

**Information Technology as a Factor of Production:
The Role of Differences Among Firms**

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Information Technology as a Factor of Production

ABSTRACT

Despite evidence that information technology (IT) has recently become a productive investment for a large cross-section of firms, a number of questions remain. Some of these issues can be addressed by extending the basic production function approach that was applied in earlier work. Specifically, in this short paper we 1) control for individual firm differences in productivity by employing a "firm effects" specification, 2) consider the more flexible translog specification instead of only the Cobb-Douglas specification, and 3) allow all parameters to vary between various subsectors of the economy.

We find that while "firm effects" may account for as much as half of the productivity benefits imputed to IT in earlier studies, the elasticity of IT remains positive and statistically significant. We also find that the estimates of IT elasticity and marginal product are little-changed when the less restrictive translog production function is employed. Finally, we find only limited evidence of differences in IT's marginal product between manufacturing and services and between the "measurable" and "unmeasurable" sectors of the economy. Surprisingly, we find that the marginal product of IT is at least as high in firms that did not grow during 1988-1992 sample period as it is in firms that grew.

I. Introduction

Until recently, there has been little evidence that computers have led to increases in output, thus forming the basis for a "productivity paradox" (see e.g. (Attewell 1993; Brynjolfsson 1993; Wilson 1993) for reviews.) In 1987, Roach (1987a) drew attention to the alarming divergence between rapidly growing IT spending in the service sector and relatively flat productivity. Loveman (1994) provided more specific evidence of an IT productivity shortfall. He used the Management of the Productivity of Information Technology (MPIT) data set which covers 60 business units of large firms from 1978-1984 to estimate an economic production function and found that the marginal product of IT could not be distinguished from zero. Barua, Kriebel & Mukhopadhyay (1991) using the same MPIT data also found that IT did not appear to be correlated with performance, but did influence intermediate measures such as inventory turnover. Morrison & Berndt (1990) analyzed industry level data (at the 2-digit SIC level) over the period 1968-1986 and found that a dollar spent on information technology returned only 80 cents on the margin. In a related study (Berndt and Morrison 1994, in press), using much of the same data, they further concluded that "there is a statistically significant negative relationship between productivity growth and the high-tech intensity of the capital."

On the other hand, Siegel & Griliches (1991) found that IT was positively correlated with productivity growth, although they found that the Census Bureau data underlying their analysis was not very reliable. In previous work (Brynjolfsson and Hitt 1993a; Brynjolfsson and Hitt 1993b), we estimated a production function for a large data set compiled by International Data Group on IT capital and spending by over 300 of the largest firms in the U.S. economy over the time period 1988-1992. We found that the gross marginal product of IT capital and of IS staff spending each substantially exceeded their reported costs. Lichtenberg (1993) confirmed these results using these same data as well as data set from an alternated source (Informationweek), and further found that the marginal product of IT was at least six times as great as the marginal product of other types of capital, which he argued represented the appropriate comparison after accounting for depreciation.

Because American firms went through a period of very visible, and painful, restructuring in the late 1980s, it is tempting to conclude that these efforts have finally enabled them to realize the potential productivity benefits of computers. As David (1989) has pointed out, such a story has historical parallels: it took decades before American businesses made the

organizational changes needed to reap the productivity pay-off from the electric dynamo. However, given the limitations of both the studies that indicated a productivity shortfall in the 1970s and early 1980s, and the more recent studies which found no shortfall in the late 1980s and early 1990s, more evidence is needed to rule out alternative explanations, such as specification error in the regressions.

We focus on three types of specification errors which may have affected the recent findings that computers were contributing to firm output. Potentially the most important issue is whether the returns to IT are indicative of benefits to computerization, or simply a marker for firms that are highly productive for other reasons. A second issue is whether the Cobb-Douglas functional form used for previous work to estimate the contribution of computers was overly restrictive leading to a biased estimate of the elasticity of IT capital and labor. A third issue is whether pooling data from a large number of different firms blurred differences between groups of the economy with different production processes such as manufacturing and services, the "measurable" versus "unmeasurable" sectors of the economy (Griliches 1994), or firms which grew and those which did not.

In this short paper, we seek to address these issues. To summarize our conclusions:

- We find that "firm effects" may account for as much as half of the productivity benefits imputed to IT in the earlier studies. Nonetheless, the elasticity of IT remains positive and statistically significant.
- The results are quantitatively similar when the less restrictive translog production function is employed.
- We find only limited evidence of differences in IT elasticity between manufacturing and services and between the "measurable" and "unmeasurable" sectors of the economy. Firms which did not grow between 1988-1992 had no lower estimated elasticity of IT than firms that did grow.

