New Evidence on the Returns of Information Systems

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New Evidence on the Returns to Information Systems

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 the potential benefits of IS have only recently been undertaken in many firms.

Our study uses new firm-level data on several components of IS spending for 1987-1991. The dataset includes 367 large firms which generated approximately $1.8 trillion dollars in output in 1991. We supplemented the IS data with data on other inputs, output, and price deflators from 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, gross return on investment (ROI) for computer capital averaged 58% in manufacturing and 81% for manufacturing and services combined in our sample. We are able to reject the 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 IS 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, there is surprisingly little formal evidence linking it to higher productivity. Several studies, such as those by Loveman (1988) and by Barua, Kriebel & Mukhopadhyay (1991) have been unable to reject the hypothesis that computers add nothing at all to total output, while others estimate that the marginal benefits are less than the marginal costs (Morrison & Berndt, 1990). 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 recent data, 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 1121 observations[1] over the period 1987-1991. The firms in our sample generated approximately $1.8 trillion dollars worth of output in the United States in 1991. Because the identity of each of the participating firms is known, we were able to supplement the IS data with data from several other sources. As a result, we could assess several econometric models of the contribution of IS to firm-level productivity.

Our examination of these data indicates that IS have made a substantial and statistically significant contribution to the output of firms (figure 1). Our point estimates indicate that, dollar for dollar, spending on computer capital created more value than spending on other types of capital. We find that the contribution of IS to output does not vary much across years, although there is weak evidence of an decrease over time. We also find some evidence of differences across various sectors of the economy. Examining subsamples of our data, we find that the rate of return to computer capital is highest in firms that have high shareholder return and return on equity, and in firms that have invested in a mix of mainframes and personal computers (PCs).

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[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 367 different firms.

For the firms in our sample, we estimate that the gross return on investment for computers to be over 50% annually. 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 investment 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

Industry-level output statistics 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 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 of the primary difficulties with industry data is that firms may use IS to redistribute customers within the industry without proportionately expanding total sales for the industry as a whole. Customers may observe improvements in existing or new products that are not fully reflected in government deflators. In this case, productivity could appear to decrease at the industry level, even when individual firms and consumers receive increased benefits.[3] One way to mitigate the measurement problems inherent in industry-level data is to use firm-level data instead, which can capture the effects at both the industry and the individual firm level.

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[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 below, 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] This is in some ways the mirror image of the R&D spillovers that led Griliches to prefer more aggregate data when assessing the contribution of R&D to output (Griliches, 1991).

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. This has made it difficult to draw generalizable results from these studies. For instance, Weill (1992) found some positive impacts for investments in some categories of IS but not for overall IS spending. However, the 33 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." (Weill, 1992.) Using different data[4], Loveman (1988) concluded: "Investments in IT showed no net contribution to total output", and Barua, Kriebel and Mukhudpadhyay (1991) found that computer investments are not significantly correlated with increases in return on assets. However, both of these studies were based on data from only 20 firms in the 1978-82 period and derived only fairly imprecise estimates of IT's relationship to firm performance.[5]

Although previous work provides little econometric evidence that computers improve productivity, Brynjolfsson (1993) reviews the overall 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 deflators, and therefore productivity statistics, do not properly reflect this value. In addition, as 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.

1.2 Approach of this Paper

The imprecision of previous estimates highlights an inherent difficulty with measuring the benefits of IT investment. To better understand the perceived benefits, 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

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[4] Specifically, the "management productivity of information technology" (MPIT) dataset, which surveyed 60 business units of 20 participating firms for the period 1978-1982.

[5] For instance, the 95% confidence interval exceeded ± 300% for the ROI implied by the estimates in Loveman (1988).

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 of the benefits of IT, other than labor savings, are not well captured in aggregate productivity or output statistics.[6]

Although Robert Solow has noted that "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 IT 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 et al. (1991), and 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.

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[6] 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.

2. METHODS AND DATA

2.1 Theoretical Basis

In our analysis, 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), IS 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). However, this approach requires that we account for inflation and the 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 approach also partially accounts for changes in product quality or variety to the extent that changes in output characteristics are incorporated into the price deflators.

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 been 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.[7]

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

In this specification, β_1 and β_3 are the output elasticity of COMPUTER CAPITAL and information systems staff (IS STAFF), respectively.[8]

2.2 Estimating Procedures

Taking logarithms of equation (2) and adding an error term (ε) provides an equation that can be estimated by linear regression. For estimation, we have organized the equations as a system of five estimating equations, one for each year[9]:

$$\text{Log } Q_{i,87} = \beta_0 + \beta_1 \text{ Log } C_{i,87} + \beta_2 \text{ Log } K_{i,87} + \beta_3 \text{ Log } S_{i,87} + \beta_4 \text{ Log } L_{i,87} + \varepsilon_{87} \quad (3a)$$
$$\text{Log } Q_{i,88} = \beta_0 + \beta_1 \text{ Log } C_{i,88} + \beta_2 \text{ Log } K_{i,88} + \beta_3 \text{ Log } S_{i,88} + \beta_4 \text{ Log } L_{i,88} + \varepsilon_{88} \quad (3b)$$
$$\text{Log } Q_{i,89} = \beta_0 + \beta_1 \text{ Log } C_{i,89} + \beta_2 \text{ Log } K_{i,89} + \beta_3 \text{ Log } S_{i,89} + \beta_4 \text{ Log } L_{i,89} + \varepsilon_{89} \quad (3c)$$
$$\text{Log } Q_{i,90} = \beta_0 + \beta_1 \text{ Log } C_{i,90} + \beta_2 \text{ Log } K_{i,90} + \beta_3 \text{ Log } S_{i,90} + \beta_4 \text{ Log } L_{i,90} + \varepsilon_{90} \quad (3d)$$
$$\text{Log } Q_{i,91} = \beta_0 + \beta_1 \text{ Log } C_{i,91} + \beta_2 \text{ Log } K_{i,91} + \beta_3 \text{ Log } S_{i,91} + \beta_4 \text{ Log } L_{i,91} + \varepsilon_{91} \quad (3e)$$

Under the assumption that the error terms in each equation are independently and identically distributed, estimating this system of equations is equivalent to pooling the data and estimating the parameters by ordinary least squares (OLS). However, it is likely that the variance of the error term varies across years, and that there is some correlation between the

[7] Other more complicated functional forms, such as the translog, could also be examined, but as noted by Griliches (1979), the Cobb-Douglas specification is theoretically fairly robust for estimating output elasticities. We consider other functional forms in section 3.3.

[8] Formally, the output elasticity of computers, E_C, is defined as: $E_C = \frac{\partial F}{\partial C}\frac{C}{F}$. For our production function, F, this reduces to: $E_C = \beta_1 e^{\beta_0} C^{\beta_1 - 1} K^{\beta_2} S^{\beta_3} L^{\beta_4} \frac{C}{e^{\beta_0} C^{\beta_1} K^{\beta_2} S^{\beta_3} L^{\beta_4}} = \beta_1$. The ROI for computers simply the output elasticity multiplied by the ratio of output to computer input: $ROI_C = \frac{\partial F}{\partial C} = \frac{\partial F}{\partial C}\frac{CF}{FC} = Ec\frac{F}{C}$

[9] For expositional simplicity, we write this equation with a single intercept β_0. In the actual analysis, this intercept is allowed to vary by year and industry or by year and sector.

error terms across years. It is therefore possible to get more efficient estimates of the parameters by using the technique of Iterated Seemingly Unrelated Regressions (ISUR).[10]

The ISUR procedure starts by estimating the coefficients by OLS to obtain and initial estimate of the error term covariance matrix, and then iteratively refines this estimate until convergence is reached at minimum error. This procedure implicitly corrects for serial correlation among the variables even when there are missing observations for some firms in some years. More traditional methods of correcting for serial correlation in panel data sets (Kmenta, 1986) require complete data and do not seem to perform well with short time dimensions (Barua, Kriebel & Mukhopadhyay, 1989).

