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DECOMPOSING PRODUCTIVITY GROWTH IN THE U.S. COMPUTER INDUSTRY

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Abstract—In this paper, we examine the sources of the productivity growth in the U.S. computer industry from 1978 to 1999. We estimate a joint production model of output quantity and quality that distinguishes two types of technological changes: process and product innovations. Based on the estimation results, we decompose total factor productivity (TFP) growth rate into the contributions of process and product innovations and scale economies. We find that product innovation associated with better quality accounts for about 30% of the TFP growth in the computer industry. Furthermore, the TFP acceleration in the computer industry in the late 1990s is mainly derived from a rapid increase in product innovation.

I. Introduction

DURING the last few decades, there has been a remarkable productivity growth in the production of information technology (IT) products such as computers, communications equipment, and semiconductors. A typical measure of productivity is total factor productivity (TFP), defined as the amount of output produced from a given amount of input. Hence, the traditional TFP approach mainly focuses on how much productivity growth is caused by the improvement in the technological efficiency of production process (process innovation).

In contrast to process innovation, productivity growth can take place in the improvement of output quality (product innovation). In particular, improvement in output quality, such as in microprocessor speed and the capacity of storage devices and memory, is one of the most prevailing characteristics in IT production. This suggests that technological innovation associated with better quality can be an important source of the TFP growth in the IT-producing industry. As Hulten (2001) pointed out, however, the TFP approach is silent about product innovation.[1] Therefore, the identification of both process and product innovations is crucial to the exploration of the sources of productivity growth in the IT-producing industry.

In this paper, we examine the sources of the productivity growth in the U.S. computer industry from 1978 to 1999. The novelty of this paper is that we separate two different technical changes in TFP growth: product innovation associated with better quality and process innovation associated with more quantity. Using both the hedonic (quality-adjusted) and list (quality-unadjusted) prices, we construct the variables of output quantity and quality. Then, we formulate the

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[1] Although some recent studies by Jorgenson and Stiroh (2000), Oliner and Sichel (2000), and Whelan (2002) have attempted to measure the TFP growth in the IT-producing industry, there have been few studies that distinguish the contributions of process and product innovations in the productivity growth in this industry.

TABLE 1.—HEDONIC AND LIST PRICES AND OUTPUT QUALITY AND QUANTITY, 1978–1999

	Electronic Computers (3571)	Computer Storage Devices (3572)	Computer Terminals (3575)	Computer Peripheral Equipment (3577)	Average
Hedonic price	−20.47	−8.59	−8.37	−12.85	−16.87
List price	−5.21	−0.48	−1.30	−8.93	−5.23
Quality of output	15.26	8.11	7.07	3.92	11.65
Quantity of output	15.41	11.55	2.15	18.10	15.13

Notes: Average growth rates of the four industries are weighted by the industry share of nominal output between two adjacent years. The growth rate of output quantity is equal to the growth rate of nominal output minus the growth rate of list price. The growth rate of output quality is equal to the growth rate of list price minus the growth rate of hedonic price.
(percentage per year)

joint production model of output quantity and quality, and estimate the joint optimization conditions of quantity and quality together with a general cost structure that accounts for scale economies and markups. Based on estimation results, we find that technical change associated with process and product innovations contributes about 70% of TFP growth in the computer industry, while the effect of scale economies explains about 30% of the TFP growth. In particular, product-oriented technical change explains about 30% of the TFP growth in the computer industry. Furthermore, we find that the TFP contribution from product innovation rapidly rose in the late 1990s, while the contribution from process innovation and economies of scale changed little.

