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TECHNICAL CHANGE IN THE PRIMARY METALS INDUSTRY

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Outline

I. Introduction

In this paper we use data on the postwar primary metals industry, a four-factor translog cost function, and a technique due to [Berndt and Wood, 1975a] to identify historical biases in technical change.

In this Section we discuss neutral and biased technical change. In Section II we describe the empirical specification we use to derive our measures. In Section III we discuss the data in detail. In Section IV we analyze the results of our estimation. Conclusions are summarized in Section V.

The central construct of production theory is the production function, a static relationship giving maximum output attainable from any set of inputs. The state of technical know-how is summarized in the functional form and parameter values of the production function. Consequently we say that technical change has occurred whenever the functional form or some parameter value of the function changes.

In order to use time series data to estimate an empirical production function, some assumption must be made about the nature of technical change over the period. Otherwise, no amount of time series data could ever identify both a production structure and changes in that structure. Traditionally, econometric research has assumed the absence of technical change; that is, that the same functional form and parameter values described production technology throughout the sample period. Together with constant returns to scale, this means that all changes in input mix are due to price-induced substitution within fixed technology, though perhaps with lags. An alternative, slightly weaker, maintained hypothesis would be that all technical change was of the

"Hicks-neutral" variety; that is, could be represented by scale contractions of the isoquants toward the origin. Still, input mix changes occur only because of factor price changes.

For reasons discussed below, however, we may wish to estimate production functions under weaker assumptions. We may wish to allow input mix changes to occur independently of relative price changes over time. This is the effect of "biased" technical change; it amounts to permitting the isoquants to be displaced in the input space.[1] Provided that we impose sufficient restriction on how these biases occur, we will still be able to separate input mix changes into substitution and technical change components. In practice, requiring that the technical change biases occurred at a constant rate throughout the sample period is sufficient to make this division; no other prior restrictions are required.

Historically, the concern with biased technical change occurred in connection with efforts to explain the functional distribution of income. This is still a valid reason to try to estimate such biases, though it assumes less importance in an industry study such as this.

Nonetheless, to assume the absence or neutrality of technical change is to impose an empirical restriction. Should the restriction in fact not be valid, then biased structure estimates will result. Especially in technologically dynamic industries or times, where the assumption of unchanged technology might be suspect, its imposition should be tested.

Another reason to estimate biases in technical change is the "induced innovation hypothesis" - the notion that technology changes in a manner which will economize on those resources growing relatively more scarce.[2] Under this notion technical change becomes a sort of dynamic analogue of substitution within fixed technology.

The induced innovation hypothesis has often been appealed to in debates concerning natural resource scarcity. For while both neutral and biased technical change represent economies on resource use, it is biased technical change which is most promising with respect to any particular resource. To be fair, however, there is little or no empirical support for the induced innovation hypothesis. For while measures of biased technical change abound, it has not been possible to relate these empirically to any sort of micro-investment processes on the part of entrepreneurs. Such an investment model, based on expected future prices and subject to diminishing marginal returns, would presumably be the heart of an induced innovation model.

Indeed, judging from recent literature, even the theory behind such a model is weaker than often supposed.[3] Once technical change was generally considered to be an exogenous process, outside the realm of economic analysis. Now the conventional wisdom is that it is largely an economic process. And yet there is little formal justification for this change in point of view. Doubtless a serious model of endogenous technical change will require much more than mere estimation of historical biases, though such measures are the first step.

II. Empirical Specification

Two developments of recent years have significantly expanded our ability to estimate "theoretically correct" production relationships and to test a variety of propositions which have generally passed as untested maintained hypotheses. These are the application of duality principles to derive estimating equations, and the development of flexible functional forms (of which the translog is an example). The empirical work which has used these developments has been diverse.

Here we estimate the production structure of the postwar primary metals industry by means of the dual cost function. Using the dual cost function, rather than the production function directly, has several econometric advantages. First, the elasticity of substitution estimates are derived as "first-order" estimates; that is, from the slope terms of our estimated factor demand equations. Using the production function, the elasticity of substitution is a "second-order" estimate; that is, we must try to estimate the curvature of an isoquant by evaluating a determinant, each of whose elements is an estimate. This is inherently a more difficult empirical task.