As equations (3a) - (3e) are written, we have imposed the usual restriction that the parameters are equal across the sample, which allows the most precise estimates of the parameter values. We can also allow some or all of the parameters to vary over time or by firm characteristics (sector, performance, size, etc.), although this additional information is generally obtained at the expense of lowering the precision of the estimates. We will explore some of these alternative specifications in the results section; however, the main results of this paper are based on the system of equations shown in (3a)-(3e).

2.3 Data Sources and Variable Construction

This study employs a unique data set on IS spending by large U.S. firms which was compiled by International Data Group (IDG). The information is collected in an annual survey of IS managers at large firms[11] that has been conducted since 1987. Respondents are asked to provide the market value of central processors (mainframes, minicomputers, supercomputers) used by the firm in the U.S., the total central IS budget, the percentage of the IS budget devoted to labor expenses, the number of PCs and terminals in use, and other IT related information.

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[10] Sometimes also called IZEF, the iterated version of Zellner's efficient estimator, ISUR yields estimates that are numerically equivalent to the maximum likelihood estimator (Berndt, 1991).

[11] Specifically, the survey targets Fortune 500 manufacturing and Fortune 500 service firms that are in the top half of their industry.

Since the names of the firms are known and most of them are publicly traded, the IS spending information from the IDG survey could be matched to Compustat II[12] to obtain measures of output, capital investment, expenses, number of employees and industry classification. In addition, these data were also combined with price deflators for output, capital, employment costs, expenses and IT capital.

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 (e.g. Maglitta and Sullivan-Trainor, 1991).

IDG reports the "market value of central processors" (supercomputers, mainframes and minicomputers) but only the total number of "PCs and terminals". Therefore, the variable for COMPUTER CAPITAL was obtained by adding the "market value of central processors" to an estimate of value of PCs and terminals, which was computed by multiplying the weighted average value for PCs and terminals by the "number of PCs and terminals".[13] This approach yields roughly equal values, in aggregate, for central processors as for PCs and terminals. This is corroborated by a separate survey by IDG (IDC, 1991) which tabulates shipments of computer equipment by category. This aggregate computer capital is then deflated by the computer systems deflator reported in Gordon (1993).

The variables for IS STAFF, NON-IS LABOR AND EXPENSE and OUTPUT were computed by taking the relevant quantity from the IDG survey or Compustat, and multiplying by a price deflator. IS STAFF was computed by multiplying the IS Budget figure from the IDC survey by the "percentage of the IS budget devoted to labor expenses...", and deflating this

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[12]Compustat II provides financial and other related information for publicly traded firms, primarily obtained through annual reports and regulatory filings.

[13] Specifically, we estimated a figure for the value of terminals and the value of PCs and then weighted them by the proportion of PCs versus terminals. For terminals, the we estimated the value as the average list price of an IBM 3151 terminal in 1989 which is $609 (Pelaia, 1993). For PCs we used the average nominal PC cost over 1989-1991 of $4,447, as reported in (Berndt & Griliches, 1990). These figures were then weighted by the proportion of PCs to terminals in the 1993 IDG survey (58% terminals). The resulting estimate was .42*$609 + .58* $4,447 = $2,835.

figure. NON-IS LABOR AND EXPENSE was computed by subtracting the deflating total expense and subtracting deflated IS STAFF from this value. Thus, all the expenses of a firm are allocated to either IS STAFF or NON-IS LABOR AND EXPENSE.

Total capital for each firm was computed from book value of capital stock, adjusted for inflation by assuming that all investment was made at an calculated average age (total depreciation/current depreciation) of the capital stock.[14] From this total capital figure, we subtract the deflated value of COMPUTER CAPITAL to get NON-COMPUTER CAPITAL. Thus, all capital of a firm is allocated to either COMPUTER CAPITAL or NON-COMPUTER CAPITAL. The approach to constructing total capital follows the methods used by other authors who have studied the rate of return to specific production factors using a similar methodology (Hall, 1990; Mairesse & Hall, 1993). A summary of the sources, construction procedure and deflator for each variable are provided in table 1, and sample statistics are shown in table 2 and 3.

2.4 Potential Data Problems

There are a number of possible errors in the data, either as a result of errors in source data or inaccuracies introduced by the data construction methods employed. First, the IDG data on IS spending are largely self-reported and therefore the accuracy depends on the diligence of the respondents. Some data elements items require some degree of judgment -- particularly the market value of central processors and the total number of PCs and terminals. Also, not all companies responded to the survey, and even those that did may not have responded in every year, which may result in sample selection bias.

Second, there are a number of reasons why IS STAFF and COMPUTER CAPITAL may be understated, although by construction these errors do not reduce total capital and total expense for the firm. The survey is restricted to central IS spending in the U.S., plus PCs and terminals both inside and outside the central department. Some firms may have significant expenditures on information systems outside the central department or outside the U.S. In addition, the narrow definitions of IS spending employed in this study may

[14]An alternative measure of capital stock was computed by converting historical capital investment data into a capital stock using the Winfrey S-3 table. This approach was used in earlier versions of this paper (Brynjolfsson & Hitt, 1993). However, the calculation shown above is more consistent with previous research (see e.g. (Hall, 1993)).

exclude significant costs that could be legitimately counted as COMPUTER CAPITAL such as software and communication networks. Furthermore, by including only the labor portion of IS expenses in IS STAFF as a separate variable (in order to prevent double counting of capital expenditure), other parts of the IS budget are left in the NON-IS LABOR AND EXPENSE category. The effects of these problems on the final results are discussed in the Results section. Despite these potential difficulties, the numbers agree with a study published by CSC/Index (Quinn, et al., 1993) that reported IS spending to be approximately 1.5% of sales and are broadly consistent with the capital flow tables for the US economy published by the Bureau of Economic Analysis.

A third area of potential inaccuracy comes from the price deflators. Aggregate price deflators were used for the input variables (COMPUTER CAPITAL, IS STAFF, NON-COMPUTER CAPITAL, NON-IS LABOR AND EXPENSE), which ignores changes in input composition among industries. However, given the relatively low rate of inflation and the relatively short time dimension of the sample (5 years), these errors are likely to be small. A more serious problem is the difficulty in deflating OUTPUT using industry-level deflators. Numerous authors (Baily & Gordon, 1988; Siegel & Griliches, 1991) have criticized the current methods employed by the BEA for constructing industry-level price deflators. It has been argued that these methods fail to fully account for quality change or other intangible improvements, which leads to an overstatement of the rate of inflation and an understatement of real output. While the optimal solution of creating firm-specific price deflators is infeasible, if consumers purchases are in part affected by intangible quality improvements, then the use of firm level data should provide some improvement in the ability to measure output than studies that have relied on industry or economy wide aggregates. Nonetheless, if firms have invested in IT for intangible benefits, it is likely that our rates of return to computer investment will be understated since the increases in output are understated.

Finally, the measurement of OUTPUT or COMPUTER CAPITAL input in certain service industries appeared particularly troublesome. For financial services, we found that OUTPUT was poorly predicted in our model, presumably because of problems in defining and quantifying the "sales" of financial institutions. In the telecommunications industry, it has been argued (Popkin, 1992) that many of the productivity gains have come from computer-based telephone switching gear, which is classified as communications equipment and not COMPUTER CAPITAL. These arguments would suggest that the return to computer capital in telecommunications would be significantly overstated. We therefore excluded all firms in the financial services industries (SIC60 - SIC69), and telecommunications (SIC48) when we describe the "manufacturing and services" sample.[15]

3. RESULTS

3.1 Basic results

The basic estimates for this study are obtained by estimating the system of equations (3a)-(3e) by ISUR (see section 2.2). In the manufacturing regressions, the intercept term β_0 is allowed to vary across industries, and across time. For the full sample, the intercept term can vary across sectors and time.

