CSLS Conference on Service Sector Productivity and the Productivity Paradox

April 11 - 12, 1997 Chateau Laurier Hotel Ottawa, Canada

Information Technology and Its Impact on Firm-level Productivity: Evidence from Government and Private Data Sources, 1977-1993

Bill Lehr and Frank Lichtenberg

Columbia School of Business, Columbia University

Session 6 “Explanations of the Productivity Paradox”

April 12 1:45 - 3:45 PM

Information Technology and Its Impact on Firm-level Productivity: Evidence from Government and Private Data Sources, 1977-1993

Prof. Bill Lehr
Graduate School of Business
Columbia University

Prof. Frank Lichtenberg
Graduate School of Business
Columbia University

Revised March 1997

Abstract

This paper examines trends in computer usage and the effect on productivity growth for a cross-industry panel of firms during the period 1977-93. We link firm-level computer asset and financial data from a variety of public and private data sources, including Computer Intelligence (a market research firm), the Census Bureau's Enterprise and Auxiliary Establishment Surveys, and Compustat. We find that computers--especially personal computers--contributed positively to productivity growth and yielded excess returns relative to non-computer capital, providing further evidence refuting the *Information Productivity Paradox*. These results appear robust with respect to econometric specifications and to choice of data. Moreover, our results suggest that the excess returns from computers first increased and then decreased over our sample period, and reached a peak in 1986 or 1987. In addition, we find evidence that computers are complementary with skilled labor and that they help reduce inventory levels.

Information Technology and Its Impact on Firm-level Productivity: Evidence from Government and Private Data Sources, 1977-1993

Prof. Bill Lehr
Graduate School of Business
Columbia University

Prof. Frank Lichtenberg
Graduate School of Business
Columbia University

Revised March 1997

1. Introduction[1]

Robert Solow's quip that "we see computers everywhere but in the productivity statistics" has prompted a large and growing literature examining what is commonly referred to as the *Information Productivity Paradox*. Economy-wide and industry studies typically fail to observe a positive contribution to productivity growth from increased investments in computer technology.[2] More recent studies utilizing firm-level data, however, have detected a significant contribution from information technology.[3] This paper confirms the results of these latter studies using firm-level computer asset and financial data for non-agricultural firms covering the period from 1977-1993 from a variety of public and private data sources, including the Census Bureau's Enterprise and Auxiliary Establishment Surveys, Compustat, and Computer Intelligence Infocrop, a market research firm.

Our principal finding, that computers--especially personal computers--do contribute positively to productivity growth, suggests that the traditional *Information Productivity Paradox* is largely a measurement problem. This is closely related to the more general problem of

[1] We would like to thank the following: NBER Sloan project on Industrial Productivity for financial support; the staff of the Center for Economic Studies at the Census Bureau for help with data; the marketing research firm Computer Intelligence for help with data; and workshop participants at the CSLS and the NBER for useful comments. Any errors that remain are our own.

[2] See for example Bailey and Gordon (1988), Loveman (1990), Morrison and Berndt (1994), Roach (1987), Strassman (1990), or Wolf (1997) for papers that fail to detect a positive contribution from computers to productivity growth.

assessing service sector productivity, because computers are used most intensively in the service sector and in the "service" functions of non-service sector firms (e.g., payroll and purchasing). As Zvi Griliches (1994) noted, these are exactly the activities that pose the greatest problems of output and productivity measurement. This problem is especially acute for computers because of the rapid pace of innovation and the fact that computers and the services they support often contribute only indirectly to final output. Moreover, although we may see computers everywhere, they still represent only a tiny fraction of our capital stock (on the order of 2% of plant, property and equipment), so aggregate effects may be hard to detect (Oliner and Sichel, 1993).

Our data indicate that computers not only contributed significantly to productivity growth during the period 1977-1993, but that computers yielded *excess returns* relative to other types of capital. The data also suggest that computer productivity may have peaked around 1986/1987,[4] that computers are complementary with skilled labor (Kreuger, 1993), and that they may allow for reductions in inventory levels. Finally, and perhaps most interesting, the evidence indicates that the *types* of computers and how they are used makes an important difference (Landauer, 1995): *personal computers* appear to have an especially large impact on productivity. This finding highlights the importance and difficulty of measuring computer inputs accurately. We interpret data on the number of PCs or PCs per employee as providing an indication of the extent of usage of computers within the firm. Therefore, firms that had higher PCs per employee would be expected to be using computers more broadly across the organization (and presumably, had a higher percentage of computer-literate employees), which may account for their higher productivity. In the near future, once virtually everyone has a computer on his or her desk, data on the number of PCs per employee will be less informative

---

[3] See for example, Brynjolfsson and Hitt (1993), Lichtenberg (1995), or Lehr and Lichtenberg (1997).

and we will need to collect even more detailed firm- or business-unit-level data in order to accurately measure the contribution of computers to productivity.

The rest of this paper is divided into four sections. In section 2 we present our econometric (production function) model. In Section 3 we describe our various data sources and summarize broad patterns of computer usage. Estimates of the model are reported in Section 4, and Section 5 contains a summary and conclusions.

2. The Model

The essence of the "productivity paradox" is, that while we seem to have been investing heavily in computers for quite a number of years[5], the rate of measured productivity growth has failed to increase, and may have even decreased. Since productivity is defined as output per unit of input, and computers are an input, we should start by asking under what conditions one would expect growth in computer intensity to raise productivity.

The contribution of computers to productivity growth may be *disembodied* or *embodied*. The embodied approach hypothesizes that output (Y) is an exponential function of factor inputs capital (K) and labor (L) times a multiplicative technology parameter (A), which yields the following Cobb-Douglas production function: $Y = A\ K^{\alpha}\ L^{1-\alpha}$. In this formulation, total factor productivity (TFP) is defined as follows:

---

[4] This is partially consistent with the findings of Morrison and Berndt (1994), who found over-investment in computers up until the 1980s, but increases in the marginal benefit-cost ratio by 1988.

[5] Investment in Office Computing and Accounting Equipment (OCA) as a share of total investment in non-residential producer durables increased from 5.9% to 13.2% in nominal terms. (Source: Bureau of Economic Analysis, Department of Commerce, Table 5.8).

$$TFP \equiv \frac{Y}{K^{\alpha} L^{1-\alpha}} = A$$

Equation 1

According to this view, computers contribute to productivity by raising A, which makes all factor inputs proportionately more productive. Computers might have this effect if their principal function were to improve coordination permitting higher levels of output from the same inputs. While this may explain part of the benefit from using computers, it is also possible that computers may contribute to technical progress directly because they are more productive than other types of factor inputs. One way to represent embodied technical progress is to model production as:

$$Y = A\left(K_0 + (1+\theta)K_1\right)^{\alpha} L^{1-\alpha}$$

Equation 2

where total capital (K) is decomposed into computer capital (K_1) and non-computer capital ($K_0 \equiv K - K_1$), α is the elasticity of output with respect to the "effective" capital stock [$K_0 + (1 + \theta) K_1$], and θ is a parameter that measures the "excess productivity" of computer capital (K_1) relative to non-computer capital (K_0). After re-arranging and taking logs, Equation 2 can be expressed as:

$$\ln Y = \ln A + \alpha \ln K + \alpha \ln(1 + \theta x) + (1 - \alpha) \ln L$$

Equation 3

where $x \equiv (K_1 / K)$ = the share of computer capital in the total capital stock. This implies the following forms for TFP and Labor Productivity (Y/L):[6]

$$\ln TFP \cong \ln A + \alpha\theta x$$

Equation 4

$$\ln\left(\frac{Y}{L}\right) \cong \ln A + \alpha \ln\left(\frac{K}{L}\right) + \alpha\theta x$$