Further, it is more likely that input prices are pre-determined variables than are input quantities. Also, the maintained hypothesis of cost minimization is slightly weaker than that of profit maximization.

Another potential advantage arises from our use of the translog functional form. A translog cost function can be estimated without prior restrictions on the degree of homogeneity. Estimation of a translog production function, however, requires constant returns to scale as a maintained hypothesis. Otherwise it is not possible to identify the logarithmic marginal products as cost shares. In this paper, however, constant returns to scale is maintained throughout.

The translog function is becoming familiar in the literature and we will discuss its properties only briefly. Assuming constant returns to scale, the cost function is written:

$$\ln TC = \alpha_o + \sum_i \alpha_i \ln P_i + \frac{1}{2} \sum_i \sum_j \theta_{ij} \ln P_i \ln P_j \qquad (1)$$

where TC is total cost, the α's and θ's are parameters, and the P_i and P_j are the factor prices; i and j vary over capital (K), labor (L), energy (E), and raw materials (M) inputs.

The function is estimated through the behavior of its cost shares:

$$\frac{\partial \ln TC}{\partial \ln P_i} = \frac{\partial TC}{\partial P_i} \frac{P_i}{TC}$$

but

$$\frac{\partial TC}{\partial P_i} = X_i, \text{ the } i^{th} \text{ factor quantity}$$

so we have the system of equations

$$M_i = \alpha_i + \sum_j \gamma_{ij} \ln P_j; \ \gamma_{ij} = \gamma_{ji}; \ i,j = K,L,E,M \qquad (2)$$

where M_i is the i^{th} cost share. We append an additive disturbance term to each equation in (2) to reflect random errors in cost minimizing behavior, and these are our estimating equations.[4]

The function is a generalization of the Cobb-Douglas form. Unlike the multi-factor Cobb-Douglas function, which restricts all elasticities of substitution to be unity, the translog form permits different elasticities between different factor pairs. And in fact, the elasticities are not constants, but instead vary at each observation.[5]

Following Berndt and Wood, we permit technical change by adding Time (T) to the cost function symmetrically as an input. That function now is:

$$\ln TC = \alpha_0 + \sum_i \alpha_i \ln P_i + \alpha_T T + \frac{1}{2} \sum_i \sum_j \gamma_{ij} \ln P_i \ln P_j + \sum_i \gamma_{iT} \ln P_i \, T + \frac{1}{2} \gamma_{TT} T^2 \qquad (1')$$

and the estimating equations become

$$M_i = \alpha_i + \sum_j \gamma_{ij} \ln P_j + \gamma_{iT} T$$

$$\qquad\qquad i,j = K,L,E,M \qquad (2')$$

$$\frac{\partial \ln TC}{\partial T} = \alpha_T + \sum_i \gamma_{iT} \ln P_i + \gamma_{TT} T$$

Note that permitting technical change not only alters the existing equations, but also adds an additional equation to the system. The L.H.S. variable of this equation, $\frac{\partial \ln TC}{\partial T}$, is the rate of change of total cost at constant input prices. Again following Berndt and Wood, we measure this as minus one times an index of Total Factor Productivity (TFP). The index of total factor productivity is calculated as the rate of change of an output index less the rate of change in a Divisia index of inputs.[6] These indices are displayed in Table 2, below.

The γ_{iT} terms are estimates of the factor saving or factor using biases of technical change, since they measure the rate of change in the cost shares not attributable to prices. Hicks neutrality implies $\gamma_{iT} = 0$ for all i, and so is directly testable. If α_T and γ_{TT} are also constrained to zero we are back at a production function without technical change.

A useful specialization of biased technical change is the factor-augmenting form. In terms of the general production function,

$$Q_t = f(A_{1_t} X_{1_t}, \ldots , A_{n_t} X_{n_t})$$

where Q is output and the A_i represent indices of attained "input efficiency." By constraining these A_i to change at constant rates, it is possible to derive estimates of this factor-augmentation rate for each input from time series data. Thus, for the production function we have

$$Q_t = f(K_t^*, L_t^*, E_t^*, M_t^*)$$

where $K_t^* = K_t e^{\mu_k T}$ etc.