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 0.0126% increase in OUTPUT, when all the other input are held constant. Because COMPUTER CAPITAL accounted for an average of 2.18% of the value of output each year, this implies a gross ROI (increase in dollar output per dollar of capital stock) for COMPUTER CAPITAL of approximately 58% 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 0.0169, implying an average ROI of 81%.

The estimates for the output elasticity for IS STAFF were 0.0145 in manufacturing and 0.0178 in the full sample, which indicates that each dollar spent here is correlated with an increase in OUTPUT of nearly $2. The surprisingly high return to information systems labor may reflect systematic differences in human capital,[16] since IS staff are likely to have more education than other workers, and is certainly consistent with Krueger's (1991) finding that workers who use computers are paid a wage premium.

As discussed in section 2, the return to COMPUTER CAPITAL and IS STAFF may be overstated because not all investment and expenses that are related to COMPUTER CAPITAL

[15] The impact of these changes in both cases was to lower the return to COMPUTER CAPITAL as compared to the results on a the full sample.

[16] We thank Dan Sichel for pointing this out.

and IS STAFF are included in these variables. In addition, the above rates of return on COMPUTER CAPITAL are gross of depreciation.[17] According to the Bureau of Economic Analysis, the average service life of "Office, Computing and Accounting Machinery" is seven years (Bureau of Economic Analysis, 1987). If a seven year service life for computer capital is assumed, then the above returns should be reduced by subtracting 14% per year, yielding a net return in manufacturing of 44% and the full sample of 67%. However, COMPUTER CAPITAL (in particular PCs) could have an average service life as short as 3 years, which implies that the net rate of return should be reduced by 33%, which yields net ROI estimates of 25% for manufacturing and 48% for the full sample.[18] As shown in table 8, for manufacturing, we can reject the hypothesis that the net ROI for COMPUTER CAPITAL is equal the the ROI for NON-COMPUTER CAPITAL assuming 7 year depreciation in COMPUTER CAPITAL (and none in NON-COMPUTER CAPITAL), while in the full sample we can reject equality of returns in the full sample for services lives as short as 3 years.

We further analyze the robustness of the regression and the rate of return calculation in section 3.4 and 3.5 below, 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 were all positive and appeared to be sensible. 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). There was no significant trend in the time dummies suggesting that, after the above factors were accounted for, there was little change in multifactor productivity. The R^2 hovered around 99%, indicating that our independent variables could "explain" most of the variance in output.

3.2 Rates of return across time, sector and subsamples

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[17] Technically, "negative capital gains" may be a more accurate term than "depreciation", since computer equipment is more likely to be replaced because of the arrival of cheaper, faster alternatives than because it simply wears out.

[18] On the other hand, firms invest in IT at least partly to move down the learning curve (Brynjolfsson, 1993) or create options (Kambil, Henderson & Mohsenzadeh, 1991), and these effects may create "assets" as large as those lost to depreciation.

The estimates described in sections 3.1, 3.2 and 3.3 were all based on the assumption that the parameters did not vary over time, in different sectors, or across different subsamples of firms. Therefore, they should be interpreted only as overall averages. By using the multiple equations approach, it is also possible to allow the parameters to vary by year, by subgroup of firms, and by sector in the full sample.

The returns on COMPUTER CAPITAL over time are presented in figures 3a and 3b. For manufacturing, the rates of return appear to peak in 1989, while in the full sample, the rates of return are fairly consistent over the period 1987-1989, and then drop in 1990-1991. We can reject the null hypothesis of equality of returns over time in the full sample ($\chi^2(4)=11.2$, $p<.02$) but not in manufacturing alone ($\chi^2(4)=4.9$, $p<.30$). However, these results should be interpreted with caution since the composition of the sample changes from year to year.[19]

The returns on COMPUTER CAPITAL across sectors are present in figure 4. The rate of return (ignoring the mining sector which includes only 10 firms and has a large standard error) varies from 10% in transportation and utilities to 127% in durable manufacturing. However, we are unable to reject the hypothesis that these rates of return are the same across most sectors due to the large standard errors on the coefficient estimates (without mining, $\chi^2(4)=6.6$, $p<.16$).

Finally, we examined three specifications in which the coefficient on COMPUTER CAPITAL could vary by firm characteristics. For this analysis, we first divided the sample into three groups (high, medium and low) based on the 1989 value of three firm-specific measures: 3-year shareholder return, 3-year average return on equity (ROE), and mainframes as a percentage of total computer capital. As reported in table 5, we found that in both cases, the rate of return to COMPUTER CAPITAL is highest for the highest performers as measured by ROE and shareholder return. The null hypothesis that rate of return is equal across groups can be rejected in both manufacturing and the full sample (see table 5). In addition, when we divide the sample into three groups based on the ratio of central processor value to PCs and terminals, we find that the rate of return is highest for firms using a more balanced mix of PCs and mainframes, and lower for firms at either extreme (although we cannot reject

[19] A decline in the returns to COMPUTER CAPITAL between 1989 and 1990 also evident in a balanced panel of 142 firms in manufacturing and 201 in the full sample for 1989-1991.

the null hypothesis of equality across groups in manufacturing, as we can in manufacturing & services).

These findings provide some confirmation that individual firm choices have an effect on the ability to achieve high returns from IT. These choices may involve both business strategy (leading to higher performance) or technical decisions such as the choice between mainframes and PCs. Clearly, this is an area for additional future study.[20]

3.3 Alternative Estimating Equations

All the results discussed previously assumed that the production function was of the Cobb-Douglas form, using only current period capital and expense quantities as inputs. While this approach is well grounded in previous research, further insight into the role of computer capital may be gained by allowing a more flexible functional form.

To examine the possibility of a time lag between IS spending and the realized return on investment, we estimated an equation which included lagged COMPUTER CAPITAL terms (table 6, column 1). When IS capital was lagged one year, the results were essentially the same as the non-lagged specification, although the elasticity on computer capital was reduced by about 20%. Given the substantial correlation between the quantities of all inputs in successive years and the fact that COMPUTER CAPITAL reflects past spending as well as current, this result is not surprising. Other specifications, such as including both current and lagged COMPUTER CAPITAL, or including lagged COMPUTER CAPITAL and a first difference, evidenced substantial multicollinearity and resulted in coefficient estimates that were not significantly different from zero. Given the short time dimension of this sample, it is unlikely that this analysis can give a precise answer to the role of lags between investment and realized return.[21]

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[20] If more data were available, a "firm effects" model would be interesting to examine.

[21] We also estimated an equation with both COMPUTER CAPITAL and IS STAFF lagged by one year, to address the possible mistakes in the matching of years between the Compustat and IDG data (see section 2.3). In this specification, COMPUTER CAPITAL remained significicant as well but IS STAFF became insignificant.

To examine the possibility of substitution effects between inputs, we estimated translog production functions with various exclusion restrictions imposed.[22] Unfortunately, when the full translog was estimated few coefficients were significant: only five (out of 14) exceeded their respective asymptotic standard error in manufacturing, and only 7 exceeded their standard error in the full sample. Restricting the squared terms to zero did not materially improve the estimates. In addition, the coefficients appear to be large and offsetting (i.e. a negative coefficient on non-IT capital squared is offset by a positive coefficient on non-IT capital), making interpretation of the coefficients difficult. These results appear to be caused by the high multicollinearity between the regressors. Nonetheless, a $\chi 2$-test rejected the null hypothesis that the translog and Cobb-Douglas specifications were equivalent in favor of the translog for both the full sample ($\chi^2(10)=87.8$, $p<.000$) and in manufacturing ($\chi^2(10)=19.2$, $p<.038$).