II. Measuring Output Quality and Quantity

Product innovation takes place in the improvement of quality or in the introduction of new products that have better quality. Thus, measuring changes in output quality, given physical units of output, is crucial to distinguish product innovation from process innovation. The hedonic price method provides us a viable solution to measure the improvement of output quality. The hedonic price corrects the list price (unit price) of output for changes in product attributes that characterize changes in output quality. The quality of output (Y_S) is given by

$$Y_S = \left(\frac{P}{P_Y}\right), \tag{1}$$

where P is the list price of output and P_Y is the hedonic price of output. It is important to note that drops in the hedonic price can be greater than true quality improvement if the list price falls because of changes in the demand factors such as declines in markup.[2]

The quantity of output (physical units of output) can be obtained from dividing the nominal value of production (V_Y) by the list price of output,

$$Y_Q = \left(\frac{V_Y}{P}\right), \tag{2}$$

where Y_Q is the quantity of output. The quality-adjusted output can be obtained from multiplying output quantity by output quality.

In this paper, we constructed output quantity and quality in four computer industries: electronic computers (3571), computer storage devices (3572), computer terminals (3575), and computer peripheral equipment (3577) (1987 SIC codes in parentheses). Using the ratio of the list price to the hedonic price, we constructed the output quality. We obtained the hedonic price for computer products from the Bureau of Economic Analysis (BEA).[3]

The list price was obtained from the *Current Industrial Reports* (CIR) published by the Census Bureau. The CIR includes the nominal values and physical units of shipments for detailed products in each industry. For example, the electronic computers industry in 1997 has eleven types of host and single-user computers, such as large- and medium-scale systems, PC servers, personal computers, workstations, and notebooks. We first construct the list price of each product by dividing the nominal value of shipments by the physical units of shipments. To avoid the bias in the list price that can result from changes in the composition of products, we use the Törnqvist index to construct the industry-level list price.[4] The growth rate of the list price at the industry level is calculated as the weighted average of the growth rates of all products in an industry, where the weight of each product is defined as an average nominal value of shipments over two adjacent years.

Table 1 presents the annual growth rates of hedonic and list prices and output quality and quantity for the period 1978–1999. As shown in equation (1), the growth rate of quality is defined as the growth rate of the list price minus the growth rate of the hedonic price. The annual growth rate of the quality improvement is about 12% on average for all industries from 1978 to 1999. This suggests that the improvement in true quality is smaller than changes in the hedonic price. Quality improvements are significantly different across industries. The quality improvement in electronic computers has been faster than those in the other three computer products. The average annual growth rate of quantity is about 15% for all industries. The growth rate of the quality-adjusted output—that is, the sum of the growth rates of quantity and quality—is about 27%. This implies that quality improvement contributes almost half of the growth of the quality-adjusted output.

III. Empirical Specification

A firm chooses both output quantity and quality to maximize its profits,

[2] The hedonic prices capture the relationship between equilibrium price and product quality, not just the valuation of the quality. The importance of the market condition in the hedonic price method is also emphasized in the studies by Rosen (1974) and Pakes (2003). Imperfect competition leads to markups being positively correlated with quality so that the hedonic price can overestimate improvement in quality (Hobijn, 2001).

[3] See BEA (1998) for the details on sources and methods of the hedonic price index.

[4] We thank an anonymous referee for suggesting that we correct for these biased results from changes in the mix of products. For example, if the share of cheaper products increases, the industry-level list price can decline without changes in each product's list price. In fact, most industries (except for computer peripheral equipment) show this pattern. Therefore, without correcting for the compositional changes, declines in the list price can be exaggerated and subsequently, the quality improvement can be underestimated. Since we construct the industry-level list price using the Törnqvist index, the industry-level quantity is not a simple sum of physical units of shipments, but is an index weighted by the share of products.

$$\pi(Y_Q,Y_S) = Y_Q P(Y_Q,Y_S) - C(Y_Q,Y_S), \tag{3}$$

where $P(Y_Q, Y_S)$ is the inverse demand function and $C(Y_Q, Y_S)$ is the cost function. The quality improvement shifts the quantity demand curve to the right and raises the curve of cost. Thus, the optimal choice of output quality depends both on the demand elasticity for quality and on the marginal cost of quality production.[5]