Equation 5

Equation 4 reveals that *increased computer-intensity (x) should increase total factor productivity only if computers are more productive than other types of capital.*[7] Under the null hypothesis of zero excess returns to computer capital, the first order conditions of profit maximization require that the ratio of the marginal products of computer to non-computer capital be equal to the ratio of the user costs of capital for computer to non-computer capital, or:

$$\frac{MP_{K_1}}{MP_{K_0}} = (1+\theta) = \frac{R_1}{R_0} = \frac{r+\delta_1 - E(p_1)}{r+\delta_0 - E(p_0)}$$

Equation 6

where MP_K is the marginal product, R_i is the user cost of capital, r is the risk-adjusted discount rate, δ_i is the depreciation rate, and $E(p_i)$ is the expected rate of price appreciation. The ratio of the user cost of computers to other types of capital ought to be approximately equal to 6.[8]

---

[6] The equations are approximate because we are substituting θ x for ln(1+θ x); the two are quite close as long as θx is small. As subsequent discussion will show, since x is on the order of 1-2%, θ may be quite large and this approximation will still be reasonable.

[7] The null hypothesis that the marginal product for computers is greater than zero is that H0: $\alpha > 0$ and $\theta > -1$.

[8] Lau and Tokatsu (1992) used long run averages to estimate r=0.07, δ_1=0.20, δ_0=0.05, $E(p_1)$=-0.15, and $E(p_0)$=0.05. Taken together, these imply that the ratio of the user cost of capital for computer to other types of capital is 6 = (.07+.20+.15)/(.07+.05-.05). This test is quite strong. For example, data from a recent New York Times suggests that the relative lease price-to-purchase price for personal computers versus automobiles (a proxy for other types of machinery and equipment capital) is approximately 3 (*i.e.,* lease-to-purchase ration for automobiles is approximately 15% and for computers is approximately 43%). Because K_0 includes structures, the comparable ratio would be somewhat higher.

With these parameter assumptions, our null hypothesis that there are no excess returns associated computers is equivalent to:

$$H_0\text{: No excess returns} \quad \Leftrightarrow \quad \theta = 5$$

Equation 7

Under the null hypothesis, TFP and (Y/L) will not depend on the share of computer capital, except perhaps because of its effect on disembodied technical progress (via A, which will be captured by the fixed year and industry/firm-level effects in our regression analyses).

If computers are more productive then other types of capital, TFP and (Y/L) will increase with the share of computer capital, but the effect will be attenuated by capital's overall expenditure share, α, which is typically estimated to be on the order of 20-30%. The small size of α implies that total factor productivity and labor productivity will be relatively insensitive even to changes in overall capital intensity.

Many popular discussions of productivity focus on labor productivity rather than TFP. One interpretation of the "productivity paradox" is that, in the last two decades, x has accelerated but (Y/L) has declined. But Equation 5 indicates that labor productivity depends on overall capital intensity (K/L) as well as on the "quality" of capital (x), so this finding would not be paradoxical if capital deepening had decelerated. This is indeed the case: the growth rate of (K/L) declined from 3.0% in 1948-73 to 2.0% in 1973-79 to 1.3% in 1979-90. The stock of computer capital may have been increasing rapidly (although high gross investment is largely offset by rapid depreciation of computers), *but the growth in the stock of other capital has been quite sluggish*.

The true structure of production is much more complicated than is indicated by the above. For example, labor is heterogeneous and output is also a function of intangible capital (generated by past R&D investment). This implies that the right-hand-side variables included in

Equation 3 are a very incomplete subset of the entire list of determinants of productivity. This increases the probability that the so-called productivity paradox is an *ecological fallacy*: the apparent lack of a simple correlation between computers and productivity in aggregate data should not lead us to infer that computers have not "paid off." To accurately assess the marginal productivity of computers, it is necessary to analyze microeconomic data, especially firm-level data, as Brynjolffson and Hitt (1993), Lichtenberg (1995), and others have done.

There is another reason (emphasized by Oliner and Sichel, 1993) to believe that using aggregate productivity data to attempt to assess the returns to computer investment may be like searching for a needle in a haystack: even today, computer capital is a small share of total capital. To illustrate this point, it is useful to consider a slightly different version of the production function:

$$\ln Y = \alpha_0 \ln K_0 + \alpha_1 \ln K_1 + (1 - \alpha_0 - \alpha_1) \ln L$$

Equation 8

In growth rates, this becomes,

$$Y' = \alpha_0 K'_0 + \alpha_1 K'_1 + (1 - \alpha_0 - \alpha_1) L'$$

Equation 9

where Y' denotes the growth rate in Y, etc. The contribution of computer growth to output growth is $\alpha_1 K_1'$. Moreover, in equilibrium, the elasticity of output with respect to computers should be equal to the marginal productivity of computers times the computer-to-output ratio, or $\alpha_1 = MP_1(K_1/Y)$. Even if the marginal productivity of computers is very high and computer capital has grown rapidly, K_1/Y is still small (on the order of 2%) and so α_1 is quite small. Therefore, the contribution to aggregate output growth would be small.

Another reason why we may fail to measure productivity gains from computers is that there may be substantial time lags before gains are realized. Paul David (1990) argues that, unlike other technologies, computers may require substantial changes in complementary infrastructure (e.g., human and knowledge capital, global communications infrastructure, etc.) before the gains to them may be realized. The longitudinal and cross-sectional depth of the data presented here offers a viable method for addressing these concerns. Moreover, by examining data in five year increments, we reduce problems associated with transient fluctuations.

Failure to adequately capture quality improvements is another important source of measurement error which tends to bias downwards estimates of returns to computer investment (Siegel, 1994).[9] If prices accurately reflect quality changes, using sales as a measure of output will help correct the problem, but typically, prices do not fully reflect quality improvements. A large share of the benefits accrue to consumers without being measured either in higher unit sales or industry revenues. Bresnahan (1986) attempted to address this problem by estimating the total social returns to computer investment for a selection of financial-sector firms by exploiting the assumption that the industry is competitive and hence all of the benefits from computers accrue to consumers and are reflected in an outward shift in the industry supply curve. This approach allowed him to impute substantial social returns to computer investment. Ceteris paribus, the implication of this effect for our results is to bias them downwards since we do not attempt to measure the effect on consumer surplus.

Perhaps offsetting the above bias is the danger that an increased share of computer capital is positively correlated with an unobserved input that is more directly responsible for the increased output, leading us to falsely assign causality to the investment in computers. A number of obvious candidates present themselves. First, computer capital may be positively correlated with labor quality (i.e., the share of skilled workers). Suppose output varies not only with capital quality (x), but also labor quality (y) as follows:

$$\ln TFP \cong \ln A + \alpha \theta x + (1 - \alpha) \pi y$$

Equation 10

where y is the share of total employment that is skilled, or y = L_1/L. If we fail to take account of the dependency of output on y, then we will obtain biased estimates of α if x and y are correlated. In Section 4, we consider evidence that shows a positive correlation between computer use and education (and wages), which suggests that (K_1/L) and y are positively correlated. However, the correlation between x and y will depend also on the overall level of capital intensity since (K_1/L) = (K_1/K)(K/L) = x(K/L). If we hypothesize that the correlation between x and y is given by γ (i.e., x = γy + ε), then we can estimate the upward bias as:

$$p \lim \alpha^* = \alpha + \gamma(1 - \alpha)\pi$$

Equation 11

The most direct solution to this problem is to include a measure of labor quality among the regressors. We follow this approach when possible.