However, despite the imprecision of the translog coefficient estimates, the calculated value of the Computer Capital elasticity was comparable to the Cobb-Douglas estimates: .0108 in the full sample and .0166 in manufacturing[23]. Furthermore, these coefficients approach significance in the full sample ($\chi^2(1)=2.5$, $p<.12$), and are significantly different from zero for manufacturing ($\chi^2(1)=5.8$, $p<.016$). This lends support to the assertion made by Griliches (1979) that the functional form issue is not critical in the estimation of output elasticities.

To reduce the collinearity problem, we estimated a series of very restricted translog production functions that each involved adding one additional term to the basic Cobb-Douglas formulation. This is the approach advocated by Griliches (1979) . The results are presented in table 6.

When a squared COMPUTER CAPITAL (C^2) term is added to the basic equation for manufacturing and for the full sample, the COMPUTER CAPITAL and the COMPUTER CAPITAL SQUARED terms are both insignificant. We cannot reject the hypothesis that there

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[22]The translog contains for each input, the value of the input, the value of the input squared and all multiplicative interaction terms between the input and all other inputs. The Cobb-Douglas production function is a special case of the translog with the square and interaction terms restricted to be zero. For four factors of production, the full translog requires that 14 coefficients be estimated (not including intercepts).
[23]The elasticity for computer capital can be calculated for the "average" firm in the sample by taking the partial derivative of output with respect to computer capital for the translog specification, and substituting the coefficient estimates and average factor input values.

are roughly constant returns to scale for investment in COMPUTER CAPITAL for our sample of firms.

When a CS CROSS PRODUCT term between COMPUTER CAPITAL and IS STAFF is included in the manufacturing regression, the coefficient on the new term is positive and significant, while the COMPUTER CAPITAL and IS STAFF terms are no longer significant. This suggests that COMPUTER CAPITAL and IS STAFF are complements, not substitutes.

Further exploration of hypotheses regarding the role of lags and interactions between inputs appears to be limited by the data. The time dimension is too short, particularly given the amount of missing data, to investigate fully the role of lags and there appears to be insufficient inter-firm variation of inputs to adequately estimate production functions much more complex than the Cobb-Douglas.

3.4 Sensitivity Analysis and Possible Biases - Econometric Issues

In deriving our estimates of the return to COMPUTER CAPITAL required that a number of assumptions be made about the econometric specification and the construction of the data set. This section and the following section explore the validity of our assumptions and generally finds that the results are robust.

The basic econometric assumptions required for ISUR to produce unbiased, efficient estimates of both the parameters and the standard errors are similar to those for OLS: the error term in each equation has constant variance in the cross section, is normally distributed, and is uncorrelated with the regressors (inputs)[24]. We attempted to address the first issue by computing OLS estimates for the pooled data both with and without heteroskedasticity-consistent standard errors[25]. The standard error estimates were within 10-20% of each other, indicating that heteroskedasticity does not appear to be a problem. To test normality of the error terms, we computed and plotted residuals from the basic specification, and found them to be roughly normally distributed. It is important to note that even if these assumptions were violated, the coefficient estimates would still be

[24] Note that if we had used OLS, a further restriction is required that all error terms have the same variance and zero correlation. There is also the untestable assumption that the error terms are mean zero.
[25] We were unable to do the White test for heteroskedasticity on these data because of limitations of our econometric software, and the large number of regressors.

unbiased, but not efficient. Since we were able to reject the null hypothesis that the computer capital coefficients were zero, this finding should not be altered by obtaining a more efficient estimator.

However, the third assumption, that the error term is uncorrelated with the inputs is potentially an issue. One way in which this assumption could be violated is if the causality is reversed: instead of increases in purchases of inputs (e.g. computers) leading to higher output, an increase in output could lead to further investment (for example, a firm spends the proceeds from an unexpected increase in demand on more computer equipment, as is likely). In this case, the assumptions for ISUR are violated since the inputs are not predetermined, and therefore the error term is likely to be correlated with them. The assumption could also be violated is if the input variables are measured with error[26] (see (Kmenta, 1986) for a complete discussion).

Regardless of the source of the error, it is possible to correct for the potential bias using instrumental variables methods -- three-stage least squares (3SLS) for ISUR or two-stage least squares (2SLS) for OLS. These methods employ instrumental variables to filter out the endogenous variation and error in the variables, which then allows consistent estimation of the parameters. However, these procedures require that firm-level instruments exist which are uncorrelated with the error term. In a single equation context, we use once-lagged values of variables as instruments since by definition they cannot be associated with unanticipated shocks in the dependent variable in the following year.[27] Table 7 reports a comparison of pooled OLS estimates with 2SLS estimates and shows that the coefficient estimates are roughly similar although somewhat higher for COMPUTER CAPITAL and lower for IS STAFF. In both cases the standard errors were substantially larger. Using a Hausman specification test, we cannot reject the null hypothesis that the error term is uncorrelated with the regressors in both the manufacturing and the full sample (see bottom of table 7 for test statistics). Unfortunately, the same method is not strictly valid for ISUR, since the instruments for one equation are endogenous variables in another. Nonetheless,

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[26] This is not the case if an input variable is systematically understated by a constant multiplicative factor. In this case, the coefficient estimates would be unchanged.

[27] However, in the presence of individual firm effects, lagged values are not valid instruments. While we did not test for firm effects, we suspect they may be important and so the results of our 2SLS and 3SLS estimates should be interpreted with caution.

when we use 3SLS with this instrument set, the coefficient estimates show little change. Overall, this provides support for our model being correctly specified.

3.5 Sensitivity Analysis and Possible Biases - Data Issues

To further explore the robustness of our results, we examined impact of the possible data errors discussed in section 2.4 that can be tested: 1) error in the valuation of PCs and terminals, 2) understatement of computer capital, and 3) errors in the price deflators.

To assess the sensitivity of the results to the assumptions of the value of PCs and terminals, we recalculated the basic regressions varying the assumed average PC and terminal value from \$0 to \$6K. (The value of zero for PCs was implicitly assumed in an version of this paper published earlier (Brynjolfsson & Hitt, 1993)). Note that as the assumed value of PCs and terminals increases, the increase in COMPUTER CAPITAL will be matched by an equal decrease in NON-COMPUTER CAPITAL, which is calculated as a residual. Interestingly, as shown in figure 5, the return to computer capital in the basic regression is not very sensitive to the assumed value of a PC, ranging from 58% if PCs are not counted to 42% if PCs are counted at \$6K in manufacturing.

Our estimates of the return to COMPUTER CAPITAL or IS STAFF may be overstated since, as discussed in section 2.3, the true cost of computer capital and IS staff 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 NON-COMPUTER CAPITAL or NON-IS LABOR AND EXPENSE which would receive the effect of the excluded computer capital). If the excluded items (primarily software, departmental computers, and data communications equipment) are complementary to our measured COMPUTER CAPITAL, our estimate would be high for the return to COMPUTER CAPITAL. If the "missing costs" are perfectly correlated with the observed costs, then they will result only in a multiplicative scaling of the variables and the estimated elasticities will be unchanged[28]. As a result, regardless of whether our COMPUTER CAPITAL or IS STAFF estimates are overestimated or underestimated, the sign

[28] This is because multiplicative scaling of a regressor in a logarithmic specification will not change the coefficient estimate or the standard error. All the influence of the multiplier will appear in the intercept term which is not crucial to our analysis.

and statistical significance of our results for the returns to COMPUTER CAPITAL and IS STAFF will be unaffected, although the precise magnitude would be affected.

