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Chapter Author: John Norsworthy, Show-Ling Jang

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4 Cost Function Estimation of Quality Change in Semiconductors

John R. Norsworthy and Show-Ling Jang

Semiconductor technology lies at the heart of the revolution in information technology. While the official price index in the national income and product accounts for computers has been revised to account for changes in the performance characteristics of computer systems (Cole et al. 1986), no comparable modification has been made to the price of semiconductor devices. Yet semiconductor devices incorporated in telecommunications equipment have been largely responsible for the technological change that led to deregulation of the telecommunications services industry. The rapid rate of adoption of advanced telecommunications equipment and the decline in cost (without a corresponding decline in quality) of telecommunications services are indirect qualitative evidence for embodied quality change in telecommunications equipment. Similarly, the new semiconductor devices have played an important role in the technological change of the computer industry. This empirical investigation is designed to develop quantitative evidence of quality change in semiconductor devices based on their use in computers and telecommunications equipment manufacture.

An econometric model, which consists of a revised translog variable cost function for quality adjustment, input demand functions, and an input quality-adjustment function, is developed and utilized in this study. The approach to quality adjustment, in the spirit of the hedonic approach, is based on two major characteristics of semiconductor products: the device density of DRAMs (dynamic random access memory) and the bit rating of microproces-

John R. Norsworthy is professor of economics and management at Rensselaer Polytechnic Institute and director of the Center for Science and Technology Policy. Show-Ling Jang is associate professor of economics at National Taiwan University.

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sors. Exponential weights for these technology indicator variables are estimated for the computer industry (SIC 3573), telephone and telegraph equipment (SIC 3661), and radio and television telecommunications equipment (SIC 3662).[1] In each industry, evidence for quality change in semiconductors is drawn from the input factor demand functions. All input factors are modeled jointly, rather than the demand for semiconductor input alone, as in the conventional hedonic model. That is, factor substitution information from other inputs—production- and nonproduction-worker labor, other purchased materials, purchased services—is brought to bear on estimation of the quality change in semiconductors used for the computer and telecommunications industries. Unlike the hedonic case, it is necessary to assume that the prices of semiconductor inputs are independent of the level of use by the decision makers who use them in production. This assumption is a standard (and minimal) one in production modeling.

In the computer industry, where output has been adjusted for performance change, it is also possible to obtain additional evidence for the characteristic-related quality change in semiconductors from the increase in the (computer) industry's total factor productivity associated with the use of semiconductors.

Within each of the industries, the quality-adjustment function is constrained to have the same parameters in all input demand functions and the cost function. However, a separate quality-adjustment function is estimated for each industry. It is found that the quality-adjusted prices for all three industries are similar but sufficiently different to reflect the different importance of the technological characteristics of semiconductors in the different industries. The results tend to confirm the approach.

The methods demonstrated here are for time-series data. The usual hedonic price index model relies heavily on cross-sectional data, often from special surveys or proprietary sources. Triplett (1989) provides an excellent summary of hedonic applications for the U.S. computer industry. It is often the case, however, that sufficiently long time series for product characteristics are either not publicly available or quite expensive to obtain.

No sources of quality change other than that associated with the quality of semiconductor input are recognized in this study. However, the specification of quality change is entirely associated with the semiconductor input as shown in equations (11) and (12) below, except in the computer industry, where an additional term is introduced. This term is introduced because the output of the computer industry is adjusted for quality change. It permits total and var-

1. SIC designations are from before the 1987 reclassification. The radio and television communications equipment industry (SIC 3662) is divided into seven categories: (1) communication equipment, except broadcast (SIC 36621); (2) broadcast, studio, and related equipment (SIC 36622); (3) alarm systems (SIC 36624); (4) search and detection, navigation, and guidance equipment (SIC 36625); (5) traffic control equipment (SIC 36626); (6) intercommunication equipment (SIC 36628); and (7) electronic systems and equipment not elsewhere classified (SIC 36629).

iable input factor productivity to change in association with the same semiconductor quality-modifying function used elsewhere in the model.

Section 4.1 of this paper shows how quality change can be estimated from industry input demand systems based on multiple characteristics or indicators of input technology. Section 4.2 explains the development of input and output prices and quantities from industry data sources at the Census Bureau and the Bureau of Labor Statistics (BLS). Section 4.3 discusses the mechanics of incorporating the technological characteristics of semiconductors in the cost function model of production. Section 4.4 presents and discusses the estimated results. Section 4.5 briefly discusses an agenda for future research based on the approach applied in the paper.

4.1 Indirect Measurement of Quality Change in Production Models

The translog cost function is a commonly used model of production that can be adapted to indirect measurement of quality change in an input.[2] The same general method can be incorporated in other functional forms. To illustrate the measurement of quality change embodied in an input in an econometric model, we first present (in sec. 4.1.1) a model without quality adjustment, consisting of a translog variable cost function and input demand equations, and then show (in sec. 4.1.2) the model with quality adjustment.

4.1.1 Translog Variable Cost Function without Quality Adjustment

This study empirically assesses the contribution of semiconductor inputs in the computer industry and two telecommunications equipment manufacturing industries. The translog restricted variable cost function model introduced by Brown and Christensen (1981) is used to model the production structure of these industries. The variable cost function recognizes disequilibrium in that the quantity of physical capital cannot be adjusted to achieve minimum total cost in the short run for a given set of input prices and the quantity of output. The conventional assumption of full equilibrium models such as the translog total cost function is simply not reasonable for industries such as semiconductors, computers, or telecommunications equipment characterized by rapid technological change.

The translog variable cost function for an industry is given by

$$
\begin{aligned}
\ln \mathrm{CV} = {} & \mathrm{a}_0 + \Sigma_i\, a_i \ln p_i + 1/2\, \Sigma_i\, \Sigma_j\, a_{ij} \ln p_i \ln p_j + b_Y \ln y \\
& + b_K \ln k + b_{ky} \ln k \ln y \\
& + 1/2\, b_{yy} \ln^2 y + 1/2\, b_{kk} \ln^2 k \\
& + \Sigma_i\, c_{iy} \ln p_i \ln y + \Sigma_i\, c_{ik} \ln p_i \ln_k,
\end{aligned}
\tag{1}
$$

2. The explanation in this section is adapted from Jang and Norsworthy (1990a).

where i, j, are the variable inputs, p_i = price of variable input i, y = deflated real gross output, k = real capital input of structures and equipment, and CV = variable cost of production.

Based on Shepard's lemma and the assumption that variable cost is minimized for a given set of input prices, the cost share s_i for the translog variable cost function is given by

$$\text{(2)} \qquad \frac{\partial \ln CV}{\partial \ln p_i} = s_i = a_i + \Sigma_j a_{ij} \ln p_j + b_{ik} \ln k + b_{iy} \ln Y.$$

Derivation of the variable cost function model and estimation of the equations for variable input cost shares with a residual error term e_i added jointly with the cost function itself are explained in Brown and Christensen (1981) and need not be repeated here. If an error term is added directly to equation (2), it will be in terms of value shares, however. In such a specification, input quality change not reflected in the price of input will be obscured because the error term contains both price and quantity components.

