Economic Analysis of Information Technology and Organization

by

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Submitted to the Alfred P. Sloan School of Management in Partial Fulfillment of the Requirements for the Degree of Doctor of Philosophy in Management

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ABSTRACT

This dissertation examines the relationships among information technology (IT) use, organizational characteristics, and productivity in three empirical essays. The first essay examines the relationship between IT and productivity growth at the firm-level. The second essay addresses the relationship between IT and internal organization (work systems, incentives, human resource practices) and the way this relationship affects productivity. The final essay examines how firm boundaries (vertical integration, diversification) are related to the level of and changes in IT investment.

Overall, there is evidence that information technology is associated with increased productivity at the firm level. The long run productivity effects are greater than the short run effects, suggesting the possibility that successful use of IT requires changes in complementary organizational characteristics over long time periods. Consistent with this argument, there is evidence that information technology is correlated with the use of a work system that involves decentralized decision authority, team-based incentives, and higher levels of human capital. Furthermore, firms that use this work system show higher returns from their IT investments. The data also suggest that IT is associated with changes in macro-organizational structure: firms that have high IT use are less vertically integrated but more diversified in both cross-section and time series.

These findings suggest that IT is an important determinant of long run firm performance and economic growth when coupled with complementary changes in internal organization and large scale firm structure. This provides the first evidence of a link between IT and economic growth at the firm level. In addition, this study is one of the first large-sample analyses to confirm the importance of combining investments in information technology with investments in organizational changes.

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Biographic Note

Lorin Hitt is an Assistant Professor in the Operations and Information Management Group at the University of Pennsylvania, Wharton School. His research interests include the impact of information technology (IT) on organizations and markets, the economics of information and organizations, and the application of econometrics to study the performance impact of IT. He holds Bachelors and Masters degrees from Brown University in electrical engineering and is a former consultant for Oliver, Wyman and Company, a strategy consulting firm that specializes in financial services.

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Doctoral Dissertation Chapter 1

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Computers and Economic Growth: Firm-Level Evidence

ABSTRACT

In advanced economies, computers are a promising source of output and productivity growth. Previous work has found that the level of computer capital is correlated with increases in output using a standard production function framework. However, because these analyses are based largely on the correlation between levels of output and levels of computer stock, they are susceptible to bias from a variety of sources, such as unobserved heterogeneity. Furthermore, inferences about the growth contribution of computers had to be based on cross-sectional elasticity estimates. This paper provides the first firm-level evidence of a relationship between computers and productivity growth by analyzing data for 600 large firms over the 1987-1994 time period.

The results suggest that growth in computer capital stock are correlated with significantly higher productivity and output growth at the firm level, although simultaneity makes it difficult to prove a causal relationship. In first difference specifications, computers appear have a return approximately equal to their costs. However, in long difference specifications, the growth contribution and returns rise substantially. Our interpretation is that the short difference estimates represent direct contributions of computers from increasing investment, while the long difference estimates may be capturing a shift in the overall production possibility set as computers enable new types of work organization.

1. INTRODUCTION

In advanced economies, computers are a promising source of output and productivity growth. Rapid technological innovation in the computer producing sector has created a long run quality adjusted price decline of computers of 20% or more per year (Berndt and Griliches, 1990; Gordon, 1990). Since these price changes have been accompanied by increased nominal investment, there has been a dramatic increase in the share of computers in capital formation. This large accumulation of capital stock over the last thirty years by itself makes computers a significant factor in economic growth (Jorgenson and Stiroh, 1995).

However, there are several more complex and subtle effects of computers that make them interesting from a theoretical standpoint. First, computers represent a substantial embodiment of technical change. Recently, Bahk and Gort (1993) suggested that industry-level knowledge gains may only result in productivity increases when they have been embodied in physical capital. This is in contrast to the traditional view (Solow, 1957) that knowledge is "disembodied" and simply raises the productivity of the economy with the passage of time. Over the 1978-1989 time period, the computer industry has had both the highest rate of productivity growth of any industry in the manufacturing sector and the highest level of R&D intensity (Griliches, 1994).

Second, the computer represents a "general purpose technology" that not only increases the marginal efficiency of production but also enables radically new production possibilities when combined with complementary investments (Bresnahan and Trajtenberg, 1991). Milgrom and Roberts (1990) argue that computers have been an important driver of the shift between "mass production" and "modern manufacturing". Advocates of reengineering (Hammer, 1990; Hammer and Champy, 1993a) have also argued that substantial productivity improvements are attainable from the IT-enabled redesign of work processes.

To date, the magnitude and even existence of computers' contribution to growth remains unsettled: several researchers have found low returns to computers, while others have found very high returns.[1] Low returns to "high-tech capital" (which includes computers) are found in a series of studies by Berndt, Morrison, and Rosenblum (Berndt, Morrison and Rosenblum, 1992; Berndt and Morrison, 1995) using industry-level data. Estimates of a generalized Leontief cost function using these data suggest that each dollar of high-tech capital contributed only 80 cents of value on the margin (Morrison and Berndt, 1990). Other examinations of these data also indicate that high-tech capital is on balance not labor-saving, and that overall returns are not significantly different from the returns to other types of capital.

On the other hand, Siegel and Griliches (1991) find a positive correlation between levels of computer usage and multifactor productivity growth in industry data; however, after auditing some of the data, they also express serious misgivings about the reliability of government figures and the consistency of industry classifications. Lau and Tokutsu (1992), Jorgenson and Stiroh (1995), and Bresnahan (1986) find large contributions of computers to productivity and consumer surplus, but these studies infer the contribution by assuming that businesses are optimally making large investments in computers rather than estimating the benefits directly.

Measurement error may partially explain the lack of definitive results in the IT and productivity literature (Baily and Gordon, 1988; Brynjolfsson, 1993). Because aggregation to the industry or economy level may increase measurement difficulties, firm level data may give better indication of computers' productivity effects. There have recently been several studies employing firm level data that have found high rates of return to computer investment. Brynjolfsson and Hitt (1993; 1995; 1996) examined data for large firms from 1988-1992 and estimated several production functions. The high output elasticities found for computers implied that there were high (and possibly excess) returns to computer investment. Using similar specifications and data, Lichtenberg

[1] See (Wilson, 1993) and (Brynjolfsson, 1993) for more comprehensive literature reviews.

(1995) confirmed these results. However, while the firm-level studies suggest a positive output contribution of computers, the results are primarily cross-sectional (due to the short time dimension and missing data). None of these studies directly estimated the effect of computers on productivity growth. In addition, cross-sectional results cannot easily address concerns of endogeneity of computer investment, errors in measurement, or unobserved heterogeneity that may result in biased estimates of computers' contributions.

In this analysis, we provide the first firm-level evidence of a direct relationship between computers and multifactor productivity growth using a new, longer, and more comprehensive panel dataset. Our sample is a nearly complete panel of approximately 600 firms over the 1987 to 1994 time period. Using additional data and improved econometrics, we also address some of the potential biases introduced by measurement and specification error that are likely to obscure the IT-productivity relationship. Our results suggest that in the short run, computers have a contribution to growth close to theoretical predictions, assuming that computers behave similarly to "ordinary" capital; however, in the long run, the marginal product and growth contribution rise substantially. An interpretation of this result is that these high returns are due to a system of organizational changes that have been enabled by computer technology.

The remainder of the paper is organized as follows. Section 2 provides some background on the role of computer technology in economic growth and discusses the measurement problems inherent in analyzing the growth contribution of computers. Section 3 discusses the theoretical framework we employ in estimating productivity effects and the data used. The regression results and growth accounting calculations are presented in Section 4. We conclude with some possible interpretations of our results in Section 5.

2. BACKGROUND

2.1. Computers as a factor input

Chip makers have been able to reduce the size of the lines forming transistor circuits by about 10% a year, leading to a doubling of microprocessor power every 18 months. As shown in Figure 1, these improvements have occurred with such consistency that the trend is generally known in the computer industry as "Moore's Law", after an observation of Gordon Moore, the founder of Intel Corp., in 1964. This technological improvement has led to annual 20-30% quality adjusted price decline for computers (Berndt and Griliches, 1990; Gordon, 1990).

An effect of this rapid price decline and the gradual diffusion of computer technology is dramatically increasing real spending on computers (Figure 2). The gains resulting from this growth in inputs have often been thought of as computer-labor or computer-capital substitution. Because of competition in the computer producing sector, computer using industries have been able to purchase computer inputs at prices below their quality adjusted value (Griliches, 1991, terms this a pecuniary spillover). This enables firms to replace labor or other types of capital with low cost computer technology. However, unless computers are mispriced when calculating the impact on economic growth (for example, failing to account for the deflation of computer prices) the gains in growth of computer-using firms results entirely from the accumulation of additional computer capital. These gains may, in part, by offset by the decline in other factors. Nonetheless, the economic impact of investment and pecuniary spillovers can be quite large (Bresnahan, 1986; Brynjolfsson, 1995; Jorgenson and Stiroh, 1995).

Computers may also appear to contribute more to output per unit than other types of capital, leading to a correlation between computer use and productivity. This is illusory, reflecting differences in rental prices between rapidly depreciating computer technology and other types of capital goods with longer useful lives (see footnote 25 for further discussion). Unless there is something unique to the way computers affect the production process, they should generally expected to have a contribution approximately equal to their (relatively high) capital costs when measured properly.

A potentially more interesting effect of computers is the ability to transform the production process itself.[2] There are numerous documented cases which show tremendous performance improvements that have been realized by combining computer investment with organizational changes. Diewert and Smith (1994) analyzed a wholesaling firm that had recently adopted a new computer-based inventory management system. Since the system introduction, the firm restructured the way inventory was handled and realized growth in multifactor productivity of over 9% per quarter. Ford reengineered its accounts payable function leading to a staff reduction from 500 to 125 without changing service levels (Hammer and Champy, 1993a). In other areas of the company, Ford is embarking on a long term effort to reduce costs by $2 billion and cut 30% off the time to market for a new car (Bartholomew, 1996). In some functions they have already achieved staff reductions as high as 95% (Hammer and Champy, 1993b). Hallmark used computer technology to facilitate product development by enabling the designs to be conducted by multidisciplinary teams (Hammer and Champy, 1993a). This reduced the time to market for a new line of greeting cards by 8 months in a process that had historically taken two to three years.

These sorts of improvements are beyond what would normally be expected by the simple substitution of computers for capital or labor. Not only are the magnitudes of the performance changes much larger than would be expected from factor substitution, the changes tend to involve more than just altering the levels of factor inputs. Accompanying the new systems are substantial investments in "organizational capital", such as the development of new procedures and work flows both within and between firms, increased staff training, and changes in firm boundaries through outsourcing, partnerships, and relational contracting. It may be the combination of computers and these complementary investments (Milgrom and Roberts, 1990; Milgrom and Roberts, 1992) that create the

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2 In the discussion of pecuniary versus non-pecuniary spillovers, it is common to treat non-pecunary spillovers as knowledge spillovers between firms operating in similar markets or employing similar technologies (Griliches; Jaffe). We will not be able to address this issue in this paper, but will analyze potential IT-related knowledge spillovers in further work.

possibility of order of magnitude improvements, enabling firms to pursue high productivity strategies that were not feasible in the past.

As Milgrom and Roberts (1996) argue, when there are complementarities between technologies and institutional characteristics, the long run impact of dramatic price decline in a technology can be magnified as other complementary organizational factors are adjusted over time. In the short term, productivity may rise because of increased quantities of computer inputs. Over time, firms will adapt their business processes, human capital and other organizational characteristics to maximize the contribution of the technology. While the identification of these complementary factors is beyond the scope of this analysis, it is possible to get some insight into their existence and impact by comparing the long run and short run productivity effects of computers.

2.2. The Mismeasurement Miasma

If advances in the computer technology imply an outward shift of the production possibility frontier of the economy or simply increase output because of increased investments in computers, the magnitude of these effects have been difficult to assess. There are three types of mismeasurement that can create systematic biases in measurements of the contribution of computers: mismeasurement of output, omitted complementary production inputs, and reverse causality between investment in computers and output.

Output mismeasurement. The outputs of many firms, especially in the service sector, have never been measured well (Baily and Gordon, 1988). If the benefits of computers are disproportionately weighted towards outputs that are difficult to measure (e.g., customer service, convenience, and variety), mismeasurement will systematically understate the contribution of computers as well as real growth in the economy. Results from a survey of information systems managers suggested that they give more weight to intangible benefits in their investment decisions than to cost savings (Brynjolfsson, 1994). In addition, much of the literature on the strategic management of information technology focuses on intangible factors such as timeliness and customer service.

If these benefits are unobserved to the econometrician but are observed by a firm's customers, firm-level data may help reduce these biases. Firms that make improvements in output quality through investments in computers will gain sales from competitors that fail to make these investments. These private benefits will appear as a correlation between output and computer investment. However, in industry or economy level data this type of redistribution will be averaged out. Unfortunately, even with firm-level data there is little that can be done about systematic understatement of quality improvement biases downward estimates of computers' contribution to output and growth.

Input mismeasurement. Random measurement error in computer investment can result in downward bias in estimates of computers' contributions by standard errors in variables arguments (see Greene, 1993). However, a more substantial problem may exist because of systematic miscounting of related computer inputs, such as telecommunications equipment, software, and complementary organizational factors (including user training as well as broader changes in work practices). The impact on the analysis depends on whether these omitted factors are counted as part of other inputs, such as capital or labor, or omitted from the growth accounting framework entirely. The effects also vary depending on the specification and the parameters of interest. This type of bias will be treated in detail in Section III. A.

Endogeneity of computer capital and other inputs. A difficulty of all productivity analyses is the proper separation of endogenous and exogenous factors. One approach is to assume that prices of input (and often output) are exogenous variables, and that firms select input quantities based on input prices. Unfortunately, for this approach to be applied, it requires firm specific data on prices and an exogenous source of price variation across firms.[3] Alternatively, researchers have estimated production functions directly, under the assumption that input quantities are exogenously chosen to produce a desired level of output. While this approach avoids the difficulty in obtaining firm-specific price data, it confounds forward causality (more inputs lead to more output) with reverse causality. For example, firms experiencing a positive demand shock may increase input quantities, including computers. To properly identify a productivity equation under these conditions requires either external instruments such as prices, internal instruments such as previous levels of inputs, or modification of the specification such that the input quantities can be treated as exogenous over the relevant time period.

3. MODEL AND DATA

3.1. Theoretical Framework

We begin by applying the standard growth accounting framework that has been extensively used for the study of the productivity of other inputs such as capital, labor, energy, and research and development (R&D) (Berndt, 1991). We assume that the production process of the firms in our sample can be represented by a production function which relates firm value-added (Q) to four inputs: ordinary capital stocks (K), computer capital stocks (C), labor (L) and in some cases, R&D (R). In addition, we assume that the production function is affected by time (t) and the industry (j) in which a firm (i) participates. This yields the following equation:

$$Q_{it} = F(K_{it}, L_{it}, C_{it}, R_{it}, i, j, t) \qquad (1)$$

At this point there are two strategies for uncovering the relationship between an input and firm growth or productivity. The "productivity" literature places relatively weak cross-firm functional form restrictions on the production process but imposes theoretical

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[3] As Griliches (1979) argues, it is not clear why there should be firm-specific price variation, which calls into question the idea of firm-level cost function estimation.

restrictions on the values of the parameters. The "production function" literature places a number of strong constraints on the form of the production function and uses econometric estimates for the values of the production function parameters.

Productivity Formulation. The productivity formulation typically begins with a Cobb-Douglas production function[4] which we implement with three inputs: ordinary capital, computer capital, and labor, written in levels or logarithms of levels (lower-case letters denote logarithms; firm and time subscripts are omitted hereafter):

$$Q = A(i,j,t)K^{\alpha} L^{\beta} C^{\delta} \qquad (2a)$$

$$q = a(i,j,t) + \alpha\, k + \beta\, l + \delta\, c \qquad (2b)$$

The term (a), usually referred to as multifactor productivity, captures differences in output across firms and over time that are not accounted for by capital or labor. This framework is usually implemented in time series settings by taking the time difference of each of the factors ($\dot{x}$ representing the time difference of x):

$$\dot{q} = \dot{a} + \alpha\, \dot{k} + \beta\, \dot{l} + \delta\, \dot{c} \qquad (3)$$

For each firm in each year, the elasticities (α, β) are estimated from their theoretical value, which under standard assumptions (cost minimization, competitive output and input markets, factors quantities in long-run equilibrium) is equal to the ratio of the cost of the input to output. This is typical done by averaging factor input shares over adjacent years. Inserting these estimates and rewriting the equation as a function of multifactor

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[4] The Cobb-Douglas form is generally preferred for firm-level productivity work because it is simple and robust. Other functional forms can be employed, but they are only incrementally useful if behavior away from the sample mean is important or substitution elasticities are needed. For the purposes of productivity assessment and growth accounting, the "local" approximation provided by the Cobb-Douglas form is usually adequate.

productivity growth ($\dot{a}$) yields (subscripts refer to time period, r, w, p are the real price of physical units of capital, labor and output respectively):

$$\dot{a} = \dot{q} - \tfrac{1}{2}\left({}^{rK_t}/_{pQ_t} + {}^{rK_{t-1}}/_{pQ_{t-1}}\right)\dot{k} - \tfrac{1}{2}\left({}^{wL_t}/_{pQ_t} + {}^{wL_{t-1}}/_{pQ_{t-1}}\right)\dot{l} - \delta\dot{c} \quad (4)$$

The elasticity of computers (δ) could be calculated using a formula similar to that for capital. Alternatively, multifactor productivity growth can be first estimated excluding the contribution of computers. Then this estimate can be used to estimate the computer elasticity by regression (after adding an error term, assumed to have the usual OLS properties):

$$\dot{a}_{\backslash c} = \hat{\lambda} + \hat{\delta}\,\dot{c} + \varepsilon \qquad (5)$$

where: $\dot{a}_{\backslash c} = \dot{q} - \tfrac{1}{2}\left({}^{rK_t}/_{pQ_t} + {}^{rK_{t-1}}/_{pQ_{t-1}}\right)\dot{k} - \tfrac{1}{2}\left({}^{rL_t}/_{pQ_t} + {}^{rL_{t-1}}/_{pQ_{t-1}}\right)\dot{l}$

Coefficients with hats ^ represent econometric estimates.