To estimate the potential impact of these omissions, we estimated the relative size of the omitted "HIDDEN IS CAPITAL" to COMPUTER CAPITAL using data from another IDG survey (IDC, 1991) on aggregate IS expenditures which includes software as well as the hardware. Assuming that the HIDDEN IS CAPITAL has an average service life of three years, we calculate that our COMPUTER CAPITAL is understated by a factor of 2.06. Adjusting for this omission by assuming perfect correlation between HIDDEN IS CAPITAL and COMPUTER CAPITAL (and reducing proportionally the amount of NON-IS LABOR AND EXPENSE), the rates of return are essentially unchanged from the basic analysis that does not include HIDDEN IS CAPITAL. When COMPUTER CAPITAL is increased without making a commensurate decrease in NON-IS LABOR AND EXPENSE, the rates of return fall to 28% in manufacturing, and 39% in the full sample.

One final contribution to error is the understatement of output due to errors in the price deflators. While it is difficult to directly correct for this problem, we estimated the basic equations year by year, where errors in the relative deflators would have no impact on the elasticity estimates. The estimated returns ranged from 18% to 73% in manufacturing versus 58% when the equations were estimated as a system, and 109% to 118% in the full sample versus 81%. The standard error on the estimates was significantly higher for all estimates, which can account for the greater range of estimates. Overall, this suggests that our basic findings are not solely a result of the assumed price deflators. However, if the price deflators systematically underestimate the value of intangible product change over time or between firms, our measure of output will be understated which implies the actual return for computer capital is higher than our estimates.

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 1000 observations on output and several inputs at the firm level for 1987-1991. The firms in our sample were primarily engaged in manufacturing and had aggregate sales of over $1.8 trillion in 1991. We tested a broad variety of specifications, examined several different subsamples of the data, and validated the assumptions of our econometric procedures to the extent possible.

The data indicate that COMPUTER CAPITAL and IS STAFF spending contribute significantly to firm level OUTPUT. Furthermore, we were able to reject the hypothesis that the (gross) 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. Even when we adjusted for depreciation using the BEA 7-year service life assumption for COMPUTER CAPITAL, the differences in return are still significant. The basic result that COMPUTER CAPITAL and IS STAFF 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 et al. (1978-1982) or Berndt & 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 firms from the period studied by the other authors. Brynjolfsson (1993) argues 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). Apparently, an analogous period of organizational redesign was necessary to unleash the benefits of electric motors (David, 1989). A pattern of increasing returns is also consistent with the strategy for optimal investment in the presence of learning-by-using: 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 & McCabe, 1993). Under this interpretation, our high estimates of computer ROI indicate that businesses are beginning to reap rewards from the experimentation and learning phase in the early 1980s.

Second, we were able to use different and more detailed firm-level data than had been available before. We argue that the effects of computers in increasing variety, quality or other intangibles are 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, in an earlier study (Brynjolfsson, Malone, Gurbaxani & Kambil, 1994), 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 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 & Roberts, 1990; Brynjolfsson, 1990) This possibility is emphasized in numerous management books and articles (see, e.g. Malone & Rockart, 1991; Scott Morton, 1991) and supported in our discussions with managers, both at their firms and during a MIT workshop[29] on IT and Productivity we helped organize for approximately 30 industry representatives.

Furthermore, our results showing a high gross rate of return may be indicative of the differences between computer investment and other types of investment. Given higher depreciation rates and shorter life span of computers, a much higher gross rate of return is necessary to simply pay back the investment cost. Another possibility is that managers perceive IS investment as riskier than other investments, and therefore require higher expected returns to compensate for the increased risk. Finally, IS is often cited as an enabling technology which does not just produce productivity improvements for individuals, but provides a vast advantage by facilitating business process redesign or improving the ability of groups to work together. In this sense, our results may be indicative of the substantial payoffs to reengineering and other recent business innovations. This is further supported by our finding that the rate of return for COMPUTER CAPITAL is highest for high performing firms -- these are presumably the firms that have engaged in the most innovative improvements.

There are a number of other directions this work could be extended. The most straightforward extension is to use value-added as a measure of output, which is likely to allow greater precision in estimating the effects of IS spending, and enable more complex production function relationships to be examined. In addition, we could further investigate the role of omitted variables, such as research and development expenditures. Although our approach allowed us to infer the value created by intangibles like product variety by

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[29] 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.

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.