We attempt to control for measurement and omitted variable problems in three ways. First, firm fixed effects control for time-invariant (or slowly-changing) unobserved variables. Second, wherever possible, we have attempted to include additional regressors to control for potential determinants of productivity that may be correlated with computer intensity. This includes the share of auxiliary employment in total employment, the number of establishments, and alternative measures of the composition of computer assets (e.g., the share of large

---

[9] We agree with the implicit assumption that product quality is improving over time.

systems that are mainframes, and the total number of personal computers). Third, by utilizing data from multiple, diverse sources, we are able to partially cross-validate our results.

3. Data Description and Trends

In the following two sub-sections we describe our data and then explore trends and other indicators of how computer usage has changed over our sample period.

3.1 Data Description

This study utilizes a mixture of public and private data on the diffusion and utilization of computers by large firms assembled from four major sources and a variety of ancillary sources covering the period 1977-93 (see Table 1). Moreover, unlike a number of earlier firm-level studies which considered only manufacturing firms, over 50% of the total employment for our sample is in non-manufacturing firms. Our data are split into two longitudinal panels, the first covering the period 1977-87 and the second covering the period 1986-93.

For the period from 1977-1987, we use U.S. Bureau of the Census data from the Enterprise Survey (ES) and the Auxiliary Establishment Survey (AUX) for 3 to 4 thousand firms, accounting for over 20 million employees.[10] The ES provides enterprise-wide financial data, while the AUX provides similar establishment-level data for all of a firm's auxiliary establishments.[11] Auxiliary establishments are non-production facilities housing what may be

---

[10] The sample of firms in the two surveys are different. The AUX includes data on 30-40,000 establishments associated with 12-17,000 firms of all sizes, whereas the ES includes data for 7-8000 firms with 500 or more employees. Between 3-4,000 firms are in both samples and approximately 40% of these firms are present in all three years.

[11] The financial data include income and balance sheet data such as sales, assets, compensation, inventories, and employment. The AUX data are aggregated to the firm level and then matched with the ES data. Initially, we had hoped to be able to estimate within-firm production functions but this did not prove feasible because the AUX data w too noisy.

thought of as the "service-sector" functions of the firm. These include administrative headquarters, R&D facilities, sales offices, warehouses, etc. Each of these surveys is conducted every five years and our sample includes data for 1977, 1982 and 1987.

The AUX data are especially interesting because of our focus on business computing (rather than factory automation). Most of a firm's support services--which contribute to what is generally referred to as "corporate overhead"--are likely to be housed in auxiliary establishments. These data allow us to examine the effect of computers on firm organization, as measured by the distribution in activity and employment between auxiliary establishments and the rest of the firm. Because these auxiliary establishments perform "service-sector" functions for the firm, they offer an opportunity to investigate how computers affect service sector productivity. Additionally, the AUX data provide detailed information bearing on the composition of non-production staff workers in six categories of employment: (1) central administrative and clerical, (2) R&D, (3) warehousing, (4) sales and sales support, (5) EDP, and (6)other auxiliary employment. This allows us to partially control for labor quality.

For each firm, we collected data on total sales (Y), the book value of plant, property and equipment (PPE or K), total investment (I), total investment in computers (I_1), and total employment (L). In addition, we collected data on the share of investment associated with auxiliary establishments, the share of PPE in auxiliary establishments, and the composition of auxiliary employment.

For the period 1986-93, we use data from the marketing research firm Computer Intelligence (CI) and Compustat. The CI data include detailed information about the composition of computer assets at Fortune 1000 and Forbes 400 firms for the years 1986, 1991 and 1993. The computer information includes the estimated replacement cost of all computer assets (K_1), as well as detailed information on the composition of computer capital (e.g., counts of the number of systems of different types such as mainframes, minis and PCs; the total number of MIPS; the total volume of DASD; etc.). We linked the CI data with Compustat financial data, resulting in a data set with approximately 1,500 observations for 500 firms accounting for total employment of over 16 million.

Our use of both the Census and CI data allows us to consider a much longer time period than would be possible with either source alone. Moreover, the partial overlap in 1986-87 allows us to investigate the relationship between computer investment and computer capital data and the relationship between both of these and output. Unfortunately, the only measure of computer inputs included in the Census data is the level of computer investment, which provides only a very noisy estimate of the computer share of total assets. We matched the Census and CI data for the years 1986/1987 for 757 firms[12] in order to estimate the relationship between the computer share of investment and the computer share of capital:

$$\frac{K_1}{K} = \alpha + \beta\left(\frac{I_1}{I}\right)$$

Equation 12

The estimated coefficients from this regression (see Table 6A) are used to "backcast" the computer share of capital for the unmatched Census firms in 1987 and all of the Census firms in 1977 and 1982.

3.2 Data Trends

Over the 16 years covered by our data, the diffusion of computers into the fabric of

[12] In the CI regressions, we rely on Compustat data for an estimate of PPE which is often unavailable. Therefore, while the the CI sample includes almost 1000 firms, the matched CI/Compustat sample includes closer to 500 firms. Because PPE is included in the Census data, we were able to match a larger number of firms for 1986/1987.

American business has been dramatic. According to the Current Population survey, the likelihood that an employee is using a computer in the workplace has nearly doubled from 1 in 4 in 1984 to almost 1 in 2 by 1993 (see Table 2). A similar pace of diffusion is evident in the firm-level data from the Census Bureau and CI. From 1977 to 1987, computer investment per employee increased from approximately \$63 to \$267 in nominal terms, representing a nominal growth rate of 16% per year. Due to the much more rapid depreciation rate for computer capital (20-30% per year), the growth in computer assets would have been slower.[13] A better indication of the diffusion of computer usage is provided by noting that in 1977, only one third of the firms in our sample reported *any* computer investment, whereas two thirds reported computer investments by 1987.

The CI data offer a clearer picture of these diffusion trends. From 1986 to 1993, the median replacement value of computer assets per employee increased negligibly to \$842 (see Table 4). However, during this same period, computer intensity increased substantially if one considers performance-based measures. For example, MIPS per employee increased 11-fold, DASD capacity per employee increased almost 3 fold, and the number of PCs and terminals per employee increased from 1:5 to 1:2.[14] (It is comforting to note how close these firm-reported figures are to those implied by the household data on work-based computer usage reported in Table 2.)

Even with this substantial growth, however, it is not surprising that computers appear to have failed to contribute to aggregate output growth. According to the CI data, the computer

---

[13] Wolff (1997, Table 5) reports investment in Office, Computing and Accounting Equipment (OCA) per employee to be \$231.8 during the period from 1977 to 1987 (in 1987 \$) which helps confirm that our sample is representative of the overall economy.

[14] These changes are computed based on median values. The means are higher, but reflect similar trends. See Table 4.

share of total assets is tiny (approximately 0.3% in 1993), and the share of Plant, Property and Equipment (PPE) was only 1% in 1993. This is consistent with the estimates reported by Oliner and Sichel (1995). Note that even if there is a significant downward bias in these estimates due to measurement error (*e.g.,* because investments in software are not included), we would still expect computers to represent a small share of total assets.