This approach was employed by Jaffe (1994) for the study of R&D productivity. Note that this specification is approximately equivalent to estimating a conventional multifactor productivity equation when computers are included as part of ordinary capital. If we estimated equation 5 with $\dot{a}$ as the dependent variable instead of $\dot{a}_{\backslash c}$ then we would obtain a parameter (call it $\hat{\delta}'$) which approximates the elasticity of computers except for a correction for double counting of computers in capital stock. Using equations derived by Schankerman (1981), we can compute the relationship between this estimate and the true elasticity of computers under some minor assumptions (see appendix D for the derivation, r_c and r are the real price per physical unit of computer capital and ordinary capital):[5]

$$\text{plim } \hat{\delta}' - \delta = -\frac{\alpha \operatorname{cov}(\frac{r_c C}{rK}\dot{c},\dot{c})}{\operatorname{var}(\dot{c})} \approx -\alpha \frac{r_c C}{r K} \qquad (6)$$

In other words, except for a downward bias (proportional to the computer share of the total capital elasticity), our approach can be interpreted as a relationship between computers and multifactor productivity as it is commonly measured. This type of correction will reappear later in this analysis when we consider the effects of miscounting the level of computer capital.

Production function analysis. Like the productivity analysis, we assume that the production process of the firms in our sample is characterized by the Cobb-Douglas functional form. However, to enable econometric estimation, we constrain the output elasticities to be constant across the sample and allow time, industry, or firm effects only to enter as additive shifts in the multifactor productivity term. For three inputs, ordinary capital, labor, and computer capital, the estimating equation (in levels) is given by:

$$q = a + \alpha k + \beta l + \delta c + \sum_{t=1}^{T-1} \gamma_t D_t + \sum_{j=1}^{J-1} \gamma_j D_j + \varepsilon \qquad (9)$$

where: t, T, j, J are index variables for time and industry
D_t, D_j are dummy variables for time and industry

This equation has been frequently employed to compute elasticities estimates for various factors of production. However, there are several drawbacks to this formulation in levels. First, the growth calculation is inferred from a cross-sectional elasticity estimate rather

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[5] Throughout the paper the symbols cov(·) and var (·) refer to estimates of the asymptotic covariance and variance respectively.

than estimated directly. Second, specification errors in other parameters (such as the elasticity of ordinary capital or labor) can result in biased estimates of the contribution of computers. Finally, we are forced to restrict the form of the production relationship to be the same across a diverse set of firms. The first two of these difficulties can be partially addressed within this framework, while the third requires the use of a "productivity" formulation given our data constraints.

Time series elasticity estimates can be obtained by using a difference or fixed effects estimator. These transformations remove the cross sectional variation in the data leaving only a time series effect, although they will magnify the effects of measurement error (Griliches and Hausman, 1986) and possibly increase the impact of other types of specification errors. One way to avoid these problems is to treat inputs that adjust relatively quickly to output shocks (such as labor) as endogenous and estimate a "semi-reduced form" (Griliches and Mairesse, 1984). This reduces biases from endogeneity of labor and may help boost the "signal" of ordinary capital and computer capital by reducing the number of regressors.

The assumptions that labor and output are endogenous, and computer capital, ordinary capital and R&D (if included) are exogenous yields the following estimating system (Griliches and Mairesse, 1984):

$$\begin{aligned} q &= \hat{\gamma}_q + \frac{\hat{\alpha}}{1-\beta}k + \frac{\hat{\delta}}{1-\beta}c + \varepsilon_q \\ l &= \hat{\gamma}_l + \frac{\hat{\alpha}}{1-\beta}k + \frac{\hat{\delta}}{1-\beta}c + \varepsilon_l \end{aligned} \qquad (10a,b)$$

These equations can be estimated directly in levels, differences, or fixed effects. Furthermore, because the error terms in these two equations are likely to be correlated, systems estimation may improve efficiency. Note that this approach does not measure elasticities directly but only as a function of the labor elasticity (which can be estimated using factor shares).

Evaluating the Contribution of Computers. Regardless of the method we have employed for obtaining elasticity estimates for computers and other factors of production, there are two ways in which these values can be interpreted. First, we can compute the marginal product of computers (the marginal increase in output for an additional unit of computer capital input) by differentiating the Cobb-Douglas production function. For computers the marginal product is given by:

$$MP_c = \frac{\partial Q}{\partial C} = \hat{\delta}\frac{p\overline{Q}}{r_c\overline{C}} \qquad (11)$$

where: $\overline{Q}, \overline{C}$ represent suitable sample average output and computer quantities

In long run equilibrium and with unbiased parameter estimates, we would expect the marginal product to equal one (each additional dollar of input results in a dollar of output). For ordinary and computer capital, it may be more intuitive to also compute a rate of return to capital stocks which is equal to marginal product multiplied by the rental price of the input.

The second way to assess the contribution of computers is to decompose output growth into the amounts contributed by each input (including computers) using the Cobb-Douglas equation written in first differences:

$$\bar{q} = \hat{\dot{\lambda}} + \hat{\alpha}\,\bar{k} + \hat{\beta}\bar{l} + \hat{\delta}\bar{c} \qquad (12)$$

where: $\bar{q}, \bar{k}, \bar{l}, \bar{c}$ are mean growth rates for the various inputs estimated from the data

The growth contribution of computers alone is represented by the ($\hat{\delta}\bar{c}$) term, while the remaining terms capture the growth contribution of "technical progress", capital, and labor respectively.

Impact of Mismeasurement and Complementarities. As we suggested earlier, there are two important sources of systematic mismeasurement that can potentially affect our elasticity, marginal product, and growth contribution estimates: omitted factors that are not accounted for elsewhere in the growth accounting estimate, and omitted factors that are miscounted in capital, labor, or materials. The simplest case is when there are complements to computers (S, which may be a function of C) that are not counted elsewhere. These factors may have a contribution (θ, an elasticity) to output of their own, either directly or because they are a noisy measure (like computers) of an overall complementary system of computers and organizational factors. This may be a good representation for knowledge or business processes that represent investments far in the past, long-lived inputs that are expensed in previous periods (e.g., software), and those acquired through non-market means. The productivity estimating equation in log-levels (9), after partialling out all other variables (primes, e.g. c', represent variables after partialling), then becomes:

$$q' + \theta s' = \hat{\delta} c' + \varepsilon' \qquad (13)$$

The simple bivariate regression formula yields the following estimate of the bias:

$$\text{plim } \hat{\delta} - \delta = \frac{\text{cov}(s', c')}{\text{var}(c')}\theta \qquad (14)$$

As long as these factors are related to computers (cov[s',c']> 0) and they have some benefit (θ>0), the estimate of the computer elasticity is biased upwards. However, this bias is actually a semantic issue: if the covariance is interpreted as a measure of complementarity, some of this upward bias could be interpreted as a "true" elasticity of an overall system incorporating computers and complementary organizational inputs.[6] However, regardless of interpretation, this type of omitted variable can create serious problems for the estimation of marginal products. While the elasticity is biased upward due to the presence of omitted factors, these additional factors are not counted at all in the factor input figure required for calculating marginal product. This leads to further upward bias in the marginal product calculation unless these omitted factors are included in the denominator.

In differences, while the mathematics are similar, the economic impact may be quite different. The bias term now includes the coefficient of the covariance of changes in s and c:

$$\text{plim}\ \hat{\delta} - \delta = \frac{\text{cov}(\dot{s}', \dot{c}')}{\text{var}(\dot{c}')}\theta \qquad (15)$$

If changes in both factors occur instantaneously over time, the behavior of the bias will be similar to that in levels. However, if changes to complementary organizational investments occur more slowly or at different times than computer investment, the covariance term may be a function of difference length. Longer differences may capture more of this correlation and, therefore, lead to increases in the measured IT elasticity. For instance, when firms are implementing a new information system, the hardware investments may occur relatively early in the process, while the organizational changes occur much later after the system has been coded and tested. If these two events do not

[6] The actual relationship depends on how we interpret what a "system" is. The coefficient of s+c and the coefficient on c only differ by the denominator, and an additional term in the numerator:

$$\delta_{P+C} = \frac{\text{cov}(q', s') + \theta\,\text{cov}(p', c') + \theta Var(s')}{\text{var}(c'+s')}, \quad \delta_{C\,only} = \frac{\text{cov}(s', c') + \theta\,\text{cov}(s', c')}{\text{var}(c')}$$

Thus, the biased coefficients, while potentially closer to the "correct" value for the entire system (s+c), are not exactly correct either. However, this calculation corresponds to the elasticity of the product (SC) rather than the elasticity of the sum (S+C) due to the logarithmic form of the estimating equation. If instead we are interested in the system in its more natural form (S+C) the equations are no longer of the same form and cannot be easily compared.

occur in the same period (e.g., one year), then longer differences will show more of the correlation.

Under this mismeasurement scenario, the marginal product estimates will be biased upward as before. Growth accounting estimates may be approximately correct if both the organizations component and the IT component are growing at the same rate. However, short difference elasticity estimates may be approximately correct. This is because they do not reflect an upward bias from organizational changes.

The situation is substantially more complex when omitted variables are included in factor inputs. The full derivation of the relationship is presented in appendix D. In general, omitted complementary factors will bias down the estimates of computer elasticity if they appear in capital and labor, although the effect is ambiguous for materials (it depends on the relative rates of output growth versus mismeasured computer growth - see Schankerman, 1981 or Griliches, 1988, Chapter 15). While marginal product will be biased upward by undercounting relevant inputs, this is partially offset by the bias in elasticity towards the opposite direction. In fact, the true marginal product can be approximated as a weighted average of the marginal products of the various factors with weights proportional to amount of computers counted in each. Growth contribution is also likely to be biased down because of the downward bias in the elasticity.

3.2. Data Sources and Construction

The dataset for this study was created by combining three separate data sources: a database of capital stock of computers provided by Computer Intelligence InfoCorp (CI), a second dataset of computer hardware and related expenses obtained through surveys conducted by International Data Group (IDG), and public financial information obtained from Compustat II (Compustat). Each of these sources is summarized below.

CI Database. Computer Intelligence InfoCorp conducts a series of surveys that track specific pieces of computer equipment in use at approximately 25,000 sites; these sites represent different locations of firms in the Fortune 1000. CI conducts telephone surveys of information systems managers (site sampling frequency ranges from monthly to annually depending on size) to obtain detailed information on each sites' information technology hardware. Each piece of hardware is then market-valued and aggregated to form a measure of the total hardware value in use at the firm.[7] We have data for the Fortune 1000 annually for the period 1987 to 1994. When compared to another source on site level data (the 1987 TRINET database), the CI dataset appears to cover approximately 40% of sites and 60% of employment listed on TRINET.[8] This suggests that CI may be undercounting the quantity of computer investment in these firms by as much as 50%. The impact of this mismeasurement will be discussed further in the Results section.

IDG Database. International Data Group (IDG) conducts an annual survey of computer usage among the largest companies in the US (the top half of the Fortune 500 manufacturing and service listings) from IS managers at each firm. 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. These data are available from 1988 to 1993 in unbalanced panel form; approximately 490 firms have responded to at least one survey over the sample period, and between 160 and 250 firms are present in any particular year. These data have been used for previous studies on IT productivity (Brynjolfsson and Hitt, 1994;

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[7] This methodology may introduce some error in the measurement of computer inputs because different types of computers are aggregated in their stock value rather than weighted by their rental price. However, the direction of this bias is unclear because it depends on assumptions about depreciation rates of various types of computers at each site.

[8] The employment figures are somewhat suspect in the early years of the database, including the year that matches Trinet. Prior to 1989, CI only tracked employment in ranges (1-5,5-10,10-50,50-100,100-500...) rather than the actual number of employees.

1995; 1996; Lichtenberg, 1995), although we have an additional year of data for 1993 that has not been used before.

Compustat. For all these sources, the identity of the firms are known. These names were matched to the Standard & Poor's Compustat II database to obtain information on sales, labor expenses, capital stock, industry classification, employment, R&D spending, and other expenses.[9] These data were supplemented with price deflators from a variety of sources to construct measures of the sample firms' inputs and outputs using standard procedures from earlier work (Hall, 1990; Brynjolfsson and Hitt, 1995).

Rental prices for ordinary capital inputs were computed using the Jorgensonian cost of capital formula, assuming an annual real rate of return of 9%, 4% expected inflation, and depreciation rates provided by the BLS for 2-digit industries over time. For computers, we use the same required rate of return but assume a 10% depreciation rate and a -20% capital gains term, reflecting the regularity in price declines of computers (Moore's law). After accounting for taxes, this results in a constant annual rental price of 42% for computers and an average rental price of 13.5% for ordinary capital. Because much of the retirement of computers is created by the devaluation due to price declines, a 10% depreciation for computers above and beyond the expected capital gains term may be too much. If this assumption is changed, the rental price of computers drops to 31%. However, we retain the original value of 42% for comparability with previous work. A detailed description of the data construction procedure can be found in Appendix A, and a description of the rental price assumptions appears in appendix B.

Sample. By combining these data sources, we are able to construct a near-balanced panel[10] of approximately 600 firms in the Fortune 1000 which combines Compustat and

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[9] Standard & Poor's Compustat data has been widely used to estimate firm-level production functions for capital, labor and other inputs. For instance, the underlying data for "The Manufacturing Sector Master File: 1959-1987" maintained at the National Bureau of Economic Research by Hall (1990) is drawn from Compustat.

[10] The panel is unbalanced because some firms enter or leave the Fortune 1000 on the margin each year, merge, or for some other reason fail to have complete financial data available for all eight years. To

the measure of computer capital stock from the CI database (N=4571). We also have matching estimates of computer stock for 1411 points from IDG. Overall the quality of the CI data is believed to be quite good, given that the surveys track specific pieces of hardware and are constructed to accurately capture year to year changes at specific sites.[11]

Across sources, the computer data shows a fairly high correlation (73%), although the magnitude of the IDG stock (average of $51.9MM) is somewhat higher than the CI computed stock (average of $21.8 MM for a matched sample). Since IDG has an overall estimate for the computers in the entire firm, while CI represents an aggregate of measured sites only, site coverage appears to be a reasonable explanation for the differences.

Sample statistics for the CI sample are tabulated in Table 1. The average factor shares of computers, capital, and labor are .005, .34 and .63 respectively, which implies roughly constant returns to scale (the sum of all input proportions is .96). The computer figure may appear to be low because we have used a relatively narrow definition of computers that omits software, information system staff, and telecommunications equipment. Furthermore, we use a relatively conservative deflator for computer investment (-20% per year) which may lead to an underestimate of the rental price of computers, and, therefore, too low a factor input quantity. There is also an effect from undercounting due to site coverage. These factors will be discussed further in the context of the growth accounting results.

The firms in the sample are quite large, averaging $1Bn in value-added. The sample has substantial coverage of both manufacturing and services (57% manufacturing, 41%

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prevent the results from being skewed by sample heterogeneity over time, we restrict the sample to those firms which participate in at least six of the 8 years of our sample. This seemed like a reasonable compromise between using a fully balanced panel (removing another 10-15% of the sample) and allowing the year-to-year participation to vary.

[11] According to Harry Henry, Research Director of Computer Intelligence, part of the phone interview involves asking whether specific pieces of equipment identified on a previous interview are still present on-site.

services, and 2% mining, construction and agriculture) and there is at least one firm present from 41 2-digit SIC industries. However, some service industries are largely excluded (banking, insurance) because many of the firms in these industries do not report ordinary capital stock on Compustat. Because these industries are particularly computer intensive, we should expect our sample to be less computer intensive than the economy as a whole.

4. RESULTS

In this section, we estimate the relationship between growth in computers and multifactor productivity growth for firms in our sample. The results are compared with findings from prior work which used the production function approach, and alternative specifications that account for the various types of measurement problems identified earlier. Finally, we use our estimates to examine the growth contribution and marginal product of computers.

4.1. Productivity

We begin by estimating a conventional multifactor productivity equation which calculates the "residual" change in output after accounting for changes in ordinary capital and labor. Using equation (4), we calculate multifactor productivity growth (excluding computers from capital), and regress this against the change in computer capital services, and in some analyses the change in R&D and dummy variables for time. If a firm does not report R&D, the logarithm of R&D is set to zero and a dummy variable is set to 1. This allows us to compare firms that report R&D with those that do not in the same regression, without dropping the R&D term.

The results of these initial regressions are shown in Table 2 for first differences.[12] In the first two columns, we report the results of a regression on multifactor productivity growth

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[12] This analysis is performed after removing several types of outliers. An outlier is defined as any point where the one year MFP change is greater than 1 (in logarithms), or a multi-year MFP change is greater

on the change in computers, and the change in computers and R&D. In both cases the elasticity of computers is about .01 and significantly different from zero (t=2.4). The R&D coefficient is positive and nearly significantly different from zero (t=1.7). When time controls are added (columns 3 and 4) to account for changes in overall economic conditions,[13] the coefficients on computers are halved and are no longer significant (t=1.1). Nonetheless, the elasticities are approximately equal to the computer factor share which is what would be expected in long-run equilibrium when computers are measured correctly.

The time dummies appear to track the broader economic conditions; we find a minimum productivity growth of -3.2% in 1991, the bottom of the recession.[14] This is somewhat worse than overall productivity growth in the U.S. economy over this time period; the Bureau of Labor Statistics reports a minimum multifactor productivity growth of -1% in 1991. This may be because adjustment costs are higher for large firms, which comprise almost all of our sample. In the longer run, productivity in this sample, as well as in the broader economy, has been flat to slightly growing.