The main purpose of our model is to quantify the contribution of both product and process innovations to productivity growth.[6] Thus, we are interested in measuring the marginal costs of both the quality and the quantity that are determined by all factors of production. To accomplish this, we use a flexible cost function that allows a general cost structure of quality and quantity production. In contrast, the quality improvement in the endogenous growth models of Grossman and Helpman (1991) and Aghion and Howitt (1992) is determined only by specific inputs such as research and development (R&D) and skilled workers.[7]

We specify a translog cost function to describe the technology of the firm as

$$\begin{aligned}\ln (c_t^v) = {} & \beta_0 + \beta_L \ln w_t + \beta_K \ln K_{t-1} \\ & + \sum_{j=Q,S} \beta_j \ln Y_{j,t} + \beta_T T_t \\ & + \frac{1}{2}\left[\beta_{LL}(\ln w_t)^2 + \beta_{KK}(\ln K_{t-1})^2 + \sum_{j=Q,S} \beta_{jj}(\ln Y_{j,t})^2 + \beta_{TT} T_t^2\right] \\ & + \beta_{LK} \ln w_t \ln K_{t-1} \\ & + \sum_{j=Q,S} \beta_{Lj} \ln w_t \ln Y_{j,t} \\ & + \beta_{LT} \ln w_t T_t \\ & + \sum_{j=Q,S} \beta_{Kj} \ln K_{t-1} \ln Y_{j,t} \\ & + \beta_{KT} \ln K_{t-1} T_t \\ & + \beta_{QS} \ln Y_{Q,t} \ln Y_{S,t} \\ & + \sum_{j=Q,S} \beta_{jT} \ln Y_{j,t} T_t,\end{aligned} \tag{4}$$

where the variable cost is given by $C^v = W_L L + W_M M$, and the variable cost and the price of labor input are normalized by the price of materials, that is, $c^v = (C^v/W_M)$ and $w = (W_L/W_M)$, respectively. The normalization imposes the homogeneity restriction on the cost function. K_{t-1} is a lagged variable of quasi-fixed capital stock and T is an index of process-oriented technical change that represents a shift in the variable cost function.

Rearranging two first-order conditions for profit maximization with respect to output quantity and quality with the translog cost function, we can derive the variable cost share equations of output quantity and quality as

$$\begin{aligned}S_{Q,t} &= (1 + \mu_Q) \frac{\partial \ln C_t^v}{\partial \ln Y_{Q,t}} \\ &= \left(\frac{1}{1+\alpha_Q}\right)(\beta_Q + \beta_{LQ} \ln w_t + \beta_{KQ} \ln K_{t-1} \\ &\quad + \sum_{j=Q,S} \beta_{Qj} \ln Y_{j,t} + \beta_{QT} T_t),\end{aligned} \tag{5}$$

$$\begin{aligned}S_{S,t} &= (1 + \mu_S) \frac{\partial \ln C_t^v}{\partial \ln Y_{S,t}} \\ &= \left(\frac{1}{\alpha_S}\right)(\beta_S + \beta_{LS} \ln w_t + \beta_{KS} \ln K_{t-1} \\ &\quad + \sum_{j=Q,S} \beta_{jS} \ln Y_{j,t} + \beta_{ST} T_t),\end{aligned} \tag{6}$$

where S_Q is the variable cost share of output quantity, μ_Q is the markup for output quantity, and α_Q is the inverse demand elasticity with respect to output quantity. S_S, μ_S, and α_S are similarly defined for the quality of output. Since α_S represents the willingness to pay for one more unit of quality, the supply of the better quality can increase revenue by way of raising the price. Thus, we can expect the positive sign for α_S in contrast with the negative sign for α_Q.

Aghion and Howitt (1992) focus on the growth implication of creative destruction due to quality innovation; a new innovation creates monopoly rents, but destroys rents from the previous innovation. In this regard, they assume that the product quality chosen by innovating firms is at the frontier. But, the optimal quality in our model is not necessarily at the frontier level, which reflects that some firms within the industry produce computers at the frontier level, but others do not. For example, Bresnahan, Stern, and Trajtenberg (1997) find that both frontier- and nonfrontier-level personal computers coexist.