In order to separate price and quantity effects, the variable input demand equations can be estimated (jointly with the cost function) rather than the cost share equations. The demand equations are readily derived from equation (2); adding a classical normal error term to the demand equations yields

$$\text{(3)} \qquad q_i = CV \cdot (a_i + \Sigma_j a_{ij} \ln p_j + b_{ik} \ln k + b_{iy} \ln Y)/p_i + \varepsilon_i.$$

Notice that the error term ε_i in equation (3) is in quantity units. We argue elsewhere that the input demand specification is preferable because errors in input quantity are minimized directly, thus leading to a better physical description of the technology of production (Norsworthy and Jang 1992, chap. 3). McElroy (1987) proposes an additive general error model based on estimation of input demand equations rather than price equations. The exact treatment specified by McElroy cannot be achieved when there are parameters that occur only in the cost function (e.g., b_y, b_k, in eq. [1]). However, the general approach and motivation for it are entirely consistent with that shown here.[3]

A major difference between the share equation and the demand equation systems is that one of the cost share equations is redundant, so that the variable cost function is estimated jointly with all but one share equation. That is, for any input r,

$$e_r = -\sum_{i \neq r} e_i.$$

3. This issue is explained in Norsworthy and Jang (1992, chap. 3). McElroy has verbally acknowledged the error.

For the demand equation system, each input equation has an independent error term. Consequently, estimation of the demand system increases the efficiency of the estimation because there are more degrees of freedom.[4]

Restrictions imposing symmetry and homogeneity of degree 1 in prices of variable inputs on the system of equations are as follow:

$$
\begin{aligned}
&\Sigma_i a_i = 1, && \\
&\Sigma_j a_{ij} = \Sigma_i a_{ij} = 0, && \text{for all } i, j, \\
&a_{ij} = a_{ji}, && \text{for all } i, j, \\
&\Sigma_i c_{ik} = 0, && \text{for all } i, \\
&\Sigma_i c_{iy} = 0, && \text{for all } i, \\
&b_{yy} + b_{ky} = 0, && \\
&b_{kk} + b_{ky} = 0, && \\
&c_{ik} = -c_{iy}, && \text{for all } i.
\end{aligned} \tag{4}
$$

4.1.2 Translog Variable Cost Function with Quality Adjustment Based on Multiple Technological Characteristics

The quality change of an input in the production model can be estimated by adjusting its quantity and price to their true values on the basis of some indicators of input technology. Either quantity or price may serve as the basis for empirical estimation of quality change in the model. The choice may affect the stochastic specification of the model, but both methods should yield similar results. Quality adjustment based on quantity of input and quality adjustment based on exogenous information such as TFP (total factor productivity) growth were developed and applied in our earlier studies (Jang and Norsworthy 1988, 1990a, 1990b). We assume here as in our earlier work that the quality of inputs is known by the producers; the task of our quality adjustment is to discovery why they behave the way they do in using the inputs. There is thus no problem of simultaneity in the estimation procedure outlined in this section.

The semiconductor input (q_s) is separated from other purchased physical materials (q_m), and purchased services (q_v) are separately treated as well. Suppose that the unmeasured quality change in semiconductor input q_s is proportional to the log of a quality-adjustment index I_s^α so that quality-adjusted input is

$$q_s^* = q_s I_s^\alpha, \quad \alpha > 0, \tag{5}$$

or

$$\ln q_s^* = \ln q_s + \alpha \ln I_s,$$

4. Degrees of freedom for estimation of a system of translog-based equations are given by the number of observations multiplied by the number of equations estimated.

where I_s is the technological characteristic index for the industry, α is an estimated coefficient, and (as before) q_s is measured semiconductor input.[5]

The corresponding quality-adjusted price for input s is

$$p_s^* = p_s/I_s^\alpha,$$

or

$$\ln p_s^* = \ln p_s - \alpha \ln I_s. \tag{6}$$

The quality-adjustment index I_s is defined below in terms of semiconductor characteristics.

If the quality-adjusted price index of inputs declines faster than the official price statistics imply, then the coefficient α will be positive; the null hypothesis $\alpha = 0$ corresponds to no unmeasured quality change, positive or negative.

The quality-adjustment function may, of course, reflect multiple characteristics of the output(s) of the supplying industry. For example, let

$$I_s^\alpha = f(t_1, t_2, \ldots, t_m), \tag{7}$$

where the t_i's are logs of technology indicators reflecting technological characteristics of input s. For the semiconductor industry, these indicators might measure performance characteristics such as device density, speed, power requirements, bit width of data and instruction paths in microprocessors, etc. For a first-order function,[6]

$$I_s^\alpha = \Sigma_i w_i t_i, \quad i = 1, \ldots, m, \tag{8}$$

where w_i's are weights estimated in the input factor demand model for each of the m characteristics included in the function. (These are comparable to the characteristics coefficients in the hedonic model.) For clarity and comparability with the single index case, however, the quality-adjustment index may be written

$$\alpha \ln I_s = \alpha[\sum_{i=1}^{m-1} z_i t_i + (1 - \sum_{i=1}^{m-1} z_i) t_m]. \tag{9}$$

Equations (8) and (9) have the same number of independent parameters: exactly m. However, changing the parameterization so that $w_i = \alpha z_i$, $i = 1, \ldots, m - 1$, and $w_m = \alpha(1 - \sum_{i=1}^{m-1} z_i)$ permits us to estimate directly the

5. α may also be a function $\alpha = f(t) = c_t t$ or $\alpha = e^{ct}$, where t is the trend variable 1, 2, 3, . . . , and the estimated coefficients c_t and c measure average annual augmentation of input s. Norsworthy and Jang (1989) argue that time trends may capture spurious effects collinear with time and that use of an alternative proxy for quality change that has economic content is preferable.

6. Higher-order functions, e.g., truncated qualities, are sometimes applied in the hedonic approach and could readily be accommodated in a sufficiently large and rich data set.

relative weights of the individual characteristics. These relative weights are readily interpreted because they sum to one.[7]

The estimated coefficient α is then directly comparable to the coefficient of the single indicator. The estimated coefficient z_i is the weight of technological characteristic i in the quality-adjustment function (9). Correspondingly, $\ln p_s$ is replaced by

$$\ln p_s^* = \ln p_s - \alpha[\sum_{i=1}^{m-1} z_1 t_1 + (1 - \sum_{i=1}^{m-1} z_i)t_m] \tag{10}$$

in all its occurrences in the cost function.

Then the variable cost function in equation (1) can be rewritten incorporating the modified expression shown in equation (11) and the parameter α estimated as part of the cost function model:

$$\begin{aligned}
\ln CV = {} & a_0 + \sum\nolimits_{i \neq s} a_i \ln p_i + a_s(\ln p_s - \alpha \ln I_s) + z_t(-\alpha \ln I_s) \\
& + 1/2 \sum_{i \neq s} \sum_{j \neq s} a_{ij} \ln p_i \ln p_j \\
& + \sum_{i \neq s} a_{is} \ln p_i(\ln p_s - \alpha \ln I_s) \\
& + \sum_{j \neq s} a_{js} \ln p_j(\ln p_s - \alpha \ln I_s) + 1/2\, a_{ss}(\ln p_s - \alpha \ln I_s)^2 \\
& + b_Y \ln Y + b_K \ln K + b_{KY} \ln K \ln Y + 1/2\, b_{YY} \ln^2 Y \\
& + 1/2\, b_{KK} \ln^2 K + \sum\nolimits_{i \neq s} c_{iY} \ln p_i \ln Y \\
& + \sum\nolimits_{i \neq s} c_{iK} \ln p_i \ln K + c_{SY}(\ln p_s - \alpha \ln I_s)\ln Y \\
& + c_{SK}(\ln p_s - \alpha \ln I_s)\ln K,
\end{aligned} \tag{11}$$

where $i, j = l, n, m, v$, for the variable inputs: production-worker labor (l), nonproduction-worker labor (n), purchased materials inputs (m), and purchased services (v).