The relatively poor productivity performance of the firms in this sample appears to be due to persistently large capital investment that has continued despite the recession. Over the sample period, the average growth rate of capital input is 6%, compared to output growth of 2.4% (see Table 7, discussed later). Over the same period, the average Tobin's Q has been steadily declining from 2.3 in 1987 to 1.6 in 1994; thus, it does not appear that this additional investment is driven by a change in the expected marginal benefits of capital.

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than 2. In addition, we require that for all years the firm has no changes in the logarithm of capital or labor greater than 2, and no changes in the logarithm of computers greater than 3. The actual distributions are much tighter than these bounds would suggest, but the goal of this outlier removal was to exclude only very extreme points. Results are similar when outliers are included.

[13] The use of time dummies for accounting for general economic trends is common, although as argued by Berndt and Fuss (1986), this correction lacks a theoretical basis.

[14] Annual productivity growth can be found by adding the appropriate time dummy to the intercept term (.024+ -.057 ~ - 3.2%)

In Table 3, we present the results of varying the difference length with and without the time dummy variables (excluding R&D). The short difference elasticities (up to 3rd differences) are all on the order of .005 to .01 as before. However, beyond third differences, the coefficients monotonically increase from .023 to .028 without time controls and .013 to .028 with time controls. Furthermore, most are statistically significant up until seventh differences where sample size reduction appears to result in a loss of power.

To probe this result further, we also estimate single year regressions at varying difference lengths (for example, in 1990 we can examine the 1990-1989, 1990-1988, and 1990-1987 difference). The shorter difference results (not shown) appear to be strongly influenced by short run economic fluctuations, although in general they are close to zero. However, the 5th, 6th and 7th differences show consistent elasticity estimates in the .02 to .03 range.

Instrumental variables estimates (using other period differences in IT as instruments) did not appear to work well, and the limited list of external instruments[15] we have available did not have sufficient first stage power ($R^2 < 10\%$) to obtain reliable estimates. Thus, we are unable to further explore potential endogeneity biases beyond what are already addressed through the productivity formulation and differencing.

This pattern of results is consistent with random measurement error in computers. The error bias decreases and the coefficient rises as the difference period is lengthened. This would imply that the true elasticity estimates are at least on the order of .025, not including additional downward bias from output mismeasurement. However, the fact that these elasticity estimates are so much larger than the computer input share (~.5%) suggests that this is not the only explanation. The high value of the elasticity estimates is

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[15] We used capital age, the ratio PCs to terminals, and the ratio of mainframes to PCs under the assumtion that firms with newer capital or computer technology face lower adjustment costs for IT investments. The lack of instruments is a difficulty that plagues most productivity or production function estimates using firm-level data.

consistent with the mismeasurement of computer inputs, but this alone does not explain why the coefficient has been rising and is still too high in any event (especially when this also results in downward bias of the estimate for double counting this "missing" input quantity in capital or labor).

A potentially more interesting explanation, consistent with these results, is that we are capturing a complementarity between computers and slow changing organizational inputs. For changes that occur in the short run, differencing will remove most of the impact of slow changing organizational factors. In the long run, the elasticity estimate will increase as the benefits of long run changes in organization become apparent. The estimates stabilize at around fourth or fifth differences which suggests that the necessary organizational adaptations require on the order of 5 years.

4.2. Production Function Estimates

Comparison to IDG. With new data we can replicate and extend previous firm-level results which included IT in a production function. We begin by estimating a base Cobb-Douglas production function with four inputs (Computers, Non-Computer Capital, Labor, R&D stock) with dummy variables for 2-digit industry and time. As before, we include a dummy variable for firms that have no reported R&D and set the value of the logarithm of R&D to zero. The results are shown in Table 4.

Overall, for estimates in levels (Table 4, columns 1 and 3) we find that computers have an elasticity of approximately .025 in the IDG sample and .030 in the CI sample. The fact that the computer elasticities are close, despite differences in the average level of computer capital, is striking. In a regression using CI data but only the points that match the IDG sample, we get an elasticity estimate of about .0203. The difference between these two elasticities (.0245-.0203 = .004) is somewhat less that what would be expected

[16]from the double counting bias calculation (equation 6).. This is probably due to the fact that the miscounted IDG capital is not perfectly correlated with the measured CI capital. However, this would suggest that there is some undercounting in the CI dataset which is on the order of the differences of these two samples (roughly a factor of 2.4).

The estimated elasticity of capital is approximately .2, which implies a rental rate of approximately 8%, and the estimated elasticity of labor is about .7, which is approximately 10% above its factor share. This would suggest some biases in the estimation of capital and labor due to a combination of errors in measurement and simultaneity.[17] The elasticity of R&D is between .03 and .06 which is on the low end of the range of previous studies of R&D productivity, although it is probably influenced by the presence of firms that do not report R&D in the sample (excluding these, the coefficient rises to .08). These results are consistent with prior work (Brynjolfsson and Hitt, 1994; Lichtenberg, 1995).

In differences, we find results similar to our productivity calculations for the CI data, with an IT elasticity estimated to be .0117 (significantly different from zero, $p<.05$).[18] The elasticity of capital is reduced to about a third of its original value, while labor remains roughly the same. In the IDG sample, the coefficient on IT is very close to zero and capital and labor are similar to the first difference CI results. This is probably due to a combination of the small sample size, errors in variables, and possible endogeneity of labor. In the IDG dataset, the results were not improved by using longer differences because it is too short and unbalanced to take longer differences and have a reasonable

[16] If the difference between the samples is omitted capital, and perfectly correlated with CI measured computers, the bias would be .007 (assuming .22 for the capital elasticity).

[17] An instrumental variables estimate and Hausman test using lagged dependent variables as instruments confirms that labor is the only endogenous factor in this specification. However, this results should be interpreted with caution since lagged dependent variables are not good instruments if there are non-random firm effects.

[18] Results are also similar to the first difference productivity analysis when time dummy variables are included. The estimated IT elasticity is approximately .006 ($t=1.1$).

sample size (for example a 3rd difference drops the sample size from 934 to 421 relative to first differences).

Using the CI observations as an instrument for the IDG measure of computers does increase the estimate in the levels, which suggests that measurement error had biased down the coefficients somewhat. However, using this instrument does not appear improve the first difference specification. Furthermore, while this instrument does help address measurement error, it is equally subject to biases from reverse causality and other types of specification error; it is thus limited in utility.

In addition to showing consistency of our analysis with previous work, there are some additional insights that can be gained from this comparison. First, we have some additional evidence that there is systematic undercounting of computers by CI, although it does not appear to bias elasticity estimates substantially. However, for comparing our estimated elasticities with theoretical elasticities, these differences may become important. Second, we have found that both improvements in specification and data may have been necessary to calculate the direct impact of computers on economic growth; there is insufficient IDG data to perform the analysis in differences and differencing the normal production function appears to adversely affect the estimates on other parameters such as capital and labor. Interestingly, the computer coefficient appears nonetheless to be moderately robust to this specification error.

Semi-Reduced Form Estimates. The remainder of the analysis will be performed exclusively on the CI dataset with a restriction that firms must be present in at least six of the eight years. Missing R&D values are handled as before.

To address specification error introduced by including labor in the regression, we estimate semi-reduced form with both labor and value-added as dependent variables and computers, ordinary capital and sometimes R&D as independent variables:

$$q = \hat{\gamma}_q + \frac{\hat{\alpha}}{1-\beta}k + \frac{\hat{\delta}}{1-\beta}c + \frac{\hat{\varphi}}{1-\beta}r + \varepsilon_q$$
$$l = \hat{\gamma}_l + \frac{\hat{\alpha}}{1-\beta}k + \frac{\hat{\delta}}{1-\beta}c + \frac{\hat{\varphi}}{1-\beta}r + \varepsilon_l \qquad (16)$$

The base estimate in first differences of the value-added equation is shown in Table 5, column 1, and the parallel labor equation is shown in Table 5, column 2. Similar results are found when R&D is excluded. A Wald test fails to reject the equality of the coefficients between equations for computers, ordinary capital and R&D (with R&D $\chi^2(4)=3.1$, $p<.5$; without R&D, $\chi^2(2)=2.7$, $p<.3$) which suggests that the assumptions underlying the semi-reduced form are reasonable. We therefore estimate all further results in this section constraining the parameters to be equal across equations for efficiency gain. The improved estimate is shown in column 3. The estimated coefficient on computers is approximately .024 which implies an elasticity estimate on the order of .009 (based on a factor share of .62 for labor). The elasticity of capital is approximately .14 which is somewhat lower than estimates in levels, although the estimates in the semi-reduced form are similar to those reported previously for capital (Mairesse, 1991). The R&D elasticity is approximately the same as before.

As before, we can partially address measurement error and also compare short and long-run effects by lengthening the period of differencing. Table 6, column 1 presents the results of lengthening the differencing period (excluding the R&D variable). Similar to the productivity analysis, we find a monotonically increasing coefficient from .025 to .115 which implies elasticity estimates ranging from .01 to about .044. The ordinary capital coefficient also rises as the length of differencing increases and appears to level off around .58. The implied capital elasticity of .22 is still somewhat lower than would theoretically be expected, although it is close to the estimate in levels. The coefficients on ordinary and computer capital rise together. This suggests that downward biases in the elasticity estimates of ordinary capital are not being transmitted into upward biases in the computer capital coefficient in the short difference specifications.

The individual year regressions (not shown) also show a similar pattern to the productivity results. For shorter differences, there is substantial year to year variation, while the longer differences appear to be more stable and are usually significant.

These results are consistent with our earlier results on productivity growth. The short run elasticity is on the order of .01, while the long run elasticity approaches .045, which is somewhat higher than the estimates calculated from the productivity approach. The standard errors in these estimates are generally lower than the standard errors in the productivity equations. This lends additional support for our earlier results.

4.3. Growth Accounting and Marginal Product Calculations

Growth Accounting. Once the output elasticities are known, the contribution of the various inputs to economic growth can be calculated directly from the Cobb-Douglas production function in differences (equation 12). For each of the four inputs (capital, labor, R&D, and computers), we calculate the relevant growth rates over the sample period and then compute the growth contributions using the various short and long difference productivity estimates.

Growth rates of inputs, outputs and multifactor productivity are presented in Table 7. Overall, growth in output has been relatively robust over this time period, averaging 2.5% per year despite the recession. Labor growth appears to track output growth fairly closely over time (aggregate rank order correlation with output growth is 61%, N=7), but there appears to be no cyclical pattern in capital of either type (correlation < 35%), and even at the bottom of the recession in 1991, computer capital input grew by 34%.

Table 8a reports the results from using first-difference productivity analysis, first difference semi-reduced form estimates, and production function estimates in levels. For each calculation, we use theoretical values based on factor shares when the actual value is not estimated.[19] In the table, two intermediate totals are shown relating to multifactor productivity growth. The line called "technical progress" is the growth in output not accounted for by ordinary capital and labor and is approximately what would be measured in a standard growth accounting exercise.[20] Technical progress can then be further decomposed into the contributions of computers, R&D, and "other technical progress".

Results using the short-run elasticity estimates indicate that computers account for approximately .25% of output growth over the sample period. When estimates in levels are used, the contribution rises substantially to .7%. Ordinary capital and labor contribute approximately 1.3% and .8% respectively, and R&D accounts for an additional .1%. Using long run estimates, computers appear to contribute between .5% and .7% of output, which is the same order of magnitude as technical progress and quite large relative to its factor share.

Because these estimates use growth rates of computers and not levels, they are robust to systematic undercounting of computer inputs if we assume that these omitted inputs grow at the same rate. However, the exact values for the growth contribution of computers are highly dependent on the deflator used for computer investment. The deflator we use (19.3%) is in the middle of previous estimates (Cartwright, 1986; Berndt and Griliches, 1990; Gordon, 1990). Given that newer technologies such as PCs appear to decrease in price faster (on the order of 30% per year; see Berndt and Griliches, 1990), our contributions to growth may underestimate the impact of computers by as much as 50%.[21]

Marginal Products. Another way to examine the impact of computer investment is to calculate the marginal product and determine if our estimates suggest that computers are

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19 We also use theoretical values for R&D elasticity because our estimates appear to be far from the expected theoretical value if we assume a rental price of 15% for R&D.

20 Technical progress would normally be measured including computers in ordinary capital. This would reduce the estimate by .04%.

21 50% = "true" deflator/assumed deflator - 1 = 30/20 - 1

earning a reasonable rate of return. As mentioned earlier, the difficulty with this approach is that the marginal product calculation relies on accurate measurement of the levels of computer investment. From our earlier arguments and results, we can explore three possible sources of these biases: 1) omitted technical complements to computers such as information systems staff and other types of hardware that are counted elsewhere (as capital or labor), 2) omitted technical complements that are not accounted for in other inputs, and 3) complementary organizational characteristics. For the calculations presented below, we will use a short run elasticity estimate of .011 and a long run estimate of .044.

From our comparison between datasets, it is possible that the quantity of computers we measure is only about 42% of the actual value according to the IDG data. In addition, a recent study by International Data Group (IDG, 1996) suggests that for a typical information systems installation based on client-server technology, the operating costs are as much as five times the hardware costs. Since most of our firms are likely to have a substantial installed base of mainframe technology which is less expensive to maintain (IDG, 1996), this factor of five is probably a high estimate. Using these figures, we estimate that there could be an additional factor of 1.4 of misclassified capital and a factor of 2.1 misclassified labor[22] that is perfectly correlated with the observed computer capital estimates. Using the equations in appendix D, this yields a marginal product estimate of computers of 1.18 in the short run and 2.4 in the long run. Thus, this correction alone does not appear to account for the high long run elasticity.

Both omitted technical complements (that do not appear elsewhere) and long-run organizational changes are at least partially accounted for in the long-run elasticity estimates by our earlier arguments. For this elasticity to imply an equilibrium marginal product of 1, there would have to be approximately $6.3 of these factors per dollar of

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22 This assumes a rental price of 42% for capital.

measured computer input (even after the miscounting correction above).[23] This appears to be too large to simply be software or other expensed items, suggesting that at least some significant component of "organizational capital" is influencing the estimates. Given that computer inputs are small relative to labor (about 1%), the presence of these additional organizational factors appears to be a plausible explanation for the high long-run elasticity. [24]

5. Discussion and Conclusion

Using conventional productivity measurement and production function estimation, we find evidence that computers contribute significantly to output and growth. In short difference analyses, computers appear to have an elasticity on the order of .01, while the estimates range from .025 to .045 for long differences. These estimates imply that computers have generated between .25% and .70% of economic growth per year for the firms in our sample.

Given the limited number of available instruments that would drive differences in computer levels or investment across firms, we are unable to fully rule out the possibility that errors in variables or reverse causality is in part causing the results. However, difference estimates and the analyses using the productivity specification make it less likely that the results are driven by econometric problems, such as sample heterogeneity. In addition, these specifications may address some types of reverse causality (see Griliches, 1979 or Brynjolfsson and Hitt, 1994 for a discussion of this issue).

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[23] The calculation of this figure is as follows: 1.4 "excess marginal product" x denominator of 4.5 times computer input share = 6.3. This is also close to the figure if the double counting was not taken into effect.

[24] Another possible story that would be consistent with the high elasticity is that computer investment represents the destruction of an option. Making an investment in computers now not only means a firm must forego future expected price decreases, but may also lock them in to a particular technology for some period of time. Therefore, the rental price of computers should ideally include the value of lost options to invest in alternative technologies. Because of the rapid technogical innovation in the computer sector, the value of these options could be quite large and account for some substantial portion of the "excess returns".

The fact that computers contribute substantially to economic growth is not necessarily surprising given that computer input quantity grows by about 25% per year. This pattern of investment should generate approximately .15% of additional economic growth per year during our sample period, and this is consistent with our short run growth estimates. However, the growth contribution appears to rise substantially when we use long difference elasticity estimates.

There are several possible interpretations of these results. First, errors in measurement of computers can result in downward bias of estimates done in differences, which are reduced as the differencing period is increased. Under this argument, the higher long run estimates are actually the true short run estimates as well; however, their large magnitude calls this interpretation into question. Alternatively, we can rationalize the high returns by attributing them to a systematic mismeasurement of computers, but as we showed earlier, the amount of mismeasurement needed to account for these returns may also be unreasonably large.

Our interpretation is that we are capturing the difference between the short run substitution effects and longer run changes in other organizational factors that are complementary to computer use. Because first differences will remove the impact of these slowly changing "firm effects", the longer differencing period allows us to capture more of the productivity impact of this sort of long run adjustment. This is consistent with Milgrom and Roberts (1996) argument about the LeChatlier principle, in which they show that if a factor is complementary to institutional or other slow changing effects, the long run impact of the factor change will be larger than the short run.

Without better measures of IT capital, better firm-level instruments for IT investment, and more direct measures of the hypothesized quasi-fixed organizational factors, it is difficult to assess the relative importance of these explanations for our results. However, they probably each account for at least a portion of the answer. Future work should be able to more directly address the source of the high measured output elasticity of information technology.

Table 1: Sample Statistics - Median and Mean Firm

Measure	CI Sample Median	CI Sample Means
Value Added	$1.00 Bn	$1.09 Bn
Computer Capital Services	$6.04 MM	$6.03 MM
Ordinary Capital Services	$227 MM	$252 MM
Labor	$582 MM	$633 MM
R&D Capital Stock (% reporting)	$314 MM 38%	$ 351 MM 38%
Factor Share - Computers	.603%	.554%
Factor Share - Ord. Capital	21.8%	34.4%
Factor Share - Labor	62.8%	61.4%
Sum of Factor Shares*	90.2%	95.8%
Sample Size	3936	3936
Time Period	1988-1994	1988-1994

* - Sum of factor shares excludes computers. This is actual sample mean/median firm, not a computation from aggregate figures.