Our analyses use the same data as that was used in our earlier work (Brynjolfsson and Hitt 1993a; Brynjolfsson and Hitt 1993b) and in the work of Lichtenberg (1993). However, we depart from earlier analyses by combining IT capital and IS labor expenses into a single IT measure. We justify this on the theoretical grounds that IT capital and labor are complements, and on the practical ground that this will enable us to analyze more complex specifications and subsamples of the original data. As a result, our findings should provide some insight into the robustness of the earlier findings to various possible specification errors. Of course, one significant drawback of our approach is that the coefficient on IT will no longer reflect purely capital or purely labor components, and therefore cannot be

used to derive a marginal product that is comparable to the marginal products of either ordinary capital or ordinary labor.

II. Production Function Framework

Much of the work on IT and productivity, e.g. (Barua *et al.* 1991; Berndt and Morrison 1994, in press; Brynjolfsson and Hitt 1993b; Lichtenberg 1993; Loveman 1994)), and the larger literature on R&D and productivity (see e.g. (Griliches 1988; Hall 1993; Mairesse and Hall 1993)) has used the economic theory of production to estimate the effects of production inputs on output. The theory of production states that the inputs a firm (*i*) uses can be related to output (*Q*) via a production function (*F*). For our purposes, we will investigate the effect of three inputs: Computer Capital and Labor (*C*), Non-computer Capital (*K*) and Non-computer Labor (*L*). In addition to inputs, the production function may also vary with differences in the industry (*j*) in which a firm operates, and differences in time (*t*) to account for short-run economic shocks and longer-run disembodied technical change. Thus we can write:

$$Q = F(C, K, L; j, t) \quad (1)$$

The Cobb-Douglas form of the production function allows direct calculation of output elasticities and can be considered a first order approximation (in logarithms) to an arbitrary production function. It is also commonly assumed that time (*t*) and industry (*j*) only result in multiplicative shifts in overall output, but do not interact with any of the inputs. These assumptions yield the following equation:

$$Q_{it} = \exp\left(\sum_t \gamma_t T_t + \sum_{j=1} \delta_j J_j\right) C_{it}^{\beta_1} K_{it}^{\beta_2} L_{it}^{\beta_3} \quad (2)$$

where: $T_t = 1$ if observation is year *t*, 0 otherwise
 $J_j = 1$ if observation is industry *j*, 0 otherwise

By taking logarithms and adding an error term, this equation can be estimated econometrically:

$$\log Q_{it} = \sum_{j=1} \delta_j J_j + \sum_t \gamma_t T_t + \beta_1 \log C_{it} + \beta_2 \log K_{it} + \beta_3 \log L_{it} + \varepsilon_{it} \quad (3)$$

where: δ , γ , and β are parameters to be estimated

In this formulation, the coefficients $\beta_1 - \beta_3$ represent the output elasticities of the various inputs, which is the percent change in output for a 1% change in the quantity of the input. Output elasticities can also be translated into a marginal product, which is the amount of additional output provided for an additional dollar of investment in the input.¹ This equation can be estimated directly for all firms, thus constraining the output elasticities to be the same across all types of firms, or targeted to particular subsamples such as manufacturing or services, which allows estimates of the output elasticities specific to these sectors. In essence, this is relaxing the restriction that output elasticities are the same for all types of firms implied by equations 2 and 3.

This paper considers three extensions of this basic framework. The first, is to allow the production function to vary by firm, instead of by industry. While the data is not sufficient to allow all the parameters to vary across firms, we can allow the intercept term (often called multifactor productivity) to vary at the firm level. This accounts for the fact that for reasons exogenous to the model, some firms may be persistently more productive than others. This will prevent us from overstating the contribution of IT in the case where IT investment is also correlated with an unmeasured productivity enhancing characteristic, causing an omitted variables bias. For example, suppose that each firm is endowed with a level of management skill which can lead to higher productivity. Then the "true" production function is:

$$\log Q_{it} = \sum_{j=1} \delta_j J_j + \sum_t \gamma_t T_t + \beta_1 \log C_{it} + \beta_2 \log K_{it} + \beta_3 \log L_{it} + \beta_4 M_i + \varepsilon_{it}$$

where: δ , γ , and β are parameters to be estimated (4)

where M denotes the management skill. Suppose further that high performing managers tend to invest disproportionately in IT, so that there is a positive correlation between M and C. Failing to account for this effect will lead to an overstatement of the return to IT since we will be partly measuring the effect of better management with our IT variable. To the extent that management skill and other potentially omitted variables can be considered to be firm characteristics which do not change over the sample time period, the omitted variables