The μ_i represent rates of factor augmentation. From the point of view of the dual, the rate of factor augmentation equals the rate of real input price decline due to packing increased "efficiency units" into each natural unit. So by substituting P_i^* for P_i in equations (2), where

$$P_i^* = P_i e^{\lambda_i T}, \qquad i = K,L,E,M$$

then expanding and collecting terms, we derive the estimating equations for the factor augmenting specification.[7] Factor augmentation is a restriction of the general case.

If one considers these augmentation rates to be the outcome of micro-investment decisions by entrepreneurs, they are directly relevant to the induced innovation hypothesis. Indeed, for this purpose they are superior to the older Hicks-bias measures. The Hicks-biases are ambiguous, since a given technical change (isoquant shift) might be either factor i-saving or factor i-using, depending on the prevailing input prices. While the technique we use to estimate the biases rules this out in our empirical work, it remains a problem for any micro-theory of induced innovation. No such problem attaches to the augmentation rates.[8]

It is possible to test a great variety of covariance structures on our estimating equations. Since the equations represent cost shares for the same cost function we expect them not to be independent. So we use a joint generalized least squares estimating procedure. One of the equations must be deleted to avoid a singular covariance matrix. This and other details of estimating translog functions are widely discussed in the literature and we will not repeat them here, except to note that we assume joint normality for the errors and that our paramater estimates are asymptotically full information maximum likelihood estimates.

III. Data

We construct the data from annual observations, 1947-1974, on the U.S. Primary Metals Industry. This "two-digit" industry group (SIC code #33) produces both ferrous and non-ferrous metals. We have been fairly meticulous with the data. While minor improvements might still be made it is not likely these would substantially alter any of the results.

The variables required are price indices for capital services, labor, an energy aggregate, and raw materials. The dependent variables are the corresponding cost shares. Finally, we require quantity measures for each input in order to construct the total factor productivity index, which serves as the dependent variable in the equation added to the system by the inclusion of technical change.

A summary of the variable construction follows. Interested readers may have full details upon request. Final data is published in the Appendix.

Prices

Energy: Weighted averages of the Bureau of Labor Statistics wholesale price indices for coal (05-1), coke (05-2), fuel oil (05-7), natural gas (05-3), and electricity to the industry. The electricity price series is the average price gotten by dividing industry purchases in dollars by kilowatt hours consumed, from the Annual Survey of Manufacturers. The weights are the corresponding shares of total energy purchases represented by each fuel type. This is continuously available only for electricity. For the others we interpolate linearly between the six Census years for which we do have observations, plus 1974, when the Annual Survey expanded its reporting for energy data.

The Census of Manufacturers and Annual Survey of Manufacturers data on energy input purchases do not include coal to be made into coke, which represents a major part of the metals group coal purchases. If we did not correct for this we would under-estimate the weight of coal in the energy aggregate, though our correction factor is of necessity based on observations for only three years; 1954, 1958, and 1962.

Also, researchers should be aware of three problems with this data. A change in Bureau of the Census accounting procedures in 1954 regarding coke oven industries resulted in reclassifying some fuels as "produced and consumed within the establishment." Series extended beyond this date must be adjusted for this change, and this adjustment can be made only on the basis of 1954 evidence since this is the only year for which data is published under both accounting conventions.

Secondly, the acquisition of bee-hive ovens by steel manufacturers results in the re-classification of coke sales into intra-firm transfers, and their disappearance from the statistics. To some extent this vertical integration occurred over the time period, but our data is not sufficiently disaggregated to permit us to make an estimate of its magnitude.

Thirdly, after 1958 the Gas Fuels price series was redefined. For a discussion of this see the BLS Wholesale Price Index for February 1958, pp.37 ff.

Raw Materials: We use a weighted average of the prices for significant inputs: iron and ferro-alloy ores, bauxite, copper ore, lead ore, zinc ore, non-metallic minerals, chemicals, machinery, and the output of the ferrous and non-ferrous components of the primary metals group. This last is to account for the significant intra-industry group flows under our gross output specification. Except for bauxite, copper ore, lead ore, and zinc ore, these price series are BLS wholesale price indices. The others are all average prices calculated from The Bureau of Mines Minerals Yearbooks supplemented in some cases by data from the Department of Commerce Census of Mineral Industries.