Notes: Geometric means are reported
Statistics only observations with MFP growth estimates (excludes 1987)
Average/Median over all years in 1990 dollars

Table 2: Varying-Difference Productivity Estimates (pooled and single year)

Coefficient	ΔMFP (1 year) IT only	ΔMFP (1 year) IT & R&D	ΔMFP (1 year) IT only	ΔMFP (1 year) IT & R&D
Intercept	.0001 (.0023)	-.0009 (.0035)	.0249** (.0058)	.0234** (.0063)
ΔComputers	.0104* (.0043)	.0103* (.0044)	.00464 (.0046)	.00456 (.0046)
Δ R&D		.0102^ (.0059)		.00798 (.0069)
R&D not present		.0014 (.0037)		.0023 (.0042)
Dummy (Year=1988)			.0191* (.0077)	.0187* (.0077)
Dummy (Year=1989)			-.0262** (.0078)	-.0263** (.0078)
Dummy (Year=1990)			-.0483** (.0076)	-.0484** (.0076)
Dummy (Year=1991)			-.0572** (.0075)	-.0572** (.0075)
Dummy (Year=1992)			-.0257** (.0076)	-.0257** (.0079)
Dummy (Year=1993)			-.0190* (.0076)	-.0191** (.0076)
R^2 Regression F	.2% p<.05	.2% p<.05	3.6% p<.001	3.6% p<.001
N	3936	3936	3936	3936

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

Table 3: Regression of Computer Growth on Multifactor Productivity Growth - Varying Difference Length

Difference	Time controls	No time controls	Sample Size
1	.0104* (.0043)	.00460 (.0046)	3936
2	.00512 (.0056)	.0138* (.0054)	3364
3	.000295 (.0066)	.00796 (.0066)	2775
4	.0129^ (.0075)	.0227** (.0072)	2190
5	.0234* (.0085)	.0244** (.0083)	1606
6	.0248* (.010)	.0245* (.010)	1020
7	.0272 (.0150)	.0277^ (.0159)	488

Key: ^ - p<.1; * - p<.05, ** - p<.01, Standard errors in parenthesis

Table 4: Comparison to Prior Work

Coefficient	CI Levels	CI 1st Diff.	IDG Levels	IDG 1st Diff.
Computer Elasticity	.0304** (.0040)	.0117** (.0041)	.0248** (.0068)	-.0015 (.0041)
Ordinary Capital Elasticity	.188** (.0058)	.0608** (.012)	.187** (.010)	.0574** (.017)
Labor Elasticity	.720** (.0064)	.743** (.0139)	.734** (.012)	.719** (.025)
R&D Dummy (1=not present)	.287** (.0250)	.00383 (.0041)	.304** (.044)	.278* (.078)
R&D Elasticity	.0464** (.0045)	.0102** (.0057)	.0550** (.0075)	.0205** (.007)
Controls	Time 2-digit SIC		Time 2-digit SIC	
R^2	95.9%	50.3%	97.1%	56.9%
N	4571	3946	1411	934

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

Table 5: Semi-Reduced Form Estimates

Coefficient	Single Eqn.: VA	Single Eqn.: Labor	System
ΔComputer Capital	.0219** (.0055)	.0251** (.0050)	.0240** (.0047)
ΔOrdinary Capital	.373** (.013)	.400** (.012)	.391** (.011)
ΔR&D	.0179** (.0070)	.0130* (.0063)	.0149* (.0060)
No R&D	.0257** (.0050)	.0281** (.0043)	.0272** (.0043)
Controls	Year	Year	Year
R^2	20.5%	24.4%	19.5%/24.3%
N	3936	3936	3936

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

Table 6: Semi-Reduced Form Specification Varying Lag Length - ISUR Estimates

Difference	ΔComputer Capital	ΔOrdinary Capital	Sample Size
1	.0247** (.0048)	.395** (.011)	3936
2	.0525** (.0058)	.432** (.012)	3364
3	.068** (.0069)	.486** (.013)	2775
4	.0775** (.0083)	.519** (.014)	2190
5	.0890** (.010)	.549** (.016)	1606
6	.0910** (.013)	.590** (.0202)	1020
7	.115** (.0193)	.580** (.0284)	488

Key: ^ - p<.1; * - p<.05, ** - p<.01, Standard errors in parenthesis

Table 7: Median Growth Rates of Output, Inputs, and Multifactor Productivity

Variable	1988	1989	1990	1991	1992	1993	1994	Overall
Value-Added	5.81%	2.57%	.704%	-.882%	1.52%	3.58%	3.87%	2.48%
Computer Capital	30.4%	8.76%	12.6%	34.4%	-12.9%	37.8%	38.2%	24.1%
Ordinary Capital	6.71%	6.74%	8.81%	5.49%	5.17%	4.65%	5.39%	5.99%
Labor	3.04%	1.74%	1.24%	-.05%	.067%	2.67%	0.00%	1.24%
R&D Capital	6.97%	2.18%	1.59%	1.29%	1.61%	1.70%	.780%	2.25%
MFP	4.57%	.270%	-.770%	-1.74%	.275%	.770%	1.69%	.317%
N	520	550	587	583	581	571	545	3936

Notes: MFP excludes IT and R&D from the calculation. This would lower the estimate.
R&D average includes the ~60% of firms which have no R&D.

Table 8a: Growth Accounting (first difference elasticity estimates)

	Theory	Productivity Estimates	Production Function Estimates	Production Fn. (levels) Estimates
Value Added	2.48%	2.48%	2.48%	2.48%
- Ordinary Capital	1.31%	1.31%	0.880%	1.12%
- Labor	0.789%	0.789%	0.789%	.892%
= "Technical Progress"	0.381%	0.381%	.811%	.468%
- Computer Capital	0.145%	0.250%	.226%	.733%
- R&D Capital	0.108%	0.108%	.108%	.104%
= Other Technical Progress	0.128%	0.023%	.477%	-.369%

Shaded areas represent numbers that are estimated from theoretical values or calculated.

Table 8b. Growth Accounting (fourth difference elasticity estimates)

	Theoretical Growth Contribution	Productivity Estimated Contribution	Production Fn. SRF Estimated Contribution
Value Added	2.48%	2.48%	2.48%
- Ordinary Capital	1.31%	1.31%	1.18%
- Labor	0.789%	0.789%	0.789%
= "Technical Progress"	0.381%	0.381%	.511%
- Computer Capital	0.145%	0.547	.695%
- R&D Capital	0.108%	0.108%	0.108%
= Other Technical Progress	0.128%	-.274%	-.292%

Shaded areas represented numbers that are estimated from theoretical values or calculated.

Figure 1: Trends in Semiconductor Manufacturing

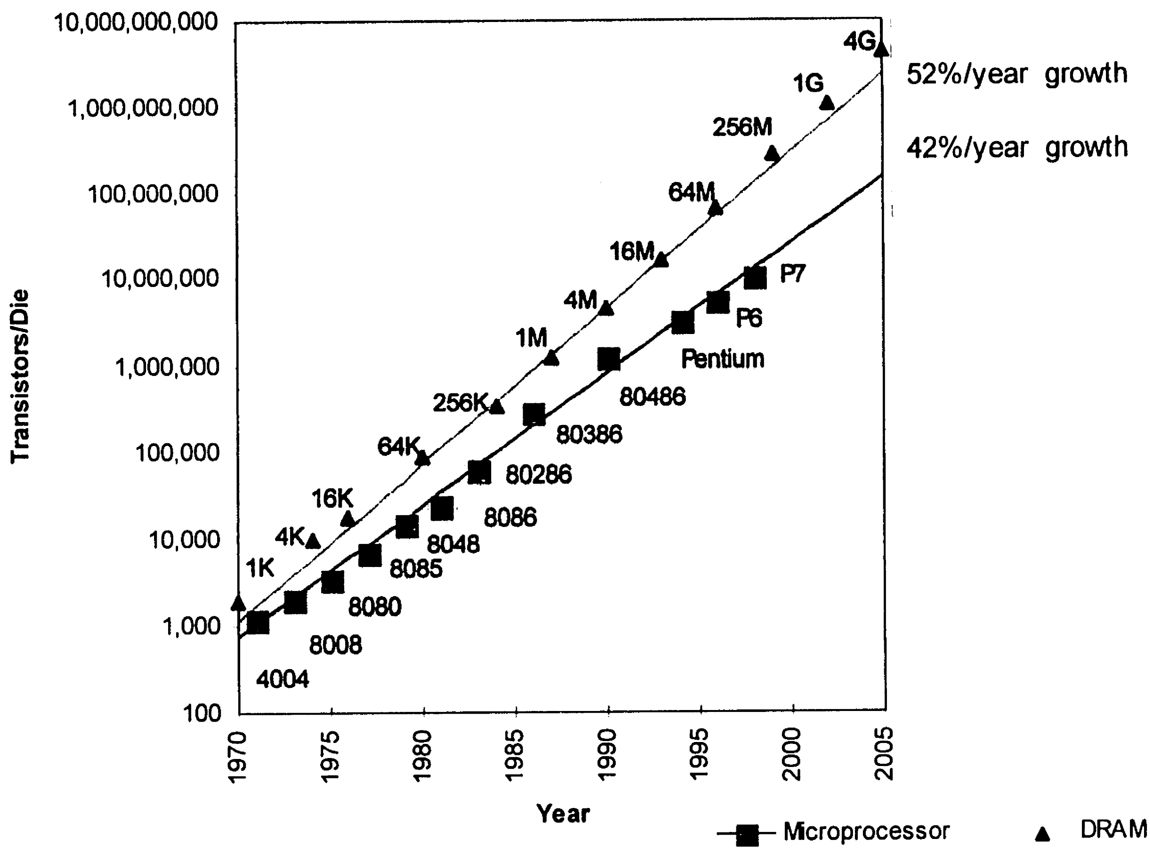
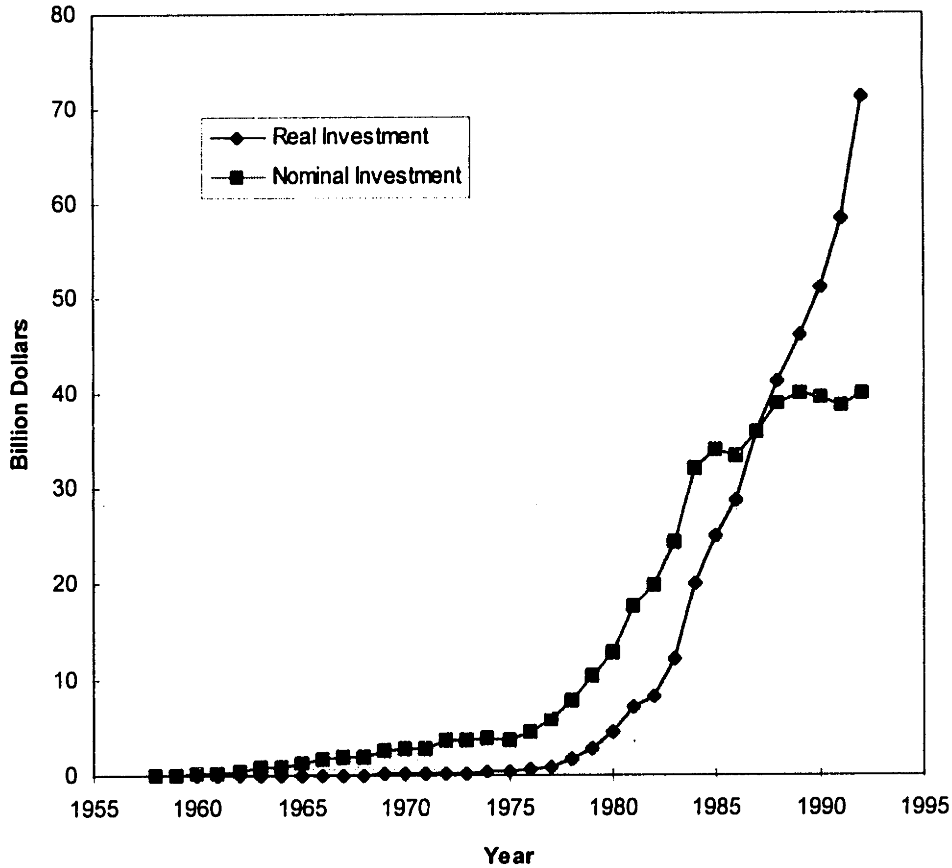


Figure 2: Real and Nominal Computer Spending



Appendix A: Variables and Data Construction

The variables used for this analysis were constructed as follows:

Sales. Total Sales as reported on Compustat [Item #12, Sales (Net)] deflated by 2-digit industry level deflators from Gross Output and Related Series by Industry from the BEA (Bureau of Economic Analysis, 1996) for 1988-1993, and estimated for 1994 using the five-year average inflation rate by industry. When industry deflators are not available, the sector level producer price index for intermediate materials, supplies, and components is used (Council of Economic Advisors, 1996).

Ordinary Capital. This figure was computed from total book value of capital (equipment, structures and all other capital) following the method in (Hall, 1990). Gross book value of capital stock [Compustat Item #7 - Property, Plant and Equipment (Total - Gross)] was deflated by the GDP implicit price deflator for fixed investment. The deflator was applied at the calculated average age of the capital stock, based on the three year average of the ratio of total accumulated depreciation [calculated from Compustat item #8 - Property, Plant & Equipment (Total - Net)] to current depreciation [Compustat item #14 - Depreciation and Amortization]. The calculation of average age differs slightly from the method in Hall (1993) who made a further adjustment for current depreciation. The constant dollar value of computer capital was subtracted from this result. Thus, the sum of ordinary capital and computer capital equals total capital stock.

Computer Capital (CI). Total market value of all equipment tracked by CI for the firm at all sites. Market valuation is performed by a proprietary algorithm developed by CI that takes into account current true rental prices and machine configurations in determining an estimate.

This total is deflated by the deflator for computer systems of -19.4% per year developed by Robert Gordon (Gordon, 1990). The time trend Gordon found in prices through 1984 is assumed to continue through 1994.

Computer Capital (IDG). Composed of mainframe and PC components. The mainframe component is based on the IDG survey response to the following question (note: the IDG survey questions quoted below are from the 1992 survey; the questions may vary slightly from year to year):

"What will be the approximate current value of all major processors, based on current resale or market value? Include mainframes, minicomputers and supercomputers, both owned and leased systems. Do NOT include personal computers."

The PC component is based on the response to the following question:

"What will be the approximate number of personal computers and terminals installed within your corporation in [year] (including parents and subsidiaries)? Include laptops, brokerage systems, travel agent systems and retailing systems in all user departments and IS."

The number of PCs and terminals is then multiplied by an estimated value. The estimated value of a PC was determined by the average nominal PC price over 1989-1991 in Berndt & Griliches' (1990) study of hedonic prices for computers. The actual figure is $4,447. The value for terminals is based on the 1989 average (over models) list price for an IBM 3151 terminal of $608 (Pelaia, 1993). These two numbers were weighted by 58% PCs and 42% terminals, which was the average reported by a separate IDG survey conducted in 1993. The total average value for a "PC or terminal" was computed to be $2,835 (nominal). This nominal value was assumed each year, and inflated by the same deflator as for mainframes.

This total Computer Capital (PCs and mainframes) is deflated by the deflator for computer systems of -19.4% per year developed by Robert Gordon (Gordon, 1990). The time trend Gordon found in prices through 1984 is assumed to continue through 1994.

Labor Expense. Labor expense was either taken directly from Compustat (Item #42 - Labor and related expenses) or calculated as a sector average labor cost per employee multiplied by total employees (Compustat Item #29 - Employees), and deflated by the price index for Total Compensation (Council of Economic Advisors, 1996).

The average sector labor cost is computed using annual sector-level wage data (salary plus benefits) from the BLS from 1987 to 1994. We assume a 2040 hour work year to arrive at an annual salary. For comparability, if the labor figure on Compustat is reported as being without benefits (Labor expense footnote), we multiply actual labor costs by the ratio of total compensation to salary.

Employees. Number of employees was taken directly from Compustat (Item #29 - Employees). No adjustments were made to this figure.

Materials. Materials was calculated by subtracting undeflated labor expenses (calculated above) from total expense and deflating by the 2-digit industry deflator for output. Total expense was computed as the difference between Operating Income Before Depreciation (Compustat Item #13), and Sales (Net) (Compustat Item #12).

Value-Added. Computed from deflated Sales (as calculated above) less deflated Materials.

R&D Capital. R&D Capital was computed by a method following Hall (1993). R&D expenditures (Compustat Item #46 - Research and Development Expense) were used as flows to create a capital stock. The first period value (1973) was multiplied by 4.3 to create an initial stock (this figures comes from the perpetual discounting of a flow that is depreciated 15% per year and discounted 8% per year - $1/(.08+.15) = 4.3$). This was deflated by an R&D deflator reported in Hall (1993). Each successive year was computed by converting flow to constant dollars, and adding to the previous year's stock which is depreciated at 15% per year. This method requires a complete series for R&D flow from 1973 to 1994. For companies that were missing 2 or less points in the series, the missing data were interpolated as the average of the nearest years. When the missing point was at the beginning or end of the series, the point was computed from the three year average growth rate in the nearest years. A total of 24 points were corrected in this way (note: this departs from the procedure used by Hall (1990). The annual R&D expense is treated as part of Materials, unless R&D capital is included in the regression, in which case it is omitted entirely.

Appendix B: Net vs. Gross Returns

The net return to investments in computer capital is the outcome of a complex interaction among several factors, including not only the traditional components of the Jorgensonian cost of capital -- interest rates, depreciation, taxes and capital gains -- but potentially also factors such as the value of options and of learning. We briefly consider how these factors would likely combine to derive an expected rate of return for computers.