¹ Formally, the output elasticity of information technology, E_C , is defined as: $E_C = \frac{\partial F}{\partial C} \frac{C}{F}$. The marginal product for computers simply the output elasticity multiplied by the ratio of output to computer input:

$$MP_C = \frac{\partial F}{\partial C} = \frac{\partial F}{\partial C} \frac{CF}{FC} = E_C \frac{F}{C}$$

bias will be mitigated by replacing the sector dummy variable with a dummy variable for each firm in the data set. Thus, we restate equation 3 with a firm-specific productivity effect:

$$\log Q_{it} = \sum_{i=1} \alpha_i I_i + \sum_t \gamma_t T_t + \beta_1 \log C_{it} + \beta_2 \log K_{it} + \beta_3 \log L_{it} + \varepsilon_{it}$$

where: α , γ and β are parameters to be estimated (5)

$I_i = 1$ if observation is firm i , 0 otherwise

This equation can be directly estimated by ordinary least squares, with a separate dummy variable for each firm. However, there are a large number of firms (>300) in this sample so this would require the estimation of over 300 additional dummy variables. An alternate approach is to find a linear transformation of the variables in equation 4 that eliminates the firm specific variable (I_i) but leaves the other coefficients unchanged. One such transformation is the "within" transformation (W) (Greene 1993, pp. 466-469), defined as:

$$W: \quad Wx_{it} = x_{it} - \frac{1}{N_i} \sum_t x_{it} = x_{it} - \bar{x}_i \quad (6)$$

where: N_i is the number of observations of firm i

Applying the within transformation to equation 4 yields:

$$W \log Q_{it} = W \sum_{i=1} \alpha_i I_i + W \sum_t \gamma_t T_t + W \beta_1 \log C_{it} + W \beta_2 \log K_{it} + W \beta_3 \log L_{it} + W \varepsilon_{it}$$

$$\log Q_{it} - \overline{\log Q_i} = \sum_{i=1} \alpha_i I_i - \sum_{i=1} \alpha_i \bar{I}_i + \sum_t \gamma_t T_t - 0 + \beta_1 (\log C_{it} - \overline{\log C_i}) +$$

$$\beta_2 (\log K_{it} - \overline{\log K_i}) + \beta_3 (\log L_{it} - \overline{\log L_i}) + \varepsilon_{it} - \bar{\varepsilon}_i$$

but since $\bar{I}_i = I_i$

$$\log Q_{it} - \overline{\log Q_i} = \sum_t \gamma_t T_t + \beta_1 (\log C_{it} - \overline{\log C_i}) + \beta_2 (\log K_{it} - \overline{\log K_i}) + \beta_3 (\log L_{it} - \overline{\log L_i}) + \varepsilon_{it}^* \quad (7a-7c)$$

This is the equation desired, where the new error term, ε_{it}^* , has the usual OLS properties if the error term in equation 5 also satisfies these properties. This essentially removes the firm-specific intercept term from the regression in a similar way to removing the overall intercept term by taking the mean of each variable. This estimator is also efficient since only one degree of freedom is lost for each firm, which is exactly the same number lost

doing OLS on equation 5. The firm effects can be recovered from this specification by plugging in the firm mean values to the estimated equation and calculating the residual from equation 7c.

A second extension is to use a more general functional form such as the transcendental logarithmic, or "translog", production function (Christensen and Jorgenson 1969), which will help minimize any biases that might result from using the more restrictive Cobb-Douglas specification. The basic translog function for three inputs can be written :

$$\begin{aligned} \log Q_{it} = & \text{intercepts} + \sum_t \gamma_t T_t + \beta_1 \log C_{it} + \beta_{11} (\log C_{it})^2 + \beta_{12} (\log C_{it})(\log K_{it}) + \\ & + \beta_{13} (\log C_{it})(\log L_{it}) + \beta_2 \log K_{it} + \beta_{22} (\log K_{it})^2 + \beta_{23} (\log K_{it})(\log L_{it}) + \\ & + \beta_3 \log L_{it} + \beta_{33} (\log L_{it})^2 + \varepsilon_{it} \end{aligned} \quad (8)$$

where: "intercepts" can vary with by industry or by firm, in addition to time

The translog production function is an improvement over the Cobb-Douglas form since it allows the elasticity of substitution to vary by type of inputs, and allows returns to scale and output elasticity to vary with the size of the inputs. Conveniently, the Cobb-Douglas form can be recovered by the translog with various coefficient restrictions,² and thus it is possible to test whether the fit is improved by employing a more flexible functional form. This increased flexibility comes at the expense of additional regressors. Output elasticities can be calculated from the translog estimates by:

$$\begin{aligned} \hat{E}_C &= \frac{\partial F}{\partial C} \frac{C}{Q} = \hat{\beta}_1 + 2\hat{\beta}_{11} \overline{\log C} + \hat{\beta}_{12} \overline{\log K} + \hat{\beta}_{13} \overline{\log L} \\ \hat{E}_K &= \frac{\partial F}{\partial K} \frac{K}{Q} = \hat{\beta}_2 + 2\hat{\beta}_{22} \overline{\log K} + \hat{\beta}_{12} \overline{\log C} + \hat{\beta}_{23} \overline{\log L} \\ \hat{E}_L &= \frac{\partial F}{\partial L} \frac{L}{Q} = \hat{\beta}_3 + 2\hat{\beta}_{33} \overline{\log L} + \hat{\beta}_{23} \overline{\log K} + \hat{\beta}_{13} \overline{\log C} \end{aligned} \quad (9a - c)$$

Finally, a third extension of the framework is to allow all the parameters to vary firm certain subsamples of the data. We do this by running separate regressions for three divisions of the data set: 1) service firms vs. manufacturing firms, 2) firms in Griliches's

²The Cobb-Douglas requires that coefficients on all squared and cross-terms are equal to zero.

"measurable" vs. "unmeasurable" sectors, and 3) firms which had revenue grow versus those with no revenue growth between 1988 and 1992.

III. Data

The data used for this analysis have been discussed extensively in a number of papers and therefore will only be briefly discussed here (see (Brynjolfsson and Hitt 1993b) for a detailed description of this data set and Lichtenberg (1993) for other comments on the IT spending data utilized in this study). The basic IT spending data was collected from a survey of central IS departments from a sample of firms drawn from the top half (by sales) of the Fortune 500 Manufacturing and Fortune 500 Service listings. These surveys, conducted annually from 1988 to 1992, collect information on the annual IS budget, the number of desktop machines, such as PCs and terminals, the amount of the IS budget devoted to labor expenses, and the market value of the central computer equipment, such as mainframes, minis and supercomputers. These data were matched to Compustat II, a database of public financial information, to obtain estimates for firm labor expenses, number of employees, non-IT capital stock, sales, other expenses and industry classification. Value-added for each firm was calculated by subtracting non-labor expenses (calculated as other expenses less labor expense) from total sales. Deflators from a number of sources were used to convert the nominal values of the various inputs and output into constant 1990 dollars to allow inter-year comparisons on the same basis. A description of the production input and output variables is shown in table 1.

While the real quantities of IT used by firms has grown dramatically over the last few years, it still represents a relatively small portion of overall inputs in our sample. Computer capital stock represents approximately 2% of gross sales, and annual IS labor expenditures represent on the order of 1% of gross sales. As Griliches (1994) points out, this, combined with poor output measures and deflators, makes it difficult to "find the needle in the haystack" which distinguishes the contribution of IT from stochastic events that affects the production characteristics of firms. As a result, although earlier research (Brynjolfsson & Hitt, 1993; Lichtenberg, 1993) reported statistically significant contributions to output by both computer capital and information systems labor in a Cobb-Douglas formulation, more detailed analyses were not possible. One way to increase the size of the IT effect is to examine an aggregate IT variable which includes both computer capital and information

systems staff labor.³ Indeed, it is likely that the majority of IS labor expenditures are employed to produce software, a capital good. In addition, previous work suggested that IS labor could be a complement for computer capital (Brynjolfsson and Hitt 1993b), undermining attempts to estimate their contributions separately in a Cobb-Douglas production function framework.

However, the two variables cannot be directly added since capital is a stock variable, representing an accumulation of spending over time, while IS staff is a flow variable representing a single annual expenditure. To create a stock variable combining the two, we made two assumptions: that current IS staff spending is a good estimate of IS spending in the recent past, and that IS staff "stock" depreciates fully in three years. Using these assumptions, an IT stock variable is constructed that equals the sum of IT capital and three times IS labor. This approach to capitalization of stock is based on that employed by the R&D accounting literature (Hall 1993) that creates an R&D stock out of an annual flow and was also the approach used by Loveman (1994) to calculate IT stock.⁴

The variables used in the analysis are summarized in table 2 along with other relevant sample characteristics.

IV. Results

Firm Effects

The production function estimates that include industry dummy variables (industry effects, but no firm effects), are shown in the Cobb-Douglas form in table 4, column 1. The comparable regression with individual firm effects, is shown in column 2. These analyses essentially represent a regression of Value Added against three inputs, IT stock, Non-IT Capital, and Non-IT labor, with dummy variables for each firm (that appears in at least two years), and for time.

In the Cobb-Douglas formulation, the elasticity of IT stock drops from .109 without firm effects to .0495 when firm effects are accounted for. All coefficients in the regressions are

³ We thank Zvi Griliches for this suggestion.

