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ABSTRACT

The "productivity paradox" of information systems (IS) is that, despite enormous improvements in the underlying technology, the benefits of IS spending have not been found in aggregate output statistics. One explanation is that IS spending may lead to increases in product quality or variety which tend to be overlooked in aggregate output statistics, even if they increase sales at the firm level. Furthermore, the restructuring and cost-cutting that are often necessary to realize these potential benefits have only recently been undertaken in many firms.

Our study uses new firm-level data on several components of IS spending for the period 1987 to 1991. The dataset includes 380 large firms which generated approximately two trillion dollars in output annually. We supplemented the IS data with data on other inputs, output, and price deflators from several other sources. As a result, we could assess several econometric models of the contribution of IS to firm-level productivity.

Our results indicate that IS have made a substantial and statistically significant contribution to firm output. We find that between 1987 and 1991, return on investment (ROI) for computer capital averaged 54% in manufacturing and 68% for manufacturing and services combined in our sample. We are able to reject the null hypothesis that the ROI for computer capital is no greater than the return to other types of capital investment and also find that IS labor spending generates several times as much output as spending on non-IS labor and expenses. Because the models we applied were essentially the same as those that have been previously used to assess the contribution of IT and other factors of production, we attribute the different results to the recency and larger size of our dataset. We conclude that the "productivity paradox" disappeared by 1991, at least in our sample of firms.

1. INTRODUCTION

Spending on information systems (IS), and in particular information technology (IT) capital, is widely regarded as having enormous potential for reducing costs and enhancing the competitiveness of American firms. Although spending has surged in the past decade (Figure 1), there is surprisingly little formal evidence linking it to higher productivity. Several studies, such as those by Loveman (1988) and by Barua, Kriebel and Mukhopadhyay (1991) have been unable to reject the hypothesis that computers add nothing at all to total output. Roach (1987), who was among the first to identify the productivity shortfall in the 1980s, is more optimistic about the current prospects for productivity growth because many firms have finally begun to realize the potential labor savings enabled by IT. However, because none of the previous estimates of IT productivity were based on data for the past five years, this hypothesis remains untested.

This study considers new evidence and finds sharply different results from previous studies. Our dataset is based on five annual surveys of several hundred large firms for a total of 1,164 observations.[1] The firms in our sample generated approximately two trillion dollars worth of output in the United States annually. Out-of-sample extrapolations will not be necessary to derive conclusions broadly relevant to the US economy because of the large number and size of the firms in our dataset. Because the identity of each of the participating firms is known, we were able to supplement and cross-check this data with data from several other sources. As a result, we could assess several econometric

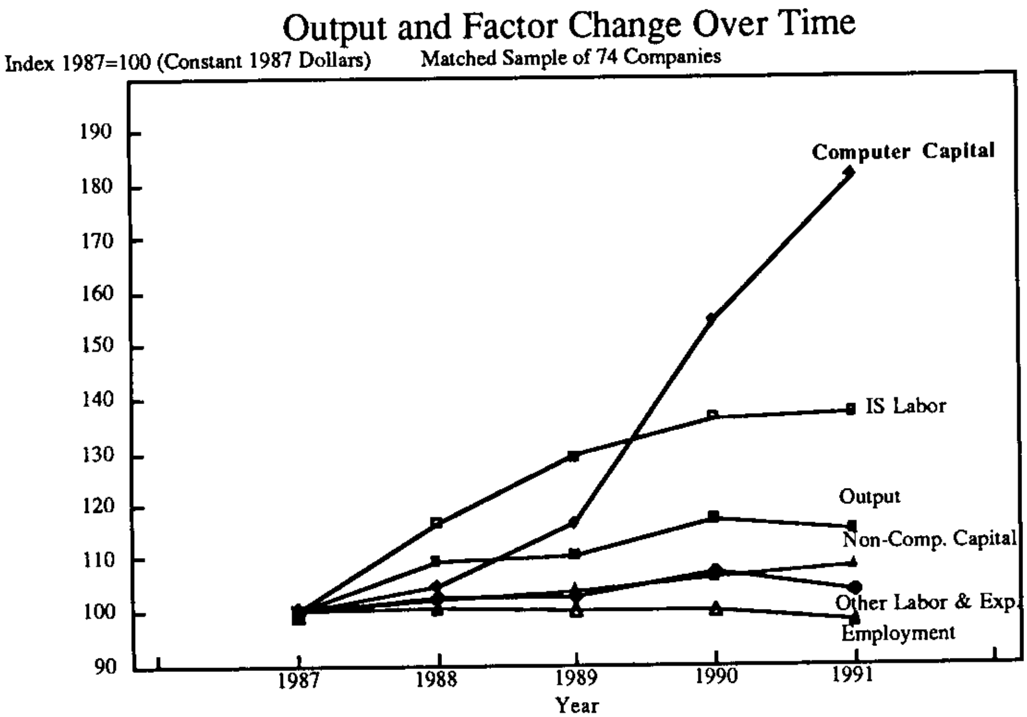


Figure 1. Changes in Outputs and Inputs Over Time

models of the contribution of IS to firm-level productivity. Furthermore, because we have data through 1991, our results are relevant to the proposition that computer investment is finally beginning to create measurable value.

Our examination of this data indicates that IS have made a substantial and statistically significant contribution to the output of firms. Our point estimates indicate that, dollar for dollar, spending on computer capital created more value than spending on other types of capital and spending on IS labor created more value than spending on other non-capital expenses. We find that the contribution of IS to output does not vary much across years, although there is weak evidence of an increase over time. We also find some evidence of differences across different sectors of the economy. For the firms in our sample, we estimate that the return on investment for computers to be over 50% annually (see Figure 2). Considering a 95% confidence interval around our estimates, we can reject the hypothesis that computers add nothing to total output. Furthermore, several of our regressions suggest that the return on investments for computers is significantly higher than the return on investment for other types of capital. Our findings suggest that if there ever was a "productivity paradox," it disappeared in the 1987-1991 period, at least for our sample of large firms.

1.1 Previous Research on IT and Productivity

Although previous work provides little econometric evidence that computers improve productivity, Brynjolfsson (1993) reviews the literature on this "productivity paradox" and concludes that the "shortfall of evidence is not necessarily evidence of a shortfall." He notes that increases in product variety and quality should properly be counted as part of the value of output, but that current output and productivity statistics do not properly reflect this value. In addition, with any new technology, a period of learning, adjustment and restructuring may be necessary to reap its full benefits. Accordingly, he argues that "mismeasurement" and "lags" are two of four viable explanations (along with "redistribution" and "mismanagement") for the collected findings of earlier studies, which leaves the question of computer productivity open to continuing debate.