In addition to the trend towards greater computer intensity in terms of both quality (as measured by the increases in computing power) and the level of financial commitment by the firm (as measured both by the levels of investment and computing capital), there was movement towards more distributed architectures as evidenced by the substantial growth in smaller systems (PCs and minicomputers), while the numbers of mainframe computers declined. This appears to be related to, and may have facilitated the increased geographical dispersion of firms. According to the CI data, between 1986 and 1993, the median growth rate in the number of sites per firm was 46% and the median number of employees per site declined 27%.[15] The Census data provides additional indirect evidence of the move towards increased decentralization and distributed systems. In 1977, 6% of the employment but 22% of the computer investment occurred in auxiliary establishments; whereas in 1993, 7% of the employment and only 6% of the computer investment occurred in auxiliary establishments.[16]

---

[15] The "median growth rate in employees per site" is computed by first calculating the growth rate in employees per site for each firm which is present in both 1993 and 1986 and then taking the median of these growth rates. Also, since virtually every site in the CI data is also listed as a data-processing site, this growth in the number of sites is not merely reflecting the diffusion of computers throughout the organization.

[16] Additional evidence of the diffusion of computer technology throughout the firm is provided by the CI data on Local Area Networks (LANs). The CI data did not collect data on the number of LANs per firm until 1991. However, even from 1991 to 1993, the median number of LANs per firm increased substantially:

	1991	1992
Median number LANs per firm	14	20
Share firms with at least 1 LAN	97%	96%
Median number employees/LAN	689	527

Computer investments are more evenly distributed across the firm in the latter period (see Table 3).

Relative to the rest of the world, the U.S. is far more computer intensive by virtually every measure (Table 5). In light of Japan's impressive productivity performance over the last decade, this data is suggestive that while computers may aid in increasing productivity they are clearly not essential and that obviously a lot of other things must change also in order for the gains from computer investment to be fruitful.

When firms are ranked by employment size, the larger firms tend to invest more per employee in computers than do smaller firms, although the difference is quite small.[17] . Moreover, the gap between larger and small firms appears to have narrowed over time.[18] Cross-industry comparisons indicate consistent trends, although non-manufacturing sectors (*e.g.*, FIRE) are more computer intensive than manufacturing. The cross-industry differences are consistent with computer usage data from the CPS (Table 2). Similarly, within the firm, auxiliary establishments (the non-manufacturing, service-sector for the firm) are more computer intensive than the rest of the firm. For example, auxiliaries account for 10% of employment but 33% of the computer investment in 1987.

While all types of workers are more likely to use computers today, there is a strong skills-bias: better educated, higher paid, managerial and professional workers are much more likely to use computers at work (Table 2).[19] This suggests that the revolution in information

---

[17] For the Census data, mean computer investment per employee was only 28% higher for the largest firms, which were almost 34 times larger than the smallest firms. We might expect larger firms to use computers more intensively both because they may be likely to face greater coordination problems which computers may help solve and because they are likely to be early adopters. In addition, there may be scale economies in computer system investments, especially with respect to mainframes.

[18] This is consistent with early adoption by large firms.

[19] Computer usage is positively correlated with education (and not surprisingly, household income): 13% or less of

technology may offer a partial explanation for the widening wage gap between skilled and unskilled workers. Computers and skilled labor are complementary and workers who use computers are likely to earn higher wages (Kreuger, 1993). Our data on the relative computer intensity of auxiliary establishments, large vs. small firms, and cross-industry comparisons (with more knowledge-intensive industries such as FIRE being more computer intensive) are consistent with these results.

As a final validation check on our data, we examined the CI data on the composition of computer assets by regressing the total value of computer assets (K1) against the number of mainframes, minicomputers, and PCs and terminals for 1986, 1991 and 1993 (see Table 6). The coefficients for these regressions provide estimates of the mean replacement value for each type of equipment. First, note that the significance of these regressions declines over time, reflecting the fact that other types of equipment (*e.g.,* LANs and other types of data communications equipment) comprise a growing share of total computer investments. Second, note that while the median number of mainframes per firm has declined while the number of PCs and terminals has increased significantly, there has been little change in the relative value shares of these types of equipment over our sample period. During our sample period, firms were not replacing mainframes with PCs, but rather replacing several older mainframes with a fewer number of significantly more powerful mainframes *and* investing in PCs and terminals to extend computer usage more widely across the firm. Third, note that the computer asset shares and prices which we estimate with our CI data are closely comparable to the value shares and prices reported in industry data for domestic shipments.

---

workers with less than a high school education use a computer, while over 69% of those with four or more years of college do. The skills-bias indicated by these statistics becomes more apparent when one considers data on usage by occupation and by industry: 68% of managers and professionals versus 15% of operators and laborers use computers; also, 79% of those in the finance and insurance industries versus 17% in construction use computers (Table 2).

4. Regression Results

In the preceding section, we presented evidence documenting the dramatic increase in computer usage across all types of firms in all industries. The question we turn to now is whether these changes have contributed to productivity growth. To test this we estimate Cobb-Douglas production functions in two basic forms:

$$\ln Y_{it} = \gamma_t + \lambda_i + \alpha \ln K_{it} + \alpha \theta x_{it} + \beta \ln L_{it} + \mu_{it}$$

Equation 13

and

$$\ln Y_{it} = \gamma_t + \lambda_i + \alpha_0 \ln K_{0,it} + \alpha_1 \ln K_{1,it} + \beta \ln L_{it} + \mu_{it}$$

Equation 14

The parameter γ_t measures disembodied technical change, λ_i is a fixed firm-effect (or in some cases, a fixed industry-effect) that captures stable, unobserved firm- (or industry-) specific determinants of productivity, and μ_{it} is a disturbance term.[20] The first of these equations follows from Equation 3, while the second is a standard Cobb-Douglas production function generalized to include two types of capital: computer (K_1) and non-computer (K_0) capital. In the following three sub-sections, we present our regression results.

4.1 Estimating Computer Asset Share for Census Data

As we noted earlier, the only measure of computer inputs included in the Census data is the level of computer investment. We therefore estimated the relationship between the

---

[20] To simplify the notation, we will drop the i and t subscripts.

computer share of PPE and the computer share of investment for a matched subset of firms that are included in both the CI and Census samples for 1986/1987 (Table 7A).[21] This matched sample also allows us to assess how noisy a proxy the computer share of investment is for the variable we wish to measure, the computer share of assets (PPE). Computers contribute positively to productivity growth in both #7A1 and #7A2, but, as one would expect, the t-statistic associated with (I1/I) in #7A2 is much lower.[22] Furthermore, when both measures are included in #7A3, (I1/I) is insignificant and the coefficient on (K1/K) is essentially the same as when the investment variable is excluded.[23]

4.2 Computer Productivity Regressions

Table 7 includes our principal productivity regression results. First, notice that the computer variable is significantly positive in all of the pooled time-series regressions. Moreover, the magnitude of these regression coefficients demonstrates excess returns to computer capital in all of the pooled regressions except #6.4 (using the test described in Equation 7). These findings suggest that the "productivity paradox" is an artifact of econometric measurement error which disappears with suitably detailed, firm-specific data.

Second, notice that the coefficients on K and L are close to there typical expenditure shares and are reasonably stable across all of the regressions. Furthermore, we cannot reject

---

[21] We adjusted the data to a common year base and scaled to account for measurement error across the two samples (e.g., mis-matched total employment or sales). Fortunately, the Census data and the CI/Compustat data matched quite well.

[22] To compare the computer coefficients in the two regressions, remember that $(I_1/I) = [(\delta_1+g_1)/(\delta+g)](K_1/K)$ where g_1 and g (and δ_1 and δ) are the growth rates (and depreciation rates) for computer capital and PPE, respectively. In the steady state these growth rates are equal to zero and $(I_1/I)=4(K_1/K)$, using the depreciation rates assumed earlier in footnote 8, *supra*. More generally, if computer capital is growing more rapidly then PPE, then the proportionality constant would be correspondingly larger.