We derive the weights using the U.S. Input-Output tables. Starting with the "Direct Requirements per Dollar of Gross Output" table we aggregate the 85x85 U.S. Input-Output table as follows: Column-Wise we add together all columns which comprise SIC group 33; that is, columns 37 and 38. (These are weighted by the gross output corresponding to each column.) Row-wise we add together those rows which correspond to one of our ten materials price indices. So now we have the direct requirements per dollar of gross output distributed over various input types. Their relative size establishes a set of weights which we apply to our materials price indices to derive a single materials price index for this industry group. We follow this procedure for 1947, 1958, 1961, 1963, and 1967; the years for which I-O tables were published or compiled. We interpolate to get a set of continuously varying weights.

Labor: We use the industry production worker wage bill, divided by the number of man-hours worked, from the Annual Survey of Manufacturers.

Capital Services: The estimation of capital rental prices is itself a major empirical task. Here we experimented with several options before settling on the manufacturing capital rental price series derived by [Christensen and Jorgenson, 1969]. We extended this through 1974 using [Berndt-Wood, 1975b] and investment data.

The average growth rates in the four nominal price indices over the period are as follows:

Capital: 3.07%

Labor: 5.30%

Energy: 4.75% (3.35% through 1972)

Materials: 4.00%

Quantities

Energy: Expenditure on energy inputs divided by our aggregate price index.

Materials: Expenditure on raw materials, adjusted for changes in inventories of materials, divided by our price index.

Labor: Production worker man-hours.

Capital: We construct our own estimates using the perpetual inventory formula:

$$K_t = I_t + (1-u)\, K_{t-1}.$$

We have constant dollar investment for each year, and capital stock benchmarks for nine of the twenty seven years. We complete the series using moving average estimated depreciation rates.

Output: Value of shipments, adjusted for changes in inventories of finished goods, divided by the BLS price index for industry group output.

Cost Shares

Each cost share is equal to expenditure on that input divided by value of shipments, adjusted for changes in inventories of finished output.

Energy input expenditure: The sum of expenditures on coal, coke, fuel oil, natural gas, and electricity.

Materials input expenditure: Value of shipments plus changes in inventories of finished goods less value added less expenditure on energy inputs plus changes in inventories of materials.

Labor expenditure: Production worker wage bill.

Capital expenditure: Value added less labor expenditure.

IV. Results

We estimate the dual cost function under four specifications. In order of decreasing generality they are

1. Biased technical change
2. Biased, factor-augmenting technical change
3. Hicks neutral technical change
4. No technical change.

We will strongly reject the hypothesis of Hicks-neutral technical change. This makes the estimates derived under the further restriction of "no technical change" a bit pointless. For the record, however, when the null hypothesis of "no technical change" is tested against the alternative hypothesis of Hicks-neutral technical change, we do not reject the null hypothesis. This implies that the bias of technical change (i.e., isoquant displacement) is more important, empirically, than the mere scale contraction of the isoquants. A corollary is that tests for technical change should use biased technical change as the alternative hypothesis, rather than Hicks-neutral technical change.

We concentrate our analysis, then, on the remaining three specifications. Coefficient estimates and summary statistics are presented in Table 1.

Table 1

Coefficient Estimates and Summary Statistics

(t-statistics in parentheses)

	Unrestricted	Factor-Augmenting	Neutrality Imposed
AK	.186 (18.66)	.186 (18.99)	.236 (56.97)
AL	.210 (35.51)	.208 (36.53)	.157 (84.10)
AE	.045 (17.56)	.045 (17.61)	.041 (84.57)
AM	.559 (49.37)	.561 (50.18)	.566 (120.67)
CKK	.057 (1.31)	.055 (.99)	-.045 (1.13)
CKL	-.000 (.01)	.001 (.10)	.057 (3.76)
CKE	-.004 (.68)	-.003 (.61)	.003 (.64)
CKM	-.054 (1.12)	-.053 (1.08)	-.016 (.34)
CLL	.136 (9.22)	.136 (5.30)	.024 (2.19)
CLE	-.021 (3.31)	-.021 (3.41)	-.029 (9.23)
CLM	-.116 (5.96)	-.116 (5.99)	-.052 (2.21)
CEE	.027 (5.17)	.027 (1.51)	.027 (5.43)
CEM	-.002 (.23)	-.003 (.24)	-.001 (.16)
CMM	.172 (2.91)	.172 (3.73)	.069 (1.06)
AT	.072 (1.45)	.001 (.84)	.022 (.95)
CKT	.0031 (5.10)	.0031 (5.21)	-
CLT	-.0032 (9.12)	-.0031 (9.02)	-
CET	-.0003 (1.84)	-.0003 (1.63)	-
CMT	.0004 (.58)	.0003 (.40)	-
CTT	-.003 (1.13)	.0003 (2.57)	-
LK	-	.053 (1.76)	-
LL	-	-.029 (4.23)	-
LE	-	-.027 (2.31)	-
LM	-	-.002 (.30)	-

Table 1, contd.