Under the assumption that managers successfully choose the optimal level of computer capital to maximize the net present value of the firm, we should observe a return equal to its implicit rental price. This is given by the Jorgensonian equation for the required rate of return on capital, which can be written as follows (Christensen and Jorgenson, 1969):

$$E\Pi = \frac{1-u_t z_t - e_t}{1-u_t}\left\{ r_t + \delta_t - \frac{(q_t - q_{t-1})}{q_t} \right\} + x_t$$

where

$E\,\Pi_t$ = expected rate of return for computer capital, in year t

r_t = investor's required nominal rate of return (the rate at which the future is discounted)

δ_τ = depreciation rate for computer capital

q_t = the relative price of computers; q_t-q_{t-1} is capital gains, or losses

u_t = the corporate income tax rate

z_t = the present value of $1 of tax depreciation allowances

e_t = the investment tax credit

x_t = effective tax rate on corporate property

According to Jorgenson and Stiroh (1995), reasonable values for these variables for 1990 are: r_t = .09; δ_τ = .10; Δq = -.199; u_t = .384; z_t = .902; e_t = 0; x_t = .01, which implies that the costs of computer capital is about 42.2%.[25] Using a slightly different formula, Lau and Tokutsu (1992) and Lichtenberg (1995) also derived a cost of computer capital of 42%.

Similar calculations yield an average estimate of 13.5% for ordinary capital, based on values of r_t = .09; δ_τ varies by industry and time; Δq = .05; u_t = .38; z_t = .8; e_t = 0; x_t =

[25] Computers do not depreciate significantly in the sense of wearing out. However, they are retired when, because of declines in the cost of computer power, the value of the services of old equipment no longer justfies incurring complementary costs of space, electricity, programming labor, etc. The value of .1 for δ_τ reflects these retirements and is estimated based on the retirement data underlying the calculations in Jorgenson and Stiroh (1993) and personal communication with Keven Stiroh.

.01.[26] This suggests that the required rate of return to computer is nearly 3 times as high as the return required for ordinary capital.

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[26] Jorgenson and Stiroh (1993) do not report aggregate values for these variables. However, Lau and Tokutsu, (1992) report that reasonable values are δ_T = .05 and = .05 for ordinary capital. The remaining values are equivalent to theose used for computer capital, with the exception of z_t, reflecting the longer service lives of non-computer capital. The investment tax credit, e, was eliminated in 1986. Before that, it was 10%. Our costs of capital may therefore be slightly too high, to the extent that capital stock in place during our sample period was purchased before 1986. If a value for e of .01 for computers and .05 for other capital were used, the costs of capital would fall to 41.5% and 10.3%, respectively.

Appendix D: Omitted Variable Bias

This derivation is based on the framework of Schankerman (1981). Consider the general case where there are various components of computer expenditure or capital that are present in estimates used for capital, labor or materials. Let these be represented by functions K_c, L_c, and M_c all of which are functions of the observed level of computers (C). Assuming that the level of computer-related spending is small relative to the magnitude of other inputs (e.g. $K_c << K$), the impact of these omitted variables can be computed. For production function estimates in levels, the equation is (using notation as before):

$$\delta_{measured} = \delta_{actual} - \frac{1}{\mathrm{var}(C)}\{\alpha \,\mathrm{cov}(\frac{K_c}{K}, C) + \beta \,\mathrm{cov}(\frac{L_c}{L}, C) + \mathrm{cov}(\frac{M_c}{Q - M_c}, C)\}$$

A similar result can be derived from the productivity analysis (define the materials price per physical unit as p_m and the output price per physical unit as p_q):

$$\delta_{measured} = \delta_{actual} - \frac{1}{\mathrm{var}(\dot{c})}\{\alpha \,\mathrm{cov}(\frac{r_{k_c} K_c}{r_k K}\dot{k}_c, \dot{c}) + \beta \,\mathrm{cov}(\frac{w_{l_c} L_c}{wL}\dot{l}_c, \dot{c}) - \mathrm{cov}(\frac{p_m M_c}{p_q Q - p_m M_c}\dot{q}.\dot{c}) + \mathrm{cov}(\frac{p_m M_c}{Q - p_m M_c}\dot{m}_c, \dot{c})\}$$

Under the assumption that the levels of the factors are uncorrelated with growth rates to a first order approximation, the expression can be simplified by removing the ratio terms (e.g. K_c/K) outside the covariance term. Ignoring the materials terms and assuming perfect correlation between measured and omitted computer inputs yields a simple equation for the relationship between actual and measured marginal product of computers. For this calculation let $K_c = \tau_k C$ and $L_c = \tau_l C$. Then with the above assumptions we have:

$$MP_{true} = \frac{1}{\tau_k + \tau_c + 1}(\tau_k MP_k + \tau_l MP_l + MP_c^{estimated})$$

In other words, the elasticity is a weighted average of the various marginal products (MP).

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Information Technology and Organizational Architecture: An Exploratory Analysis

Doctoral Dissertation Chapter 2

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Information Technology and Organizational Architecture:

Firm-level Evidence

Abstract

The diffusion of information technology (IT) into the modern workplace may be associated with a shift in the structure of organizations analogous to earlier industrial revolutions. This paper explores the relationship between information technology and the organizational architecture of firms, focusing on how this relationship affects firm productivity. A simple model is presented that relates the use of information technology to three aspects of organizational architecture: the allocation of decision rights, the importance of skills and education, and incentive systems. These relationships are then investigated using detailed data on organizational practices, information technology use, and productivity for 273 large firms.

There is evidence that greater use of information technology is associated with greater decentralization of decision rights and related organizational practices. Furthermore, firms that use this decentralized work system show higher productivity from their information systems investments. This relationship is robust to alternative productivity specifications, measures of work systems, and assumptions of causality. These findings lend support to the idea that organizational practices are important determinants of the productivity of IT.

1. Introduction

Technological innovation has often been closely linked to changes in organizational structure. In the late 19th century, the development of the railroad and the telegraph enabled coordination of economic activity over long distances. This contributed to the emergence of large firms and the realization of their associated scale advantages (Milgrom and Roberts, 1992). The shift to mass production and the associated system of Taylorist work practices coincided with the transition in the economy from handicraft to machine production in the early 20th century. In addition, the tremendous productivity gains that can accompany the use of new production technologies may not appear until complementary organizational changes have been made. For example, the electric motor had little impact on economic growth until factories were reorganized to take advantage of natural work flows rather than being organized around the location of power transmitting shafts (David, 1990).

Recently, a number of authors have suggested that the tremendous diffusion of information technology into the modern workplace may have an analogous impact on work organization and productivity. Milgrom and Roberts (1990) cite the exogenous price decline of information technology as a key driver in the shift between "mass production" and "modern manufacturing". More broadly, the rise of information technology investment has occurred concurrently with a shift in work organization toward increased delegation of authority, greater use of teamwork, and the substitution of knowledge work for manual labor. The magnitude of this shift has been compared in scale and scope to industrial revolutions. For instance, Drucker (1988) calls it the "third period of change: the shift from the command-and- control organization...to the information-based organization, the organization of knowledge specialists." In addition, the relationship between IT and decision rights has been formally modeled by Wyner and Malone (1996), who concluded that decreases in communications costs enabled by IT would lead organizations to decentralize decision-making.

This paper explores the relationship between information technology (IT) and organizational architecture.[27] First, a model is presented in which the increased ability to share and process information with IT is optimally combined with a decentralized organizational architecture. This includes greater use of teams and decentralized decision rights, increased levels of education and training, and incentive systems which emphasize subjective or team-based measures. Second, we empirically examine the relationship between these work practices and information technology use, and how the combination of IT and decentralized work systems affects firm productivity. This is accomplished using detailed data on organizational practices, information technology use, and productivity for 273 large firms.

Overall, the results suggest that firms that use a decentralized work system show higher benefits from their IT investments. While it is difficult to rule out all forms of misspecification, this result is robust to alternative measures of decentralization and changes in the productivity specification. There is also evidence that the overall use of information technology is correlated with the use of a decentralized work system as well as its individual components, which is consistent with the productivity findings. These results are broadly consistent with the argument that information systems investment may be related to the shift toward decentralized organization and that the combination of the technological and organizational investments lead to higher productivity.

This research relates to a number of different areas of the management and economics literature. This paper builds on earlier work on information systems management that has linked IT use to changes in work organization (Attewell and Rule, 1984; Malone, 1985; Zuboff, 1988; George and King, 1991; Orlikowski, 1992; Brynjolfsson, 1994), theoretical studies that have argued that IT is a complement to teams, knowledge sharing, and

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[27] This term was originally used by Gerstein et. al. (1992) to draw a parallel between the design of buildings and the design of organizations. While their definition is consistent with the spirit of our analysis, our definition is closer to that recently proposed in the economics literature. Brickley, Smith and Zimmerman (1996), following work by Jensen and Meckling (1992), define organizational architecture as the allocation of decision rights and incentive systems (measurement and rewards). In addition, we add the dimension of human capital (skills, training) because of its relevance to this analysis.

decentralized authority (Anand and Mendelson, 1995; Malone, 1995; Wenger, 1996; Wyner and Malone, 1996), and recent work that has found substantial productivity benefits from the use of information technology (Brynjolfsson and Hitt, 1994; 1995; 1996). In the broader organizations literature, the work system identified by the theoretical model are closely related to what has been termed "high performance work systems" (Ichniowski and Kochan, 1995), and this paper may help explain both the diffusion and performance impact of this type of work organization. Finally, the empirical approach and theoretical model is closely related to work on the economics of complementarities (Milgrom and Roberts, 1990; Milgrom and Roberts, 1992; Holmstrom and Milgrom, 1994).

The remainder of the paper is as follows. Section 2 briefly reviews some of the relevant empirical and theoretical literature. The model is presented in section 3. Section 4 describes the empirical methodology and data. Section 5 presents the results, and the paper concludes with a brief summary and discussion in section 6.

2. Previous Literature

2.1 New Work Systems

There have been a number of empirical studies on the relationship between organizational practices and performance at the firm level (Dunlop and Weil, 1993; Huselid, 1994; Ichniowski, Shaw and Prunnushi, 1994; Lawler, Mohrman and Ledford, 1995; MacDuffie, 1995). In general, these studies have often found large economic benefits from the use of certain systems of organizational practices, which raises a question as to why the they are not more widespread (Osterman, 1994). The practices that have been examined include: team-based production, the allocation of decision authority between workers and managers, skill levels and training, broadening of jobs, quality circles, total quality management, incentive systems, hiring practices, and organizational culture. However, while there is some general consistency between the studies, the theoretical justification and operationalization of work systems differ substantially across studies. A comparison of work systems components that have been used in prior work appears in appendix C.

For discussion purposes, these practices can be broadly grouped into three areas: *decision authority*, which includes the use of teams and the allocation of individual decision rights; *knowledge work and skills,* which includes skills, training, and supporting practices (e.g. pre-employment screening); and *incentives*, which includes various forms of performance pay, promotions, and incentives for skill acquisition. These categories cover much of what has been discussed in the work systems literature and map closely to the theoretical model presented later.

2.2 Trends in Information Technology Use

Driven by advances in microelectronics, the quality adjusted price of information technology hardware has been dropping by 20-30% annually for the last thirty years (Berndt and Griliches, 1990; Gordon, 1990). This has led to a tenfold increase in share of computers in capital stock since 1970. This large and relatively exogenous capital accumulation is now of sufficient magnitude to potentially alter the costs and benefits of various types of organizational structures.

The development of the personal computer in the early 1980s led to a shift in the location of this computing power from large centralized "utilities" to workers' desktops. While in 1987 there was a personal computer (PC) for every 30 employees in Fortune 1000 firms, by 1994 there was one PC for every six.[28] There has also been tremendous growth in technologies such as local area networks, databases, and "groupware" which support communication and collaboration among workers. These changes have transformed computers from their traditional role as "back-office" support of accounting,

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28 This number was computed from one of our datasets on computer expenditures. It refers to all Fortune 1000 firms with publicly reported employment information.

finance, and logistics to being fully integrated in the regular work process. The development of decentralized computing technologies has also coincided with the emergence of business process redesign, which emphasizes radical changes in work organization supported by investments in information systems (Hammer, 1990; Hammer and Champy, 1993).

2.3 Information Systems and Organization

A number of authors have proposed a direct link between the diffusion of information technology and changes in the economics of organizations. Wyner and Malone (1996; Malone, 1995) describe a model in which decreases in communications costs created by IT ultimately result in decentralization of decision-making in organizations. Malone, Yates and Benjamin (1987) argue that to the extent that IT reduced coordination and transaction costs, it would differentially favor market organization over hierarchical organization. Milgrom and Roberts (1990) cite the exogenous price decline of IT as the primary driver in the shift from "mass production" to "modern manufacturing". Ichniowski and Kochan (1995) argue that one possible reason that "high performance work systems" have not diffused rapidly, despite large economic benefits, is that they need to be coordinated with changes in information technology. Brickley, Smith and Zimmerman (1996) in their description of the factors that influence organizational design, describe computers as an important factor in the business environment. Other arguments suggest links between information technology and various components of new organizational forms, such as the rise of knowledge work and team-based organization (Attewell and Rule, 1984; Applegate, Cash and Mills, 1988; Drucker, 1988) and the choice between centralized and decentralized authority within or between firms (Leavitt and Whisler, 1958; Malone, Yates and Benjamin, 1987; George and King, 1991; Gurbaxani and Whang, 1991; Malone, 1995; Wenger, 1996; Wyner and Malone, 1996).

Altogether, there is substantial reason to believe that information technology use is related to a shift in the economics of organizations towards increasing communications and information intensive structures. The next section presents a model that relates the various work system components identified earlier to the use of information technology.

3. Theory

A key insight from recent work on the management of information technology investment is that effective use of IT often requires changes in decision rights, incentive systems, skills, or other aspects of work organization. New technologies enable new ways of organizing activity or alter the distribution of information in an organization which facilitates or necessitates a shift in organizational structure. The motivation for this argument is most clearly evident in case studies on the implementation of Lotus Notes,[29] a computer-based tool for supporting information sharing and collaboration.

Orlikowski (1992) describes the experience of a consulting firm (Alpha Corp.[30]) which made a executive-level decision to install Lotus Notes on all the computers in the firm. Because there was a need to share specialized knowledge across the firm, management at Alpha believed that the necessary level of collaboration could be obtained simply by making collaboration technologically feasible. However, when the technology was actually introduced, most employees took little advantage of the information sharing capabilities. One possible explanation for this outcome is that the incentive systems at Alpha stressed individual effort and expertise, rather than group or organizational level performance. Because time spent on information sharing came at the expense of "billable hours", there was little incentive to invest in it.

An interesting contrast is provided by another organization (Info Corp.) which implemented the system in their telephone customer support area. This group had a long

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[29] Lotus Notes is probably the most familiar of a class of applications known as "groupware". The Notes System allows users to enter text, numeric, or graphics information into semi-structured forms which are stored in a database accessible to other users with suitable access permission. Facilities exist for the sorting, editing, locating, transmitting and automatically processing data stored in these forms.

[30] Company names in these case studies are disguised.

history of collaborative work and employed team-based subjective incentive systems (Gallivan, Goh, Hitt and Wyner, 1993). The system was fully accepted almost immediately, leading to substantial improvements in service levels without staffing increases. Over time, Info Corp. began to expand the range of capabilities of the system by linking the telephone support group to other departments in the firm and altering the structure of work group to better utilize workers' specialized skills.

Several economic insights are suggested by these cases. First, the appropriate combination of technology and organization is not known to all managers. Some firms are experimenting with new technologies and not all of these experiments are successful. Second, individually oriented objective incentives may lead to underinvestment in information sharing, even when sharing is technologically possible and desirable. Third, team based structures may be an effective way to coordinate activity when information needs to be shared and work is inherently difficult to objectively evaluate. Finally, new types of structures may emerge as the costs of information sharing are decreased and the appropriate incentives are in place to achieve better use of specific knowledge.

Model. This model considers two ways in which information systems can alter optimal internal organization. First, as in the Lotus Notes example, IT lowers the cost of information sharing and, therefore, raises the optimal level of sharing. Second, IT may also enhance the ability of agents to process information that has been shared, raising the marginal benefits of sharing. Both of these changes create a situation where objective incentives (e.g. piece rates or billable hours) can be detrimental if they encourage allocation of effort away from sharing. In place of these incentives, group or team oriented rewards may be used. Furthermore, since increased education, skills, or decision authority can make shared knowledge more valuable, these practices should also be associated with IT. Altogether, this argument links increased use of IT to subjective or team based incentives, increased decentralization of decision rights, and increased importance of education and training. These arguments will be formalized below.

A natural model for examining the impact of a new activity (sharing) on organizational architecture is the multitask model (Holmstrom and Milgrom, 1991). Consider a principal-agent model where the principal desires the agent to perform two activities: production (t_1) and sharing (t_2). This will be modeled using the standard linear model setup: a risk neutral principal with a benefit function $B(t_1,t_2)$, a risk averse agent with CARA utility (e^{-rs} where s is the transfer to the agent and r is the coefficient of risk aversion)[31] and reservation utility U_0, and an increasing and convex cost of effort $C(t_1, t_2)$. Furthermore, assume that different types of effort are substitutes in the agents cost function ($C_{12}>0$ where subscripts on functions C, B represent derivatives) but that $B_{12} = 0$ (the benefits of the various activities are independent of the level of the other). Taken together, these two assumptions are one way of capturing the idea that there are tradeoffs (in terms of social value) between effort spent on the two activities.