The demand equation for the quality-adjusted input s then becomes

$$q_s^* = (CV/p_s/I_s^\alpha)[a_s + \sum_{j \neq s} a_{sj} \ln p_j + a_{ss}(\ln p_s - \alpha \ln I_s)] + \varepsilon_s^*. \tag{12}$$

The substitution shown in equation (10) for the price of quality-adjusted semiconductor input is applied throughout the model, and the estimated coefficients α and z_i are constrained to be nonnegative. The first-order term $(-\alpha \ln I_s)$ with estimated coefficient z_t is the overall variable factor productivity gain or cost reduction effect associated with quality improvement in semiconductors (given the level of output and inputs). This effect can be reliably estimated only for the computer industry, where the output price has been

7. This reparameterization procedure was applied in earlier studies by Norsworthy and Jang (1991) and Norsworthy and Zabala (1990).

adjusted for quality change. Because adjustment for quality change has not been made for the price of output of either of the telecommunications equipment industries, there is a downward bias in measured total (and variable) factor productivity. Under these circumstances, any estimate of the effect of improvement in semiconductor quality on industry productivity would be unreasonably low; measured total factor productivity growth in the industries is very nearly zero, while true total factor productivity growth is certainly larger. This first-order term is therefore included only in the computer industry model.

The restrictions in equation (4) are not modified by the quality adjustment. The modified cost function with the restrictions applied is still homogeneous of degree 1 in input prices, including the modified price of semiconductor input. Estimates of a quality-adjusted price for semiconductor input may then be calculated after the estimation of the cost function (11) and the corresponding input demand equations.

Applying this procedure assumes that enterprises using input s do so on the basis of its technological characteristics; that is, the users perceive the input in terms of the quality-adjusted relation between price and quantity. Thus, the demand equation for the input s is stated in terms of *adjusted* quantity and price.[8]

In this framework, we can also test the hypothesis that $\alpha = 0$, that is, that there is no significant quality change except that reflected in the current official price index for semiconductors. The simplest test is based on the t-test; the significance of the contribution of the quality-based price adjustment to the estimated model as a whole may also be captured in a likelihood ratio test.

In the estimation procedure, the quantity demanded of semiconductor input, q_s^*, must be adjusted to agree with the quality-adjusted price, p_s^* from equation (10). We applied the following iterative estimation procedure:

1. For the initial value of α, compute q_s^* using equation (5).
2. Estimate α as part of a full information maximum likelihood (FIML) estimation of the cost function model.
3. Recompute q_s^* from (5) using the new value of α.
4. Reestimate α by FIML estimation of the cost function model using the parameter values from the prior iteration.

8. The dependent variable, and hence the error term, in the share equation for the quality-adjusted input s is invariant to the adjustment; i.e., s_s does not change in magnitude when quality adjustment for semiconductor input is introduced. However, while $s_s = s_s^*$, the dependent variable and error term in the demand equation for semiconductor input differ according to whether the input s is quality adjusted. That is,

$$q_s^* \neq q_s \quad \text{and} \quad \varepsilon_s^* \neq \varepsilon_s .$$

In other words, the stochastic specification of the model changes with the quality adjustment, necessitating the iterative estimation procedure described below.

Steps 3 and 4 were repeated until successive values of q_s^* for each year differed by a cumulative total of less than .05. This procedure converged in three iterations for SIC 3661, four for SIC 3662, and three for SIC 3573.

The final stage estimate of the quality-adjusted quantity of semiconductor input results in a larger q_s^* and smaller p_s^* than the initial estimate. The larger q_s^* changes the stochastic specification of the model by increasing the relative importance of errors in semiconductor input. The smaller p_s^* affects the elasticity of substitution estimates (through the a_{ij} coefficients), in principle for all pairs of inputs. Consequently, the iterative procedure is necessary.[9]

4.1.3 Comparison with the Standard Hedonic Approach

It is important to make clear how this approach relates to conventional hedonic studies of technology-intensive products, such as Dulberger (chap. 3 in this volume). Triplett provides a thorough statement of the hedonic approach to price deflation (Triplett 1987) and its applications to capital goods (Triplett 1989). The explanation that follows is keyed to the latter discussion.

The conventional hedonic function may be expressed as

$$P = h(c), \tag{13}$$

where P is a vector of prices of n varieties of the good in equation (12), and c is a matrix measuring each of k characteristics of each of n varieties of the good (Triplett 1989, eq. [1], p. 128). The production function that corresponds in our study to Triplett's equation (2) (Triplett 1989, 130) is the short-run function

$$y = f(q_L, q_N, q_M, q_V, q_S; K), \tag{14}$$

where y is output. K is fixed capital input, and q_i, $i = L, N, M, V, S$, are the variable inputs noted for equation (11) above. (Equation [11] above is the dual to eq. [14].) The quality adjustment of q_s, semiconductor input, is achieved by mapping q_s into semiconductor characteristics space:

$$q_s = q(T_1, \ldots, T_m), \tag{15}$$

where the T_i, $i = 1, \ldots, m$, are the quantities of the various characteristics in the aggregate q_s. By estimating the function that carries out transformation (15) in the context of the production model, we obtain weights for the semiconductor characteristics embodied in the aggregate input q_s. These weights measure the marginal productivity in the industry being studied. This point is worth stressing: the weights obtained from the cost function for the industry

9. We utilized the FIML estimation procedure in program SORITEC. This procedure cannot update q_s^* shown in the demand equation for semiconductor input as part of the iterative process of determining parameter values, thus necessitating the iterative procedure.

are specific to the production technology used in that industry; they also reflect the mix of characteristics peculiar to input S in that industry.[10]

The quality-adjusted quantity of semiconductor input is thus denoted q_s^*, where

$$(16) \qquad q_S^* = q_S \cdot I,$$

and I is a quality index based on the transformation of the quantity of semiconductors into characteristics space. We specify the index I in logarithmic form:

$$(17) \qquad \ln(q_s^*/q_s) = \ln I = (w_1 t_1 + \ldots + w_m t_m) = \Sigma_i w_i t_i,$$

where t_i is the (log of the) representative measure of characteristic i for semiconductors. Its dimensions are units of characteristic i per unit of semiconductor input. (Ideally, t_i should represent the quantity of characteristic i in semiconductors input for the industry; however, that information was not available to us.) The coefficients w_i are estimated transformation coefficients and measure units of base year input S per unit of characteristic i. Consequently, the quality-adjustment expression for semiconductor input is given by

$$(18) \qquad q_S^* = q_S \cdot \exp(\Sigma_i w_i t_i).$$

The form in which equation (18) is estimated is altered somewhat to permit direct testing of the proposition that proportional changes in the characteristics lead to equal proportional changes in the quality of semiconductor input. Thus, for estimation, the log of the quality index in equation (17) is rewritten

$$(19) \qquad \ln I = \alpha(\Sigma z_i t_i),$$

where $z_m = 1 - \Sigma_{i=1}^{m-1} z_i$ and $w_i = \alpha z_i$.