Applying Shephard's lemma to the variable cost function, we derive the cost share equations of labor ($S_L = W_L L/C^v$). The variable cost share of materials can be derived as $S_M = 1 - S_L$. Using the envelope theorem, we can derive the long-run equilibrium condition for a quasi-fixed factor of capital. In the long-run equilibrium, the optimal quantity of the capital stock is determined by the condition that the rental rate of capital is equal to the magnitude of the reduction in variable cost due to an increase in an additional unit of the capital stock. This condition yields the variable cost share equation of the capital stock ($S_K = W_K K/C^v$), where W_K is the user cost of capital.

The growth rate of TFP is traditionally defined as the difference between the growth rate of output and the growth rate of all inputs. Since the growth rate of the quality-adjusted output is equal to the sum of growth rates of output quantity and quality, the rate of TFP growth in a two-output case can be given by

$$T\dot{F}P_t = \sum_{j=Q,S} \dot{Y}_{j,t} - \sum_{i=L,M,K} \frac{1}{2}(\tilde{S}_{i,t-1} + \tilde{S}_{i,t})\dot{X}_{i,t}, \tag{7}$$

[5] If the cost structure for quality production has a property of constant returns to scale, the choice of quality production is dependent upon the demand condition but is independent of the cost structure.

[6] Athey and Schmutzler (1995) emphasize complementarities between product (demand-enhancing) and process (cost-saving) innovations, which suggests that the two innovations cannot be separately determined in the model.

[7] Scherer (1984) suggests that more than 90 percent of R&D in the computer industry is devoted to product innovation, which implies that investment in R&D can be an important source of product innovation. Since we consider both the product and process innovations, adopting R&D in our model also requires separate R&D expenditures on the product and process innovations. This is beyond the scope of our study and will be addressed in future research.

where a dot over the variable denotes the rate of growth and $\tilde{S}_t$ is the total cost share of input i.

Following the methodology of the TFP decomposition in a multiple-output case proposed by Denny, Fuss, and Waverman (1981) and Nadiri and Nandi (1999), we can decompose the growth rate of TFP into three factors as

$$T\dot{F}P = \left(1 - \frac{1}{\rho_Q}\right)\dot{Y}_Q + \left(1 - \frac{1}{\rho_S}\right)\dot{Y}_S - \eta_T,$$

$$\text{where} \quad \rho_j = \frac{1 - \eta_K^v}{\eta_j^v},\ \eta_K^v = \frac{\partial \ln C^v}{\partial \ln K},$$

$$\eta_j^v = \frac{\partial \ln C^v}{\partial \ln Y_j},\ \eta_T = \frac{\eta_T^v}{1 - \eta_K^v}, \tag{8}$$

$$\eta_T^v = \frac{\partial \ln C^v}{\partial T} \quad \text{for} \quad j = Q,S.$$

η_K^v is the variable cost elasticity with respect to the capital stock, η_Q^v and η_S^v are the variable cost elasticities with respect to output quantity and quality, respectively, and η_t^v is the variable cost elasticity with respect to the time variable. Scale economies are measured as the inverse of cost elasticity with respect to output quantity. After correcting for the effect of a quasi-fixed factor of the capital stock on the variable cost, ρ_Q measures scale economies in the long run. There are economies of scale if ρ_Q is greater than 1. In a similar vein, ρ_S measures the degree of the cost efficiency for product innovation, which can be a source of productivity growth if ρ_S is greater than 1. Process-oriented technical change can be measured with $-\eta_T$ that represents a shift in the cost function. On the right-hand side of equation (8), the first term is scale effect, the second term is the effect of product innovation, and the last term is the effect of process innovation.[8]

IV. Results

We estimate a system of equations consisting of the variable cost function, the variable cost share equations of labor and capital, and two optimality conditions for output quantity and quality using the nonlinear three-stage least squares (3SLS).[9] We use a set of instrumental variables: lagged variables and macroeconomic variables such as oil price, defense spending, population, GDP per capita, the share of nonmanufacturing sector, and corporate income tax rate.[10, 11] We also estimated the model with various sets of instruments. In particular, lagged variables are not good instruments if the error terms are autocorrelated. Thus we corrected for first-order autocorrelation in the error terms and estimated the model without lagged variables, but the elasticity estimates are qualitatively not different.