The principal cannot observe effort (t_1, t_2) directly but receives independent signals of effort (μ_1, μ_2) of the form:

$$\mu_1 = t_1 + \varepsilon_1 \qquad \varepsilon_1 = N(0, \sigma_1^2)$$

$$\mu_2 = t_2 + \varepsilon_2 \qquad \varepsilon_2 = N(0, \sigma_2^2)$$

The problem is to design a linear incentive contract $[s(\mu_1, \mu_2) = \alpha_1 \mu_1 + \alpha_1 \mu_2 + \beta]$ that provides the maximum expected social surplus subject to agent individual rationality (IR) and incentive compatibility (IC) constraints. Using the assumptions above, the expected utility maximization program can be simplified to:

$$\max_{\alpha_1,\alpha_2} B(t_1,t_2) - C(t_1,t_2) - \tfrac{1}{2} r\alpha_1^2\sigma_1^2 - \tfrac{1}{2}\alpha_2^2\sigma_2^2$$

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[31] Constant absolute risk aversion (CARA) utility is used because it greatly simplifies the analysis. In addition, when the amount of variable income is small relative to the agent's total wealth, CARA can be considered a first order approximation to a general utility function (Milgrom and Roberts, 1992).

subject to:
$$IC \quad (t_1, t_2) \in \arg\max \alpha_1 t_1 + \alpha_2 t_2 + \beta - C(t_1, t_2)$$
$$IR \quad \alpha_1 t_1 + \alpha_2 t_2 + \beta - C(t_1, t_2) - \tfrac{1}{2} r\alpha_1^2\sigma_1^2 - \tfrac{1}{2} r\alpha_2^2\sigma_2^2 > U_0$$

Given this basic setup, it is possible to explore several cases that are of interest. First, consider the situation where production is a measurable activity ($\sigma_1^2 = c < \infty$), but there is no way to measure sharing ($\sigma_2^2 = \infty$). In practice, sharing could be unmeasurable because it is difficult to construct an objective measure of information; even if the amount of shared information could be observed, there would be no way to measure the value of this information nor, in most cases, the effort expended in producing or sharing it.

The effect on incentives can be found by solving the model as structured above and then taking the limit as $\sigma_2^2 \to \infty$. From the IR constraint, it is clear that the $\alpha_2 = 0$. The expression for α_1 is given by (see appendix D):

$$\alpha_1 = \frac{B_1 - B_2 \frac{C_{12}}{C_{22}}}{1 + r\sigma_1^2 (C_{11} - \frac{C_{12}^2}{C_{22}})}$$

This can be compared to the incentive levels for activity 1 if there were no other activities:[32]

$$\alpha_1^* = \frac{B_1}{1 + r\sigma_1^2 C_{11}}$$

This is also the expression if the two activities are independent in the agent's cost function (C_{12}=0). It can be shown that if C_{12}>0, then α_1 is decreasing in C_{12},. This implies that α_1*> α_1; incentives on "production" are lower than they would be if there

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[32] This also corresponds to the situation where the agent is unwilling to share any information without an incentive. For the purposes of the discussion we are assuming that even with zero incentive there will be some information sharing, which probably is reasonably consistent with actual practice (Holmstrom and Milgrom, 1991).

were sufficient incentives for "sharing". Furthermore, if production itself gets harder to measure (e.g., involves more difficult to measure knowledge work), the optimal level of individual objective incentives will also be decreased.

While the reduction in incentives is desirable for ensuring the proper balance of effort, this reduction also leads to overall effort levels being further removed from the optimal full information solution (where the principal can observe effort directly: t_1,t_2 s.t. $B_1=C_1$, $B_2=C_2$). One remedy is to base incentives on larger aggregates of agents (assuming that overall group output also reflects some benefits of sharing). For simplicity, assume that there are now two identical agents (a,b) that work independently but have some need to share information. Furthermore, assume that the principal can observe a composite of efforts:[33]

$$\mu_g = t_1^a + t_2^a + t_1^b + t_2^b + \varepsilon_g \qquad \varepsilon_g \sim N(0,\sigma_g^2)$$

The principal can then compute a signal of sharing from this composite:

$$\mu_s = \mu_g - \mu_1^a - \mu_1^b = t_2^a + t_2^b + \varepsilon_s \qquad \varepsilon_s = N(0,\sigma_g^2 + 2\sigma_1^2) = N(0,\sigma_s^2)$$

This model has the same characteristics of the two-signal, single agent model as before but with a finite variance on the sharing measure. The equations that characterize the solution of this model are somewhat cumbersome and are presented in appendix D. However, in general, incentives on both activities are increased; sharing incentives are increased because sharing can now be measured and production incentives are increased because the agent has less reason to substitute away from sharing.

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[33] The avoids complications in identifying the contribution of the sharing components for more general measures and computing the appropriate variances. The actual functional form is unimportant except to the extent that given a value of the function, the principal can deduce total effort (with some random noise). For example, a production function that takes as its argument total effort would be a suitable signal.

These analyses have so far assumed that the marginal benefits of sharing (B_2) are simply a function of the effort level in sharing. They can also be influenced by other factors. Since the provision and receipt of information is inherently an intellectual task, it is likely that the performance of these activities can be increased when agents have greater levels of education and training. In addition, information is only valuable to the extent that agents have the ability to act on it. This suggests that increased individual decision authority will be more valuable when agents are well informed. These arguments would suggest an additional complementarity between sharing, decentralized decision rights, and human capital.

These can be incorporated in the model by assuming that the benefit function is increasing in the components outlined above:

$$B = B(t_1, t_2;\ H, D),\ B_{2H} > 0\ B_{2D} > 0 \text{ for } D>D^*,\ H>H^*$$

where: H is a measure of human capital

D is the extent of decentralized decision authority

D^*, H^* are the optimal levels of human capital before information technology changed the value of sharing

To determine the ultimate effect on incentives of human capital and decision rights in this model, the relationship between human capital and the value of production effort needs to be specified. Assuming that the firm was optimally organized before information sharing was important, total net benefits cannot be increasing in either D or H above the levels D^* and H^* without a change in some other parameter. This allows the following conclusions to be drawn if the firm makes any investment in increasing sharing ($t_2 > t_2{}^*$):

α_1 is decreasing in H, D

α_2 is increasing in H, D

or alternatively:

$-\alpha_1$, α_2, H, D have a covariance matrix with all positive elements

This implies that decreased individual objective incentives, increased team-based incentives, increased acquisition of skills and education, and decentralization of decision authority are all *complementary*. While this type of modeling allows us to formalize the link between IT and organizational architecture, it also highlights the limitations of objective incentives when work is difficult to measure. Ideally, firms would rather increase the strength of incentives to approach first best levels of effort. However, they are limited because of the effects on the agents' allocation of attention.

One strategy to improve incentives when objective measures are insufficient is to use various types of subjective incentives. Kandel and Lazear (1992) argue that social incentives ("guilt" and "shame") can be used to overcome free riding in team production and increase overall incentive intensity when work is organized in teams. The strength of these incentives may be increased when agents are more socially obligated to the team, which provides an economic justification for culture and team-building activities (these can include both team skills such as team communications and group decision making as well as activities for building team cohesion such as inter-team competitions, retreats, company sponsored events, etc.). More broadly, when workers can observe each other in ways in which the principal cannot, incentives can be improved by allowing the team more discretion to divide revenue or allocate costs based on private information (Milgrom and Roberts, 1990). This would suggest an additional role of self-management in teams. Self-management can also be interpreted as a way of providing incentives through residual rights which is one way to avoid problems of contractual incompleteness (see Hart, 1988 or Wenger, 1996 for a model specifically about information sharing). For example, the workers on a self-managing team may be able to "skim" some of the benefits they create and, therefore, have improved incentives.

Subjective incentives can also be used to complement objective incentives, although an additional mechanism needs to be identified to prevent principals from reneging. Without some sort of credible commitment, the optimal strategy is for principals to renege, and agents forecasting this result, discount incentives based on subjective measures. Baker, Gibbons and Murphy (1994) present a model in which subjective incentives can be used when managers and workers are engaged in repeated interactions.

Subjective evaluations can also be particularly effective in promotion tournaments (Milgrom and Roberts, 1992, p. 369) when management is precommitted to promoting at least one agent. This would suggest increased use of subjective incentives, such as bonuses and promotions, when work is difficult to objectively measure.

Overall, this model describes a link between information sharing which is supported by information technology and a system of work practices which includes: 1) a substitution of team-based incentives, subjectively-based incentives, or performance-based promotions for objective incentives, 2) self-managing teams and other forms of decentralized decision authority, and 3) greater levels of investment in skills and education.

One way to interpret this system of practices is the shift from centralized, command and control style organizational architecture, to a decentralized organizational architecture where decision rights are allocated to line workers. Wyner and Malone (1996) and Malone (1995), using a different argument, arrive at a similar relationship between IT and decentralization. As communications costs drop, firms that are centralized can gain increased efficiency in the use of local knowledge by allowing agents to interact directly with each other, leading to a "connected decentralized" organizational structure. Our model identified additional complementary organizational characteristics that support decentralization such as the use of team-based decentralization of authority, subjective and team-oriented incentives, and increases in education and training. For the rest of the paper, this work system will therefore be described as decentralization or a decentralized organizational architecture.

4. Empirical Implementation

4.1 Firm-level, Multi-industry Data

The relationships proposed in the theoretical discussion will be examined using multi-industry, firm-level data on information technology characteristics, work practices, and organizational performance. Multifactor productivity will be used as the performance measure since it has as well established theoretical framework and has been used in previous work on IT and firm performance (Milgrom and Roberts, 1992; Brynjolfsson and Hitt, 1994; 1995; 1996; Lichtenberg, 1995).

The analysis focuses on firm level data, rather than plant-level data for a number of reasons. First, when comparing the costs and benefits of alternative work systems, it is important to clearly define the boundaries of the unit of analysis. For many types of costs and benefits, it may not be meaningful to treat establishments within a firm as separate entities. Information technology networks often span multiple establishments within the same firms, as do managerial decision-making activities, yet neither is likely to be reflected in the accounting ledgers of the individual establishments. The common management and technology infrastructure of establishments within a firm may be associated with common human resource practices, work systems, and "corporate culture" (Milgrom and Roberts, 1992). More generally, incomplete contracts theory (Grossman and Hart, 1986; Hart, 1988) argues that because firm boundaries are set to address problems of contractual incompleteness, the presence of multiple establishments in a single integrated firm suggests some difficulty that prevents these establishments from operating on a stand-alone basis.

For these and other reasons, substantially more data are publicly available on firms than on plants or business units. This information is important for various parts of this analysis, particularly for performance measurement. Unlike firms, individual establishments do not have audited financial statements and the data that are available at an unconsolidated level are subject to intra-firm reporting biases that can add substantial error (Kaplan, 1989).

A multi-industry approach is used because it enables generalizable findings. Previous case-based or industry-specific studies have left open the question of whether findings generalize to the broader economy (Ichniowski and Kochan, 1995). The relationship between IT and organizational architecture may differ on a case by case basis depending on unobserved, idiosyncratic factors in a particular company or industry. Broader trends, if any exist, may be more apparent in a more diverse sample.

4.2 Data Sources

The data set used for this analysis is a cross sectional survey of organizational practices conducted in 1995 and matched to a five year panel of information technology spending and productivity metrics over the 1990-1994 time period. A brief description of each data source follows:

Computer Technology: The measures of information technology use were derived from the Computer Intelligence Corporation installation database that details information technology spending by site for companies in the Fortune 1000 (approximately 25,000 sites were aggregated to form the measures for the 1000 companies that represent the total population). This database is derived from telephone surveys of establishments that detail the ownership for information technology equipment and related products. Most sites are updated at least annually with greater sampling for larger sites. The year-end state of the database from 1990 to 1994 was used for the IT measures. These data include variables capturing the total capital stock of information technology (central processors, personal computers (PCs), and peripherals) as well as measures of computing power, number of PCs, and the use of networking technology (number of local area network nodes).

Organizational Practices Survey: This survey was prepared based on the organizational characteristics identified in the theoretical section. Questions were adapted from prior surveys on human resource practices and workplace transformation (Huselid, 1994; Ichniowski, Shaw and Prunnushi, 1994; Osterman, 1994). These questions address various types of firm incentives and decision authority, the extent of computerization, the effects of computers on various organizational dimensions, and other miscellaneous characteristics of the workplace (further detail appears in the Results section).

The survey was administered to senior human resource managers or their designees and asked questions about organizational practices at the most typical plant. The approach of Osterman (1994) was followed in focusing on a single class of employee who are termed "production employees" (which corresponds to Osterman's "core employee"). A production employee was defined as "non-managerial, non-supervisory personnel directly involved in producing a firm's product or delivering its service".

Data collection was accomplished in two waves using phone interviews and targeting a subsample of the Fortune 1000. The first wave, conducted in Summer, 1995, yielded 133 usable responses from a population of approximately 447 relevant firms. The instrument was then revised and administered by a different research company in Fall, 1995 to an additional sample of 250 firms, netting an additional 138 responses for a total of 273 used in this analysis. The most common explanations for non-response were "company policy" or "didn't have time". Copies of the instruments appear in Appendix E.

The means on some of the variables differ somewhat between the two samples, although at least some of this difference is attributable to different levels of production worker skill. Because all the questions that were revised were factual, it is less likely that changes in the instrument introduced any significant bias. To test for this possibility, we entered a survey identifier into some of the key analyses and found that the results are not significantly different between the two samples (see footnote 43).

Compustat. Where available, Compustat data was used to construct various performance metrics and provide additional firm information not covered by other sources. For the calculation of productivity, the procedures in Hall (1990) were followed; these have been used previously for similar work (Brynjolfsson and Hitt, 1994). Measures were created for output, capital, labor, and value-added to calculate a production function relationship between value-added and the various inputs. Details on this construction are provided in Appendix A.

In interpreting the results, it is important to keep in mind the limitations of the study design. By matching cross-sectional data on organizational characteristics to panel data on productivity, this approach is consistent with the attempt to use workplace characteristics to explain long-run differences in productivity. However, it does limit the ability to address issues of causality. While it would have been ideal to have panel data on organizational characteristics as well, these data were unavailable historically and extensive retrospective surveying was deemed too unreliable.

Summary statistics on the sample are provided in Table 1. The firms in and out of the sample are roughly similar in terms of financial performance and production inputs, although the average firm is slightly smaller and uses slightly more IT.[34] Approximately 53% of the sample is in manufacturing, mining, or construction and 47% are in services. To validate the data collection procedures, the revised instrument contained questions about how representative production workers were in terms of total employment and the uniformity of work practices for these workers. Overall, for the average firm in the second survey subsample, production workers account for 65% of total employment and organizational practices are found to be fairly uniform: on average, 88% of production workers are covered by same practices and 65% of the firms report complete uniformity of practices. This suggests that the work organization of production workers is

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34 This comparison is restricted to firms that have complete production input data on Compustat.

sufficiently important to have an economic impact on the firm as a whole. Furthermore, the survey may be capturing the work practices of this group fairly accurately.

5. Results

5.1 Correlations - Work Practices

In this section, we examine the relationship between IT and a work system encompassing the three factors we described earlier: decision rights, education and skills, and incentives. All correlational analysis in this and subsequent sections is done using Spearman rank order correlations[35] between various measures of IT and the work system variables (which tend to be non-metric), controlling for firm size (employment), production worker occupation, and industry.[36] Five measures of IT are considered, four from the CI database [total value of installed based (ITCAP), total central processing power[37] in millions of instructions per second (MIPS), number of PCs (TOTPC), and number of local area network nodes (LAN)] and a five-point measure of the computerization of the workplace on the organizational practices survey (COMP). Multiple measures are employed because they capture slightly different aspects of computerization (for example, MIPS measures centralized computing, while TOTPC measures decentralized computing), and they give some sense of the consistency across different measures.

IT and Decision Rights. The survey captures two aspects of decision authority: structures that decentralize authority such as self-managing teams and employee involvement groups, and the allocation of individual decisions on various aspects of the production process, such as the pace or method of work. The correlations with IT of

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35 Results are similar when probit or ordered probit regression is used. We report Spearman correlations because they are easier to interpret given the multi-level nature of most of our work system variables and do not require outlier removal for some firms with extreme values of information systems inputs.

36 Included are separate controls for mining/construction, high technology manufacturing (instruments, transportation, electronics, computers), process manufacturing (paper, chemicals, petroleum), other non-durable manufacturing, other durable manufacturing, transport, utilities, trade, finance, and services.

37 Total central processing power does not include the processing power of PCs.

these measures are shown in Table 2a. In terms of structural decentralization, the results show strong correlations between the use of self-managing teams and IT as well as some evidence that high IT firms employ broader job classifications. However, there is little relationship with employee involvement groups. In terms of individual decision rights, the results consistently indicate that IT is associated with increased decentralization, but the strength of the relationship varies substantially by measure of IT.

The revised survey expanded the individual decision authority scale to cover seven items and broadened the scale from 3 points to 5. The individual items are almost all positively correlated with the various measures of IT. When a composite scale is created by adding up the standardized values of the 7 decision authority variables (Cronbach's alpha=.73)[38] there is a consistent positive correlation with decentralization, significant at $p<.01$ for two of the measures. Unfortunately, this improved measure is only available for 135 observations. As a compromise, a similar measure was computed as the sum of the standardized values of the pace and method decisions variables (Cronbach's alpha=.41), which also shows positive correlation; however, the strength of the relationship appears to be weakened by measurement error in the first wave of the survey. On balance, there is substantial evidence that information technology is broadly related to decentralized authority.

IT and Skills/Education. The analysis is repeated for the various measures of human capital: workforce composition, skills and education, and skill acquisition (Table 2b). IT across a number of measures is related to a higher proportion of managers and professionals and lower proportions of unskilled workers. There is little net correlation with clerical or skilled blue collar workers. In terms of education level and work skill content, there is a consistent positive relationship between skill levels and a positive but insignificant relationship between education, although this appears to be product of the

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[38] This approach requires the assumption that the decision authority variables, which are measured on a five point scale, can be treated as metric variables. This is one of the situations in the paper where this assumption is necessary. However, despite the strong assumptions inherent in this approach, this strategy is quite common in the psychometric research literature.

measure that was used.[39] These results are broadly consistent with the conjecture of capital-skill complementarity (Griliches, 1969) and recent evidence that "high-tech" capital is a complement to white-collar work (Berndt, Morrison and Rosenblum, 1992).