		Unrestricted	Factor-Augmenting	Neutrality Imposed
R^2	MK	.5309	.5306	.4038
	ML	.7040	.6981	.1164
	ME	.8429	.8423	.8244
	MM	.2946	.2913	.2304
	TFP	.0468	.0076	–

Log-likelihood, evaluated at maximum:

	Unrestricted	Factor-Augmenting	Neutrality Imposed
	329.051	328.274	303.804

Technical Change

Hicks-neutrality is a restriction on the more general hypothesis. We test the restriction with a likelihood ratio test:[9]

H_n: Neutral technical change in primary metals, 1947-1974

H_a: $\sim H_n$.

Number of restrictions = 4

$\chi^2_{critical} = 9.488 \quad (\alpha = .05)$

$\hat{\chi}^2 = 50.494$

Conclusion: Reject the neutrality hypothesis.

The rejection is a strong one. Further, three of the four estimates of Hicks-biases are significantly different from zero, at least at the $\alpha = .1$ (two-tail) level. The effect of biased technical change on energy and materials inputs has been only marginal. The capital-using, labor-saving biases have been much stronger, in each case amounting to an annual three-tenths of one percentage point change in the cost shares not attributable to substitution within unchanged technology. This means that had production technology remained static over the period, the share of labor in output would have been about 8.5% larger than it is, and the share of capitalists about 8.5% smaller. Note that it is the capital and labor prices which have had, respectively, the slowest and fastest rates of growth.

The labor saving result should surprise no one familiar with the data. Despite large increases in output and in every other input, the number of manhours of labor going into primary metals production has remained almost constant since 1947.

The index of total factor productivity generated as a dependent variable is displayed in Table 2. The output change index shows wider variation

Table 2

year ending	% rate of change in output	%rate of change in input	% rate of change in Total Factor Productivity
1948	3.8	.2	3.6
1949	-17.2	-6.3	-10.9
1950	22.9	12.4	10.5
1951	8.5	10.0	-1.5
1952	-9.1	-2.1	-7.0
1953	17.3	10.5	6.7
1954	-25.9	-11.2	-14.6
1955	26.7	13.9	12.8
1956	1.6	2.6	-1.1
1957	-5.7	- .3	-5.4
1958	-24.4	-17.8	-6.5
1959	14.2	8.6	5.6
1960	.9	4.1	-3.2
1961	-2.8	-1.9	-1.0
1962	7.4	5.6	1.8
1963	4.9	1.3	3.5
1964	9.1	7.1	2.0
1965	9.4	5.4	4.1
1966	6.9	4.3	2.6
1967	-7.0	0.0	-6.9
1968	4.3	2.7	1.5
1969	4.4	3.8	.5
1970	-10.3	-5.8	-4.5
1971	-3.4	-5.3	2.0
1972	17.1	6.2	10.9
1973	3.9	4.4	-.5
1974	4.5	2.6	2.0

than the input index, hence the productivity index has the pro-cyclical variation common to most productivity indices. The effects of the steel strike of 1949 and the slowdowns of 1954 and 1958 are apparent.

While year to year fluctuations in the productivity index may mean little, it has a distinct upward trend at an average rate of 2.2% per year. This is the rate at which isoquants are presumed to contract toward the origin in the Hicks-neutral model.[10]

Factor-augmentation also represents a restriction of the general biased technical change case, though only a slight one. We impose five independent restrictions and introduce four new variables; net the number of restrictions is one. The explanatory power of both models is essentially equivalent, as are the estimates of those parameters that the two versions share.