[23] While this approach may produce reasonable estimates of the computer asset share for 1987 and even 1982, we suspect that our estimates for 1977 may not be accurate.

the hypothesis of constant returns to scale for the first two regressions with industry effects.[24] Moreover, the estimated coefficients for the computer variables are remarkably close across regressions #6.1 and #6.2, in spite of the fact that these are two completely different data sets covering two different periods.

Third, when we introduce firm effects in #6.3 and #6.4, the computer coefficients are reduced significantly, but still are sufficiently large to support a finding of excess returns. This suggests that there are omitted variables that are positively correlated with computer inputs and that also contribute to productivity growth. Obvious candidates include "knowledge capital" and a higher quality labor force. We explore these possibilities further below.

In the second half of Table 7, we show the estimate for the computer variable when each of the years is estimated separately with industry effects. These results suggest that computer productivity increased from 1977, reached a peak in 1986/1977, and then began to decline. This would be consistent with high adjustment costs initially[25] followed by rapid expansion of computer assets which would exhaust opportunities to realize excess returns from further computerization as firms approached the optimal level of computer capital. Alternatively, the insignificant coefficients in 1977, 1991 and 1993 may be due to increased measurement error. We have already discussed how the need to estimate (K_1/K) for 1977 using coefficients computed for 1987 is likely to have contributed to measurement error. The potential for increased measurement error during the latter period is more worrisome but is to be expected as a smaller share of total computer inputs are included in the cost of traditional computer hardware (*e.g.,* investments in data communications equipment, software and a variety of

[24] Although the regressions with firm fixed effects appear to show decreasing returns to scale, we suspect that this is due to the exacerbation of measurement error in within-firm estimation (*i.e.,* using fixed firm effects).

[25] For example, because needed infrastructure was missing (David, 1990) or there was a need to train for computer literacy.

computer services such as maintenance, etc.).

Table 8 presents various sensitivity tests using the Census data. Regression #8.1 replaces (K_1/K) with (I_1/I), yielding similar conclusions but less significant results, as expected. Regression #8.2 adds the share of employment in auxiliaries. The coefficient on (L_1/L) is significant, which suggests that auxiliary employees are more productive than other employees. But their excess productivity is less than their wage differential, suggesting that they yield below normal returns.[26] Similar results are provided by Regressions #8.5 and #8.6, which further decompose auxiliary employment into separate categories. Notice that only Electronic Data Processing (EDP) employees yield excess returns relative to other types of workers.[27] It is also worth pointing out that inclusion of these proxies for labor quality differences does not significantly affect the computer coefficient estimates, suggesting that computers are not simply proxying for unobserved labor quality differentials.[28]

Finally, Regression #8.3 and #8.4 decompose capital into machinery and equipment (K_2) and structures (K_0). These show that computers yield excess returns relative to other types of machinery and equipment.[29]

Table 9 presents analogous sensitivity results for the CI data as well as productivity estimates based on Equation 14. Regressions #8.1 to #9.7 experiment with different ways of measuring computer assets. This new form for the production function requires a slightly

---

[26] The ratio of the coefficient on (L1/L) to the coefficient on ln L ought to be equal to 0.98, because average auxiliary compensation is 1.98 times higher than non-auxiliary compensation. Instead, the ratio is 0.46.

[27] According to the 1991 Annual Survey of Manufacturers, the average wage was $38K for workers in the computer and office equipment industry and the average auxiliary wage in our sample was $41K per year, so we can apply the same test as described in footnote 26, *supra*.

[28] Similarly, we included R&D expenditures and R&D employment to partially control for unobserved knowledge capital and found that this did not affect the computer coefficient.

[29] It is necessary to revise the assumption underlying the hypothesis test outlined in Equation 7 to reflect the higher depreciation rate and price changes for equipment (δ_2=0.083, E(p2)=-0.05, assumed). With this change, the appropriate hypothesis test becomes, H_0: $\alpha_1/\alpha_2=3 \Leftrightarrow$ no excess returns.

different hypothesis test, but this new test also indicates that there are significant excess returns to computer capital, indicating robustness of our principal findings to alternative econometric specifications.[30] Regressions #9.2 through #9.7 substitute *counts* of various computer types for the replacement value of computers; in all cases we find a significant contribution from computers, which leaves the other coefficients reasonably constant. What is perhaps most interesting is the magnitude of the coefficient on the number of PCs and terminals. This coefficient is huge and highly significant. Moreover, the coefficient is unaffected by inclusion of MIPS and DASD (measures of computer capacity) and is much larger than the coefficient on mainframes. This suggests that raw computing power matters less than how computers are used.[31] More PCs means that computers are distributed more widely throughout the firm and that users are more likely to be on networks which allow them to take advantage of such applications as electronic mail.

Table 9B repeats regressions #9.1 and #9.7 by year. Regressions #9B.1-.3 provide further support for our finding that computer productivity seems to have peaked in 1986/1987 and declined thereafter. While the coefficients are all significant, excess returns are earned only in the first year. Regressions #9B.4-.6 show that the coefficient on PCs and terminals remains fairly constant and significant over the entire sample period. This suggests that the reduced productivity gains from computers are not associated with further deployment of PCs but may be due to excessive investments in maintaining legacy systems. Still better data on the composition of computer assets and their use will be needed to test these ideas more fully.

---

[30] The test for excess returns for Equation 14 is slightly different because the ratio of marginal products is different:

$$H_0 : \frac{MP_{K_1}}{MP_{K_0}} = \frac{\alpha_1 K_0}{\alpha_0 K_1} = \frac{\alpha_1}{\alpha_0}\frac{(1-x)}{x} = \frac{\alpha_1}{\alpha_0}\frac{(1-0.02)}{0.02} = \frac{R_1}{R_0} = 6 \Leftrightarrow \frac{\alpha_1}{\alpha_0} = 0.12 \Leftrightarrow \textit{no excess returns}$$

Equation 15

4.3 Inventory Regressions

Computers facilitate outsourcing and can enable "just-in-time" inventories. Computers can also permit firms to design, manufacture, distribute and inventory a much wider selection of goods. If the first effect dominates, we would expect computers to reduce inventory levels. Alternatively, the second effect would tend to increase inventory levels. In Table 10 we present regressions of the inventory-to-sales ratio against the computer share of PPE, controlling for firm size by including total PPE. In all of the regressions, across both the Census and CI samples, the point estimates on (K_1/K) are negative although not always significant. Perhaps the most interesting of these regressions are #9.3-#9.4, with fixed firm effects. In both cases, we find computers have a significant negative impact on inventory levels.

Regressions #9.5-9.7 decompose inventories into raw materials, work-in-progress, and finished goods. One might suspect that computers would affect each class of inventories differently, depending on how they were used. For example, average work-in-progress might increase with just-in-time inventories, while raw material inventories are likely to decrease. Unfortunately, the Compustat inventory data do not appear to be very reliable.

5. Conclusions

This paper examines trends in computer usage and the effect on productivity growth for a cross-industry panel of firms over the period from 1977 to 1993. We link firm-level financial and computer asset data for non-agricultural firms from a variety of public and private data sources, including Census Bureau data from the Enterprise and Auxiliary Establishment

---

[31] Notice that the point estimates on MIPS and DASD are negative (and insignificant).

Surveys, Compustat, and the market research firm, Computer Intelligence.