Despite the measurement problems with industry-level output statistics, they have historically been the only data that are available for a broad cross-section of the economy. Morrison and Berndt (1990) examined industry-level data using a production function that controlled for changes in other inputs and found that each dollar spent on "high tech" capital[2] increased measured output by only 80 cents

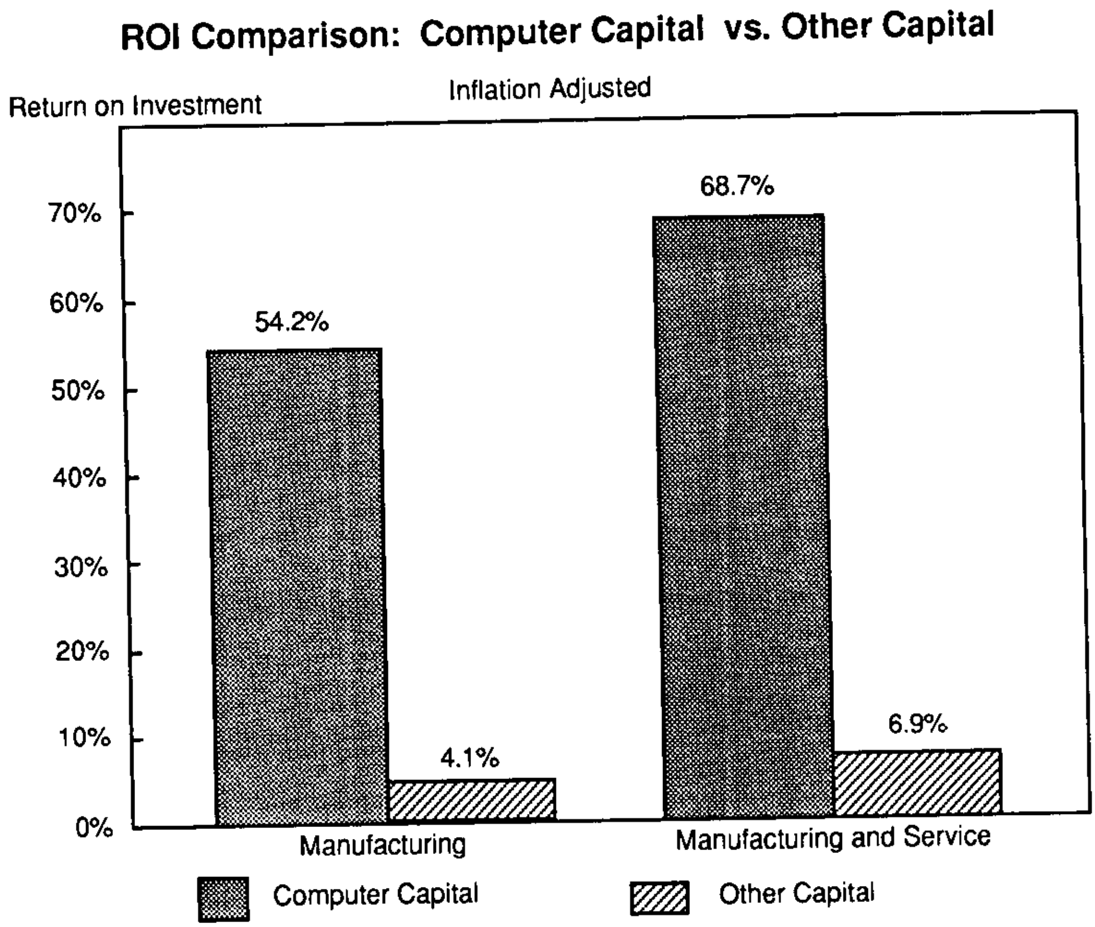


Figure 2. Summary of Results: Return to Computer Capital versus Other Capital

on the margin. In a related study using much of the same data, Berndt and Morrison (1992) conclude "there is a statistically significant negative relationship between productivity growth and the high-tech intensity of the capital." However, they also point out: "it is possible that the negative productivity results are due to measurement problems."

One way to mitigate the measurement problems inherent in industry-level data is to use firm-level data instead. For example, if consumers value a benefit such as variety, then they are likely to *shift* their purchases away from firms offering only mass-produced products toward firms offering more customized products. Because the cost per unit at the customizing firm may be higher, it may appear to have lower productivity by conventional measures if similar products are compared. However, the increased sales by the customizing firm would indicate that they are adding real value to their products. Note that while the benefits of spending (and the costs of not spending) would show up as increases in sales at the firm level, industry revenues as a whole do not necessarily increase, so data on aggregate industry revenues could be misleading.

On the other hand, a weakness of firm-level data is that it can be painstaking to collect and therefore studies with firm-level data have historically focused on relatively narrow samples. Therefore, it has been difficult to draw generalizable results from these studies. For instance, Weill (1992) found some positive impacts for investments in transactional IS but not for overall IS spending. However, the thirty-three strategic business units in his sample from the valve manufacturing industry accounted for less than $2 billion in total sales, and he notes, "the findings of the study have limited external validity." Using different data,[3] Loveman (1988) concluded "Investments in IT showed no net contribution to total output," and Barua, Kriebel and Mukhopadhyay (1992) found that computer investments are not significantly correlated with increases in return on assets. However, both of these studies derived only fairly imprecise estimates of IT's relationship to firm performance. For instance, the 95% confidence interval exceeded ± 300% for the ROI implied by the estimates in Loveman. A more detailed discussion of these and other studies of IT productivity can be found in Brynjolfsson (1993).

1.2 Approach of this Paper

The imprecision of previous estimates highlights an inherent difficulty with measuring IT productivity. The mismeasurement problem is exacerbated by the fact that the value created by intangibles may be an important part of the benefits from computerization. We conducted several interviews with managers which revealed that they focus on five principal rationales for investing in IT: labor savings, improved quality, greater product variety, better customer service, and faster response time. In principle, all of these benefits should be incorporated in the government price deflators that convert nominal sales to real output. In practice, the value of many benefits of IT, other than labor savings, is not well captured in aggregate productivity or output statistics.[4]

Although "we see computers everywhere," they represent on the order of 1% of firms expenses in most historical data sets. This makes it very difficult to distinguish the contribution of information technology from random shocks that affect productivity. As Simon (1984) has observed:

> In the physical sciences, when errors of measurement and other noise are found to be of the same order of magnitude as the phenomena under study the response is not to try to squeeze more information out of the data by statistical means; it is instead to find techniques for observing the phenomena at a higher level of resolution. The corresponding strategy for economics is obvious: to secure new kinds of data at the micro level.

A convincing assessment of IS productivity would ideally employ a sample which included a large share of the economy (as in the Berndt and Morrison studies), but at a level of detail that disaggregated inputs and outputs for individual firms (as in Loveman 1988; Barua, Kriebel and Mukhopadhyay 1991; Weill 1992). Furthermore, because the recent restructuring of many firms may have been essential to realizing the benefits of IS spending, the data should be as current as possible. Lack of such detailed data has hampered previous efforts. While our paper applies essentially the same models as those used in earlier studies, we use new firm-level data which is more recent, more detailed and includes more companies. We believe this accounts for our sharply different results.