We can then test the proposition that $\alpha = 1$ by computing the t-statistic for $\alpha - 1$ after estimation of the model.

The quality index I must preserve the cost of input s in nominal terms, that is,

$$(20) \qquad p_S q_S = p_S^* q_S^*,$$

where we obtain

$$(21) \qquad \begin{aligned} p_S^* &= p_S/I, \\ \ln p_S^* &= \ln p_S - (w_1 t_1 + \ldots + w_m t_m). \end{aligned}$$

The right-hand side of expression (21) replaces $\ln p_S$ in the estimated translog model, equation (11) above.

The prices of characteristics may be obtained by simultaneously solving the system of simultaneous equations

10. There is no industry-specific information available to us to identify industry-specific composition of aggregate semiconductor input.

(22) $$p_i = [(\Sigma_i\ w_iT_i)/p_S^* - (p_Sq_S - p_iT_i)]/T_i,$$

subject to the conditions that $p_sq_s = \Sigma_i p_iq_i$ and $p_i > 0$ for all i.

The formulation assumes that information is available that quantifies technological characteristics in the aggregate semiconductor input. In this application, we did not have that information; consequently, our estimates of the weights z_i (and the corresponding w_i) contain elements that reflect industry-specific adjustments not only for the transformation coefficients w_i but also for the T_i/q_s as well. Thus, in order to derive characteristics prices according to equation (22) from this application, it would be necessary to obtain estimates of T_i for each industry. A similar limitation applies to the technique used by Dulberger, as noted in section 4.4.2 below concerning industry-specific hedonic weights.

4.2 Data Sources, Measurement, and Concepts

The data used in this study are the historical U.S. time-series data at the four-digit SIC level for telephone and telegraph apparatus (SIC 3661), radio and television communications (other telecommunications) equipment (SIC 3662), and computers (SIC 3573).

To estimate the econometric models, the information required is total cost (TC), variable cost (CV), the price and quantity of output (Y), net capital stock (K), production-worker labor (L), nonproduction-worker labor (N), semiconductors (S), purchased services (V), and (other) intermediate input, "materials" (M).[11] These measures are derived and constructed on the basis of several data sources. The major sources are the Census of Manufactures (CM) and the Annual Survey of Manufactures (ASM) of the Census Bureau, the producer price index (PPI) program of the BLS, and *The Detailed Input-Output Structure of the U.S. Economy* (Bureau of Economic Analysis 1963, 1967, 1972, 1977). Following is a detailed description of the sources and methodology used to create the input, output, and price data for these industries.

4.2.1 Labor

Two components of labor input are distinguished in this study, namely, production-worker labor (L) and nonproduction-worker labor (N). Production workers are defined by the CM as workers (up through the line-supervisor level) closely associated with production operations at the establishment. The number of nonproduction workers is computed by subtracting the number of production workers from the number of all employees given in the CM or

11. Disaggregation of production and nonproduction labor in high-technology industries results in substantial improvement in the resulting model (Jang 1987) because the compensation and employment trends differ considerably for the two categories of workers. The Division of Productivity Research at BLS separates nonenergy intermediate input into purchased services and other materials because price and input trends for services are quite different, as William Gullickson of that agency has argued for many years.

ASM for each year; payroll for nonproduction workers is computed similarly. Supplemental labor costs are added into the payrolls of both production workers and nonproduction workers in proportion to their shares in total payroll. The augmented payroll of nonproduction workers divided by the number of nonproduction workers is the annual salary per nonproduction worker. (Employment of nonproduction workers is used as the unit of measure because hours of nonproduction workers are typically not measured, or not measured well.) The hours worked by production workers and their hourly wage rates based on the augmented production-worker payroll are derived from the CM and ASM and used as the quantity and price of production workers, respectively.

4.2.2 Semiconductors

From a technological perspective, semiconductors are one of the most important materials in the manufacture of communications equipment and computers. We separate semiconductors (SIC 3674) from other intermediate materials, which includes all physical materials and electric and gas utilities, shown in the CM and ASM. The ratio of expenditure on purchased semiconductors to expenditure on total intermediate materials is taken from the input-output tables in the CM years. These ratios are interpolated for each year. The price index for semiconductors comes from gross output deflators developed in the BLS economic growth program.

4.2.3 Materials

The levels of annual materials expenditures excluding semiconductors (and most purchased services) are taken directly from the five-year CM and the ASM. The real quantity of materials input is obtained by deflating materials expenditure. The aggregate price deflator for materials, P_M, is constructed as follows:

$$P_M = \sum_{i=1}^{n} W_i P_i, \quad i = 1, \ldots, n,$$

where i designates a particular materials input category. Twenty to thirty-five categories of materials and services inputs together were treated, depending on the industry. On the basis of the detailed input-output table, all physical materials and services purchased from the manufacturing sector and electric, gas, water, and sanitary services are included. The prices (P_i) of these detailed materials are obtained from the producer price indexes of BLS. The weight (W_i) of each individual material in aggregate intermediate input in these industries is computed from the input-output tables. First, we compute the weight from the input-output tables of 1958, 1963, 1967, 1972, and 1977; then we interpolate these weights to obtain the approximate weights for each year. The 1982 CM was used to extend the weights for materials.

4.2.4 Purchased Services

The services provided by the transportation, communications, wholesale and retail trade, finance, insurance and real estate, and government sectors, especially computer services, have become more and more important in the production process, but the cost of materials measured in the CM and ASM does not include the cost of these purchased services.

The ratio of purchased services expenditures to total cost for each industry is taken from the input-output tables for the CM years, and the ratio is interpolated between these values for each intermediate non-CM year. Using the approach applied to materials, we developed the price index for purchased services by aggregating the detailed purchased services shown in the input-output tables.

4.2.5 Variable Costs after Adjustment for Holding Inventories

Besides the direct costs of variable input factors such as labor, semiconductors, materials, and purchased services discussed above, manufacturers must pay the costs of holding work-in-process inventories. These costs can be measured in terms of holding related variable inputs. We thus compute the total cost of holding the work-in-process inventories by multiplying the quantity of the inventories in current dollars by the rate of return in the industry. This cost is then distributed to the individual variable inputs by their shares in total variable cost. Thus, the cost of holding raw materials inventories is added to total materials expenditures after deflation to obtain the real quantity of materials inputs. Thus, the price of materials is increased by the cost per unit of materials input of holding work-in-process inventory. The cost of holding the work-in-process inventory is thus treated as part of the cost of the variable inputs, with the cost allocated according to the shares in the variable cost of production. Semiconductor and other materials inputs are treated the same since there is no separate information on inventories of semiconductors and other materials.

4.2.6 Capital Stocks for Physical Assets and Financial Assets

The quantities of capital stocks of equipment and structures in these industries were computed by the perpetual inventory method. Investment data series are taken from the ASM and CM. The rates of economic depreciation applied for different types of producers' durable equipment and for private nonresidential structures from Hulten and Wykoff (1981) are used here as in many productivity studies, notably Jorgenson, Gollop, and Fraumeni (1987). The Hulten-Wykoff asset depreciation rates are not specific to industries, nor do they change through time. Depreciation rates for capital stock in these industries are developed as follows. First, the shares of the different types of durable equipment and structures in total expenditures on capital goods for each industry are computed on the basis of the capital flow tables for 1963, 1967, 1972, and 1977 from the associated input-output studies. These shares are interpolated between CM years. Using these shares as weights, the depreciation rates are summed for all types of equipment and structures from the Hulten-Wykoff study to obtain more reasonable depreciation rates for these two elements of the capital stock for each industry. The depreciation rates vary through time because and only because the weights change.