These results suggest that high IT firms have higher levels of human capital on average. To further probe this result, additional measures of skills were considered: pre-employment screening for education and incentives for skill acquisition (pay for skills and the weight of skill acquisition on the promotion decision). Consistent with earlier arguments, various measures of IT are correlated with the percentage of the workforce receiving training and the importance of education in hiring. In addition, there is some weak evidence of a relationship between IT and the use of pay for skills programs and promotion based on skill acquisition.[40] Interestingly, the positive correlation between IT and investments in skills remains when controls for the prior level of skills are included. This provides additional, albeit circumstantial, evidence of a complementarity between IT and skill.

IT and Incentives. The survey contains measures that capture a range of incentive instruments including: 1) objective contractual incentives involving overall incentive pay and the various types of pay for performance systems, 2) subjective incentive pay, 3) promotion incentives on individual performance, 4) team building and team-based promotion incentives, and 5) "menu of contracts" performance pay. The results of these correlational analyses are contained in Table 2c. There is evidence that high IT firms are

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[39] In the second wave of the survey the education question was changed to have a continuous distribution. This resulted in stronger correlations between the use of PCs and total computer processing power. The original question asked the respondent to rate the average level of education of the workforce on a five point scale where most of the respondents replied high school or some college. The revised measure had the respondent allocate percentage of the workforce between 3 categories: high school or less, some college and college or more. The correlations generally improve and tend to be significant with the new measure, despite the smaller sample size. Furthermore, we find that IT is a complement to college educated workers, neutral for workers with some college, and negative for those with a high school or less education.

[40] The relatively low correlations may again be partially caused by the lack of variation in these measures: pay for skills programs are relatively uncommon (adopted by only 28% of the firms, and are particularly uncommon outside of manufacturing), and most firms rate skill acquisition as being very or extremely important (4 or 5 on a 5 point scale).

less likely to use objective performance pay, especially at the level of individuals. In contrast, IT is correlated with the use of subjective incentives and performance-based promotions, and there is even stronger evidence of a relationship with team-based incentives, particularly team building. There is some evidence, with one measure of IT, that more computerized firms are more likely to use a "menu of contracts" incentive plan. Overall, this suggests that IT is associated with *decreased* observability of work on balance and, thus, systems that rely less on third-party observability and more on team-based incentives.

5.2 Measuring Work Systems

The earlier arguments and results suggest the emergence of a work system that incorporates subjective and team based incentives, the use of team-based organization, decentralization of decision rights, and increased levels of skills and education. Because the theoretical argument suggests that these factors are all likely to be correlated, a single measure is constructed that captures the adoption of these practices as a system. As an alternative, we also use a single measure - the use of self-managing teams - that appears empirically to be the most representative of the work system scale. Use of this measure avoids assumptions required for aggregating non-metric scales. Both of these measures will be used to investigate the relationship among IT, decentralization and productivity.

To examine whether these practices tend to be adopted together as the theory would predict, a principal components analysis of the 14 relevant measures of work practices was conducted. For discussion purposes, these measures were subdivided into three groups that correspond to earlier arguments: incentives, teams and decision authority, and human capital.

The correlation matrix between aggregates of the work system measures in shown in Table 2d. The three factors that make up a decentralized work system are positively (and significantly) correlated suggesting that these factors do tend to appear as a system. Furthermore, they are individually correlated with the use of information technology.

The principal components analysis is shown in Table 2e. The first principal component accounts for approximately 25% of the variance, and a Scree plot (Figure 1) suggests that this is the only non-noise factor. The factor loadings are broadly consistent with the work system arguments and the weights on most of the work system measures are .4 or higher. The only unusual result is the relatively low loading on education (which appears strongly on the second factor). To examine this further, the analysis is repeated using only the revised survey which includes more accurate measures of both education and individual decision authority. As expected, the loadings on both these variables improve, suggesting the presence of some measurement error but confirming the overall factor structure. The self-managing teams variable shows the highest loading, suggesting that decentralization is well proxied by this variable alone. Based on this analysis, a variable is constructed (SYSTEM) by summing the sum of the sign-corrected standardized values of all variables included in the factor analysis. The resulting Cronbach's alpha is .76 which indicates adequate reliability. To facilitate interpretation in the regression analysis, this variable is standardized to a mean of zero and a variance of 1.

As before, information technology is also correlated with this system, although it is possible that this relationship is due to workforce composition or industry rather than a direct relationship with IT. Firms that employ a disproportionate number of professionals are likely candidates for both increased use of information technology as well as the adoption of decentralized work structures. To test for this possibility, the correlations are repeated without controls and then successively controlling for firm size (employment), production worker occupation, industry, and workforce composition. While the correlations (Table 3) do appear to decline somewhat as additional control variables are added, the results do not appear to be driven only by human capital differences across firms. Interestingly, the results are strongest for the local area networks variable, which is possibly the closest measure of decentralized IT use.

One explanation for the correlation we find between IT and decentralized work systems is that they are complements: firms that adopt one are more likely to adopt the other.

However, it is difficult to rule out the existence of a variety of other third factors that might simultaneously lead firms to use more IT and adopt decentralized structures without there being any link between the two. One way to address this problem is to examine the productivity impact of these factors. If the correlation between IT and decentralization is solely a result of random exogenous factors, then on average there should be no productivity differences between firms that adopt the practices together and those that do not. However, if there is a difference between firms that are both high IT and decentralized (and low IT and decentralized), it becomes substantially more difficult to construct an alternative hypothesis that is consistent with the data.

The fact that the correlations are not perfect is helpful for the subsequent productivity analysis. If all firms were optimally combining IT and decentralization according to the model, then there would be perfect correlation between IT and decentralized work systems and no differences in performance.[41] If firms were completely random in the adoption of both, it should be possible to obtain relatively precise productivity comparisons, but the correlations would be near zero. Evidence from case studies suggest that there is likely to be some combination of suboptimization and other exogenous factors that allow us to observe different combinations in practice.

5.2 IT and Work Systems: Evidence from Productivity Analyses

In order to calculate productivity, we use the standard approach that has been used to study the effects of various inputs on productivity such as R&D (Griliches, 1986). This framework has also been applied in previous work on the relationship between IT and productivity (Brynjolfsson and Hitt, 1994; 1995; 1996; Lichtenberg, 1995). Several variations of a production function were estimated relating firm (i) value added (VA) to three inputs: IT Capital (C), Non-IT Capital (K) and Labor (L), industry (j) and time (t). Assuming that the production relationship is suitably captured by the Cobb-Douglas form, the equation is:

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[41] The existence of correlations also presumes some sample variation from exogenous factors.

$$VA = A(j,t)C^{\alpha_c}K^{\alpha_k}L^{\alpha_l}$$

The Cobb-Douglas formulation can be considered a first-order approximation to any arbitrary production function; thus, all functional forms should give approximately the same results for parameter estimates close to the sample mean. This assumption also simplifies the introduction and interpretation of the work system variables. From this specification, an estimating equation can be derived by taking logarithms and appending an error term with the usual OLS properties:

$$\log VA_{i,t} = \alpha_0 + \alpha_c \log C_{i,t} + \alpha_k \log K_{i,t} + \alpha_l \log L_{i,t} + \sum_{j=1}^{J-1} \gamma_j D_{j,t} + \sum_{t'=1}^{T-1} \gamma_{t'} T_{t',t} + \varepsilon$$

where: T_t and D_j are dummy variables for time and industry

The coefficient α_0 represents the overall efficiency of the firms in the sample, and the other parameters (α_c, α_k, α_l) represent the output elasticities for each of the three factors (roughly, the percentage increase in output for a 1% change in the use of an input). Work systems will be incorporated in two ways. First, to examine the overall effect of the work system on productivity, multifactor productivity can be modeled as a function of the work system variable by simply entering it additively in the equation. Second, to examine technical complementarity, an IT-work system interaction variable can also be added to the equation.

5.2.2 Basic Production Function Estimates

A comparison of a baseline productivity regression and regressions adding work system variables is shown in Table 4a. In the base regression, the output elasticity of IT is clearly positive (t=3.7) and the magnitudes of all coefficients are comparable with previous estimates using different firm-level data (Brynjolfsson and Hitt, 1994). When the system variable is entered alone,[42] it has a positive but statistically insignificant impact on productivity and the direct coefficient on IT drops slightly.

However, the effect of the SYSTEM is substantial when combined with IT. When the interaction between SYSTEM and IT is added, the coefficient is large and significant: a one standard deviation increase in SYSTEM increases the elasticity of IT by about 55%.[43] This implies that firms that adopt both high levels of IT use and decentralized work system show significantly better performance than firms that just adopt one or the other. Conversely, firms that adopt a centralized system and have low IT investments are also better off. This provides strong additional evidence of our theoretical argument and correlational results that information technology is related to decentralized work practices. In the remainder of this section, the robustness of this result to changes in specification will be considered.

To test whether this complementarity is unique to IT or just an artifact of an overall complementarity with all input factors, the model is reestimated with interaction terms with ordinary capital and labor. Both of these terms are insignificant and the IT interaction remains significant and approximately the same magnitude. However, the standard error doubles, probably because of multicollinearity with the other interaction terms.

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[42] An added quadratic term of the SYSTEM variable was negative and insignificant.

[43] When additional two additional terms are added to capture survey differences (System x Survey ID and IT x System x Survey ID) the two added terms are not significant individually or jointly (χ^2=2.6, p=.29). This suggests that differences among the surveys have not influenced the results.

As a second robustness check, the system variable is replace by five dummy variables representing the different levels of the self-managing teams variable as a proxy for decentralized work systems. As we mentioned earlier, it is the team variable that appears to be most associated with the SYSTEM construct, and estimating the equation using multiple dummy variables avoids the econometric assumptions involved in aggregating discrete variables to form a scale. The results are broadly similar to the SYSTEM variable, although it appears that teams themselves may have a negative impact on productivity before the complementarity effect is considered. As before, the work system-IT interaction is positive and significant (monotonically increasing in increased adoption of teams, with the two ends of the scale being statistically different).

One difficulty of using the three input Cobb-Douglas production function is that the overall explanatory power in the regression is dominated by the input terms, particularly labor. Furthermore, it is quite possible that labor is at least partially endogenous in this regression since firms with unexpectedly high or low demand may be able to adjust their labor input within a single year. This would lead to a correlation between labor and the error term in the productivity regressions and possible unknown biases in the other estimates. To correct for this possibility, we estimate a partial productivity specification, which fixes the elasticity of labor at its theoretical value.[44] The results of this analysis are similar to those reported earlier although somewhat stronger in terms of statistical significance and magnitude of the effect (Table 4b).[45] Results are also similar when labor is dropped entirely and the equation is specified as a "semi-reduced form" (Griliches and Mairesse, 1984).[46]

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[44] The theoretical value for the labor elasticity is its factor share, defined as average labor divided by average output. To be conservative, we also allow for a 10% return to labor which places the elasticity at .61, where the actual factor share is .55. Regressions using a labor elasticity of .55 show an even higher return to capital and IT.

[45] A Hausman test confirms that both labor and capital are endogenous when using twice lagged capital and labor as instruments. However, in terms of economic effect, the difference in the estimates are small, and lagged variables are not preferred instruments when there is serial correlation or fixed effects. We therefore focus on the OLS results rather than instrumental variables.

[46] The semi-reduced form regression treats output and labor as endogenous, and computers and capital as exogenous. The specification is the same as the Cobb-Douglas production function without labor included as a regressor except the coefficients on capital and computers now represent the ratio of their elasticities to

This comparison shows the overall contribution in terms of the output elasticity of IT but does not indicate whether these firms are more effective users of IT in terms of average or marginal product since these firms also tend to use more IT. A straightforward calculation yields the marginal product of computer capital (MP_c) based on the Cobb-Douglas production function specification used earlier:

$$MP_c = \frac{\partial VA}{\partial C} = \frac{VA}{C}\frac{\partial \log VA}{\partial \log C} = \frac{VA}{C}\alpha_c$$

However, this calculation provides marginal rather than average returns. Whether marginal returns and average returns are correlated depends on the relative location of the marginal benefit curves. If higher marginal returns are assumed to result from shifts in the marginal benefit (demand) curve, then differences in return are indicative of performance differences. However, if all firms lie on the same curve, a high return is a sign of *underinvestment*. There are several special cases in which these situations can be distinguished. In particular, if the shape of the marginal benefit curves is the same for all firms and marginal return is higher at a higher level of investment, then the marginal benefit curve must lie strictly higher (greater return per unit of investment).

Interestingly, after estimating average factor input as a function of the SYSTEM variable, the results suggest that the level of investment in IT and the marginal rate of return both increase with increasing use of decentralized work systems. To get a sense of the magnitude, firms that are one standard deviation above the mean on the SYSTEM variable use approximately 13% more IT than the mean firm and earn a rate of return (before costs) that is about 34% higher. A similar result is found for the self-managing teams variable. These results are consistent with the conjecture that firms that use decentralized work systems are more effective users of information technology in terms of economic and statistical significance.

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one minus the labor elasticity (i.e. the sum of the ordinary capital and computer capital coefficients is 1 if

5.2.3 Time-Series Evidence (Fixed Effects).

Although the survey contains primarily cross sectional data, some aspects of the time dimension can also be considered. First, the base production function specification with the IT-decentralization term is estimated as a fixed effects model This is possible because there is variation in the IT component of the cross product even though the decentralization measures are constant over time. A positive coefficient on this term would be evidence that the benefits from increased IT investment are greater in decentralized firms than in centralized firms. An advantage of this specification is that it removes all cross-sectional variation and, therefore, the results cannot be driven by sample heterogeneity. This makes causal inferences more reliable. On the other hand, this specification can increase biases due to errors in measurement.

The results of several variations on this fixed effect regression are presented in Table 5. The most promising of these specifications is the fixed effects analysis in semi-reduced form, which provides further control for endogeneity of labor. This specification shows the least change in the other coefficients (ordinary capital, IT capital). However, regardless of specification, the IT-System interaction is positive, significant, and approximately the same order of magnitude as before. These regressions help rule out the possibility that the IT-system interaction was a spurious result from uncontrolled firm heterogeneity, although the changes in the other coefficients would suggest some caution in interpretation.

Another approach is to take advantage of the limited amount of time series information in the survey. The survey asked the respondent to name when the last time there has been a restructuring of production work and to describe the change. Approximately 8% of the firms (21 firms) reported that they had moved to a more team-based organization within the sample period. No firms reported moving away from such an organization. From this

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there are constant returns to scale).

information, a variable is constructed which captures the time series variation in team adoption: zero in all years if the firm did not report any restructuring or before any team-oriented restructuring was reported and 1 for all observations after the date of team-oriented restructuring. This resulted in 54 post restructuring observations and approximately 900 pre-restructuring observations in the sample (the remainder are missing observations on the restructuring variable). This variable and its interaction with IT was then included in a productivity regression. Despite the relatively small number of post-restructuring observations, the direct effect is negative and insignificant, while the interaction term (IT x post restructuring) is positive and significant (t=2.7). This result is complementary to our earlier results: firms that have undergone team-oriented restructuring show higher productivity from their IT investments. As a final analysis, we combined the fixed effects analysis with use of this restructuring variable, simultaneously looking at changes in IT and changes in the use of teams. The results are no longer significant, presumably because there is insufficient statistical power to distinguish this second-order effect. However, the coefficient on the interaction term remains positive.

In summary, the time series results are consistent with the previous interpretation that a complementarity exists between IT and decentralization. Decentralized firms derive bigger benefits when they increase their IT investments, and IT-intensive firms derive bigger benefits when they switch to more decentralized work systems.

5.2.4 Instrumental Variables

In order for the production function analyses to have any statistical power, it must be possible to observe firms with different combinations of information technology and work practices. However, if all firms are jointly optimizing their information technology use and work systems subject to the same exogenous conditions, there should be no true sample variation. There are two possible reasons why we could expect to find different combinations in practice: some firms are not optimizing, or firms face different conditions. There is reason to believe both effects are present in practice. As the Notes example highlights, practitioners and researchers may not fully understand the linkages between IT and organization which lead them to be late adopters or make incorrect adoption choices. For IT, this may be a particular problem because many of the technologies, such as groupware, are very new. Firms may also face very different costs of organizational change which lead some to adopt these changes faster than others. Factors such as environmental turbulence and past decisions can impact the rate at which organizations change and lead to wide variation in the adoption of new technologies and work practices.

There are three sets of variables from the organizational practices survey that are potentially useful for modeling variation in the adoption of IT and complementary work systems but are not likely to influence productivity directly for reasons outside the model. First, there is a battery of questions on how managers believe that IT is influencing their organization. We hypothesize that firms which rate IT as leading to job upgrading, such as increasing worker skill or providing workers more freedom of action, are more likely to adopt decentralized work systems with IT than those that view IT as primarily a way of reducing staff or increasing control (e.g., decreasing number of workers, increasing monitoring). Second, since firms that are undergoing major restructuring may have more opportunity to make radical changes in work organization, six dummy variables are included that capture whether the firm underwent a major change (acquisition, divestiture, senior management change, downsizing or layoff, removing levels of hierarchy, strategy change) during the sample period. Finally, firms which employ more educated staff may be better able to adapt to a changes in organization (Bartel, Lichtenberg and Vaughan, 1989) which would suggest education and skill levels as instruments. We also include twice lagged values of the input variables (capital, labor and IT) along with the interactions of lagged IT and the other work system instruments. Thus, only industry and time are assumed to be completely exogenous.

Productivity estimates using these instruments are shown in Table 6. The first column contains the regression results using the full instrument list and the SYSTEM variable as previously defined. The second column contains the regression results when a similar instrument list is used but excluding human capital levels from the system variable (but not human capital acquisition).

In both cases, the results are very similar to earlier analyses. Interestingly, the system variable is somewhat larger in magnitude than the earlier analyses and strongly significant in both regressions. This suggests that the measurement error or endogeneity may have biased down the OLS results.[47] Overall, the IV analysis confirms the earlier results and suggests that they are robust to explicitly modeling the sample variation in work system and IT choices.