The remainder of the paper is organized as follows: in section 2, we describe the methodology and data of our study. The results are presented in section 3. In section 4, we conclude by discussing the implications of our results.

2. METHODS AND DATA

2.1 Theoretical Basis

It is important that any statistical analysis be based soundly in theory, to reduce the potential for spurious correlation (Banker et al. 1993). We draw on standard production theory from economics: the output that a firm produces is a function of the inputs it uses. In particular, we assume that the firms in our sample produce a quantity of output (Q) via a production function (F), whose inputs are computer capital (C), non-computer capital (K), information systems staff labor (S), and other labor and expenses (L). In addition, we assume that other factors, such as the industry or business sector (i) in which the company operates and year (t) in which the observation was made, may affect the relationship between inputs and outputs. Thus, we can write:

$$Q = F(C, K, S, L; i,t) \qquad (1)$$

Output and each of the input variables can be measured in either physical units or dollars. The advantage of measuring in dollar terms is that results will then more closely reflect the ultimate objective of the firm (profits or revenues less costs). In particular, we hypothesize that a significant portion of the output from increased use of information systems will take the form of greater product variety and quality. Measurement of output in dollars instead of units produced will enable us to better value variety and quality. However, this approach requires that we account for inflation and changing prices of different inputs and outputs over time and in different industries. This can be done by multiplying the nominal dollar value of each variable in each year by an associated "deflator" to get the "real" dollar values. This is the approach we take. In particular, we have 1,164 observations of the real dollar values for each of the above variables.

Some companies will be more efficient than others at converting inputs to outputs. The amount of output that can be produced for a given unit of a given input is often measured as the return on investment of the input. When examining differences in the returns of a factor across firms or time periods, it is important to control for the effects of changes in the other inputs to production. One way to do this is to assume that the production function, F, has some general form, and then estimate the parameters of it. This approach has a basis in economic theory and has been extensively applied empirically (Berndt 1991, pp. 449-460). In our analysis, we assume that the production function conforms to the Cobb-Douglas specification, which in our context yields the following equation.

$$Q = e^{\beta_0} C^{\beta_1} K^{\beta_2} S^{\beta_3} L^{\beta_4} \quad (2)$$

In this specification, β_1 and β_3 are the output elasticity of computer capital and information systems staff (IS labor), respectively.[5] Estimating these parameters will yield an estimate of the amount of additional output that can be attributed to information systems spending.

These parameters may vary depending on the industry and time period examined, although it is common practice to assume they are constant within the sample. By constraining the parameters across time it is possible to get more efficient estimates of the parameters at the expense of disregarding possible changes over time. In our analysis, we also examined models in which some parameters were allowed to vary across time or across different sectors of the economy; however, our main results are based on the constrained regressions.

2.2 Econometric Estimation Procedure

Of course, when estimating an equation such as (2), the relationship will not hold exactly for every observation. There are other external and internal disturbances that affect the relationship between inputs and outputs, but which are not captured in any dataset. In addition, even the variables for which we do have observations are likely to be measured with some error. Accordingly, when estimating the parameters of the production function, we have included an error term. By taking the natural logarithm of both sides of equation (2) and including an error term, ε, we can derive an equation that can be estimated econometrically.

$$\text{Log } Q_{it} = \beta_0 + \beta_1 \text{Log } C_{it} + \beta_2 \text{Log } K_{it} + \beta_3 \text{Log } S_{it} + \beta_4 \text{Log } L_{it} + \varepsilon \quad (3)$$

where

Q_{it} = output of a firm in industry i in year t
C_{it} = computer capital
K_{it} = non-computer capital
S_{it} = information systems staff labor
L_{it} = other labor and expenses
β is a vector of parameters to be estimated, and
Log denotes the natural logarithm

Depending on the nature of the error term, ε, different econometric procedures may be called for, as discussed in the results section. However, in each case, equation 3 is the basis for our estimates.

2.3 Data Sources and Construction

This study employed a unique data set on IS spending by large U.S. firms that was compiled by International Data Group (IDG). The information was collected in a survey of IS executives that has been conducted annually from 1987 to 1991. The survey is intended to cover the largest companies in the U.S. and is derived from the Fortune 500 manufacturers plus other large service companies such as banks and utilities that are not included in the Fortune 500.[6] In 1991, data for over 500 firms were collected. Of these, 279 had matching data from Compustat and were used in our analysis. The firms in our sample had 1991 revenues of over $2.1 trillion (nearly half of US GDP) and represented 48 industries as classified by 2-digit SIC code. Respondents are asked to provide the market value of central processors used by the firm in the U.S. (mainframes, minicomputers, and supercomputers), the total central IS budget, the percentage of the IS budget devoted to labor expenses, and the number of PCs and terminals in use. To our knowledge, this is the only available source of IT spending data at the firm level for a broad cross section of the U.S. economy.

The firm names in the IDG data set were then matched to Compustat, a database of historical financial statement information, to obtain data on output, capital investment, expenses, number of employees and industry classification.

There is some discretion as to how the years are matched between the survey and Compustat. The survey is completed at the end of the year for data on the following year. Since the figure we are primarily interested in is computer capital stock and the survey is timed to be completed by the beginning of the new fiscal year, we interpret the survey data as a beginning of period value, which we then match to the end of year data on Compustat (for the previous period). This also allows us to make maximum use of the survey data and is the same approach used by IDG for their reports based on these data.

The series for the value of non-computer capital stock was constructed using a standard procedure described in Berndt (1991, pp. 227-232) using a fifteen year series of investment data and the Winfrey S-3 table (Bureau of Economic Analysis 1987) with a ten year service life assumption. This method was chosen for comparability to other research and is also the method currently used by the Bureau of Economic Analysis (BEA).

Table 1. Data Sources, Construction Procedures, and Deflators

Series	Source	Construction Procedure	Deflator
Computer Capital	IDG Survey	"Market Value of Central Processors" converted to constant 1987 dollars	BEA Deflator for Computer Capital (Gorman 1992)
Non-Computer Capital	Compustat	Total Property, Plant and Equipment Investment converted to constant 1987 dollars and aggregated to create capital stock. Computer capital was subtracted from this result.	GDP Implicit Deflator for Fixed Investment (Bush 1992)
IS Labor	IDG Survey	Total IS Budget times percentage of IS Budget (by company) devoted to labor expense. Converted to constant 1987 dollars.	Index of Total Compensation Cost (Private Sector) (Bush 1992)
Non-IS Labor and Expenses	Compustat	Total Labor, Materials, and other non-interest expenses converted to constant 1987 dollars. IS labor was subtracted from this result.	Producer Price Index for Intermediate Materials, Supplies and Components (Bush 1992)
Output	Compustat	Total sales converted to constant 1987 dollars.	Industry or sector level deflators based on *Gross Output and Related Series by Industry, BEA (1977-89)* and the PPI for Intermediate Materials Supplies and Components

To construct the series for computer capital, we converted the current reported market value of central processors from the IDG survey into constant 1987 dollars. Since the survey reports current market value of the computer capital stock, no further adjustment is needed.