To compute the service prices of capital equipment and structures, we use Jorgenson et al.'s approach, somewhat modified. Besides equipment and structures, other assets, especially financial assets, are also important in most manufacturing industries. These financial assets must also earn a normal return. Their omission from calculation of the rate of return on physical assets imparts an upward bias to that rate of return. Interindustry differences in rates of return on capital should in principle reflect productivity differences. However, differences in rates of return measured in this way will result not only from differential productivity of physical assets but also from different requirements for financial assets.

The rate of return on capital, which includes equipment and structures as well as other assets—financial assets and all types of inventories—is computed by dividing total property income by the sum of nominal values of all assets at the end of the prior year. The values of equipment and structures are the products of their asset prices and quantities, respectively, which are derived as described above. The value of financial assets is estimated by multiplying the ratio of financial assets to the physical assets in the industry by the value of the physical assets. The ratios are taken from the financial statements in the Compustat data base for SIC 3661 and 3573. Balance sheets of nonfinancial corporate business from the Federal Reserve Board of Governors is used as a proxy for SIC 3662, for which Compustat lists no companies at all. A serious deficiency in coverage arises with the financial data for both industries because AT&T, a major producer of both types of equipment as well as of computers, is not listed in either SIC 3661, SIC 3662, or SIC 3573 in the Compustat data base. The omission of AT&T financial data amounts to assuming that the capital requirements for production of telecommunications equipment in that company are the same as those of nonfinancial corporations in general. While this assumption is dubious, the resulting correction for the return to financial assets is surely better than the assumption that they earn no return at all.

4.2.7 Total Cost and Output

The sum of shipments and changes in inventories of finished goods in current prices that come from the CM and ASM is the total cost before adjustment for the cost of holding financial assets and inventories. The cost of holding financial assets and inventories is measured by multiplying the amounts of financial assets and inventories by the rate of return in the industry. To get the true total cost for production, the costs of holding financial assets and finished goods are subtracted from the sum of shipments and changes in inventories.

Production of output is thus separated from production of shipments, and the two are priced separately. The quantity of real output is the deflated value of total revenue after the adjustments noted above. Output is deflated using the appropriate BLS price indexes from the PPI.

The quantities and prices of variable inputs are normalized to 1.00 in 1977. Quantity indexes are then obtained by dividing expenditures on the input by the normalized price.

4.3 Semiconductor Characteristics for Quality Adjustment in a Cost Function Model

Appendix table 4A.1 shows the technology frontiers chosen to represent the seventy-fifth percentile of performance for two types of semiconductor devices: DRAMS and microprocessors. The original data went back only to 1972; extrapolations to 1968 were based on the perceived history of the industry and have not been objected to in discussions with semiconductor specialists.[12] (These data were not adjusted to "tune" the estimation results.) Polynomial smoothing (a quadratic function of time) was applied to reflect the mix of devices of both types. It would be most appropriate to use value weights for the mix of DRAMs and microprocessors used in each industry applied to the indicators. We judged that such a procedure would result in roughly comparable smoothing. From 1968 to 1977, the normalized performance indicators move about the same distance (from -3.4 to 0), although in different patterns. After 1977, the depicted advance in DRAM characteristics is about four times faster than that of microprocessors. The two series of technological characteristics clearly show different patterns, however imprecise they may be.

In a study based on cross-sectional as well as time-series data, a much richer description of semiconductor technology than employed here would be possible. Such a study could be based in part on plant-level data from the Longitudinal Research Data file at the Census Bureau. In terms only of the number of characteristics included, this study is inferior to the conventional hedonic approach. However, the model explains more than 99 percent of the observed variation in input demand.

This approach has innovative features that compare favorably with the usual hedonic study, however. The weights of the characteristics of semiconductor devices are permitted to change by industry. (While we have not yet done so, we would expect to reject the hypothesis that the quality-adjustment functions are the same across industries.) Second, the interaction of semiconductors with other major categories of inputs is incorporated into the model through the joint estimation of the input demand functions and the cost function. Third, in the case of the computer industry, it is also possible to include evi-

12. However, we regard the 1968–71 data as preliminary.

dence for the semiconductor quality adjustment from the effect on total factor productivity in the industry. An ideal approach, in our view, would combine cross-sectional data with the cost function–based model applied here, enabling the analysis of more technological characteristics.

4.4 Empirical Application to Three Industries

4.4.1 Estimation Results

The cost function estimations outlined above were carried out for the telecommunications equipment and computer manufacturing industries SIC 3661, 3662, and 3573 by the FIML method in the SORITEC econometrics package. The results for each of these industries are shown in tables 4A.2, 4A.3, and 4A.4, respectively.

The coefficients of the estimated variable cost function models suggest that most of the model characteristics are satisfactory.[13] All variable input demand curves slope downward at all points, except as noted below, based on the BY parameters.[14] All industries show increasing returns to scale (in varying degrees) as expected; scale measures are in "credible" ranges: greater in computers, reasonably close to one elsewhere. Second-order parameters are reasonable in size; models characterized by overfitting often show second-order parameter values exceeding one.

With the exception of the demand for production-worker labor in industry 3662, the input demand functions are concave in their own prices, as the elasticities in table 4A.5 show. The shadow cost of capital, b_k, however, is effectively zero. The coefficient, b_k, was constrained to be nonpositive in all models. As noted in the data section, the absence of financial data for AT&T from the industry aggregate makes the capital results for SIC 3661 and 3662 less than complete. Because there are parameter constraints connecting the capital and output coefficients, this problem may also affect the estimates of economies of scale, which show increasing returns of about 40 percent in SIC 3661. The Durbin-Watson statistics (after first-order autocorrelation correction in SIC 3661) indicate that there may be downward bias in the estimated standard errors owing to serial correlation of the residuals for SIC 3662 and 3573.

13. It may be that the method for computing standard errors and t-statistics in FIML estimation results in downward bias in the standard errors when our iterative method of estimation is applied. A characteristic of many FIML estimation techniques is that the standard errors of the estimated coefficients are determined empirically on the basis of changes in the provisional coefficient estimates just prior to convergence. In consequence, when the estimation tolerance is extremely small—a practice to ensure reproducibility of the results and comparability across models—the variance-covariance matrix of the estimated coefficients gets quite small, and the t-statistics explode. In this constrained choice set, we chose the accuracy of the parameter estimates over that of their standard errors in order better to identify the interindustry differences among the quality-adjustment functions. It may be possible to correct this deficiency in the near future.

14. The parameters in the appendix tables have been rewritten as uppercase entities because of the limitations of computer software.

We did not expect the rates of quality augmentation inferred from the three industries to be the same. Lancaster's (1971) theory of demand based on characteristics of goods represents an individual product as a bundle of characteristics. As an example, device density and microprocessor capacity[15] for semiconductor inputs could be expected to yield different advantages in different kinds of communications equipment and computers. (In fact, this appeared to be so, but with little effect on the correlations of the resulting quality-adjusted prices.) Further, a considerable number of different devices are grouped together as output of the semiconductor industry, with large differences in function and prices per unit. Because our technology indicators include only two characteristics, DRAM density and microprocessor bit width, we thought it reasonable that the effects of embodied technical change might differ significantly in value per unit among the three industries. This proved to be the case, but the differences are somewhat smaller than we expected.