5. TABLES AND FIGURES

Figure 1: Comparison of Gross Return on Investment

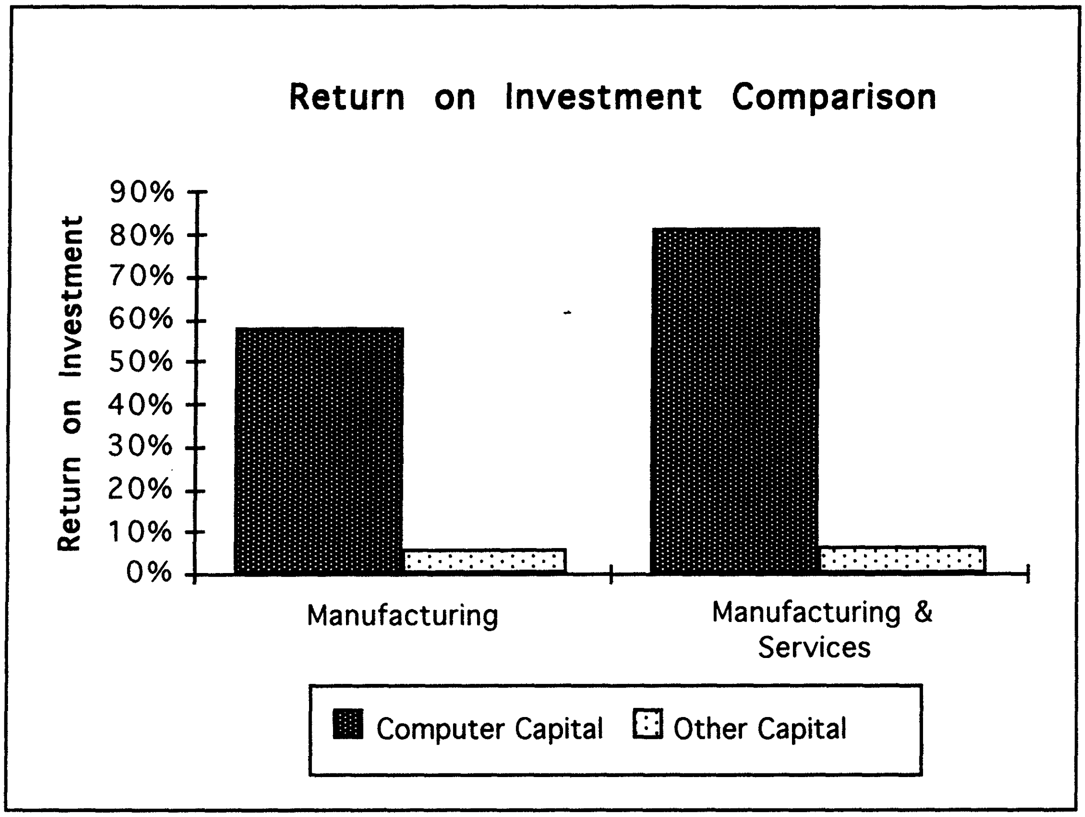


Figure 2: Changes in IT Inputs over Time

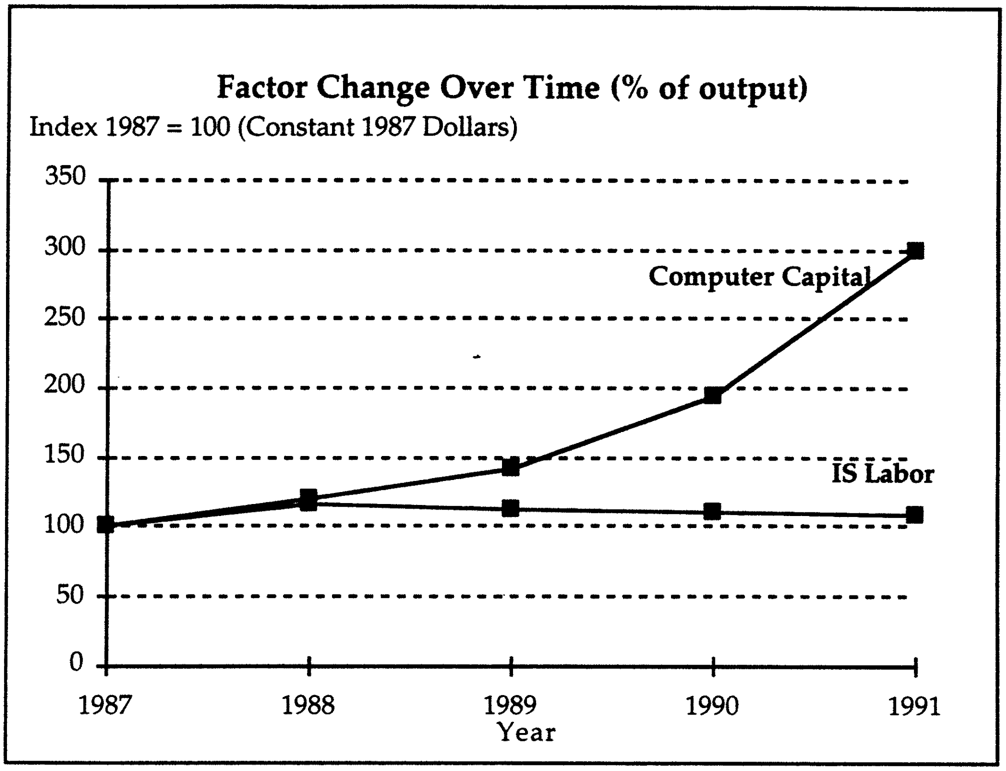
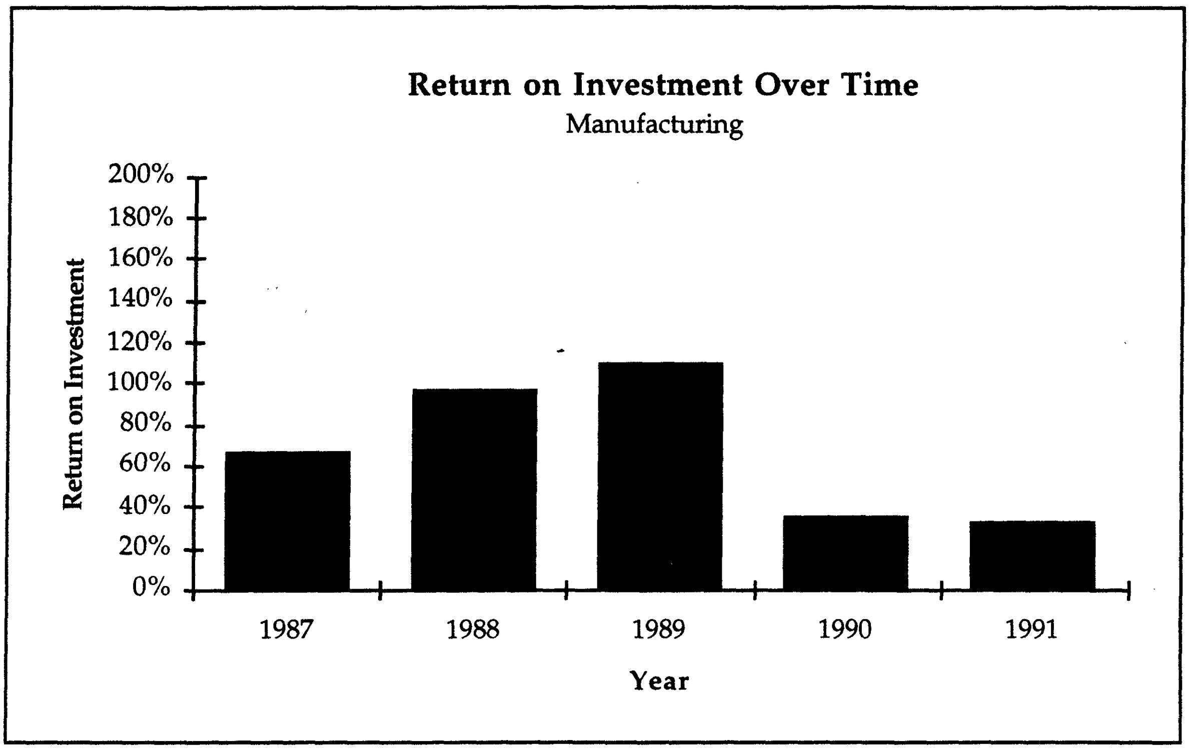


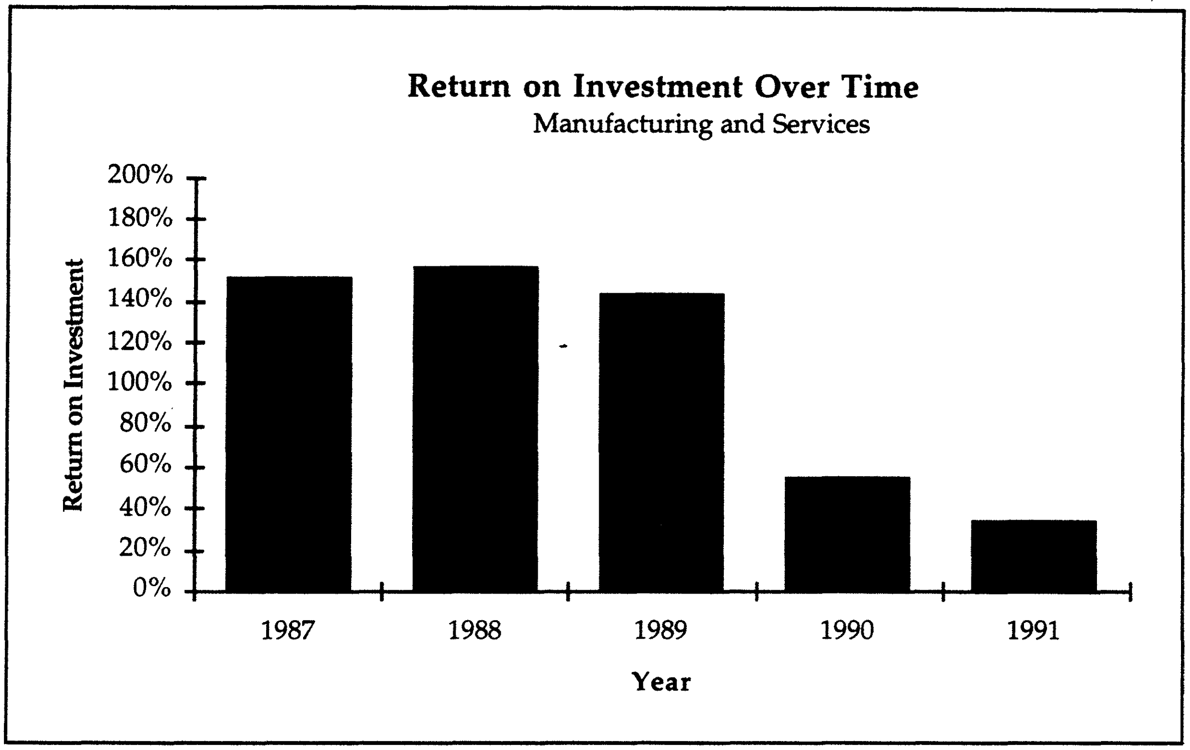
Figure 3a: Gross Return on Investment over Time - Manufacturing



	1987	1988	1989	1990	1991
Coefficient	.00770	.0142**	.0190***	.00850	.0129**
Std. Error	(.00900)	(.00711)	(.00692)	(.00565)	(.00592)
N	104	92	188	198	192