The estimated augmentation rates are significant (again at the $\alpha=.1$ level) for capital (-5.3%), labor (2.9%), and energy (2.7%). Again note the correlation between average rates of augmentation and factor price growth rates. Labor, whose price grew most rapidly, was augmented at the highest rate. Capital, whose price grew least rapidly, was augmented at the lowest rate. Indeed, a significantly negative augmentation rate was estimated for capital. A negative augmentation rate may seem counter-intuitive. It would be possible to estimate the equations restricting all augmentation rates to be non-negative, but this was judged inappropriate. We felt that the theory of technical change is not strong enough to justify imposing such strong priors on our estimates.

The factor price rates of change and the technical change measures are summarized in Table 3, below.

Table 3.

	Rate of change in price	Annual Augmentation Rate	Hicks-bias
Capital	3.07%	-5.3%*	.0031* (capital using)
Labor	5.30%	2.9%*	-.0031* (labor saving)
Energy	4.75%	2.7%*	-.0003* (energy saving)
Materials	4.00%	-0.2%	.0003

*significant at $\alpha = .1$

Prodūction Structure

Below we report the estimated elasticities of factor demand and of substitution, evaluated at the means of the data, under the biased and neutral technical change specifications. Structure estimates under the factor-augmenting specification are virtually identical to those of the general, biased technical change specification, and so are not separately reported.

Elasticity of demand for

	Unrestricted	Neutrality Imposed
Capital	-.51 (2.13)	-.95 (5.72)
Labor	-.14 (2.35)	-.69 (9.96)
Energy	-.37 (3.35)	-.29 (2.39)
Materials	-.13 (1.25)	-.31 (2.69)

(t-statistics in parentheses)

Elasticities of Substitution Between

	Unrestricted	Neutrality Imposed
Capital and Labor	1.00 (4.03)	2.54 (6.24)
Capital and Energy	.58 (.94)	1.32 (2.60)
Capital and Materials	.48 (1.03)	.88 (2.51)
Labor and Energy	-1.17 (1.50)	-3.50 (6.89)
Labor and Materials	.01 (.08)	.41 (1.56)
Energy and Materials	.92 (2.21)	.94 (2.37)

(t-statistics in parentheses)

Because the translog is a flexible functional form the estimated elasticities vary at each observation. The actual variation is relatively small, except in the demand for labor. At observations away from the mean the own-price elasticities of demand for labor become slightly positive. This indicates the failure at these observations of certain regularity conditions on the derived demand equations, conditions implied by concavity of the dual cost function. This is discussed further below.

Otherwise the elasticity estimates are all of reasonable magnitude, especially if one believes that time-series estimates reflect short-run adjustment.

The substitution elasticities are Allen partial elasticities of substitution. A positive value indicates technical substitutes; a negative value, technical complements. The elasticity estimates from the unrestricted specification are generally of smaller magnitude than those from the neutral specification. This is to be expected since some of what is classified as substitution response under one specification is re-classified as technical change under the other.

One result of particular interest is the positive elasticity of substitution between capital and energy. [Berndt and Wood, 1975b] find these to be complementary at the level of aggregate manufacturing. If this is the case there is a potential conflict between energy conservation policy and fiscal policy. This is because fiscal policies such as investment tax credits stimulate capital intensive production techniques, which will also be heavily energy using if capital and energy are complements. At this level of aggregation, however, we find no evidence for this complementarity. The primary metals industry is, however, a fairly energy intensive industry, and accounts for almost 20% of manufacturing energy consumption in the U.S.

We also test for separability of the production function between materials and other inputs. Such separability is a necessary condition for the validity of production structure estimates derived from value-added specifications. Typically such separability has been assumed, though it is a testable proposition. (For the form of the restrictions see [Jorgenson and Lau, 1975].)

H_n: Explicit separability of the production function in materials inputs.

H_a: $\sim H_n$

Number of restrictions = 3

$\chi^2_{critical} = 6.251$ ($\alpha = .1$)

$\hat{\chi}^2 = 29.076$

Conclusion: Reject separability.

We reject this separability of the production function, and find that its imposition significantly alters the estimate of the elasticity of substitution between capital and labor. While such a result is not surprising, it is an unpleasant reminder of the problems of economic data, since it is typically data restrictions that lead us to use value-added specifications in the first place.

Concavity of the cost function

The power of using duality relationships to derive estimating equations is that we know that the demand relationships we estimate from a "well-behaved" dual cost function will correspond to some quasi-concave production function. In order for the cost function to be well-behaved it must be monotonically increasing and concave in input prices.