Estimates of the coefficients for quality adjustment of semiconductor input in this study for the three industries are shown in tables 4A.2–4A.4. The estimated coefficients alpha (α) are quite close for the telecommunications equipment industries. Computer manufacture is similar to telephone and telegraph equipment, but with even higher weight for DRAMs. That is, the values of α are 1.34 for SIC 3661, 1.38 for SIC 3662, and 1.28 for SIC 3573.[16] As table 4A.6 shows, the weights for the DRAM and microprocessor characteristics are about ⅔ and ⅓, respectively, in telephone and telegraph equipment and computers (SIC 3661 and 3573) and are reversed for other telecommunications equipment (SIC 3662). Preliminary discussion with semiconductor and telecommunications industry sources suggests that the relations among the weights for the three industries are plausible.[17] The great similarity between the manufacture of computers and the manufacture of telecommunications switching devices has been widely noted (e.g., Flamm 1989). The similar weights for technological characteristics found in the patterns of usage by the two industries confirm that observation. In contrast, microprocessor performance seems to be more important in other telecommunications equipment (SIC 3662).

The t-statistics reported in tables 4A.2–4A.4 are biased upward as a consequence of the iterative estimation procedure and are therefore inappropriate for testing hypotheses concerning the effect of quality change on the models.

15. Microprocessor capacity is expressed as "bit width"—our own term (not to be confused with "band width," which is only tangentially related). Integrated circuit technology has packed more functions on successively larger microprocessor "CPUs" (central processing units) so that bit width is an indicator of circuit integration and microprocessor speed as well as the data path and instruction repertoire that bit width directly measures.

16. The overall effect in computers is much larger despite the smaller value for alpha because an additional term, z_t, is included, representing the effect on total factor productivity in the industry.

17. Conversations with Jerry Junkins, chief executive officer, and Vladmire Catto, chief economist, Texas Instruments.

In order to test the hypothesis that adding quality adjustment to the models *does not* improve their explanatory power, we adopt the likelihood ratio test (see, e.g., Judge et al. 1985, 182–84). The test statistic is

$$\lambda = 2(U - R),$$

where U is the log of the likelihood function (LLF) of the unrestricted model (the model with technology-based quality adjustment, and R is the LLF of the restricted model (the model without quality adjustment). The test statistic λ has a chi-squared distribution with degrees of freedom equal to the number of parameter restrictions: two each for the telecommunications equipment industries and three for the computer industry. The LLF for the unrestricted model is based on the first pass of the iterative estimation procedure because the left-hand side of the model is changed in subsequent passes. Thus, the unrestricted LLFs reported in the text table below (showing hypothesis tests for effects of quality change in semiconductors) are not comparable to those reported in tables 4A.2–4A.4:

Industry	Unrestricted	Restricted	df	λ	$\chi^2(.05)$
3661	216.21	195.17	2	42.08	5.99
3662	121.95	116.32	2	10.63	5.99
3573	85.31	63.82	3	42.98	7.81

The overall effect of semiconductor quality improvement in computers is much larger than in telecommunications equipment because a term is included in the model representing the variable input factor productivity effect of improvement in the quality of semiconductors. This effect is about 6.3 percent per year, as table 4A.6 shows. Such an effect is quite large: for U.S. manufacturing as a whole, total factor productivity growth is about 1 percent per year before removal of scale effects. The coefficient estimated in table 4A.4 that leads to the effect reported in table 4A.6 is adjusted for scale effects because the scale coefficient b_y is estimated as part of the same model.

It is interesting to speculate why the exponential weights for the quality-adjustment functions are all greater than one. That is, the implied input demand effects (including substitution and, in the computer industry, cost reduction) of semiconductors are greater than DRAM density and microprocessor bit width changes would imply. This result may be interpreted as the effect of omitted characteristics. Dulberger (chap. 3 in this volume) suggests that the answer may lie in improved "packaging" of the devices: adaptation of the techniques that combine the semiconductor devices with other components and each other in the construction of complete systems. Whatever the cause, however, it is remarkable that the evidence from all three industries suggests that the growth in performance characteristics of semiconductor devices as measured here *understates* the growth in their comparative value in production of computer and telecommunications equipment.

Table 4A.7 shows the resulting quality-adjusted semiconductor prices for these three industries as well as the official price index for the computer industry (Cartwright 1986). The price index for computers used in the GNP accounts described by Cartwright is adjusted for quality change using a hedonic approach introduced by Cole et al. (1986). In comparison with this computer price index, our estimated prices of semiconductor devices used in all industries decline much more rapidly. Such a pattern would result in correspondingly higher growth of real output and productivity in the semiconductor industry than the measures obtained from the official price statistics.

Table 4A.8 shows the correlation coefficients for the quality-adjusted price indexes and their changes, expressed both in levels and in natural logarithms. While the correlation coefficients are all extremely high, the adjusted prices nevertheless exhibit rather different behavior. Quality adjustment for computer industry use of semiconductors shows the largest decline over the period studied, with the decline about twice as rapid both before and after the index year 1977, compared to the adjusted price of input to other telecommunications equipment. Another source of differences in quality-adjusted prices among industries could result from the adjustment of semiconductor input prices to reconcile production and shipments costs. (It should be noted that we made no postestimation or "feedback" adjustment of any of the model data to "tune" the results.) However, comparison of tables 4A.8 and 4A.9 shows that the quality-adjusted semiconductor prices are more highly correlated across industries than are the prices of semiconductor input before quality adjustment.

Table 4A.10 shows the effects of changes in performance characteristics of semiconductors on production costs in the U.S. computer industry for the period 1969–86 and for three subperiods. The cost-reducing effect declines from an annual rate of more than 2 percent in 1969–73 to about 0.67 percent in 1979–86. However, the value of the cost reduction increases from the earliest to the latest period because the total volume of sales in the computer industry increases.

4.4.2 Comparison with Dulberger's Method

It is useful to compare this approach with that applied by Dulberger (chap. 3 in this volume). (Note that Dulberger's analysis is based on data that were not available to us during the course of our study.) The Dulberger hedonic price index can be applied to deflate semiconductor input to an industry only if the detailed composition of that input is known in terms of characteristics. In other words, if the Dulberger deflator is applied to deflate input to the computer industry (SIC 3573) or telecommunications industries equipment (SIC 3661 and 3662), then the deflation will be based implicitly on the composition of the hedonic sample in the absence of data on composition of the semiconductor input in that specific industry. Unlike the hedonic deflator from the Dulberger application, the deflator derived from our approach reflects the technology of production in each of the industries studied, and the hedonic weights reflect the input demand transactions carried out by each industry. That is, the Dulberger hedonic index, like the Lancaster formulation, reflects the combinations of characteristics in the buyer's opportunity set but is mute concerning the buyer's actual choices. Our variant reflects the results of the buyer's choices but does not identify the original opportunity set.[18]

4.5 Conclusions and Implications for Future Research

This study examines three related equipment manufacturing industries that are central in different ways to the information revolution. Our key findings are as follows.