The optimal choice of output quantity and quality depends on two different demand conditions as well as cost structures that are jointly estimated in this study. We introduce the industry dummy variables for intercepts in all equations, and also allow the industry dummy variables for time coefficient to capture different process innovations among the four industries. The majority of the parameter estimates are statistically significant.[12]

A. *Cost Elasticity and TFP Growth Decomposition*

Table 2 presents the short-run and long-run cost elasticities with respect to output quantity and quality, input prices, a quasi-fixed factor of the capital stock, and time variable. The short run implies that production is conducted when the level of the capital stock is fixed, while in the long run, cost can be minimized with the adjustment of capital.

Since elasticity estimates are nonlinear functions of parameters, the standard errors are obtained by using the bootstrap method with replacement 1,000 times.[13] We also calculated the standard errors using the delta method, which uses a first-order variance approximation under a normality assumption. Both the bootstrap and the delta methods standard errors are very close to each other.

In table 2, an interesting result is that the cost elasticity of output quality is smaller than that of output quantity. This suggests that the production of quality entails less cost than the production of quantity. Producing better-quality goods is not subject to sharply increasing cost if there are learning-by-doing and spillovers of new technologies. For example, Irwin and Klenow (1994) find that learning-by-doing is an important source of cost reduction in semiconductor production. The variable cost elasticity of the time variable suggests that the variable cost has declined about 6.7% annually, given production of the same amount of output quantity and quality.[14]

The bottom panel of table 2 presents the decomposed contribution to TFP growth that includes the effects of process and product innovations and scale effect. An average TFP growth rate for the four industries is about 15%, but the TFP growth rates vary considerably across the industries. For example, the TFP growth rate in the electronic computers industry is approximately 18%, while the growth rate in the terminals industry is only one-third of the rate in the electronic computers industry.

The contribution of product innovation is about 4.2%, which accounts for about 30% of TFP growth in the computer industries. Process innovation explains about 40% of TFP growth in these industries, while scale effect accounts for about 30%. The sum of process and product innovations in total explains about 70% of the TFP growth, which implies that the rapid TFP growth in the U.S.

[8] Nadiri and Nandi (1999) decomposed scale effect into several exogenous components such as changes in exogenous demands and factor prices. Unless either quantity or quality is assumed to be exogenous, we cannot decompose the scale and quality effects into other exogenous factors because of the property of the joint determination of quantity and quality.

[9] In addition to output quantity and quality, we use the NBER-CES Manufacturing Industry Database (Bartelsman & Gray, 1996) to construct the quantity and price of labor, capital, and materials. Since the NBER-CES database covers only up to 1996, we expanded the database to 1999 with the *Annual Survey of Manufactures* and the *Census of Manufactures.*

[10] Since computers are more intensively used in the nonmanufacturing than in the manufacturing sector, we use the nonmanufacturing share as an instrument for the demand for computers in the U.S. business sector. To avoid endogeneity in GDP per capita, we also excluded the value added of the computer industry from GDP.

[11] Using the method proposed by Stock and Yogo (2005), we performed a relevance test on instrumental variables for the two detrended endogenous variables of the computer quantity and quality indexes. Results from the relevance test on the set of instrumental variables reject the null hypothesis of weak instruments.

[12] The parameter estimates are available from the authors upon request.

[13] See Efron and Tibshirani (1993) for the details on the bootstrap standard error and Eakin, McMillen, and Buono (1990) for its applications in the standard errors of elasticity estimates in a cost function.