The Census Bureau data cover the years 1977, 1982 and 1987, while the Computer Intelligence data cover the years 1986, 1991 and 1993. The former source offers relatively rich information about the composition of employment, but only limited data on computer assets (*i.e.*, we observe computer investment, but not the level of computer assets); while the latter source includes only total employment, but rich data on the composition of computer assets. After linking the Census data for 1987 and the Computer Intelligence data for 1986, we estimate the relationship between computer investment and the level of computer assets and use this to estimate the value of computer assets in the rest of the Census sample. We then estimate production functions for both the Census and Computer Intelligence data with both fixed industry and firm effects. While shifting to fixed firm effects significantly reduces the magnitude of the elasticity of computer capital, we still observe excess returns to computers. The reduction in our estimated elasticity is consistent with the interpretation that computer assets are positively correlated with unobserved firm-specific features that contribute positively to productivity growth. These results are robust across both data sub-samples. Moreover, because the magnitude of the parameter estimates is not affected by the inclusion of regressors intended to control for differences in labor composition, we do not believe that the reduction in the estimated computer elasticity with firm effects is due to unobserved differences in labor quality.

The Census Bureau data on auxiliary establishments (*i.e.*, support, headquarters and other non-operating business units) allows us to explore the relationship between firm structure, overhead and computers. We find that computers are complementary with auxiliary establishment employment, but the data appear to be too noisy to enable us to detect significant effects of computerization on the composition of employment within auxiliary establishments (which may, perhaps, be regarded as comprising the "*within-firm* service sector"). Although our firm-level analysis finds excess returns to computer investments for both manufacturing and non-manufacturing sub-samples, it also illustrates the difficulties of overcoming data limitations when seeking to investigate the effects of computer investments on service productivity.

The Computer Intelligence data for the latter period allow us to investigate the relationship between productivity (and other operating characteristics of the firm, *e.g.,* inventory-to-sales ratios) and the *composition* of computer assets. This analysis revealed that productivity is very strongly related to the number of *personal computers* used by a firm, and that raw computing power matters less than how computers are used.[32] More PCs means that computers are distributed more widely throughout the firm and that users are more likely to be on networks that allow them to take advantage of such applications as electronic mail.

However, our comparison of Census and Computer Intelligence data for 1986 and 1987 indicates the superiority of using asset values instead of investment data to measure computer inputs. The data on equipment counts does not adequately account for quality differences, especially with respect to counts of mainframes and minicomputers. Data on computer investments is much more volatile than data on computer assets, which explains the superiority of the latter as a measure of computer inputs.

The overall conclusion from this research is that computers do contribute positively to productivity growth, yielding excess returns. These excess returns, however, appear to have

[32] Notice that the point estimates on MIPS and DASD are negative (and insignificant).

peaked in 1986/1987.[33] These excess returns appear in both the service and non-service sectors of the economy, although the data limitations remain an important problem for research in this area. We believe that further improvements will require analysis of firm-level and business-unit data, especially since a huge share of service-sector activity takes place within on-service sector firms. Moreover, computers appear to be changing the way in which firms are organized and operated, allowing firms to become more decentralized and altering employment composition. However, better data are needed to account for the effects of these changes.

---

[33] This does not mean, however, that there are not a number of interesting paradoxes associated with the use of computers. For example, why is there such variability across firms in the productivity of computers and how computers are used? Or, why is it the case that productivity gains which are clearly realized at the business-unit level (*e.g.*, when computers permit significant headcount reductions) often fail to flow through to the firm's bottom line?

References

Bailey, M. and R. Gordon, "The Productivity Slowdown, Measurement Issues, and the Explosion of Computer Power", Brookings Papers on Economic Activity vol 2 (1988) 347-432.

Bresnahan, T. (1986), "Measuring the Spillovers from Technical Advance: Mainframe Computers in Financial Services", American Economic Review, vol 76., no. 4 (September) 742-755.

Brynjolfsson, E., and L. Hitt (1993), "Is Information Spending Productive? New Evidence and New Results," unpub. paper, MIT Sloan School, June; forthcoming in the Proceedings of the 14th International Conference on Information Systems.

David, P. (1990), "The Dynamo and the Computer: An Historical Perspective on the Modern Productivity Paradox," American Economic Review, 80 (May) 355-361.

Griliches, Z., (1994) "Productivity, R&D, and the Data Constraint", American Economic Review, vol 84, no 1, March 1994, 1-23.

Kreuger, A. (1993), "How Computers Have Changed the Wage Structure: Evidence from Microdata: 1984-1989", Quarerly Journal of Economics, February 1993, 33-60.

Lau, L. and I. Tokutso (1992), "The Impact of Computer Technology on the Aggregate Productivity of the United States: An Indirect Approach," unpub. paper, Stanford Univ. Dept. of Economics, August.

Lichtenberg, F. (1995), "The Output Contributions of Computer Equipment and Personnel: A Firm-Level Analysis," Economics of Innovation and New Technology, 3 (1995) 201-217.

Loveman, G., "An Assessment of the Productivity Impact of Information Technologies", mimeo, Massachusetts Institute of Technology, September 1990.

Morrison, Catherine, and Ernst Berndt (1991), "Assessing the Productivity of Information Technology Equipment in U.S. Manufacturing Industries," NBER Working Paper No. 3582, January.

Oliner, Stephen, and Daniel Sichel, "Computers and Output Growth Revisited: How Big is the Puzzle?," Brookings Papers on Economic Activity

Roach, S., (1987) "America's Technology Dilemma: a Profile of the Information Economy", Morgan Stanley Special Economic Study, New York, April 1987.

Siegel, D., "The Impact of Technological Change on Employment and Wages: Evidence from a Firm-level Survey of Long Island Manufacturers", mimeo, September 1994.

Strassman, P., The Business Value of Computers, New Canaan, CT: Information Economics Press, 1990.

Wolff, E. (1997), "Indirect Measures of Productivity Growth in the Service Sector", draft mimeo, New York University, February 1997.

Table 1: List of Major Data Sources

Enterprise Survey (Census Bureau)

Enterprise Surveys for 1977, 1982 and 1987 offer data on computer investments (but not computer assets) and other balance sheet and income statement variables for 6,000 to 8,000 firms.

Auxiliary Establishment Survey (Census Bureau)

Auxiliary (i.e., non-production) Establishment Surveys for 1977, 1982 and 1987 offer data on computer investments (but not computer assets) and other balance sheet and income statement variables for 31,000 to 38,000 auxiliary establishments.

Computer Intelligence Infocorp

Company-level data (derived from site-level survey) for 1986, 1991 and 1993 on computer assets, by type of computer, for 1,000 -1400 large U.S. firms.

Compustat

Enterprise data for 1986, 1991 and 1993 for income statement, balance sheet and other financial variables for firms covered by Enterprise Survey and Computer Intelligence Infocorp data.

Table 2: Probability of Using a Computer at Work[1]

(Source: Current Population Survey)

	1984	1989	1993
Overall:	25%	37%	46%
By age:			
18-21		23%	26%
22-24		37%	42%
25-34		41%	49%
35-44		42%	51%
45-54		37%	50%
55-64		27%	37%
65+		14%	20%
By education:			
<9th grade		3%	4%
9-11		10%	13%
12		29%	34%
13-15		46%	53%
16+		58%	69%
By household income:			
<$10K		18%	18%
$10-15K		20%	24%
$15-20K		28%	32%
$20-25K		35%	36%
$25-35K		39%	43%
$35-50K		48%	51%
$50-75K		53%	62%
>$75K		53%	67%

[1] Current Population Survey of Census Bureau is a household survey for years 84, 89, 91, 93 and includes responses to the question, "Did you use computer at work?" for 55,000 households.