1. Advances in semiconductor technology have profoundly influenced the patterns of production in telecommunications equipment and computer manufacture. These technological advances are captured in physical characteristics of semiconductors.

2. These technological advances constitute largely unmeasured quality change in semiconductors. After adjustment, the prices per unit of performance fall dramatically (table 4A.7) and—as expected—faster than quality-adjusted prices of computers.

3. Consequently, the producer price indexes for semiconductor devices greatly understate quality change and thus the quantity of semiconductor input of constant performance.

4. The relative weights of DRAM device density and microprocessor word size vary among industries and are highest for DRAMs in the computer industry. (All three industries might be better understood and modeled as multiproduct industries so that the roles of the semiconductor inputs could be clarified by estimation of separate parameters linking them to different output categories in the using industries.)

5. Cost function–based estimation of hedonic price indexes offers substantial promise for finding industry-specific price deflators. The required assumption that producers minimize the short-run variable cost of production is

18. Despite the data limitations that our application necessarily reflects, the resulting input deflators are industry specific and perhaps not implausibly different from one another. There is no doubt, however, that a more specific data set in the particulars noted would improve our method. Our method has been applied in a recent doctoral dissertation at Rensselaer Polytechnic Institute (Pitt 1991). In that application, technological characteristics of aircraft are the basis for obtaining airline-specific indexes of the quality of the fleet of aircraft. Each fleet year for each carrier is represented by a vector of technological characteristics based on the composition of the fleet in that year. (The current value of the aircraft is used to weight its contribution to overall fleet technological characteristics.) Thus, in that case, where the data were available, the method applied here used detail of the type represented in Dulberger's analysis.

also required to interpret conventional hedonic price indexes as reflecting value in use.

6. Finally, cost function–based estimation of hedonic price indexes permits the unambiguous attribution of cost changes and associated productivity changes to quality change in the subject input, as demonstrated above for the U.S. computer industry.

We believe that the methods applied here also hold considerable promise for investigation of quality change in other industries. Particularly if applied to pooled plant-level time-series/cross-sectional data, these methods could accommodate a wider range of technological characteristics and thus provide more detailed and more reliable results than industry time-series data can support. (As noted in sec. 4.4, there is evidence for unmeasured characteristics.) A major strength of the approach is that identifying information for the value of different technological characteristics is derived from demand for other inputs as well as the one under study and from the cost function itself. There are literally dozens of studies in the past twenty years that attest to the improvement that interrelated factor demand models bring to studies of production. Much of this promise can be realized in quality-adjusting input factors for unmeasured quality change, that is, in adapting a hedonic or characteristics-based approach in cost function modeling.

The role of technological change in telecommunications equipment on telecommunications would be better understood through a study of the telecommunications services industry itself. Such a study could incorporate descriptions of the technological advances embodied in telecommunications equipment as this study uses DRAM density and microprocessor word size to describe the performance of semiconductors. Jang and Norsworthy (1990b) have outlined a method for assessing the effect of technological change in telecommunications equipment on telecommunications services. Such a study could provide an improved estimate of quality change of telecommunications equipment and thus an improved estimate of real output in SIC 3661. That information in turn would permit estimation of the contribution of semiconductors to the (quality-adjusted) growth of total factor productivity in telecommunications equipment, in the fashion applied to the computer industry in this paper. We are currently conducting such a study for the New York State Public Service Commission.

In the broader context of analysis of technological change, such a study would represent an important addition to the vertical tracing of the effects of semiconductor technology through equipment manufacture to the delivery of information services. A comparable study of the role of computers in financial and other services as well as manufacturing would complement the telecommunications sequence nicely.

Ultimately, however, studies from currently available data sources cannot substitute for the systematic collection of data for quality adjustment of products whose technological characteristics are rapidly evolving. For the detailed sort of information required to permit the PPI and CPI programs to keep up with accelerating technological change, considerably more resources will be required both for data collection and for empirical research based on those data. Studies such as this, and even those possible with the Census Bureau's Longitudinal Research Data file, can provide only "targeting" information for industries where technological change has outrun industrial price measurement programs. Certainly, the semiconductor industry is one such.

Appendix

Table 4A.1 Technological Characteristics of Semiconductors Used for Quality-Adjustment, Natural Logarithms (1977 = 0)

	DRAM		Microprocessor	
Year	Density Smoothed	Density Indicator	Word Size Smoothed	Word Size Indicator
1968	−3.38946	−3.46574	−3.22815	−3.46574
1969	−3.00345	−3.46574	−2.74520	−3.46574
1970	−2.61980	−3.46574	−2.29332	−2.07944
1971	−2.23849	−2.07944	−1.87251	−2.07944
1972	−1.85953	−2.07944	−1.48276	−0.693147
1973	−1.48292	−2.07944	−1.12408	−0.693147
1974	−1.10867	−0.693147	−0.796460	−0.693147
1975	−0.736761	−0.693147	−0.499908	0.00000
1976	−0.367206	−0.693147	−0.234421	0.00000
1977	0.000000	0.00000	0.000000	0.00000
1978	0.364855	0.00000	0.203356	0.00000
1979	0.727360	0.00000	0.375646	0.00000
1980	1.08751	0.693147	0.516871	0.00000
1981	1.44532	0.693147	0.627031	0.00000
1982	1.80077	2.07944	0.706125	0.693147
1983	2.15388	2.07944	0.754154	0.693147
1984	2.50463	2.07944	0.771117	0.693147
1985	2.85303	2.07944	0.757015	0.693147
1986	3.19908	3.46574	0.711848	1.38629

Table 4A.2 Estimated Translog Variable Cost Function, U.S. Telephone and Telegraph Apparatus Industry (SIC 3661), Quality Adjustment Based on Technological Characteristics of Semiconductors

Coefficient Name	Value of Coefficient	t-Statistic
AO	4.27823	2,825.12
AN	0.185892	179.697
AM	0.536192	521.608
AS	−0.162901E-01	−19.3494
ALPHA	1.3416	−2,692.00
ZR	0.64450	3,039.89
AV	0.790003E-01	47.3942
ANM	−0.345065E-01	−48.9988
ANS	−0.408186E-03	−0.895394
ANV	0.137574	369.008
AMS	−0.546782E-02	−8.69463
AMV	−0.374891E-01	−12.7577
ASV	−0.408221E-02	−4.20729
ANN	0.332749E-01	87.7688
AMM	0.684195E-01	142.557
ASS	−0.552270E-02	−9.58593
AVV	−0.444951E-01	−359.275
BY	0.720430	1,038.59
BK	−0.893981E-05	−0.0943134
BEK	−0.592812	−2,767.58
CNK	0.249345E-01	14.6355
CMK	−0.187211E-03	−0.163427
CSK	0.125610E-01	18.5945
CVK	−0.265574E-01	−16.9188
RL	−0.739801E-01	−127.501
RN	−0.478550	−706.962
RM	−0.178418	−140.741
RS	1.10119	1,541.58
RV	0.475493	524.840

LLF = 123.15

	R^2	D=W
Variable cost function	0.9980	1.0850
Input demand equations:		
Production workers	0.8607	0.9811
Nonproduction workers	0.9103	0.9726
Materials	0.9949	0.9249
Semiconductors	0.9203	0.3198
Purchased services	0.9795	0.8463

Table 4A.3 Estimated Translog Variable Cost Function, Other Communications Equipment (SIC 3662), Quality Adjustment Based on Technological Characteristics of Semiconductors