[14] In addition to cost elasticities, the estimates of two demand-side parameters of α_Q and α_S are -0.387 and 0.519, respectively. This implies that the demand elasticity of quantity ($1/\alpha_Q$) is higher than that of quality ($1/\alpha_S$). The finding also suggests that the computer product market is more competitive in quantity than in quality.

TABLE 2.—COST ELASTICITY AND TFP GROWTH DECOMPOSITION

	Electronic Computers (3571)	Computer Storage Devices (3572)	Computer Terminals (3575)	Computer Peripheral Equipment (3577)	Average
Short-run elasticity					
Quantity of output	0.829	0.730	0.705	0.713	0.787
	(0.040)	(0.036)	(0.034)	(0.035)	(0.038)
Quality of output	0.702	0.619	0.597	0.604	0.666
	(0.041)	(0.037)	(0.035)	(0.036)	(0.039)
Time	−0.090	−0.002	−0.022	−0.049	−0.067
	(0.008)	(0.005)	(0.003)	(0.007)	(0.006)
Price of labor input	0.232	0.305	0.311	0.286	0.255
	(0.013)	(0.013)	(0.013)	(0.012)	(0.008)
Price of materials	0.768	0.695	0.689	0.714	0.745
	(0.013)	(0.013)	(0.013)	(0.012)	(0.008)
Capital stock	−0.093	−0.120	−0.108	−0.073	−0.092
	(0.013)	(0.012)	(0.013)	(0.012)	(0.008)
Scale	1.206	1.369	1.418	1.402	1.271
	(0.063)	(0.072)	(0.074)	(0.075)	(0.066)
Long-run elasticity					
Quantity of output	0.759	0.652	0.636	0.664	0.720
	(0.038)	(0.033)	(0.031)	(0.033)	(0.035)
Quality of output	0.643	0.552	0.539	0.563	0.610
	(0.038)	(0.033)	(0.033)	(0.033)	(0.036)
Time	−0.082	−0.002	−0.020	−0.046	−0.061
	(0.007)	(0.005)	(0.003)	(0.007)	(0.006)
Price of labor input	0.212	0.272	0.281	0.266	0.234
	(0.012)	(0.012)	(0.012)	(0.012)	(0.008)
Price of materials	0.703	0.621	0.621	0.665	0.682
	(0.015)	(0.013)	(0.013)	(0.014)	(0.010)
Scale	1.318	1.534	1.572	1.505	1.389
	(0.072)	(0.084)	(0.082)	(0.082)	(0.074)
TFP growth decomposition[a]					
TFP growth rate	18.463	7.999	5.996	10.905	15.059
Scale effect	3.755	4.078	0.681	6.104	4.255
	(0.592)	(0.378)	(0.066)	(0.605)	(0.551)
Effect of product innovation	5.295	3.555	3.300	1.650	4.230
	(0.579)	(0.269)	(0.231)	(0.131)	(0.413)
Effect of process innovation	8.193	0.199	2.013	4.600	6.147
	(0.716)	(0.471)	(0.276)	(0.680)	(0.578)
Residuals	1.221	0.166	0.002	−1.448	0.427
	(0.272)	(0.244)	(0.218)	(0.266)	(0.182)
Industry output share	0.616	0.130	0.034	0.220	

Notes: Numbers in parentheses are the standard errors that are evaluated at their mean values and are also obtained by using the bootstrap method with replacement 1,000 times. Average elasticities, scales, and decomposed effects of the four industries are weighted by the industry share of nominal output.
[a] percent per year.

computer industries is mainly attributable to fast improvement in technologies.