The series for IS labor, non-IS labor and expense and output were also converted to constant 1987 dollars using appropriate deflators — an aggregate deflator for each input and an industry-specific deflator for output. The sources, construction procedure, and deflator for each series is described in Table 1. Summary statistics for the sample are presented in Tables 2 and 3. The sample includes 1,164 observations spread across five years on 380 distinct companies.

There are a number of possible errors in the data, either as a result of the errors in source data or inaccuracies introduced by the data construction methods employed. First, the IDG data on IS spending are self-reported and therefore the accuracy of the data depends on the diligence of the respondents; there is potential sample selection bias since participation is voluntary, and some items require judgement, particularly the market value of computer capital. Second, the numbers only include the *central* IS spending, which may exclude IS spending by other departments; this could result in an understatement of total IS spending which may vary across firms in the sample. Third, only the labor component (IS labor) of the IS budget could be included to prevent double counting of capital expenditures. However, this figure is likely to be correlated with other IS expenditures leading to an overstatement of the contribution of IS labor in our estimates. Finally, the narrow definition of computer capital (central processors) excludes PCs, which is a potentially significant omission. Overall, this would suggest that the figures for computer capital and IS labor may be understated and subject to error.

These difficulties notwithstanding, the numbers agree with a recent study published by CSC/Index (Quinn, Craumer and Weaver 1993) that reported average IS spending as a percentage of sales to be about 1.5%. They are also broadly consistent with the values reported by Cartwright (1986) for computer investment in the overall US economy.

Errors are also introduced by the methods used to create capital stock from capital investment, and the use of aggregate input deflators. Given the short length of the sample (five years) and the relatively low level of inflation in this period, the overall error contribution of these assumptions is likely to be small.

Table 2. Summary Statistics

Sample Statistics — 1991 Constant 1987 Dollars			
Data item	Full Sample	Manufacturing & Service	Manufacturing Only
Output	$2,103 Bn	$1,905 Bn	$1,426 Bn
Computer Capital	$25.4 Bn	$21.8 Bn	$17.85 Bn
Non-Computer Capital	$1,491 Bn	$1,222 Bn	$995 Bn
IS Labor	$14.8 Bn	$12.3 Bn	$9.76 Bn
Non-IS Labor & Expenses	$1,647 Bn	$1,520 Bn	$1,115 Bn
Number of Companies	292	270	202

*This sample used for sector based analyses. It excludes SIC48 and Finance.

Table 3. Five-Year Average Factor Shares and Correlation Matrix

Five Year Average Factor Shares Percent of Output in Constant 1987 Dollars			
Factor	Full Sample	Manufacturing & Services*	Manufacturing Only
Computer Capital	0.987%	0.890%	0.956%
Non-Computer Capital	69.8%	63.5%	69.1%
IS Labor	0.726%	0.677%	0.721%
Non-IS Labor & Expenses	80.3%	81.8%	80.7%
Number of Firms in Sample	1164	1055	788

*This sample used for sector based analyses.

A more serious problem is the difficulty in deflating industry output. It has been argued (Baily and Gordon 1988; Siegel and Griliches 1991) that the government methods fail to properly account for variety and quality change (particularly in service industries), which leads to an overstatement of the rate of price inflation and an understatement of output. The ideal would be to have accurate firm level deflators for output that capture the value of intangibles, but that would be tantamount to assuming away the measurement problem. On balance, in the absence of reliable industry-level measures of the intangible aspects of output, we consider firm level data to be the best way to assess the contribution of IT. We may still miss some of the benefits of IT, but the estimates should be better than those relying on more aggregate data.

In the full sample, we excluded firms in SIC48 (telecommunications) and the entire financial services sector because of potential measurement error in inputs (for telecommunications) and output. The exclusion of these firms reduced our effective sample to 1,110 overall. Furthermore, it is likely that measurement issues are particularly troublesome in the service sector, and therefore the analysis will focus primarily on the manufacturing sector. Other than the specific cases discussed above, all samples with complete data for all variables were included in the regression analyses.

While the dataset is imperfect, we believe it to be no worse overall, and in some respects superior to, the data used in previous studies of IT and productivity.

3. RESULTS

To make maximum use of the available data, while deriving unbiased and robust estimates, we analyzed the data as a system of simultaneous equations and used the appropriate regression techniques. In addition, we examined a number of subsamples of the data and considered specifications that allowed the parameters to vary across time periods and industries. In each case, we found that computer capital and IS labor were positively and significantly associated with increased output.

3.1 Basic Results

We organized the data into five distinct estimating equations as follows, one for each year:

$$\text{Log } Q_{i,87} = \beta_0 + \beta_1 \text{ Log } C_{i,87} + \beta_2 \text{ Log } K_{i,87} + \beta_3 \text{ Log } S_{i,87} + \beta_4 \text{ Log } L_{i,87} + \varepsilon \quad (4a)$$

$$\text{Log } Q_{i,88} = \beta_0 + \beta_1 \text{ Log } C_{i,88} + \beta_2 \text{ Log } K_{i,88} + \beta_3 \text{ Log } S_{i,88} + \beta_4 \text{ Log } L_{i,88} + \varepsilon \quad (4b)$$

$$\text{Log } Q_{i,89} = \beta_0 + \beta_1 \text{ Log } C_{i,89} + \beta_2 \text{ Log } K_{i,89} + \beta_3 \text{ Log } S_{i,89} + \beta_4 \text{ Log } L_{i,89} + \varepsilon \quad (4c)$$

$$\text{Log } Q_{i,90} = \beta_0 + \beta_1 \text{ Log } C_{i,90} + \beta_2 \text{ Log } K_{i,90} + \beta_3 \text{ Log } S_{i,90} + \beta_4 \text{ Log } L_{i,90} + \varepsilon \quad (4d)$$

$$\text{Log } Q_{i,91} = \beta_0 + \beta_1 \text{ Log } C_{i,91} + \beta_2 \text{ Log } K_{i,91} + \beta_3 \text{ Log } S_{i,91} + \beta_4 \text{ Log } L_{i,91} + \varepsilon \quad (4e)$$

Although, in principle, each of these equations can be estimated separately, by estimating them simultaneously using the technique of Iterated Seemingly Unrelated Regressions (ISUR), it is possible to get more efficient estimates. We chose the ISUR procedure since it can directly address serial correlation in the data,[7] can properly handle missing observations, and allows the use of cross-equation constraints to increase the precision of the estimates.