Table 2: Probability of Using a Computer at Work[1]

(Source: Current Population Survey)

	1989	1993
By occupation:		
Manag. & Professional	56%	68%
Tech Sales Admin	55%	66%
Service	10%	15%
Prec Prod Craft	15%	23%
Operators, Labor	10%	15%
Farm, Forest, Fish	4%	9%
By industry:		
Agriculture	8%	14%
Mining	31%	46%
Construction	13%	17%
Manufacturing	36%	44%
Trans, Comm, Util	40%	49%
Wholesale/retail	28%	37%
Finance, Insurance	71%	79%
Services	39%	48%
Forest/Fisheries	38%	38%
Public Admin	62%	74%

[1] Current Population Survey of Census Bureau is a household survey for years 84, 89, 91, 93 and includes responses to the question, "Did you use computer at work?" for 55,000 households.

Table 3: Census Data on Computer Investment[1]

	1977	1982	1987
Number of firms	3,318	3,734	3,714
% which report:			
Computer investment>0	32%	64%	77%
Computer investment in auxiliary>0	23%	43%	48%
		Median Values	
Computer investment per employee	$0	$28	$68
% employment in auxiliary	6%	6%	7%
% total investment in computers	0%	2%	3%
% computer investment in auxiliaries	22%	11%	6%
		Unweighted Mean Values	
Computer investment per employee	$63	$152	$267
% employment in auxiliary	8%	10%	10%
% total investment in computers	3%	6%	8%
% computer investment in auxiliaries	46%	39%	33%
Computer investment per employee (weighted by employment)	$129	$298	$339

[1] For subset of firms in Enterprise Survey which report having Auxiliary Establishments.

Table 4 : Corporate Computer Utilization[1]

	1986	1991	1993
Number of Firms	455	501	533
Total Employment (000s)	16,119	16,301	16,747
		Median	
Employment per firm (000s)	15	13	13
Computer Assets per employee	$680	$516	$736
Mainframes per firm	5	3	2
MIPS per 1000 employees	3	19	33
DASD per employee	6	14	16
PCs and Terminals per employee	0.17	0.43	0.49
PCs per employee	0.03	0.13	0.17
Computer share of PPE	1.4%	0.8%	1.0%
Computer share of Total Assets	0.5%	0.3%	0.3%
		Mean	
Employment per firm (000s)	35	33	31
Computer Assets per employee	$995	$872	$1,256
Mainframes per firm	11	8	6
MIPS per 1000 employees	4	47	116
DASD per employee	11	26	32
PCs and Terminals per employee	0.24	0.57	0.66
PCs per employee	0.05	0.19	0.24
Computer share of PPE	2.5%	1.6%	2.1%
Computer share of Total Assets	0.7%	0.5%	0.6%

[1] Source: Computer Intelligence Enterprise-level data for Fortune 1000 firms.

Table 5 : Computer Utilization, International Comparisons

	United States	United Kingdom	France	Germany	Japan
Information Technology spending/GDP, 1994[1]	2.7%	2.2%	1.7%	1.6%	1.5%
%Households with PCs, 1994[2]	37%	24%	15%	28%	12%
Internet hosts per 1000 population, 1995[3]	12.42	4.17	1.62	2.58	0.78
Telephone lines per 100 population, 1992[4]	56.5	45.2	52.5	43.9	46.4
Fax machines per 100 telephone lines, 1992[5]	6.25	3.83	2.09	4.09	9.59

1 Source: OECD, *Information Technology Outlook*, 1995, Figure 2.2a, page 17. Values are approximate since interpolated from graph.

2 Source: OECD, *Information Technology Outlook*, 1995, Table 2.2, page 25.

3 Source: OECD, *Information Technology Outlook*, 1995, Figure 3.5, page 35.

4 Source: OECD, *Communications Outlook*, 1995, Table 4.2, page 40.

5 Source: OECD, *Communications Outlook*, 1995, Table 4.7, page 45.

Table 6 : Composition of Computer Assets Regressions[1,2]

	Regression Coefficients (Standard Errors)			Est. Share of Total Value of Computer Assets[3]			Domestic Shipments[4]	
	1986	**1991**	**1993**	**1986**	**1991**	**1993**	**1991 Share**	**1991 Avge. Unit Price**
Mainframes	$927,928 (65,276)	$922,210 (94,501)	$1,873,866 (142,106)	40%	32%	38%	31%	$1,173,878
Minicomputers	$66,948 (1,708)	$24,346 (2,720)	$23,664 (2,189)	11%	16%	16%	28%	$54,522
PCs and Terminals	$1,795 (111)	$849 (62)	$920 (69)	49%	52%	46%	41%	$2,546
Mean Value of Computer Assets ($000s)	$20,605	$19,783	$27,086	100%	100%	100%	100%	
Number of observations	957	935	968					
R^2	0.85	0.76	0.73					

---

[1] In regressions, dependent variable is replacement value of computer assets measured in current dollars. Independent variables are number of mainframes, minicomputers, and PCs and terminals. The data are from Computer Intelligence.

[2] Standard errors are in parentheses below estimates. All coefficients are significant at the 1% level.

[3] Share of computer asset value is computed by multiplying mean count of each type of computer by its corresponding regression coefficient.

[4] Source: CBEMA, *Information Technology Industry Data Book, 1960-2004I,* Table 4-5.

Table 7A: Census Regressions
Matched sub-sample for 1987 (N=757)

Relationship between K_1/K and I_1/I
$(K_1/K) = \alpha + \beta(I_1/I)$

α	β
0.015	0.097
(6.88)	(6.06)

Production Function Regressions[1]
$\log(Sales) = \alpha \log(K) + \beta \log(L) + \delta(I_1/I) + \gamma(K_1/K)$

	#7A1	**#7A2**	**#7A3**
log(K)	0.346	0.270	0.345
	(12.8)	(10.2)	(12.8)
log(L)	0.545	0.617	0.547
	(16.8)	(18.9)	(16.9)
K1/K	3.606		3.541
	(8.15)		(7.9)
I1/I		0.410	0.281
		(2.24)	(1.6)

[1] K is PPE, L is employment, I is total investment, K_1 is replacement value of computer assets, and I_1 is computer investment. The values in parentheses below the regression estimates are t-statistics.

Table 7 : Production Function Regressions

Census and Computer Intelligence Data, 1977-1993[1,2]

$\log(\text{sales}) = \alpha_0 \log(K) + \alpha_1 x + \beta_0 \log(L)$

	#6.1 Census	#6.2 Computer Intelligence	#6.3 Census	#6.4 Computer Intelligence
Fixed effects?	Industry	Industry	Firm	Firm
	1977-1987	1986-1993	1977-1987	1986-1993
ln(K)	0.276 ***	0.293***	0.148***	0.249***
	(0.006)	(0.016)	(0.008)	(0.027)
ln(L)	0.714 ***	0.602***	0.724***	0.532***
	(0.008)	(0.019)	(0.013)	(0.027)
x (=K1/K)	2.282***	2.261***	1.681***	0.808**
	(0.334)	(0.476)	(0.337)	(0.298)

Estimated Coefficients for Share of Computer Assets (x), by Year[3]

1977	-1.02
	(0.800)
1982	2.561***
	(0.756)
1987	3.063***
	(0.439)
1986	3.169***
	(0.868)
1991	2.188
	(1.451)
1993	1.078
	(1.073)

---

[1] All regressions include fixed year effects. Industry effects are 3-digit SIC codes for 1977-1987 and 4-digit for 1986-1993. Standard errors in parentheses. "***" denotes significant at 1% level, "**" denotes significant at 5% level, "*" denotes significant at 10% level. Dependent variable is log of sales.

[2] K is Plant, Property and Equipment (PPE); L is Total Employment; and x is the share of computer assets in total PPE. Because we do not observe K1 directly for the Census regressions, x is imputed or predicted using the share of investment in computers and the regression of the computer share of assets (dependent variable) against the computer share of investment (independent variable) for the matched sample of firms which appear in both the Census and the CI data in 1986/1987. This regression is included in Table 6A in the appendix.