Our estimate of TFP contribution from product innovation can be downward biased if the BEA hedonic price underestimates improvement in quality. Recently, Pakes (2003) pointed out possible biases in the official hedonic indexes that resulted from inappropriate sample selection correction for the high attrition rate of computers as well as estimation variances of hedonic indexes. In a similar vein, Berndt, Dulberger, and Rappaport (2001) also show that the hedonic price estimation is very sensitive to the choice of model specification. In spite of a possible underestimated quality in the BEA hedonic price, our estimate provides at least a lower bound of product innovation.[15]

B. *Implications for Productivity Growth in the Aggregate Economy*

There was a remarkable resurgence in the productivity growth from the early to late 1990s. Determining the source of the productivity revival in the aggregate economy, some recent studies (Jorgenson & Stiroh, 2000; Oliner & Sichel, 2000) focus on the role of the IT-producing industry. Table 3 shows that the contribution from the computer industry to the aggregate TFP growth is on average 0.22, which accounts for almost one-third of the aggregate TFP growth.[16] Moreover, the TFP contribution of the computer industry has risen about two times from the early to late 1990s. The TFP acceleration in the computer industry from the early to late 1990s explains about 40% of the acceleration in the aggregate TFP growth.

Our approach contrasts the conventional TFP accounting in two ways. We explicitly consider the effect of product demand and economies of scale, which enables us to identify nontechnological factors in the TFP growth. In contrast, Oliner and Sichel (2000) and Whelan (2002) assume constant returns to scale and perfect competition, and thus they may overestimate the degree of technological

[15] We thank two anonymous referees for suggesting to us the possible biases in the hedonic prices.

[16] We also compare our TFP growth rate in the computer industry with that of Oliner and Sichel (2000) measured by the dual approach. The TFP growth rates are different between this study and their study during the second half of the 1990s. One of the main reasons for the difference is that they assume the same cost structure between the IT-producing industry and other industries.

TABLE 3.—CONTRIBUTION OF THE COMPUTER INDUSTRY TO TFP GROWTH IN THE NONFARM BUSINESS SECTOR

	1978–1990	1991–1995	1996–1999	1978–1999
TFP growth rate in the nonfarm business sector:[a]				
BLS (2001)	0.303	0.603	1.098	0.516
TFP growth rate in the computer industry:[a]				
Oliner and Sichel (2000)	11.2[b]	11.3	16.6	12.2[c]
This study	13.98	12.37	22.05	15.06
Domar weight of the computer industry:				
Oliner and Sichel (2000)	0.011[b]	0.014	0.016	0.012[c]
This study	0.014	0.014	0.017	0.015
Contribution from the computer industry to TFP growth in the nonfarm business sector:[a]				
Oliner and Sichel (2000)	0.12[b]	0.16	0.26	0.15[c]
This study				
Total contribution	0.193	0.170	0.370	0.220
	0.070	0.052	0.024	0.058
Scale effect	(0.009)	(0.007)	(0.005)	(0.008)
	0.037	0.046	0.171	0.064
Effect of product innovation	(0.004)	(0.005)	(0.018)	(0.006)
	0.088	0.082	0.102	0.089
Effect of process innovation	(0.010)	(0.008)	(0.012)	(0.008)
	−0.003	−0.009	0.072	0.009
Residuals	(0.003)	(0.006)	(0.011)	(0.003)

Notes: The contribution of the computer industry to the aggregate TFP growth is calculated from a weighted sum of the TFP growth rates of the four computer industries with the domar weights. Domar weight is defined as the ratio of gross output in the computer industry to value added in the nonfarm business sector. Numbers in parentheses are the standard errors that are evaluated at their mean values and are also obtained by using the bootstrap method with replacement 1,000 times.

[a] percent per year.

[b] includes the period of 1974–1990.

[c] includes the period of 1974–1999.

change in the industry.[17] In fact, we find that the scale effect explains almost 30% of the contribution, suggesting that this contribution is associated with nontechnological factors.

Second, we identify the contribution of product innovation in the computer industry to TFP growth in the aggregate economy, but the conventional TFP accounting models do not. As Grossman and Helpman (1991) pointed out, quality improvement has played a central role in economic growth. However, studies measuring the contribution of quality improvement in economic growth are rare. Focusing on the computer industry's experiencing rapid improvements in quality, we try to quantify the contribution of product innovation in this industry to the aggregate productivity growth.