As reported in column 1 of Table 4, our estimate of β_1 indicates that computer capital is correlated with a statistically significant increase in output in the manufacturing sector. Specifically, we estimate that a 1% increase in spending on computer capital is associated with a 0.00518% increase in output, when all the other factors are held constant. Because computer capital accounted for an average of less than 1% of the value of output each year, this implies an ROI (increase in dollar output per dollar invested) for computer capital of approximately 54.2% per year, holding other inputs constant.

For the full sample which also included non-manufacturing firms, the output elasticity of computer capital was estimated at 0.00610, implying an average ROI of 68.7%, although the estimate was less precise. The estimates for the output elasticity for IS labor were 0.0146 in manufacturing and 0.0274 in the full sample, which indicates that each dollar spent here is correlated with an increase output of over two dollars.

Because not all types of computer capital were included in our data and we did not have data on overhead costs, the estimates for the output elasticity of computer capital and IS labor may be too high. We analyze the robustness of the regression to such data omissions in section 3.4 and find that the basic results hold under reasonable assumptions. Our confidence in the regression taken as a whole is further increased by the fact that the estimated output elasticities for the other factors of production appeared to be sensible. For instance, non-computer capital had estimated returns of 4.14% in manufacturing (and 6.86% overall). Furthermore, the elasticities summed to just over one, implying constant or slightly increasing returns to scale overall, which is consistent with the estimates of aggregate production functions by other researchers (Berndt 1991). The R^2 hovered around 99%, suggesting that our independent variables could "explain" most of the variance in output.

3.2 Using Instrumental Variables to Control for the Direction of Causality

When estimating production functions, one danger is that the causality may be reversed: instead of increases in purchases of inputs (e.g., computers) leading to increases in output, it may be that increases in output lead the firm to increase levels of investment. If this is the case, the assumptions necessary for ISUR to be unbiased are violated. In particular, if spending on computer capital is procyclical — it increases more than other inputs during upturns and decreases more during downturns — then the estimate of β_1 will be biased upward, and conversely β_1 will tend to be underestimated if computer capital spending is countercyclical.

Table 4. ISUR/3SLS Regressions — Parameters β_1, β_2, β_3, β_4 and Sector Dummes Constrained to be Equal Across Years

	Manufacturing		Manufacturing & Services[1]	
	ISUR	3SLS	ISUR	3SLS
β_1 (Computer Capital)	.00518** (2.08)	.00634* (1.64)	.00610** (2.12)	.00516 (1.09)
β_2 (Non-Computer Capital)	.0286*** (6.26)	.0226*** (3.53)	.0462** (10.7)	.0234*** (3.86)
β_3 (IS Labor)	.0146*** (3.57)	.0145*** (2.61)	.0274*** (6.32)	.0235*** (3.67)
β_4 (Non-IS Labor and Expense)	.945*** (132.4)	.962*** (99.4)	.095*** (143.5)	.947*** (99.2)
Dummy Variables[3]	Industry & Year	Industry & Year	Sector & Year	Sector & Year
R^2 (1991)	99.3%	99.6%	98.6%	98.7%
N (1991)	202	171	272	222
N (total)	788	489[2]	1055	639[2]

Key: *** = $p < .01$; ** = $p < .05$; * = $p < .1$; † = $p < .2$ (two-tailed); ratio of coefficient estimate to asymptotic standard error in parenthesis (analogous to t-statistics)

1 Excludes SIC48 and Finance. Including them yields:

β_1 = 0.0125*** (t = 3.61)
β_2 = 0.0488*** (t = 9.99)
β_3 = 0.0345*** (t = 6.84)
β_4 = 0.0893*** (t = 118.6)
N = 1164

2 N (total) value of 3SLS is lower because each observation requires data for the current period and the previous period; this eliminates observations for all of 1987 and some in the other years.

3 χ^2-tests reject the hypothesis that all sector/industry dummy variables simultaneously zero at $p < .01$. χ^2-tests on the year dummies reject the hypothesis that year dummies are each individually equal to zero at $p < .01$.

Fortunately, regardless of the direction of the potential bias, it is possible to correct for it by using the technique of three stage least squares (3SLS) using instrumental variables which are designed to filter out any endogenous variation in the independent variables.[8] We used once-lagged values of the independent variables as instruments, since by definition, they could not be affected by unanticipated shocks in the dependent variable in the following year. The results using this technique are reported in Table 4, columns 2 and 4. The return on computer capital is approximately the same as for the ISUR regressions: 62.2% for manufacturing and 54.8% for the full sample. The estimates for IS labor are also comparable to those in the previous specification.

3.3 Examining Potential Differences Over Time and in Different Sectors

The estimates described in sections 3.1 and 3.2 were all based on the assumption that the parameters did not vary over time or in different sectors. Therefore, they should be

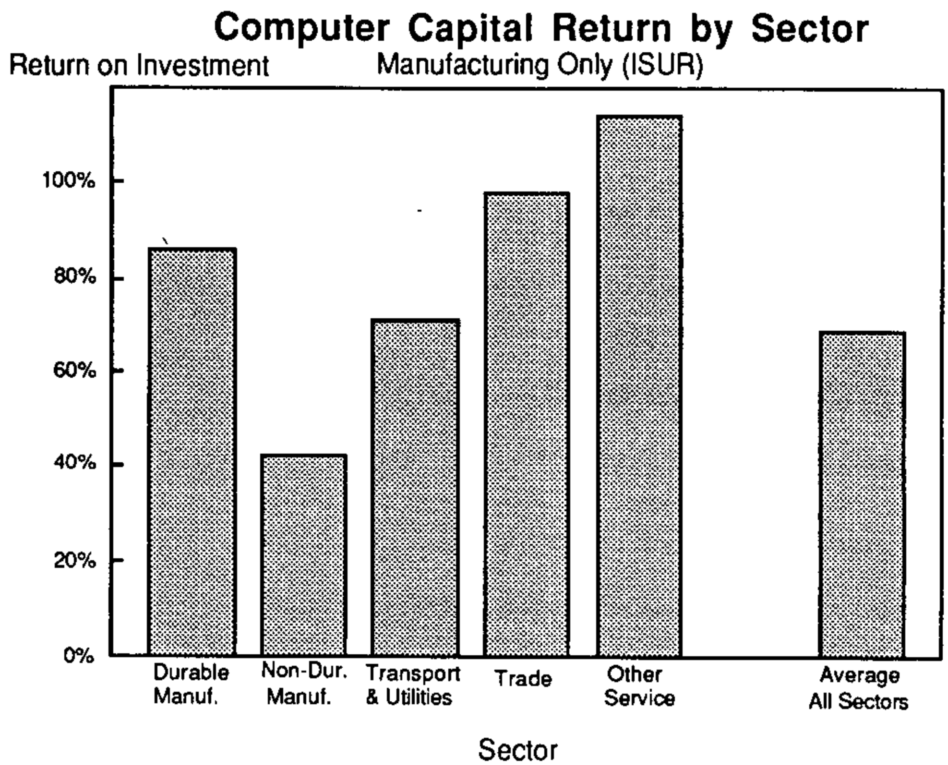
Table 5. ISUR and 3SLS Estimates Unconstrained by Year