The monotonicity requirement presents no problem. Our estimated functions are always monotonically increasing, and we will not discuss this any further.

Concavity is a condition on the principal minors of the Hessian matrix, which we can evaluate at each observation, and also at the means of the data. Evaluated at the means, our cost function estimated under the biased technical change specification satisfies the concavity conditions. But as we move out from the mean the conditions are not met at 20 of the 27 observations.

Thus our unrestricted specification appears not to correspond to a concave cost function when we move away from the means. (The test is non-parametric. We do not know if the non-concavity is "significant".) Curiously, when we impose neutral technical change (a restriction which we reject, statistically) the non-concavities disappear. We have no economic explanation for this, although Berndt and Wood report the same phenomenon. (See [Berndt and Wood, 1975a, esp. fn. 19.])

It is clear from inspection of the relevant formulae that the neutral specification satisfies the concavity conditions because of a lower estimate for γ_{LL} From an econometric point of view this is due to the deletion of Time from the labor share equation under the Hicks-neutral specification. Since γ_{LT} was negative when Time was included, and Time and the labor price index are positively correlated, this results in a negative "left-out variable" bias in the γ_{LL} estimate. The regression equation is demanding that Time be included. That is, there is variation in labor's share which is not explained by prices but which is function of Time. It is the R^2 on the labor share equation which falls most dramatically upon imposition of Hicks-neutral technical change.

V. Summary and Conclusions

We use a translog dual cost function to estimate production structure in the U.S. post-war primary metals industry, under both neutral and biased technical change specifications. Reasonable elasticity estimates are derived.

We reject neutrality of technical change, and also separability of the production function in materials inputs. Technical change has been strongly labor-saving and capital-using over the time period, with weaker (but still significant) effects on energy and raw materials inputs. Significant and reasonable factor augmentation rates are derived.

We note that our estimated cost function is not globally well-behaved under the biased technical change specification, though this problem disappears when neutrality is imposed. We restrict our discussion of elasticities to the data means, where all functions are well-behaved.

We find no evidence at this level of aggregation for the technical complementarity of capital and energy which Berndt and Wood reported. We find all inputs are technical substitutes except for labor and energy.

Footnotes

1. Throughout we use the terms "neutral" and "Hicks-neutral" synonymously. The following is the definition of the Hicks-bias:

Let M_i be the i^{th} cost share. Then

$$\left.\frac{\partial M_i}{\partial T}\right|_{\overline{P}} \begin{matrix} > \\ = \\ < \end{matrix} 0 \quad \begin{matrix} \to \text{i-using} \\ \to \text{neutral} \\ \to \text{i-saving} \end{matrix}$$

It should be pointed out that there have been various definitions of bias, occasionally differing in substance. For a fuller discussion see [Wills, 1976].

2. In this century the idea is usually attributed to [Hicks, 1935]. One can find passages that suggest that the idea was recognized in the Classical literature, see [Smith, 1776, p.86]. But such speculation is suspect. The notion of biased technical change must be distinguished from that of substitution within unchanged technology. In order to draw this distinction carefully it is necessary first to have a fairly formal concept of the production function, which the Classicists did not.

3. See [Binswanger, 1974], [Nordhaus, 1973], [Wills, 1976]. A general conclusion is that simple neo-classical assumptions about the "production of technical change" do not necessarily imply an induced innovation process.

4. Note that $\gamma_{ij} = \gamma_{ji}$ is an identity which must be maintained. It is possible to estimate a system of equations like (2) but where these cross-equation restrictions are not imposed. But such a system is not derived from anything resembling (1). Even if $\theta_{ij} \neq \theta_{ji}$, still $\gamma_{ij} = \gamma_{ji}$. Henceforth we will use γ's in both the cost function and the share equations, to conform to the literature.

5. The formula is

$$\sigma_{ij} = \frac{M_i M_j + \gamma_{ij}}{M_i M_j}$$

so the γ_{ij} appear as terms shifting the elasticity of substitution away from the Cobb-Douglas unity. The formula for cross price elasticities of factor demand is

$$\varepsilon_{ij} = M_j \sigma_{ij}$$

and for own price elasticities

$$\varepsilon_{ii} = \frac{M_i^2 - M_i + \gamma_{ii}}{M_i} .$$

For a derivation of these formulae see [Wills, 1976, pp. 110-112].