Although the contribution of process innovation to the TFP growth in the aggregate economy is greater than that of product innovation, an increase in the product-oriented technical change in the late 1990s explains about 60% of the acceleration in the computer industry's TFP contribution. The contribution from the nontechnological factor of scale economies also changed little from the early to late 1990s. Therefore, the findings suggest that the productivity acceleration in the aggregate economy associated with the computer industry during the late 1990s is largely attributable to acceleration in the product innovation in this industry.

Furthermore, table 3 shows that the contribution of product innovation rose in the sample period, while the contribution from process innovation and economies of scale changed little. Filson (2001) also finds an increasing trend in product innovation in the computer industry, but a decreasing trend in the automobile industry. The time series pattern of product and process innovations in the computer industry challenges the prediction of the industry life cycle theory that new industries experience product innovation early and process innovation later (Gort & Klepper, 1982; Cohen & Klepper, 1996).

[17] See Nadiri and Prucha (2001) more detailed explanations on possible biases in measuring TFP due to economies of scale and imperfect competition.

V. Conclusion

In this paper, we provide an empirical framework for exploring the different sources of productivity growth in the U.S. computer industry. The empirical results of this study show that technological changes associated with both process and product innovations have been a major source of the TFP growth in the computer industry. Furthermore, we quantify the contribution of quality improvement in computers to the productivity growth in the U.S. economy. We find that a rapid increase in the quality of computers has a significant contribution to the TFP acceleration of the U.S. economy in the late 1990s.

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A NEW PROOF OF UZAWA'S STEADY-STATE GROWTH THEOREM

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Abstract—This note revisits the proof of the steady-state growth theorem, first given by Uzawa in 1961. We provide a clear statement of the theorem, discuss intuition for why it holds, and present a new, elegant proof due to Schlicht (2006).

I. Introduction

THE steady-state growth theorem says that if a neoclassical growth model exhibits steady-state growth, then technical change must be labor augmenting, at least in steady state. It is sometimes added that an alternative is for the production function to be Cobb-Douglas. But this is really subsumed in the original version of the theorem since technical change can always be written in the labor-augmenting form in steady state if the production function is Cobb-Douglas.

It did not escape the attention of economists, either in the 1960s or more recently, that this is a very restrictive theorem. We often want our models to exhibit steady-state growth, but why should technical change be purely labor augmenting? The induced-innovation literature associated with Fellner (1961), Kennedy (1964), Sanmelson (1965), and Drandakis and Phelps (1966) explicitly pondered this question without achieving a clear answer. Recently, Acemoglu (2003) and Jones (2005) have returned to this puzzle.

Perhaps surprisingly, given its importance in the growth literature, we have been unable to find a clear statement and proof of the theorem. In addition, exactly why the result holds is not something that is well understood. What is the intuition for why technical change must be labor augmenting?

Uzawa (1961) is typically credited with the proof of the result,[1] and there is no doubt that he proved the theorem. However, Uzawa is primarily concerned with showing the equivalence of *Harrod-neutral* technical change (that is, technical change that leaves the capital share unchanged if the interest rate is constant) and labor-augmenting technical change, formalizing the graphical analysis of Robinson (1938). It is, of course, only a small and well-known step to show that steady-state growth requires technical change to be Harrod neutral. But the modern reader of Uzawa will be struck by two things. First is the lack of a statement and direct proof of the steady-state growth theorem. Second is the absence of economic intuition, both in the method of proof and more generally in the paper.

Barro and Sala-i-Martin (1995, chapter 2) come close to providing a clear statement and proof of the theorem. However, their statement of the theorem is more restrictive: if technical change is factor augmenting at a constant exponential rate, then steady-state growth requires it to be labor augmenting. This leaves the door open to the possibility that there might be some perverse nonfactor augmenting twist of technical change that could be consistent with steady-state growth. McCallum (1996) also comes close, providing a proof of the

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[1] For example, see Barro and Sala-i-Martin (1995) and Solow (1999).