⁴ The major departure is the use of current spending rather than the discounted accumulation of past spending. However, given the rapid depreciation rate assumed for IS labor, and the relative stability of IS staff spending (correlation of IS labor spending in firms with adjacent years of data was .94), this further approximation is not likely to introduce substantial additional error.

statistically significant at the .01 level or greater in both specifications. Even accounting for individual firm productivity differences, IT makes an important contribution to firm output. These estimates imply that roughly half of the elasticity of IT is attributable to individual firm effects, while the remaining are attributable to the pure effect of IT spending. The elasticities for the other capital is not significantly affected by the inclusion of firm effect, although the labor's output elasticity does drop somewhat. Because the factor share of IT, including both computer capital and capitalized IS labor spending was .0935 in this sample, firm effect estimates imply a marginal product for IT stock of approximately 53%. Recall that IT's service life was assumed to be over three years and that this marginal product estimate is gross of depreciation, taxes and other capital costs, but is after accounting for inflation.

Translog Specification

The analysis is repeated in the translog form in table 4, columns 3 and 4, and elasticities (calculated using equations 9a-c) and the relevant standard error estimates are shown in the table. While the individual coefficients show a considerable amount of variation, the estimated elasticities are comparable to the Cobb-Douglas estimates. In this analysis, the elasticity of IT stock drops from .0815 to .0459 when firm effects are added. Nonetheless, even in the translog firm-effects specification, which demands much of the data, we are able to strongly reject the hypothesis that the return to IT stock is zero ($p < .01$).

In the basic translog form, the elasticities of non-IT factors, Capital and Labor, are comparable to the Cobb-Douglas estimates, however in the firm effects equation, the elasticity of Non-IT capital is changed substantially – this appears to be a result of the multicollinearity between Capital and Capital-squared which have a simple correlation of over .98. However, a Wald test of the Cobb-Douglas restrictions is rejected for both the firm effects and industry effects specification, which indicates that the translog provides a better fit (firm effects: $\chi^2(6)=139$, $p < .01$; industry effects: $\chi^2(6)=264$, $p < .01$).⁵

Overall, this analysis shows that while firm effects can account for some of the differences in the IT elasticity estimates among firms, IT stock still makes an economically and statistically significant contribution to the output of firms in our sample. This result is

⁵ Note that this rejection of the Cobb-Douglas restrictions does not necessarily undermine the use of this form if one is only interested in estimating output elasticities (Griliches 1979). Indeed, the resulting elasticities are still roughly the same as for the translog formulation.

robust to the use of a more flexible functional form, the translog, and therefore cannot be attributed to a spurious correlation created by an overly restrictive specification.

Interestingly, the finding of significant firm effects for IT, suggests that in addition to its direct effect, IT may also be a "marker" for some unspecified variables or strategies which also increase firm productivity. Specifically, our results are consistent with the argument by David (1989) and others (Scott Morton 1991) that achieving the full productivity impact of computers requires fundamental changes in many aspects of firms which can take years to implement. For instance, IT is considered an important component of "modern manufacturing" strategy, which includes a cluster of practices and technologies which are purported to increase productivity (Milgrom and Roberts 1990), is often more broadly associated with new organizational strategies and structures (Malone 1987).

These results must be interpreted with caution. First, the use of firm effects tends to magnify the impact of errors in variables, which can bias the coefficients (Greene 1993) by the same process that increases errors in variables bias when using first differences (Griliches and Hausman 1986). Although, in general, the direction of errors in variables bias in multivariate regression is indeterminate, the particular structure of this problem is such that there likely to be a strictly negative bias on all coefficients. This is because of two conditions that hold approximately for our data set: 1) the regressors in the fixed effects specification are nearly orthogonal to each other with correlations between $-.05$ and $.1$, and 2) it is reasonable to assume errors in measurement are uncorrelated not only between observations, but also between the various input variables (IT, Capital, Labor) since they were drawn from different sources. Given these two conditions, and the standard OLS assumptions (except for the measurement error on each variable) the direction of the bias can be derived in a straightforward manner as shown in Appendix A. Second, while the firm effects approach can mitigate the problem of simultaneity, it does not necessarily eliminate it, so the IT coefficient may still reflect some lingering effects running from changes in demand in a particular firm in a particular year to changes in IT investment in the firm that year.

Sectoral Differences.

Another weakness of earlier work with the IDG data is that the estimates did not account for differences in the production processes between firms operating in different industries, but rather sought to fit them all with the same functional form, allowing only the constant

term to vary between sectors. While our use of value-added rather than sales should help to make the production process of, say, a retailing firm more comparable to a manufacturing firm, we find that there are substantial differences in the factor composition between economic sectors, which suggests that they may have different production functions (table 3).