Key: *** - p<.01, ** - p<.05, * - p<.1, standard errors in parenthesis

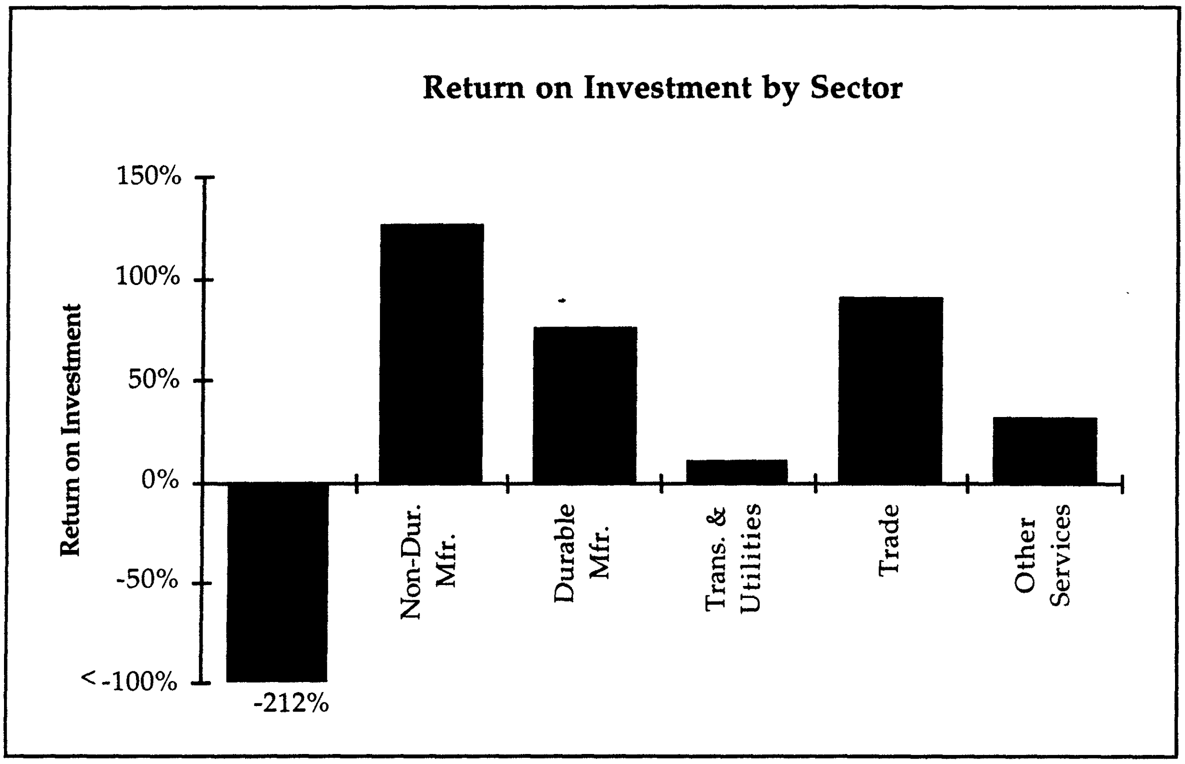
Table 3a: Gross Return on Investment Over Time - Manufacturing & Services



	1987	1988	1989	1990	1991
Coefficient	.0177**	.0222***	.0239***	.0125**	.0121**
Std. Error	(.00721)	(.00646)	(.00657)	(.00574)	(.00594)
N	135	133	274	286	293

Key: *** - p<.01, ** - p<.05, * - p<.1, standard errors in parenthesis

Figure 4: Gross Return on Investment by Sector



	Mining	Non-Dur. Mfr.	Durable Mfr.	Trans. & Utilities	Trade	Other Service
Coefficient	-.0286	.0122*	.0348***	.00227	.0129	.0153
Std. Error	(.0218)	(.00691)	(.00678)	(.0111)	(.00921)	(.0354)
N (total)	28	414	360	171	123	25

Key: *** - p<.01, ** - p<.05, * - p<.1, standard errors in parenthesis

Figure 5: Gross Return on Investment for Computer Capital with different PC value assumptions

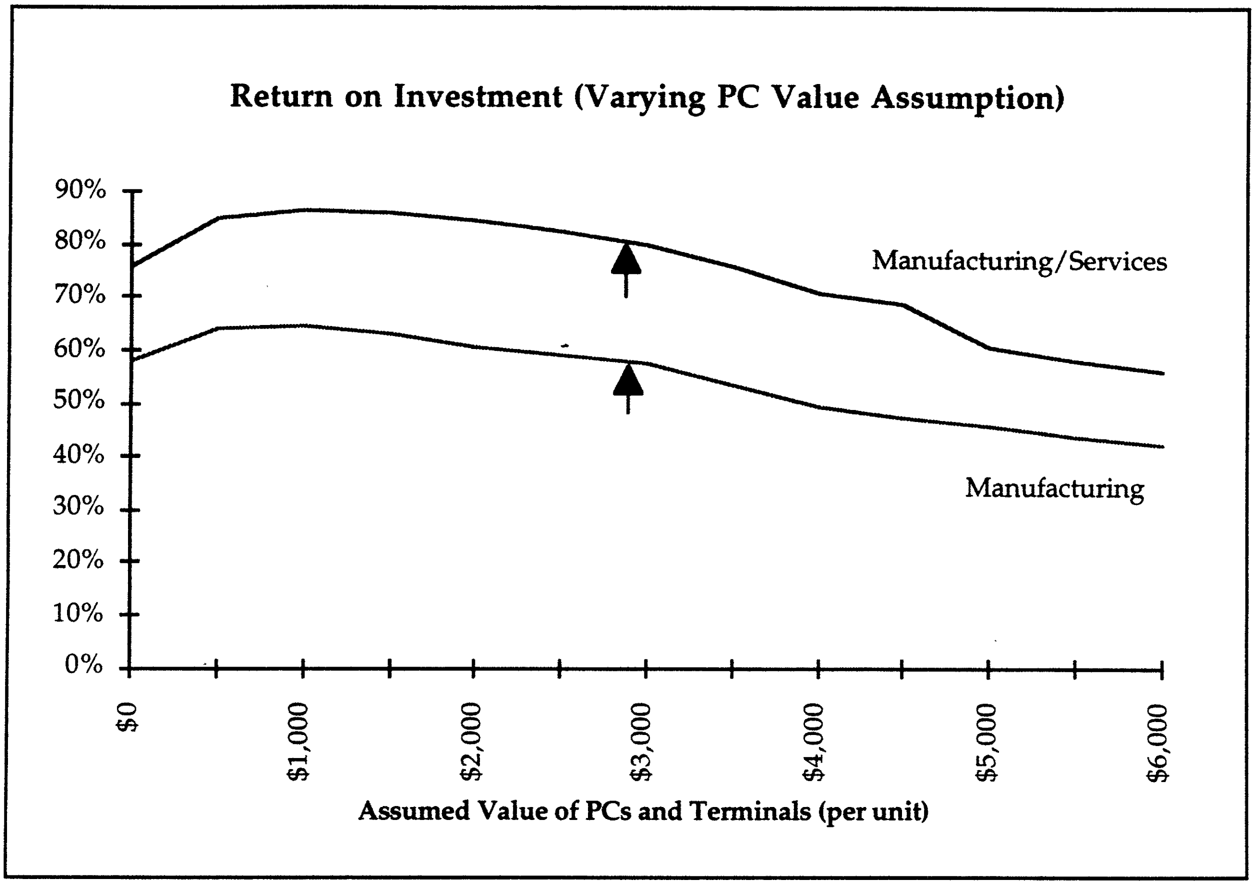


Table 1: Data Sources, Construction Procedures, and Deflators

Series	Source	Construction Procedure	Deflator
Computer Capital	IDG Survey	"Market Value of Central Processors" converted to constant 1987 dollars.	Deflator for Computer Systems (Gordon, 1993)
Non-Computer Capital	Compustat	Total Property, Plant and Equipment Investment converted to constant 1987 dollars. Adjusted for retirements using Winfrey S-3 Table (10 year service life) and aggregated to create capital stock. Computer capital as calculated above was subtracted from this result.	GDP Implicit Deflator for Fixed Investment (Bush, 1992)
IS Staff	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 Expense	Compustat	Total Labor, Materials and other non-interest expenses converted to constant 1987 dollars. IS labor as calculated above 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 Specific Deflators from *Gross Output and Related Series by Industry, BEA (1977-89)* where available (about 80% coverage) - extrapolated for 1991 assuming average inflation rate from previous five years. Otherwise, sector level Producer Price Index for Intermediate Materials Supplies and Components. (Gorman, 1992)