[3] Includes industry fixed effects.

Table 8: Production Function Regressions
Census Data, 1977-1987[1,2]

	#6.1	#6.3	#7.1	#7.2	#7.3	#7.4	#7.5	#7.6
Fixed effects?	Industry	Firm	Industry	Industry	Industry	Industry	Industry	Industry
ln(K)	0.276***	0.148***	0.272***	0.272***			0.274***	0.272***
	(0.006)	(0.008)	(0.006)	(0.006)			(0.006)	(0.006)
ln(K0)					0.062***	0.059***		
					(0.006)	(0.006)		
ln(K2)					0.230***	0.227***		
					(0.008)	(0.008)		
ln(L)	0.714***	0.724***	0.718***	0.719***	0.693***	0.699***	0.716***	0.719***
	(0.008)	(0.013)	(0.008)	(0.008)	(0.009)	(0.009)	(0.008)	(0.008)
x (=K1/K)	2.282***	1.681***		2.166***			2.194 ***	2.148***
	(0.334)	(0.337)		(0.334)			(0.335)	(0.335)
x2 (=K1/K2)					1.271***	1.220***		
					(0.137)	(0.137)		
y (=L1/L)				0.328***		0.384***		
				(0.050)		(0.051)		
x3 (I1/I)			0.123***					
			(0.042)					
%EDP of L							1.849***	1.221**
							(0.457)	(0.483)
%CAO of L								0.259***
								(0.081)
%WHS of L								0.504***
								(0.175)
%R&D of L								0.264
								(0.300)
%Other of L								0.201*
								(0.111)
%Sales of L								0.395
								(0.359)

[1] All regressions include fixed year effects. Industry effects are 3-digit SIC codes. Standard errors in parentheses. "***" denotes significant at 1% level, "**" denotes significant at 5% level, "*" denotes significant at 10% level. Dependent variable is log of Sales.

[2] K is Plant, Property and Equipment (PPE); K0 is PPE that is not computer assets; K2 is machinery and equipment; K1 is computer assets; L is Total Employment; L1 is Auxiliary Employment; I is Total Investment; I1 is computer investment; %EDP is electronic data processing employment share of L; %CAO is central office administration employment share of L; %WHS is warehouse employment share of L; %R&D is research and development share of L; %Sales is sales and customer support employment share of L; and, %Other is remainder of auxiliary employment share of L.

Table 9 : Production Function Regressions
Computer Intelligence Data, 1986-1993[1,2]

	#6.2	#8.1	#8.2	#8.3	#8.4	#8.5	#8.6	#8.7
	SICCOD	SICCOD	SICCOD	SICCOD	SICCOD	SICCOD	SICCOD	SICCOD
Log(L)	0.602***	0.570***	0.586***	0.505***	0.524***	0.589***	0.591***	0.505***
	(0.019)	(0.021)	(0.020)	(0.022)	(0.021)	(0.020)	(0.020)	(0.022)
Log(K)	0.293***							
	(0.016)							
Log(K0)		0.238***	0.247***	0.217***	0.222***	0.242***	0.245***	0.218***
		(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
x (=K1/K)	2.261***							
	(0.476)							
Log(K1)		0.077***						
		(0.013)						
SYSTEMS			0.063***					
			(0.012)					
MAIN				0.052***				0.053***
				(0.017)				(0.017)
MINIS				0.007				0.010
				(0.011)				(0.013)
PCTERM				0.129***	0.151***			0.136***
				(0.018)	(0.016)			(0.021)
MIPS						0.054***		-0.007
						(0.010)		(0.015)
DASD							0.048***	-0.003
							(0.010)	(0.012)

[1] All regressions include fixed year effects. Industry effects are 4-digit SIC codes. Standard errors in parentheses. "***" denotes significant at 1% level, "**" denotes significant at 5% level, "*" denotes significant at 10% level. Dependent variable is log of Sales.

[2] K is Plant, Property and Equipment (PPE, $millions); K0 is PPE which is not computers ($millions); K1 is value of computer assets ($millions); L is Total Employment (000s); SYSTEMS is the number of mainframes (MAIN) plus minicomputers (MINIS); PCTERM is the number of PCs and terminals (000s); MIPS is the number of MIPS; and DASD are the megabytes of disk storage (000s).

Table 9B: Production Function Regressions
Computer Intelligence Data, 1986-1993[1,2]

	#8B.1	#8B.2	#8B.3	#8B.4	#8B.5	#8B.6
	1986	**1991**	**1993**	**1986**	**1991**	**1993**
Log(L)	0.548***	0.587***	0.586***	0.504***	0.526***	0.508***
	(0.054)	(0.037)	(0.036)	(0.058)	(0.041)	(0.037)
Log(K0)	0.128***	0.280***	0.276***	0.126***	0.265***	0.253***
	(0.038)	(0.029)	(0.027)	(0.037)	(0.030)	(0.026)
Log(K1)	0.168***	0.059**	0.039*			
	(0.036)	(0.024)	(0.024)			
MAIN				0.034	0.055	0.060*
				(0.047)	(0.034)	(0.031)
MINI				-0.031	0.024	0.044
				(0.028)	(0.027)	(0.028)
PCTERM				0.140**	0.151***	0.134***
				(0.059)	(0.043)	(0.036)
MIPS				0.055	-0.076**	-0.047
				(0.049)	(0.035)	(0.029)
DASD				0.019	0.013	-0.013
				(0.038)	(0.027)	(0.021)

[1] All regressions include fixed year and industry effects. Industry effects are 4-digit SIC codes. Standard errors in parentheses. "***" denotes significant at 1% level, "**" denotes significant at 5% level, "*" denotes significant at 10% level. Dependent variable is log of Sales.

[2] K is Plant, Property and Equipment (PPE, $millions); K0 is PPE which is not computers ($millions); K1 is the value of computer assets ($millions); L is Total Employment (000s); SYSTEMS is the number of mainframes (MAIN) plus minicomputers (MINIS); PCTERM is the number of PCs and terminals (000s); MIPS is the number of MIPS; and DASD are the megabytes of disk storage (000s).

Table 10: Inventory Regressions
for Census and Computer Intelligence Data, 1977-1993[1,2]
$\log(\text{inventory/sales}) = \alpha_0 \log(K) + \alpha_1 x$

	#9.1	#9.2	#9.3	#9.4	#9.5	#9.6	#9.7
Dependent variable:	Total Inventory	Total Inventory	Total Inventory	Total Inventory	Raw Materials Inventory	Work-in-Progress Inventory	Finished Goods Inventory
	1977-1987	1986-1993	1977-1987	1986-1993	1986-1993	1986-1993	1986-1993
Fixed effects?	Industry	Industry	Firm	Firm	Firm	Firm	Firm
ln(K)	0.071***	-0.067***	0.105***	0.140***	-0.101	-0.054	0.149
	(0.005)	(0.021)	(0.014)	(0.045)	(0.102)	(0.116)	(0.096)
x (=K1/K)	-1.968***	-1.303	-1.134*	-2.023**	-2.310	-2.795*	-0.725
	(0.574)	(1.079)	(0.662)	(0.812)	(1.505)	(1.571)	(1.320)

[1] All regressions include fixed year effects. Industry effects are 3-digit SIC codes for 1977-1987 and 4-digit for 1986-1993. Standard errors in parentheses. "***" denotes significant at 1% level, "**" denotes significant at 5% level, "*" denotes significant at 10% level.

[2] K is Plant, Property and Equipment (PPE); K1 is computer assets; and, x is the share of computers in total capital.