the industry's own expenditures, plus the proportional expenditures of its suppliers from the original formulation, to each industry in the sample [column (5) of Table 1 in this Reply]. Using the asymmetrical stepwise procedure of equation (23), the original formulation is better—in the sense of yielding a higher $R^2$ (corrected) and significant coefficients on both variables—in the durables group. In the nondurables, however, the $R^2$ (corrected) is improved, but the coefficient on education is rendered insignificant. When the symmetrical procedure is used as below, the equations with double counting in research in the nondurables have no explanatory power; in the durables the only notable change is a further widening of the difference between the elasticities on education and research. The new variable is shown in Table 1, column (5), which contains the decomposition of the interindustry research weights that Mr. Terleckyj requested.

We can only accept, with a seemly humility, the arching of Mr. Weisbrod's eyebrows at our assumption of competition. But, the distributed lag in the wage rate variable was specifically introduced to admit the

TABLE 1

*Input-Output Research Variables*

(dollars in millions)

| Industry and SCB[a] Number | Receiving Industry Research Expenditure, 1958 (1) | Receiving Industry Research Expenditure Delivered to Itself (2) | Delivering Industry Research Expenditures to Receiving Industry (3) | (2) + (3) Weights Used for Table 4 (4) | (1) + (3) Weights Used for Reply (5) |
|---|---|---|---|---|---|
| (1) Food (14) | $83.0 | $13.45 | $12.12 | 25.57 | 95.12 |
| (2) Textiles (16-18) | 18.5 | 4.24 | 47.21 | 51.45 | 65.71 |
| (3) Paper (24, 25) | 42.0 | 6.20 | 14.86 | 21.06 | 56.86 |
| (4) Chemicals (27-30) | 792.0 | 91.74 | 6.89 | 98.63 | 798.89 |
| (5) Primary metals (37, 38) | 119.0 | 28.44 | 1.48 | 29.92 | 120.48 |
| (6) Fabricated metals (39-42) | 133.0 | 3.32 | 27.93 | 31.25 | 160.93 |
| (7) Machinery except electrical, (43-52) | 781.0 | 46.85 | 78.48 | 125.33 | 859.48 |
| (8) Automobiles (59, 61) | 831.0 | 215.23 | 75.20 | 290.43 | 906.20 |

[a]SBC refers to the industry numbers used in M.R. Goldman, M.L. Marimont, and B.N. Vaccara, "The Interindustry Structure of the United States, "*Survey of Current Business*, November, 1964, pp. 10-29.

possibility of disequilibrium into the test, which is a far cry from a rigid assumption of perfect competition. Further, under plausible conditions, the presence of imperfect competition requires only proportionality between marginal products and factor prices, expressed in terms of the price of the product. A departure from the competitive assumption implies no fundamental changes in the specification of the model and no change at all in the estimating equations.

The estimation problems are immense. There were barely enough observations in our data to support the variables of direct interest; the possibility of adding demand and supply elasticities was unthinkable. Conscious of the unlikelihood of competition, or even of a comparable degree of imperfection in the several markets we were using in the cross sections, we engaged in some "ad hockery," or what Griliches might call "fishing." We looked for a pattern in the residuals and then in the industry dummies from the covariance procedure that might fall systematically along some array of market imperfections. Nothing convincing appeared. Finally, we tried other grouping criteria, a host of them, including capital intensity, research intensity, the relative size of the elasticity of substitution, and rough notions of concentration. The average concentration ratio is, in fact, higher in the durables than in the nondurables group. But observe that we ran our tests on the variance of the durables independently of the variance of the nondurables. And, since monopoly power is argued to be roughly homogeneous within the groups, we have effectively held the degree of monopoly power constant in our procedure. In the first stage, we were really using $w/p$ $(1 - e)_i$ to correct the productivity index, where $e$ is the elasticity of factor demand and $i$ is an industry index. At least in the log-linear case, the effect of the $e$'s could be to bias the intercept but not the coefficient. In the second stage, the industries were grouped in a manner such that the $e$'s were roughly comparable within each group. Hence, the disparate estimates we obtained for these variables in the two groups could not be attributable to differences in monopoly power.

The Malinvaud-Griliches criticism correctly raises the issue of the error in the dependent education and research variables due to the asymmetry of the estimating procedure. In order to eliminate the primary-factor substitution effects and the short-run cyclical effects from our fitted relationship, we used an adjusted, or constrained, productivity variable, computed as the residual from regressions of output per unit of labor upon relative wage movements and a cyclical index. The independent variables in the final "constrained" equation—education and research—were not adjusted in a parallel fashion. To the extent that the resulting discrepancy or error in the variables is correlated with the true values, the estimated parameters will be biased and, furthermore, inconsistent.

If education and research are independent of the wage term and time (and capacity utilization, as well), the inconsistency will be minimized. In fact, there is considerable correlation in the nondurables between the research variables (in both the original and double-counting versions) and the wage term. Recall that the two variables are a deflated wage term, specified in terms of a second- or third-order distributed lag, and a fifteen-year inverted V, lagged research variable, the lagged observations stretching back in time from the date of the observation. The correlation in the nondurables is simply the result of the common trend. Removing the spurious wage "effect" from the lagged research expenditures (the regression on the cyclical term was never significant), reduced the explanatory power of research and depressed the $R^2$ to insignificance. In the symmetrical procedure for durables, the education coefficient suffers when the old research variable is used, and the differences between the elasticities increase when the new variable is used, as noted above.

When the residuals were taken from pooled regressions of research and education on the wage and cycle terms, which gives scope for the interindustry differences and depends less completely on the common trend, the results are those shown in Table 2 of this Reply. For the durable goods group, comparing our original and new regression, the education parameter is increased, as might have been expected, and the $R^2$ (corrected) is improved slightly. There is a redistribution of reliability, for in the symmetrical regression the education parameter as well as the research parameter are now significant at the .05 level. Moreover, the relationship between the sizes of the two parameters is roughly the same as in our original regression—or, at least is not reversed. In the nondurables group there is no significant change in the parameters, the $t$ ratios decline, and the $R^2$ is reduced drastically. But even though the $t$ ratios fall, they still hover around 2.0, and it is possible to infer

TABLE 2

*Revised Estimates for Equation (23)*

| | Education $E$ | Research $R$ | Constant | $R^2$ |
|---|---|---|---|---|
| Equation as in text, where $z = (x_0 - x_1) - \sigma\rho - a^s$: | | | | |
| Durable goods: | 1.236 | 0.300 | −1,892 | .844 |
| Fabricated metals, machinery, primary metals, automobiles | 1.585 | 5.432 | | |
| Nondurable goods: | 0.182 | 0.200 | −0.358 | .580 |
| Food, chemicals, paper, textiles | 2.905 | 7.033 | | |
| Symetrical stepwise procedure, where $z = (x_0 - x_1) - \sigma\rho - a^s$, $E = x_3 - \beta\rho - \gamma s - a_1 t$, $R = x_4 - \beta\rho - \gamma s - a_1 t$ | | | | |
| Durable goods: | 2.895 | 0.237 | 0.203 | .872 |
| Fabricated metals, machinery, primary metals, automobiles | 2.865 | 3.158 | | |
| Nondurable goods: | 0.176 | 0.173 | 0.350 | .115 |
| Food, chemicals, paper, textiles | 1.930 | 2.054 | | |

that the parameter estimates are significant. Hence, using the symmetrical procedure, which presumably does not underestimate the standard errors as our original procedure did, we find essentially the same pattern of results as before. Specifically, education and research have markedly different effects on productivity in the two groups of industries. We need not modify our conclusions in the text.