Coefficient Name	Value of Coefficient	*t*-Statistic
AO	4.96015	115485
AN	0.267009	512.181
AM	0.327592	683.261
AS	0.649659E-01	294.571
ALPHA	1.3843	−49,596.3
ZR	0.582204	6,450.42
AV	0.153946	624.417
ANM	0.691214E-01	368.229
ANS	−0.475510E-02	−20.2399
ANV	0.439374E-01	279.605
AMS	−0.773440E-02	−16.0016
AMV	−0.904379E-01	1,275.38
ASV	−0.937887E-02	−60.5852
ANN	−0.547744E-01	1,616.57
AMM	0.523390E-01	590.507
ASS	0.953483E-02	101.642
AVV	0.796024E-01	1,619.52
BY	0.964603	40,780.1
BK	0.141558E-03	32.4336
BEK	−0.401418	−89,902.6
CNK	0.311857E-01	1,271.62
CMK	0.185577E-01	206.153
CSK	−0.257856E-01	−69.4602
CVK	−0.251170E-01	143.386

LLF = 110.28

	R^2	D=W
Variable cost function	0.9949	1.0850
Input demand equations:		
Production workers	0.6358	0.9811
Nonproduction workers	0.9442	0.9726
Materials	0.9798	0.9249
Semiconductors	0.9999	0.3198
Purchased services	0.9963	0.8463

Table 4A.4 **Estimated Translog Variable Cost Functions, U.S. Computer Manufacturing (SIC 3573), Quality Adjustment Based on Technological Characteristics of Semiconductors**

Coefficient Name	Value of Coefficient	*t*-Statistic
AO	6.11539	36,859.8
AN	0.345391	328.308
AM	0.272393	176.175
AS	0.402017E-01	45.8208
ALPHA	1.28181	2,991.85
ZR	0.830143	585.567
ZT	−0.629755E-01	−226.155
AV	0.175130	154.050
ANM	−0.210291E-01	−10.2198
ANS	−0.250516E-01	−30.6193
ANV	0.189820	275.013
AMS	0.926313E-02	8.85685
AMV	0.579878E-01	121.829
ASV	−0.856720E-02	−16.5092
ANN	−0.591376E-01	−145.826
AMM	−0.190384E-01	−61.8067
ASS	−0.533597E-02	−14.8061
AVV	−0.236525	−2,681.77
BY	0.468209	121.687
BK	−0.477556E-01	−197.401
BEK	−0.717143E-01	−38.8456
CNK	0.957002E-01	125.170
CMK	−0.185323E-01	−12.7616
CSK	0.427278E-02	4.47603
CVK	−0.318193E-01	−39.7112

LLF = 46.426

	R^2	D=W
Variable cost function	0.9981	1.307
Input demand equations:		
Production workers	0.9529	1.499
Nonproduction workers	0.9550	1.250
Materials	0.9934	1.393
Semiconductors	0.9957	1.499
Purchased services	0.9961	1.053

Table 4A.5 Own Price Elasticities of Inputs, Quality-Adjustment Models Based on Technological Characteristics of Semiconductors,[a] (1967–86)

	SIC 3661	SIC 3662	SIC 3573
Production-worker labor	0.1552	−0.1778	−1.7692
Nonproduction-worker labor	−3.2001	−3.4818	−2.4502
Materials	−0.6445	−1.6033	−2.9221
Semiconductors	−106.9720	−12.9657	−29.1951
Purchased services	−23.0867	−1.8441	−12.9602

[a]From models reported in tables 4A.2–4A.4.

Table 4A.6 Coefficients of Quality-Adjustment Function for Semiconductor Inputs in Telecommunications Equipment and Computer Industries[a]

	SIC 3661	SIC 3662	SIC 3573
Alpha (α)	1.3416	1.3843	1.2818
DRAM density (Z_s)	0.6445	0.5822	0.8301
Microprocessor word size	0.3555	0.4178	0.1699
TFP growth (annual from Z^t)			0.056

[a]The estimated variable cost function does not include the capital input so that we have no way of estimating the capital saving associated with improvement in the quality of semiconductors. Accordingly, we have assumed no capital saving and reduced the estimated variable factor productivity increase in accordance with the share of capital in total cost: about 14.2 percent.

Table 4A.7 Semiconductor and Computer Price Indexes after Quality Adjustment (1977 = 100)

		Quality-Adjusted Prices Based on Technological Characteristics of Semiconductors Used In:			
Year	PPI	SIC 3661	SIC 3662	SIC 3573	Official Computer Price Index
1969	93.54	4,912.9	5,074.5	11,458.3	309.11
1970	92.29	2,845.1	2,825.0	3,476.1	276.46
1971	91.46	1,673.0	1,511.2	2,884.0	237.26
1972	89.99	987.2	934.3	1,539.6	204.36
1973	91.29	607.1	571.7	866.3	184.93
1974	99.75	406.5	383.0	528.0	145.77
1975	101.75	256.8	247.2	300.4	132.75
1976	100.06	158.1	154.0	170.4	115.72
1977	100.00	100.0	100.0	100.0	100.00
1978	99.16	63.4	65.5	59.0	84.78
1979	100.16	41.4	33.9	36.3	73.21
1980	107.21	29.0	33.2	23.8	58.84
1981	106.57	19.0	23.2	15.0	53.78
1982	103.29	12.3	16.1	9.2	50.08
1983	109.44	8.8	12.4	6.3	38.61
1984	113.15	6.2	9.7	4.4	34.30
1985	112.11	4.2	7.3	2.9	. . .
1986	113.72	3.0	5.7	2.1	. . .
Average annual rate of change (%)	.47	−17.86	−16.39	−20.76	−5.97

Table 4A.8 Correlation Matrices for Quality-Adjusted Prices of Semiconductor Inputs for Three Using Industries, 1969–86[a] (price indices: 1977 = 1)

	Levels			Changes		
SIC	3661	3662	3573	3661	3662	3573
3661	1.0			1.0		
3662	0.9996	1.0		0.9993	1.0	
3573	0.9943	0.9969	1.0	0.9947	0.9977	1.0

[a]Changes are correlated from 1970–86.

Table 4A.9 Correlation Matrices for Prices of Semiconductor Inputs before Quality Adjustment for Three Using Industries, 1969–86[a] (price indices: 1977 = 1)

	Levels			Changes		
SIC	3661	3662	3573	3661	3662	3573
3661	1.0			1.0		
3662	0.9986	1.0		0.9923	1.0	
3573	0.9847	0.9881	1.0	0.9304	0.9309	1.0

[a]Changes are correlated from 1970–86.

Table 4A.10 Technological Characteristics of Semiconductors and Effects on Computer Industry Cost, Average Annual Rates of Change,[a] Selected Periods, 1969–86

	1969–86	1969–73	1973–79	1979–86
Average change in DRAM density	36.4855	38.0132	36.8380	35.3103
Average change in microprocessor word size	20.3355	40.5281	24.9954	4.8028
Cost effect of DRAM density	−0.9275	−1.3886	−1.0334	−0.5733
Cost effect of microprocessor word size	−0.2904	−0.6705	−0.3252	−0.0435
Average total effect of semiconductors	−1.2180	−2.0591	−1.3586	−0.6169

[a]Computed by differences in logarithms.

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