	Manufacturing (ISUR)	Manufacturing & Services[1] (ISUR)
$\beta_{1,91}$ (Computer Capital)	.00510 (1.115)	.00198 (0.03)
$\beta_{1,90}$ (Computer Capital)	.00481† (1.43)	.00704 (1.35)
$\beta_{1,89}$ (Computer Capital)	.00612† (1.50)	.00702 (1.40)
$\beta_{1,88}$ (Computer Capital)	.00244 (0.45)	.00811 (1.54)
$\beta_{1,87}$ (Computer Capital)	.00907 (0.87)	.00694 (1.06)
β_2 (Non-Computer Capital)	.0323*** (7.43)	.0461*** (10.7)
$\beta_{3,91}$ (IS Labor)	.0163*** (2.75)	.0358*** (5.14)
$\beta_{3,90}$ (IS Labor)	.0163*** (3.31)	.0301*** (4.64)
$\beta_{3,89}$ (IS Labor)	.0142** (2.81)	.248*** (4.20)
$\beta_{3,88}$ (IS Labor)	.0413*** (2.12)	.0261*** (4.20)
$\beta_{3,87}$ (IS Labor)	.0048 (0.46)	.0211*** (2.81)
β_4 (Other Expense)	.944*** (132.0)	.906*** (143.2)
Dummy Variables[2]	industry & year	sector & year
R^2 (1991)	99.3%	99.83%
N (1991)	202	280
N (total)	788	1110

Key: *** = $p < .01$; ** = $p < .05$; * = $p < .1$; † = $p < .2$ (two-tailed); ratio of coefficient estimate to asymptotic standard error in parenthesis (analogous to t-statistics)

1 Excluding SIC48

2 χ^2-tests reject the hypothesis that all sector/industry dummy variables simultaneously zero at $p < .01$. χ^2-tests on the year dummies reject the hypothesis that year dummies are each individually equal to zero at $p < .01$.



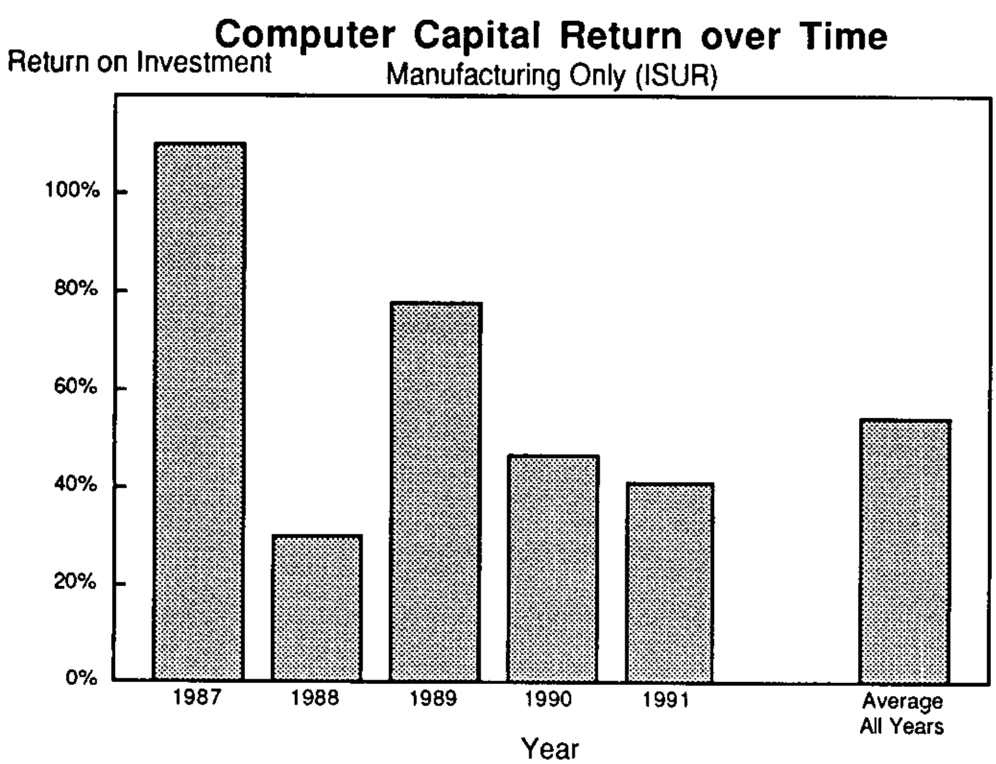


Figure 3. Computer Capital ROI by Sector and Over Time

interpreted only as overall averages. By using the simultaneous equations approach, it is also possible to allow the parameters to vary by year or sector in the full sample. The estimates of the unconstrained equations are presented in Table 5 and are shown graphically in Figure 3.

The estimates for both computer capital and IS labor for different years are fairly consistent with one another, although there is some evidence that they are increasing slightly between 1988 and 1991.[9] In 1991, the return on investment in computer capital is estimated to be 41% in our sample of manufacturing industries, while each dollar spent on IS labor is correlated with increased revenues of $2.38.

When the output elasticity of computer capital was allowed to vary across sectors, the estimates were positive for five of the sectors but negative for mining. However, because of high standard errors in the unconstrained specifications, we were unable to reject the null hypothesis that the ROI on computer capital was significantly different from ROI for other capital in any sector except for durable manufacturing (see Table 6).[10]

3.4 Sensitivity Analysis and Possible Biases

Our estimates of the return to computer capital may be overstated since, as discussed in section 2.3, the amount of

Table 6. ISUR Estimates — IT Coefficients Uncontrained by Sector[2]

	Manufacturing & Services[1]		Manufacturing & Services[1]
$\beta_{1,MD}$ (Computer Capital)	.0107*** (2.54)	β_1 (Computer Capital)	.00653** (2.02)
$\beta_{1,MN}$ (Computer Capital)	.00299 (0.61)	β_2 (Non-IS Capital)	.0476*** (10.11)
$\beta_{1,SR}$ (Computer Capital)	.0225 (1.00)	$\beta_{3,MD}$ (IS Labor)	.0273*** (4.62)
$\beta_{1,TR}$ (Computer Capital)	.0055† (1.72)	$\beta_{3,MN}$ (IS Labor)	.0316*** (4.83)
$\beta_{1,MI}$ (Computer Capital)	-.0093 (0.53)	$\beta_{3,SR}$ (IS Labor)	.0853*** (3.25)
$\beta_{1,TU}$ (Computer Capital)	.0071 (0.75)	$\beta_{3,TR}$ (IS Labor)	.0302*** (2.23)
β_2 (Non-IS Capital)	.0494*** (10.5)	$\beta_{3,MI}$ (IS Labor)	.0093 (0.51)
β_3 (IS Labor)	.0293*** (5.96)	$\beta_{3,TU}$ (IS Labor)	.0179† (1.61)
β_4 (Non-IS Labor and Expenses)	.902*** (128.4)	β_4 (Non-IS Labor and Expenses)	.904 (128.4)
R^2 (1991)	98.6%	R^2 (1991)	98.6%
N (1991)	272	N (1991)	272
N (total)	925	N (total)	925