Three subsamples are considered for this analysis based on issues raised in the IT & productivity debate. First, it has been argued that while productivity improvements are beginning to appear in the manufacturing sector, the jury is still out for IT productivity in the service sector where technology is increasingly important (Quinn *et al.* 1987; Roach 1991). To investigate this assertion, we examine separate translog production functions for manufacturing and services⁶, the results of which are shown in table 5. Overall, we find that the elasticity of IT stock is comparable between the manufacturing sector (elasticity = .0770) and the service sector (elasticity = .0955). When firm effects were controlled for, the IT elasticities dropped to .0409 in manufacturing and .0368 in services. Using a Chow test, we cannot reject the null hypothesis that the IT elasticities are equal for manufacturing and services ($t=.9$), nor can we reject the equality of the Marginal Product of IT in the two subsamples ($t=1.0$). However, differences in the elasticities of other production factors do suggest the existence of substantially different production relationships. For instance, we reject the hypothesis that capital elasticities in manufacturing and services are equal ($t=7.9$ $p<.001$).

Second, Griliches (1994) has argued that the differences in measured productivity growth may not be so much the difference between manufacturing and services, but the differences between sectors of the economy where output is "measurable" (manufacturing, mining, transportation and utilities), to those where output is "unmeasurable" (retail & wholesale trade, financial services, other services). While the majority of our sample (85% of observations) falls into Griliches's "measurable" sector, it is still possible to get reasonable estimates of the output elasticities for these two groups. Using the same method described in the previous paragraph, we find that the IT stock elasticities are comparable between the two groups, .0679 for measurable sectors and .0774 for unmeasurable sectors (Chow test

⁶ Manufacturing sectors consist of durable manufacturing and non-durable manufacturing (SIC20-SIC39). Service sectors include wholesale and retail trade, transportation and utilities, financial services, and other services. Mining is excluded from the analysis.

for equality, $t=3$, cannot reject equality).⁷ As before, the elasticities for other factors differed substantially, indicating differences in the overall production process.

A third interesting subdivision of the data is to look at differences between growing firms and those with no growth over the sample period. While firms in both groups increased their IT capital over the sample period (growing firms increased IT capital stock by 38% per year while non-growing firms increased stock by 26% per year compared to a price decline for IT of 20% per year), growing firms have the luxury of being able to add IT spending without making the tough choices of cutting back on other inputs such as labor. In contrast, firms with no revenue growth can only spend more on IT if they spend less elsewhere. A regression limited to firms with no growth should be less subject to the bias that would be caused if firms have a propensity to spend their free cash flow disproportionately on IT.⁸ In other words, such a regression should have less simultaneity bias. We examined this question by running separate regressions in firm effects allowing all parameters to vary between the two subsamples. Surprisingly, we find that firms that are not growing actually have higher IT elasticity: .0729 vs. .130 (Chow test for equality rejects, $t=2.4$, $p<.01$) for firms that grew during the sample period when the sector effects form was used, although the elasticities are essentially the same when the firm effects (translog) specification is used.

The results on different sectors suggests that, despite substantial problems of output measurement in certain sectors (see e.g. (Griliches 1992)), the link between IT and output may apply as much to the service sector as it does to the "measurable" manufacturing sector. Thus, at least for our sample of large firms, IT was found to be an important contributor to output across all sectors of the economy. However, these results should be interpreted carefully, since a relatively small portion of the unmeasurable sector is included in this analysis, and the analysis excludes entirely industries such as insurance which do not have financial information comparable to the other firms in the sample.

The result that growing firms have lower or equivalent IT elasticities does not support the hypothesis that IT gets a disproportionate share of new spending. Instead, it may be that other factors, such as labor, are the preferred place to spend new revenues or equivalently, that firms are reluctant to slash IT budgets even in bad times. This is consistent with

⁷ When firm effects were controlled for, the IT elasticities dropped to .0389 for measurable sectors and .0494 in unmeasurable sectors which, as before, are not significantly different from each other.

⁸ We thank Jerry Hausman for this suggestion.

contemporaneous arguments by Mead (1990) that IT investment is driven by competitive challenges rather than current economic difficulties. Ironically, such a policy raises the possibility that simultaneity biases down the IT coefficient. As second explanation notes that the elasticity estimates reflect the contribution of IT at the margin, not average returns. If firms that are not growing underinvest in IT, perhaps because of the pain the attendant layoffs would require, then their marginal returns may exceed their marginal (pecuniary) costs. Finally, the most intriguing explanation is that painful restructuring, such as that described by David (1989) is required to bring the full benefits of IT to the bottom line. This is certainly the conventional management wisdom (Hammer 1990) and has some academic support as well (Caves and Krepps 1993). If so, the fat, happy, growing firms may be the ones who are missing the opportunity to restructure and thereby are foregoing some of IT's potential benefits!