6. See [Jorgenson and Griliches, 1967].

7. The final equations, then, are very complex and non-linear. The Hicks-biases can be derived as linear functions of the estimated coefficients.

8. A technical change which is factor i-augmenting might be either i-saving or i-using, depending on the structure.

9. In a sense, of course, we should be concerned here with controlling for Type II rather than Type I errors; by making our significance level high enough we could always end up not rejecting H_o, The likelihood ratio test will not do this, though with such a convincing rejection here the chance of a Type II error is also small.

10. In the biased technical change model a somewhat faster rate, 7.2%, is estimated. In the factor augmenting model the estimate is only .1%. This is the only case of a significant difference between the factor augmenting and the general biased technical change estimates.

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Appendix: Data

	MK	ML	ME	MM
47	0.121206	0.217623	0.515700E-01	0.609601
48	0.121729	0.195935	0.471910E-01	0.635145
49	0.131692	0.203042	0.575730E-01	0.607783
50	0.167795	0.183895	0.495400E-01	0.598770
51	0.169101	0.187577	0.469480E-01	0.596374
52	0.153280	0.208080	0.488710E-01	0.589769
53	0.162655	0.195151	0.466340E-01	0.595560
54	0.173367	0.230512	0.499530E-01	0.541163
55	0.196120	0.192335	0.439610E-01	0.567584
56	0.188843	0.187160	0.417680E-01	0.582229
57	0.177551	0.197750	0.439530E-01	0.580746
58	0.194483	0.228377	0.403360E-01	0.536604
59	0.201666	0.217974	0.382560E-01	0.542102
60	0.185882	0.220999	0.403300E-01	0.552789
61	0.183418	0.223396	0.402530E-01	0.552933
62	0.183086	0.221688	0.406950E-01	0.553931
63	0.211243	0.217055	0.389730E-01	0.532729
64	0.204562	0.211628	0.376690E-01	0.546141
65	0.213877	0.203959	0.351240E-01	0.547040
66	0.228952	0.199299	0.329970E-01	0.546752
67	0.215769	0.209880	0.348500E-01	0.539501
68	0.208641	0.208537	0.343650E-01	0.546257
69	0.203245	0.206233	0.338350E-01	0.556686
70	0.183395	0.209077	0.367650E-01	0.564763
71	0.186764	0.211051	0.395220E-01	0.562663
72	0.169577	0.186011	0.360080E-01	0.608404
73	0.197804	0.193452	0.388780E-01	0.569866
74	0.216049	0.160546	0.423370E-01	0.581068
	1	2	3	4

	PK	PL	PE	PM
47	0.695178	0.466298	0.622399	0.614880
48	0.818927	0.496584	0.735717	0.685389
49	0.815267	0.524886	0.738067	0.664084
50	0.886261	0.545865	0.748622	0.724192
51	0.939036	0.603084	0.780993	0.813550
52	0.888050	0.654526	0.787837	0.814781
53	0.853504	0.696698	0.820874	0.850072
54	0.871702	0.709491	0.790500	0.855694
55	0.965423	0.752716	0.795993	0.914131
56	0.928117	0.799718	0.857572	0.984163
57	0.933576	0.852683	0.919367	0.977141
58	0.909919	0.906548	0.944688	0.957156
59	0.979982	0.943014	0.947175	0.979538
60	0.944495	0.951986	0.955390	0.985508
61	0.949045	0.986198	0.957564	0.973152
62	0.997270	1.01407	0.951679	0.955957
63	1.01365	1.04050	0.950778	0.951704
64	1.03094	1.06356	0.949231	0.983650
65	1.10282	1.09921	0.950866	1.02474
66	1.13558	1.12561	0.968579	1.05169
67	1.07006	1.15137	0.979154	1.06076
68	1.18016	1.22215	0.987467	1.08500
69	1.14104	1.29019	1.02564	1.14992
70	1.04277	1.35000	1.20108	1.23494
71	0.945405	1.46130	1.37658	1.23102
72	1.04095	1.60421	1.43779	1.26292
73	1.33667	1.72925	1.57421	1.38202
74	1.59236	1.95631	2.24416	1.81258
	1	2	3	4