Key: *** = $p < .01$; ** = $p < .05$; * = $p < .1$; † = $p < .2$ (two-tailed); ratio of coefficient estimate to asymptotic standard error in parenthesis (analogous to t-statistics)

1 Excluding SIC48

computer capital is likely to be understated. The actual effect on the estimate is dependent on how closely correlated the excluded computer capital is to our measured computer capital. If they are uncorrelated, our estimate for the return to computer capital is unbiased (although there may be a small effect on other capital or other expense that would receive the effect of the excluded computer capital). If the excluded items (mainly PCs and departmental minicomputers) are complementary to our measured computer capital (positive correlation), our estimate would be high for the return to computer capital. For instance, if actual computer capital were twice as large as our observed value for computer capital, and if the excluded items are perfectly correlated with our measured computer capital, then the our ROI estimate of 54.2% should be revised to 27.1%. Similarly, our calculated values for the return to IS labor may be overestimates because we could not include corporate overhead and other IS expenses that are likely to increase proportionately with measured IS labor.[11]

However, regardless of whether our computer capital and labor estimates are overestimated or underestimated, our result that the returns to computer capital and labor are positive (and statistically significant) holds.

As discussed in sections 1.2 and 2.3, the output price deflators we used may fail to properly account for variety and quality change, which leads to an understatement of output. This would bias the estimated IT coefficients downward in our estimates if firms have invested in IT to improve variety or quality. Even using firm-level data, underestimates will result to the extent that firms *simultaneously* invest in IT. In such cases, although the "bar has been raised," no individual firm gains a competitive advantage. Furthermore, the counterfactual — firms that didn't invest and lost sales or went out of business — would not exist in the data. The value of variety and quality to consumers, although real, would therefore appear in neither of the two places we looked: the industry deflators and the relative changes in firm revenues.

As an additional check of the robustness of our results we plotted the regression residuals from the pooled cross-sectional analysis and found that they roughly correspond to a normal distribution. We also checked for heteroskedasticity by comparing White (heteroskedasticity-consistent) standard errors to the regular standard error estimates and found little change for pooled, single equation regressions. Finally, we computed the correlation coefficients to check for collinearity between regressors which could lead to higher estimates of the standard errors. All correlations were less than .8 suggesting that collinearity, while present, is not excessive.

On balance, we may have underestimated both IS input and final output. The directions of the resulting biases go in opposite directions but under reasonable assumptions they do not appear to obviate the basic finding that the return on IS capital and labor spending is statistically significant and exceeds that of other types of capital and labor.

4. CONCLUSION

4.1 Summary of Findings

We examined data which included over 1,000 observations on output and several inputs at the firm level for the period 1987-1991. The firms in our sample were primarily engaged in manufacturing and had aggregate sales of about two trillion dollars in 1991. We tested a broad variety of specifications and examined several different subsamples of the data.

The data indicate that computer capital and IS labor spending contribute significantly to firm level output (summaries of ROI are presented in Table 7 and Figure 3). Furthermore, as reported in Table 8, for several specifications we were able to reject the hypothesis that the ROI for computer capital was equal to the ROI for non-computer capital in favor of the hypothesis that the ROI for computer capital was higher. In almost every specification, we could conclude that the return from spending on IS labor was higher than the return from spending on non-IS labor and expenses. The basic result that computer capital and labor contribute significantly to total output are robust to reasonable assumptions about measurement error due to exclusion of unmeasured factors.

4.2 Comparison with Earlier Research

Several other studies have failed to find evidence that IT increases output. Because the models we used were similar to those used by several previous researchers, and follow in a long tradition of estimating production functions, we attribute our different findings primarily to the larger and more recent data set we used. Specifically, there are at least three reasons why our results may differ from previous results.

First, we examined a later time period (1987-1991) than did Loveman (1978-1982), Barua, Kriebel and Mukhopadhyay (1978-1982), or Berndt and Morrison (1968 -1986). The massive build up of computer capital is a relatively recent phenomenon. Indeed, the delivered amount of computer power in the companies in our sample is likely to be at least an order of magnitude greater than that in comparable

Table 7. Return on Investment for Computer Capital — Analysis Summary

Point estimtes and 95% (one-tailed) confidence intervals

Analysis	Manufacturing Only ISUR	Manufacturing Only 3SLS	Manufacturing & Services ISUR	Manufacturing & Services 3SLS
Simultaneous Equations	54.2% ±42.9%	62.2% ±62.3%	68.7% ±53.3%	54.8% ±82.7
By Year - 91	40.8% ±58.4%	106.3% ±137.6%	16.8% ±787.5%	-42.0% ±230.3%
By Year - 90	46.4% ±53.4%	59.8% ±77.5%	75.5% ±92.0%	62.4% ±1141.4%
By Year - 89	77.8% ±85.3%	23.9% ±87.2%	94.1% ±110.6%	-57.5% ±145.4%
By Year - 88	30.1% ±110.1%	-43.8% ±171.7%	106.3% ±113.5%	-177.5% ±273.0%
By Year - 87	109.9% ±207.9%		87.3% ±135.5%	
By Sector - MD			86.3% ±55.9%	
By Sector - MN			42.5% ±114.5%	
By Sector - SR			114.2% ±187.9%	
By Sector - TR			98.2% ±93.9%	
By Sector - MI			-211.8% ±657.5%	
By Sector - TU			71.05% ±185.5%	

firms from the period studied by the other authors. Brynjolfsson (1993) calculates that even if the ROI of IT were twice that of non-IT capital, its impact on output in the 1970s or early 1980s would not have been large enough to be detected by conventional estimation procedures. Furthermore, the changes in business processes needed to realize the benefits of IT may have taken some time to implement, so it is possible that the actual returns from investments in computers have increased over time. In particular, computers may have initially created organizational slack which was only recently eliminated, perhaps hastened by the increased attention engendered by earlier studies that indicated a potential productivity shortfall and suggestions that "to computerize the office, you have to reinvent the office" (Thurow 1990). A pattern of increasing returns is also consistent with the strategy for optimal investment in the presence of learning-by-doing: short-term returns should initially be lower than returns for other capital, but subsequently rise to exceed the returns to other capital, compensating for the "investment" in learning (Lester and McCabe 1993). Under this interpretation, our high estimates of computer ROI indicate that businesses are reaping the rewards from the experimentation and learning phase in the early 1980s. Even within our sample, we find some evidence that returns are higher for later years when we allow the parameter on computer capital to vary over time.