V. Summary and Conclusion

The research on IT and productivity is still at a relatively early stage. This paper seeks to address three important gaps in previous work: the lack of controls for firm effects, the restrictiveness of the Cobb-Douglas specification, and possibility that a single production function does not fit firms in all sectors of the economy.

We find that although firm effects are important, the contribution of IT is large and statistically significant even after controlling for individual firm differences in multifactor productivity. Because our method can provide a ranking of firms by multifactor productivity, an interesting extension would be to identify characteristics of the highly productive firms and thereby examine some of the conventional wisdom regarding management best-practice. Furthermore, our method assumes that firm effects are constant over the sample period. Jensen (1986) and Lichtenberg (1990) have argued that significant changes in efficiency often accompany changes in management. A natural extension of the firm effects approach would be to consider different firm effects for each management regime, to the extent that the data allowed it.

We also find no significant differences in the contribution of IT when the restrictiveness of using a Cobb-Douglas specification is relaxed, or between manufacturing and services, or measurable and unmeasurable sectors of the economy. These results are encouraging insofar as they imply that inferences based on the simpler Cobb-Douglas specification and the easier-to-measure manufacturing sector may also be more broadly applicable.

Nonetheless, the hypothesis that IT's effects are identical for all subsamples of the data is clearly unrealistic. The most interesting subsamples to explore in the future may be those based on organizational form and management strategy. For instance, more direct tests of the efficacy of less hierarchical structures and the "reengineering" of business processes as ways to better harness IT's potential could be very valuable.

Finally, the striking finding that firms that are not growing appear to have at least equally high IT elasticities as growing firms does not support the hypothesis that simultaneity between growth and IT investment is what is driving the high estimates of IT elasticity in the full sample. This finding is consistent with previous results using lagged independent variables as instruments which also found no evidence of simultaneity (Brynjolfsson and Hitt 1993b). However, unless better firm-level instruments can be found, the simultaneity question will remain unresolved.

The high IT returns among firms that were not growing also suggest some intriguing possibilities for future research to see whether firms facing a crisis are more likely to undertake the restructuring that may be required to use IT effectively. This has been a common theme in the recent management literature (Hammer 1990; Quinn 1992). Indeed, as discussed in the introduction, one of the most important differences between our sample and those examined in studies which found little or no contributions from IT may be the prevalence of restructuring and downsizing in the 1988-92 period.

Table 1: Data Sources, Construction Procedures, and Deflators

Series	Source	Construction Procedure	Deflator
Computer Capital and Labor	IDG Survey	<p>Equal to Computer Capital plus 3 times IS Staff (see below).</p> <p>Computer Capital. "Market Value of Central Processors" converted to constant 1990 dollars plus value of reported number of PCs (assuming a constant value of \$2,835 in 1990 dollars).</p> <p>IS Staff. Total IS Budget times percentage of IS Budget (by company) devoted to labor expense. Converted to constant 1990 dollars.</p>	Deflator for Computer Systems (Gordon 1993) for Computer Capital portion, Index of Total Compensation Cost (Private Sector) (Council of Economic Advisors 1992) for IS Staff.
Non-IT Capital	Compustat	<p>Book Value of Total Property, Plant and Equipment converted to constant 1990 dollars.</p> <p>Deflator year based on calculated average age of capital stock (determined from total depreciation divided by current depreciation). Computer Capital (see above) subtracted from this result.</p>	GDP Implicit Deflator for Fixed Investment (Council of Economic Advisors 1992)
Labor	Compustat	Number of Employees, as reported	None
Labor Expense	Compustat	Labor expense when reported. Otherwise, estimated from average wage for the sector multiplied by number of employees. Converted to constant 1990 dollars.	Index of Total Compensation Cost (Private Sector) (Council of Economic Advisors 1992)
Value Added	Compustat	Total sales converted to constant 1990 dollars minus Labor Expense as computed above.	Industry Specific Deflators from <i>Gross Output and Related Series by Industry, BEA (1977-90)</i> where available (about 80% coverage) - extrapolated for 1992 assuming average inflation rate from previous five years. Otherwise, sector level Producer Price Index for Intermediate Materials Supplies and Components.