Table 2: Summary Statistics

Sample Statistics - 1991 Constant 1987 Dollars		
Data Item	Manufacturing	Manufacturing & Services
Output	$1,271 Bn	$1,834 Bn
Computer Capital Stock	$49.3 Bn	$64.7 Bn
Non-Computer Capital Stock	$1,240 Bn	$1,900 Bn
IS Labor	$9.5 Bn	$12.3 Bn
Non-IS Labor & Expenses	$1,096-Bn	$1,531 Bn
Number of Companies	192	293

Table 3: Five-year Average Factor Shares

Five Year Average Factor Shares Percent of Output in Constant 1987 Dollars		
Factor	Manufacturing	Manufacturing & Services
Computer Capital Stock	2.18%	2.09%
Non-Computer Capital Stock	88.1%	97.2%
IS Staff	0.74%	0.68%
Non-IS Labor & Expenses	82.5%	83.3%
Number of Firms in Sample	774	1121

Table 4: Base Regressions - Coefficient Estimates and Implied Gross Rates of Return

All parameters (except year dummy) constrained to be equal across years.

	Manufacturing		Manufacturing & Services	
Parameter	Coefficients	Returns	Coefficients	Returns
β_1 (Computer Capital)	.0126*** (.00465)	58.0%	.0169*** (.00431)	81.0%
β_2 (Non-computer Capital)	.0473*** (.00659)	5.36%	.0608*** (.00466)	6.26%
β_3 (IS Staff)	.0145*** (.00539)	1.96	.0178*** (.00526)	2.62
β_4 (Other Labor & Exp.)	.928*** (.00938)	1.11	.883*** (.00724)	1.07
Dummy Variables	Year*** & Industry***		Year*** & Sector***	
R^2 (1991)	98.8%		97.5%	
N (1991)	192		293	
N (total)	774		1121	

Key: *** - p<.01, ** - p<.05, * - p<.1, standard errors in parenthesis

Table 5: Split Sample Regression Results

Coefficient Estimates and Rates of Return for β_1,(Computer Capital)

Each Cell contains coefficient estimate, (standard error), ROI

Sample Split	Highest	Middle	Lowest	Statistical Ordering[1]
Total Return (Manufacturing)	.0167*** (.00362) 100%	.0100*** (.00347) 38.6%	.00541 (.00350) 22.9%	Hi>Med.>Low (p<.000)
Total Return (Manufacturing and Services)	.0151*** (.00377) 92.6%	.0115*** (.00358) 48.5%	.00439 (.00361) 18.1%	Hi>Med.>Low (P<.000)
Return on Equity (Manufacturing)	.0185*** (.00524) 93.9%	.00910* (.00514) 45.5%	.00282 (.00515) 10.7%	Hi>Med.>Low (p<.000)
Return on Equity (Manufacturing & Services)	.0180** (.00513) 90.0%	.0122** (.00493) 62.9%	.00825 (.00504) 34.5%	Hi>Med.>Low (P<.000)
Mainframes/PCs Ratio (Manufacturing)	.00909* (.00542) 39.5%	.00989* (.00572) 50.9%	.00865 (.00579) 36.6%	Hi=Med=Low (p<.443)
Mainframes/PCs Ratio (Manufacturing and Services	.0113** (.00500) 49.1%	.0159*** (.00528) 79.5%	.0117** (.00521) 58.2%	Med>(Hi,Low) (p<.03)

Key: *** - p<.01, ** - p<.05, * - p<.1, standard errors in parenthesis

1 - Ordering by χ^2 tests of return differences. P-value shown represents null hypothesis of equality across groups.

Table 6: Regression Results for Manufacturing - Lags and Interaction Terms

Parameter	Once Lagged Computer Capital	Base + Computer Capital Squared	Base + Computer CapitalxIS Labor
β_1 (Computer Capital)	n/a	-.0105 (.0152)	-.00200 (.00698)
Lagged β_1 (Computer Capital	.00962* (.00564)	n/a	n/a
$\beta_1 * \beta_1$ (Computer Capital -Squared)	n/a -	.00268 (.00167)	n/a
$\beta_1 * \beta_3$ (Computer Capital x IS Labor)	n/a	n/a	.00525*** (.00189)
β_2 (Non-computer Capital)	.0334*** (.00743)	.0479*** (.00656)	.0475*** (.00652)
β_3 (IS Staff)	.0121* (.00626)	.0147** (.00537)	-.0103 (.0104)
β_4 (Non-IS Labor & Exp.)	.953*** (.0114)	.925*** (.00942)	.925*** (.00933)
Dummy Variables	Year*** & Industry***	Year*** & Industry***	Year*** & Industry***
R^2 (1991)	99.5%	98.8%	98.8%
N (1991)	172	192	192
N (total)	489	774	774

Key: *** - p<.01, ** - p<.05, * - p<.1, standard errors in parenthesis

Table 7: Specification Test - Comparison of OLS and Two-Stage Least Squares
All parameters (except year dummy) constrained to be equal across years.

	Manufacturing		Manufacturing & Services	
Parameter	OLS Estimates	2SLS Estimates	OLS Estimates	2SLS Estimates
β_1 (Computer Capital)	.0151** (.00712)	.0273** (.0131)	.0284*** (.00723)	.0435*** (.0126)
β_2 (Non-computer Capital)	.0449*** (.00836)	.0438*** (.00932)	.0489*** (.00668)	.0481*** (.00702)
β_3 (IS Staff)	.0160** (.00742)	.00832 (.0107)	.0191*** (.00795)	.00727 (.0116)
β_4 (Non-IS Labor & Exp.)	.919*** (.0130)	.916*** (.0153)	.881*** (.0113)	.879 (.0125)
Dummy Variables	Year*** & Industry***	Year*** & Industry***	Year*** & Sector***	Year*** & Sector***
R^2	99.2%	99.2%	98.3%	98.3%
N (total)	493	493	702	702
Durbin-Watson Statistic	.814	.83	.415	.42

Key: *** - p<.01, ** - p<.05, * - p<.1, standard errors are in parentheses
Note: OLS estimates are for sample of same firms as were available for 2SLS regression.

Hausman Test Results (instruments are lagged independent variables):
Manufacturing: χ^2 (4) = 4.68, (p<.32) - cannot reject exogeneity
Manufacturing & Services: χ^2 (4) = 6.40, (p<.17) - cannot reject exogeneity

Table 8: $\chi 2$ Tests for Differences in Rates of Return between Computer Capital and Other Capital

Return Difference Tests

Net returns calculated assuming 7 year life for Computer Capital

	Manufacturing		Manufacturing and Services	
Specification	Gross	Net	Gross	Net
Iterated SUR	58.0%***	43.7%*	81.0%***	66.7%***
Pooled OLS	84.8%***	70.5%**	134.2%***	119.9%***
Pooled 2SLS	112%**	97.7%*	186.6%***	172.3%***

Key: *** - p<.01, ** - p<.05, * - p<.1, two-tailed tests

A significant test indicates that the return on computer capital is greater than the return on other capital

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