Table 8. χ^2 Tests[1] for Return Differences Between Computer Capital and Other Capital[2]

Return Difference Tests				
Specification	Manufacturing		Manufacturing and Services	
	IT Capital	Other Capital	IT Capital	Other Capital
ISUR	54.2%*	4.1%	68.7%	6.9%
3SLS	62.2%†	3.3%	54.8%	3.5%

Key: *** = p < .01; ** = p < .05; * = p < .1; † = p < .2

1 χ^2 tests used since F-tests are not valid for hypothesis testing when non-linear estimation procedures 9ISUR, 3SLS) are employed. For our sample, χ^2 and F-test statistics would be approximately equal as a result of the large sample size.

2 A significant result indicates that the return on computer capital is greater than the return for other capital.

Second, we were able to use different and more detailed firm-level data than had been available before. The effects of computers in increasing variety, quality or other intangibles is more likely to be detected in firm level data than in the aggregate data. Unfortunately, all such data, including ours, is likely to include data errors. It is possible that the data errors in our sample happened to be more favorable (or less unfavorable) to computers than those in other samples. We attempted to minimize the influence of data errors by cross-checking with other data sources, eliminating outliers, and examining the robustness of the results to different subsamples and specifications. In addition, the large size of our sample should, by the law of large numbers, mitigate the influence of random disturbances. Indeed, the precision of our estimates was generally much higher than those of previous studies; the statistical significance of our estimates owes as much to the tighter confidence bounds as to higher point estimates.

Third, our sample consisted entirely of relatively large "Fortune 500" firms. It is possible that the high IS contribution we find is limited to these larger firms. However, when we disaggregated the data into three groups by size, the smaller firms in our sample used IS just as effectively as the larger firms. In fact, an earlier study (Brynjolfsson et al. 1991) found evidence that smaller firms may benefit disproportionately from investments in information technology. In any event, because firms in the sample accounted for such a large share of the total US output, the economic relevance of our findings is not heavily dependent on extrapolation of the results to firms outside of the sample.

4.3 Managerial Implications and Extensions to the Study

If the spending on computers is correlated with significantly higher returns than spending on other types of capital, it does not necessarily follow that companies should increase spending on computers. The methods employed in our study can and do indicate correlations between computer spending and output, but cannot prove causality. The firms with high returns and high levels of computer investment may differ systematically from the low performers in ways that can not be rectified simply by increasing spending. For instance, recent economic theory has suggested that "modern manufacturing," involving high intensity of computer usage, may require a radical change in organization (Milgrom and Roberts 1990). This possibility is emphasized in numerous management books and articles (see, e.g., Malone and Rockart 1991; Scott Morton 1991) and supported in our discussions with managers, both at their firms and during a recent MIT workshop[12] on IT and Productivity we helped organize for approximately thirty industry representatives.

There are a number of other directions this work could be extended. Although our approach allowed us to infer the value created by intangibles such as product variety by looking at changes in the revenues at the firm level, more direct approaches might also be promising. For instance, other variables can be collected to see whether computer productivity is systematically related to characteristics such as variety of product line, or the average defect rate in their output. It would also be interesting to explore more carefully the roles of environmental variables such as the extent of foreign and domestic competition. Furthermore, our data set already includes a number of variables that can further disaggregate the components of IT spending, including the number of PCs and the amount spent on training. As shown by Weill (1992), different types of IT can have very different productivities. An attempt to replicate his findings and the findings of others using our new dataset could also help to build a cumulative tradition of research in this area.

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8. ENDNOTES

1. An observation is one year of data on all variables for a specific firm. We did not have all five years of data for every firm, but the data set does include at least one year of data for 380 different firms.

2. The precise definition of "IT" varies from study to study. Morrison and Berndt included scientific instruments, communications equipment, photocopiers and other office equipment as well as computers in their definition. Others define IT even more broadly, including software, services and related peripheral equipment. As described in section 2.3, the definition used in our study is fairly narrow and includes separate estimates for the effect of corporate computer capital and corporate IS labor.

3. Specifically, the "management productivity of information technology" (MPIT) dataset, which surveyed sixty business units of twenty participating firms for the period 1978-1982.

4. As the National Bureau of Economic Research (1961) put it: "If a poll were taken of professional economists and statisticians, they would designate the failure of price indexes to take full account of quality changes as the most important defect in these indexes." No good methodology exists for incorporating some of the other benefits, such as variety. Baily and Gordon (1988) estimate that "true" annual productivity growth might be as much as 0.5% higher overall than reported in official statistics.

5. Formally, the output elasticity of computers, E_C, is defined as: $E_c = \frac{\partial F}{\partial C}\frac{C}{F}$. For our p roduction function, F, this reduces to:

$$E_c = \beta_1 e^{\beta_0} C^{\beta_1} K^{\beta_2} S^{\beta_3} L^{\beta_4} = \frac{C}{e^{\beta_0} C^{\beta_1} K^{\beta_2} S^{\beta_3} L^{\beta_4}} = \beta_1 \ .$$

The ROI for computers is simply the output elasticity multiplied by the ratio of output to computer input:

$$ROI_C = \frac{\partial F}{\partial C} = \frac{\partial F}{\partial C}\frac{CF}{FC} = Ec\frac{F}{C} \ .$$

6. Companies the entered or exited the Fortune 500 over the period were included in the sample provided they had complete survey data and matching information on Compustat. Results on a matched sample that excluded all entrants and exits were not qualitatively different except for higher standard errors.

7. We could not use more traditional methods of modeling serial correlation in panel data sets due to the short time dimension and missing data.

8. This is also an appropriate correction for potential measurement error in one or more of the independent variables (Pindyck and Rubinfeld, 1991, p. 160-161).

9. This could be interpreted as evidence of growth in multifactor productivity over this period. We also examined regressions for each year individually. Except for higher standard errors, they are not qualitatively different from the estimates using systems of equations, as reported in the paper.

10. These hypothesis tests were done using χ^2 tests at the 90% level of significance. Note that in each case, the null hypothesis is that return to computers or to IS labor is the same as that for non-IT capital and labor, respectively. Thus, when we fail to reject the null hypothesis, it should be interpreted as neither praise nor censure for IS, because failing to reject the null

may simply be the result of a hypothesis test with low power.

11. In addition, an analogous argument could be made for other unmeasured factors, such as R&D capital, which might be correlated with IS spending; the contribution of these unmeasured factors might erroneously increase the IS estimates if the correlation were positive or decrease it if it were negative.

12. The MIT Center for Coordination Science and International Financial Services Research Center jointly sponsored a Workshop on IT and Productivity which was held at MIT in December, 1992.