Table 2 - Sample Characteristics

Production Inputs and Outputs (1990 Dollars, Five Year Arithmetic Average)				
	Full Sample		Firm Effects Subsample*	
	Average Firm (\$)	As % of Value Added	Average Firm (\$)	As % of Value Added
Computer Cap. & Labor	\$290 MM	9.35%	\$301 MM	9.35%
Non-IT Capital	\$8.23 Bn	266%	\$8.66 Bn	266%
Labor Expense	\$1.69 Bn	54.6%	\$1.75 Bn	54.5%
Value Added	\$3.10 Bn	100%	\$3.22 Bn	100%
Number of Observations	1248		1185	

* - The firm effects subsample is restricted to firms with 2 or more observations over the five year sample period.

Table 3 - Full Sample Sector Characteristics

Inputs as a Percentage of Value Added (1990 Dollars, Full Sample, Arithmetic Mean)				
Sector	Computer Cap. & Labor	Non-IT Capital	Labor	Number of Observations
Mining	6.8%	590%	45.8%	27
Non-Durable Manufacturing	7.6%	310%	48.6%	421
Durable Manufacturing	10.7%	154%	64.4%	377
Trade	8.7%	156%	62%	122
Transport & Utilities	9.4%	440%	48.2%	235
Financial Services	11%	48.0%	32.0%	41
Other Service	15.7%	147%	54.0%	25
Total	9.35%	266%	54.6%	1248

Table 4 - Cobb-Douglas and Translog Estimates for the Firm Effects Subsample.

[Heteroskedasticity-consistent] standard errors are in parentheses.

	Cobb-Douglas Sector Effects	Cobb-Douglas Firm Effects	Translog Sector Effects	Translog Firm Effects
E _C (Computer Capital & Labor)	.109 (.00941)	.0495 (.0121)	.0815 (.00933)	.0459 (.00810)
E _K (Non-IT Capital)	.209 (.00772)	.235 (.0350)	.195 (.00738)	.137 (.0254)
E _L (Labor Expense)	.634 (.0110)	.475 (.0294)	.703 (.0116)	.644 (.0238)
R ²	95.0%	99.3%	95.9%	99.4%
N (total)	1185	1185	1185	1185
Durbin-Watson Statistic	.65	2.1	.68	2.2

Table 5 - Sample Splits - Translog Production Function Estimates with Sector Effects
 [Heteroskedasticity-consistent] standard errors are in parentheses.

Production Function Estimates (full sample)

(Sample sizes vary because of exclusions unique to each analysis, as describe in the text)

	Manufacture	Services	Measurable	Unmeasurable	Growing	Not Growing
E_C (Computer Cap. & Labor)	.0770 (.0109)	.0955 (.0168)	.0679 (.00979)	.0774 (.0281)	.0729 (.0102)	.130 (.0213)
E_K (Non-IT Capital)	.152 (.00863)	.285 (.0145)	.200 (.00730)	.176 (.0339)	.226 (.00863)	.163 (.00132)
E_L (Labor Expense)	.764 (.0146)	.594 (.0185)	.721 (.0120)	.630 (.0349)	.670 (.0127)	.711 (.0227)
R^2	96.6%	95.5%	96.4%	94.3%	96.9%	94.9%
N (total)	798	423	1060	188	840	375
Durbin-Watson Statistic	.74	.83	.78	.89	.55	.70

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Appendix A: Derivation of Errors in Variables Bias

Model: $Y = X\beta + \varepsilon$,

X (rank n) is only observable as: $X^* = X + U$

where U is a set of i.i.d random column vectors, with mean zero and covariance Σ_{uu}

Using standard results from Greene (1991):

$$E(\hat{\beta}) = \beta - \beta[(X^{*'} X^*) + \Sigma_{UU}]^{-1} \Sigma_{UU}$$

Since the columns of X^* are orthogonal:

$$X^{*'} X^* = \begin{bmatrix} \sigma_{11} & 0 & \dots & 0 \\ 0 & \sigma_{22} & \dots & 0 \\ 0 & 0 & \dots & 0 \\ 0 & 0 & \dots & \sigma_{nn} \end{bmatrix}$$

Since errors in measurement are uncorrelated:

$$\Sigma_{UU} = \begin{bmatrix} \eta_{11} & 0 & \dots & 0 \\ 0 & \eta_{22} & \dots & 0 \\ 0 & 0 & \dots & 0 \\ 0 & 0 & \dots & \eta_{nn} \end{bmatrix}$$

therefore:

$$[(X^{*'} X^*) + \Sigma_{UU}]^{-1}_{ii} = \frac{1}{\sigma_{ii} + \eta_{ii}}$$

$$E(\hat{\beta}_i) = \beta_i \left(1 - \frac{\eta_{ii}}{\sigma_{ii} + \eta_{ii}}\right) < \beta_i \quad \text{for } \beta_i > 0 \quad \text{Q.E.D}$$