5.2.5 Other Within-Sample Changes

A key assumption in these productivity analyses is that the organizational characteristics remain fixed over our 5 year sample period, or at least any biases introduced by changes in work systems over time are small.[48] Within our sample period approximately 43% of the sample reported some sort of substantial restructuring. However, based on content analysis of change descriptions, 8% reported a change toward team-based organization and no firms reported a move toward centralization. Furthermore, many of the changes represented events such as downsizing, changing internal reporting relationships, or equipment changes with no explicit mention of further work reorganization. This would generally suggest that while restructuring is prevalent, work system change is a gradual process and the impact of our assumptions that work systems were constant across the sample period is somewhat small.

To examine this econometrically, we compare firms that report a change to those that do not in three ways. First, the analysis is conducted separately for firms that restructured

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[47] IV estimates in fixed effects led to insignificant results, probably because of lack of power in the first stage regressions.

[48] We consider an additional robustness test in Appendix B, where we pool the data over five years and estimate a "between" model. Again, we find the results are robust to this specification change.

and those that did not. Second, the two samples are pooled and analyzed with separate coefficients on the IT-SYSTEM interaction for the restructuring and non-restructuring group. Finally, the panel structure of our data is used to refine the estimate by adding two interaction terms: one that includes all the points post-restructuring (and zero for firms that did not restructure or for points in restructuring firms before the event) and a second interaction that includes all the pre-restructuring points (and zero following restructuring). Thus, the sample is split into two parts, but the split point (in time) potentially occurs at a different point for each firm. In all three analyses, there is a consistent result. The magnitudes of the interaction terms are not significantly different from the earlier estimates in any analysis and are not significantly different from each other (t=.80, t=.83, and t=1.1 for the comparison of the interaction terms in each analysis respectively). Again, this suggests that the results do not appear to be substantially biased by within-sample changes.

6. Summary and Discussion

This paper argued that information technology may be related to a substantial shift in the economics of organizations toward greater use of teams and decentralized authority, increased importance of human capital, and incentive systems that addressed the measurement difficulties of team-based, knowledge-intensive work. Using data on organizational practices for 273 large firms, we find two types of support for this hypothesis: 1) IT intensive firms are more likely to use the individual practices associated with decentralization as well as the overall decentralized work system, and 2) firms that use decentralized work systems show greater productivity from their IT investments. This is robust to alternative work system measures, productivity specifications, and assumptions about causality. While the analysis is primarily cross-sectional, the effect also appears in a fixed effects analysis; firms that have decentralized work systems have greater benefits from increasing IT investments.

The most straightforward explanation of these results is that IT is complementary (in the Milgrom and Roberts, 1990 sense) to decentralized work systems. This may partially explain why early studies on the productivity of information technology found little benefits, while more recent studies suggest large productivity gains attributable to IT. Firms may be making the necessary changes in organization to support their IT investments. Furthermore, the difficulty of making concurrent technological and organizational change may partially explain why some firms appear to earn persistent excess returns to IT. Reversing this argument, this also suggests why "organizational innovation" (Osterman, 1994) has been relatively slow to diffuse, despite potentially large economic benefits.

It is difficult to construct alternative hypotheses that are consistent with our results. Any alternative explanation would have to explain why firms that have high levels of IT and decentralized work systems *and* firms that have low levels of IT and centralized work systems are both more productive than firms that use one but not the other. One possibility is that the IT is acting as a proxy for other organizational characteristics, such as the presence of knowledge or information assets. It is likely that these types of characteristics are also complementary to decentralized work systems. However, this does not necessarily argue against the complementarities interpretation but, rather, relabels it. While it may be inappropriate to attribute all of the value of this larger system (IT, decentralization, knowledge) to the components measured in this study, the basic underlying argument is the same: there are complementarites between technology and organizational characteristics that may lead to changes in firm structure.

As with all empirical studies of this nature, errors in specification or measurement are always a potential issue. The study was designed to minimize such biases by using survey strategies found in prior work and obtaining data on productivity, organizational characteristics, and IT from different sources. Ideally, one would like panel data on both organizational characteristics and information technology spending. This would facilitate a direct model of the various types of mutual causation that are likely to be present. In addition, it may be important to distinguish the various uses of information technology. Because IT is a "general purpose technology", there are likely to be a variety of ways firms use the same amount of IT, some of which are more likely to lead to (or require) substantive organizational change.

Limitations notwithstanding, this study provides some of the first large sample evidence of a broad correlation between IT use and decentralized work systems and that work organization influences the relationship between information technology and productivity. The quality-adjusted investment in IT by firms is likely to continue to increase by 20% annually for at least a decade, suggesting that the issues addressed in this paper will become increasingly important (and more evident empirically) in the future.

Tables and Figures

Table 1: Summary Statistics (Year End 1994) - Mean Firm

Variable	Sample	Remainder of Fortune 1000
Employment	25,400	29,300
Capital Stock (non-IT)	$4.47 Bn	$4.58 Bn
Labor Costs	$910 MM	$1060 MM
Computer Capital	$75 MM	$66 MM
Value Added	$1.70 Bn	$1.81 Bn
Pretax Return on Assets	4.5%	4.5%
Shareholder Return (1 year)	17.6%	18.2%
Sales Growth (1 year)	9.8%	9.9%
Number of Firms	260	532

Note: Sample sizes reduced because we limit the calculations to firms with a complete set of production inputs (capital, labor, value-added, IT). Total sample size is N=273.

Table 2a: Correlations between IT and Decision Authority

Spearman rank order correlations controlling for size, industry, and production worker occupation (N=242-260)

Measure (scale in parenthesis)	IT Capital	MIPS	LAN	TOTPC	COMP
Structural Decentralization					
Self-Managing Teams (1-5)	.18***	.29***	.33***	.27***	.20***
Employee Inv. Grps. (1-5)	.04	.07	.08	.08	.05
Broad Jobs (1-5)	.09	.19***	.15**	.13**	.21***
Individual Decentralization					
Pace of Work (1-3)	.07	.03	.05	.07	.12*
Method of Work (1-3)	.11*	.13**	.05	.10	.16**
Composite: Pace/Method	.11*	.12*	.06	.10	.17**
Composite: 7 Measures^	.16*	.15	.14	.24***	.26***
Individual Control & DA^	.14	.24**	.01	.12	.21***

Key: * - p<.1, ** - p<.05, *** - p<.01

^ - Limited to second wave survey (N=130)

Table 2b: Correlations between IT and Human Capital

Spearman rank order correlations controlling for size, industry, and production worker occupation (N=245-260)

Measure (scale in parenthesis)	IT Capital	MIPS	LAN	TOTPC	CCMP
Skills/Education					
Skill Levels (1-5)	.12*	.21***	.08	.16**	.40***
Education (1-6)	.07	.05	-.05	.08	.22***
Workforce Composition					
Clerical (%)	-.10	-.03	-.03	-.09	-.04
Unskilled Blue Collar (%)	-.17**	-.14*	-.17**	-.16**	-.14*
Skilled Blue Collar (%)	.00	-.06	.00	.11	.03
Managers (%)	.19***	.16**	.08	.13*	.09
Professionals (%)	.37***	.44***	.30***	.29***	.12
Skill Acquisition					
Training (% staff)	.14**	.14**	.12*	.13*	.22***
Pay for Skills (0/1)	.06	.05	.22***	.16**	.05
Promote for Skill (1-5)	-.03	.12*	.02	.04	.13**
Screen for Education (1-5)	.14**	.17***	.13**	.23***	.32***

Key: * - p<.1, ** - p<.05, *** - p<.01

Table 2c: Correlations between IT and Incentives

Spearman rank order correlations controlling for size, industry, and production worker occupation (N=230-260, unless noted)

Measure (scale in parenthesis)	IT Capital	MIPS	LAN	TOTPC	Prod. Comp.
Contractual Incentives (N=160)					
Variable Incentive Pay (%)	-.14*	-.14*	-.17**	-.16**	.00
Individual Incentives (%)	-.15*	-.22**	-.17**	-.16**	.00
Group Incentives (%)	.09	.10	.00	.08	.01
Company Incentives (%)	.05	.12	.09	.04	.05
Subjective Performance Pay					
Subjective Perf. Pay (0/1)	.02	.01	.13*	.08	.16**
Individual Promotions					
Promote on Performance (1-5)	.00	.13**	.08	.04	.02
Promote on Seniority (1-5)	-.08	-.08	-.21***	-.08	-.18*
Team Incentives					
Team Building	.24***	.25***	.31***	.29***	.14**
Promote for Teamwork	.08	.15**	.12*	.05	.09
Private Info Incentives					
Use Menu of Contracts (0/1)	.02	-.02	.01	.10	.27***

Key: * - p<.1, ** - p<.05, *** - p<.01

Table 2d: Correlation Matrix of Four Work System Components

Spearman rank order correlations controlling for size (N=230)

	Teams/DA	Incentives	Human Capital
Teams/DA Variables (4)			
Incentives (7)	.41***		
Human Capital (3)	.25***	.31***	
IT Capital (1)	.14**	.13**	.23***

Key: ** - p<.05, *** - p<.01

Table 2e: Unrotated Principal Components for System Variable Construction

	Full Sample		Second Wave Survey	
Variable	First PC	Second PC	First PC	Second PC
Self Mg. Teams	.74	-.28	.53	-.24
Composite: DA	.57	-.13	.64	-.19
Employee Inv. Grps	.51	-.43	.32	-.32
Skilled Work	.55	-.11	.42	-.49
Education	.26	.39	.55	-.00
Training	.39	-.19	.38	-.45
Screening for Education	.57	-.03	.31	-.10
Promote Skill	.33	.57	.43	.61
Promote Performance	.38	.68	.39	.69
Promote Seniority (-)	.36	.52	.57	.26
Subjective Incentive Pay	.42	.04	.30	.19
Pay for Skills	.54	-.24	.03	-.06
Team Building	.65	-.26	.56	-.31
Promote for Teams	.46	.44	.55	.36
Percent of Variance Explained	25%	13%	20%	13%

Table 3: Correlations between SYSTEM and IT Variables

Spearman rank order correlations controlling for size, industry, and production worker occupation

Measure	IT Capital	MIPS	LAN	TOTPC	COMP
Base (occupation, size)	.15**	.33***	.33***	.28***	.31***
+ industry	.15**	.26***	.31***	.24***	.27***
+ individual human cap.	.13*	.22***	.30***	.20***	.19***
+ workforce comp.	.09	.17**	.27**	.15*	.18**

Key: * - p< .1, ** - p<.05, *** - p<.01

Table 4a: Productivity Regression: Work Systems

Variable	Baseline	System & IT-System Interaction	System & All Factor-System Int.	Teams & All Factor-Team Int.
α_c (IT Elasticity)	.0371*** (.0101)	.0381*** (.0105)	.0382*** (.0105)	.0293** (.0136)
α_k (Capital Elasticity)	.174*** (.0127)	.176*** (.0126)	.177*** (.0125)	.171*** (.010)
α_l (Labor Elasticity)	.699*** (.0182)	.690*** (.0184)	.689*** (.0184)	.696*** (.0190)
System		.00190 (.00753)	.00202 (.00798)	
IT x System		.0211*** (.00448)	.0166* (.0127)	
Capital x System			.00842 (.00826)	
Labor x System			-.00190 (.0114)	
IT x Team=2				.00428 (.0167)
IT x Team=3				.0206 (.0176)
IT x Team=4				.0389** (.0182)
IT x Team=5				.0703*** (.0198)
Controls	Sector*** Year	Sector*** Year	Sector*** Year	Sector*** Year Teams***
R^2	93.8%	93.9%	93.9%	93.9%

Key: * - p<.1, **- p<.05, *** - p<.01, Heteroskedasticity-consistent (White) Standard Errors in parenthesis

Note: In team regression, IT elasticity represents the baseline at Team=1. It is therefore not comparable to the other estimates. The reported interactions represent incremental changes from this base.

Table 4b: Partial Productivity Regressions with IT-SYSTEM Interactions

Variable	Baseline	System & IT-System Interaction	Teams & All Factor-Team Int.
α_c (IT Elasticity)	.0641*** (.00861)	.0614*** (.00888)	.0500*** (.0122)
α_k (Capital Elasticity)	.206*** (.0110)	.205*** (.0110)	.199*** (.0111)
α_l (Labor Elasticity)	fixed at .61	fixed at .61	fixed at .61
System		.00580 (.00790)	
IT x System		.0251*** (.00448)	
IT x Team=2			.00242 (.0163)
IT x Team=3			.0251 (.0177)
IT x Team=4			.0609*** (.0177)
IT x Team=5			.0777*** (.0206)
Controls	Sector*** Year	Sector*** Year	Sector*** Year Teams***
R^2	69.8%	70.5%	70.6%

Key: * - p<.1, **- p<.05, *** - p<.01, Heteroskedasticity-consistent (White) Standard Errors in parenthesis

Note: In team regression, IT elasticity represents the baseline at Team=1. It is therefore not comparable to the other estimates of IT elasticity. The reported interactions represent incremental changes from this base.

Table 5: Fixed effects estimates

Variable	SRF Fixed Effects	Const. Labor Fixed Effects	3 Factor Fixed Effects
a_c (IT Elasticity)	.0065 (.0072)	-.0241** (.0105)	-.0305** (.0102)
a_k (Capital Elasticity)	.188*** (.0133)	.130*** (.0198)	.0373 (.0220)
a_l (Labor Elasticity)		.61 (fixed)	.881*** (.0235)
IT x System	.0167** (.0078)	.0357*** (.0112)	.0324** (.0108)
Controls	Firm	Firm	Firm
R^2	97.3%	94.3%	98.9%

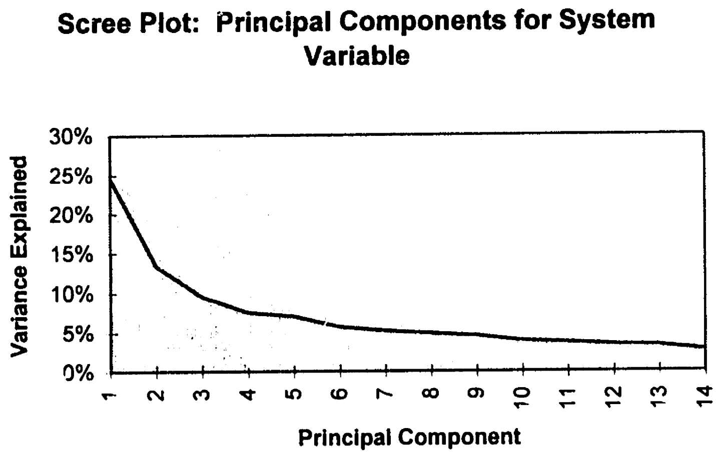
Key: * - p<.1, **- p<.05, *** - p<.01

Table 6: Instrumental variables estimates

Variable	IV System	IV System without Human Capital
a_c (IT Elasticity)	.0692*** (.0109)	.0457*** (.0123)
a_k (Capital Elasticity)	.167*** (.0119)	.169*** (.0112)
a_l (Labor Elasticity)	.664*** (.0171)	.693*** (.0159)
System	-.0158 (.0143)	-.00538 (.017)
IT x System	.0801*** (.0169)	.0633*** (.0144)
Controls	Sector*** Year	Sector*** Year
R^2	93.1%	93.8%

Key: * - p<.1, **- p<.05, *** - p<.01

Figure 1: Scree Plot of Work System Factor Analysis



Appendix A: Variables and Data Construction for Productivity Calculation

The variables used for this analysis were constructed as follows:

Sales. Total Sales as reported on Compustat [Item #12, Sales (Net)] deflated by 2-digit industry level deflators from Gross Output and Related Series by Industry from the BEA for 1988-1992, and estimated for 1993-1994 using five-year average inflation rate by industry. When an industry deflator is not available, the sector level producer price index for intermediate materials, supplies and components is used (Council of Economic Advisors, 1995).

IT Capital. We take total purchase value of computer equipment as reported by Computer Intelligence Corp. and deflate it using an extrapolation of Gordon's (1990) deflator for computers (price change -19.3% per year).

Ordinary Capital. This figure was computed from total book value of capital (equipment, structures and all other capital) following the method in (Hall, 1990). Gross book value of capital stock [Compustat Item #7 - Property, Plant and Equipment (Total - Gross)] was deflated by the GDP implicit price deflator for fixed investment. The deflator was applied at the calculated average age of the capital stock, based on the three year average of the ratio of total accumulated depreciation [calculated from Compustat item #8 - Property, Plant & Equipment (Total - Net)] to current depreciation [Compustat item #14 - Depreciation and Amortization]. The calculation of average age differs slightly from the method in Hall (1990) who made a further adjustment for current depreciation. The constant dollar value of IT capital (as calculated above) was subtracted from this result. Thus, the sum of ordinary capital and IT capital equals total capital stock.

Labor Expense. Labor expense was either taken directly from Compustat (Item #42 - Labor and related expenses) or calculated as a sector average labor cost per employee multiplied by total employees (Compustat Item #29 - Employees), and deflated by the price index for Total Compensation (Council of Economic Advisors, 1995). The average labor expense per employee was taken from BLS data on hourly cost of workers (including benefits) for 10 sectors of the economy. For firms which had labor expense directly reported on Compustat which did not include benefits (identified by Compustat Item - Labor Expense Footnote), we adjusted the labor figure by multiplying reported labor expense by the total compensation/wages ratio for each sector as reported by BLS.

Employees. Number of employees was taken directly from Compustat (Item #29 - Employees). No adjustments were made to this figure.

Materials. Materials was calculated by subtracting undeflated labor expenses (calculated above) from total expense and deflating by the industry level output deflator. Total expense was computed as the difference between Operating Income Before Depreciation (Compustat Item #13), and Sales (Net) (Compustat Item #12).

Value-Added. Computed from deflated Sales (as calculated above) less deflated Materials.

Appendix B: "Between" Estimation

In this section, we examine the behavior of a between estimator which averages the time-series variation across the five years. Intuitively, one would expect the coefficients to be roughly comparable, although less efficiently estimated (under the hypothesis that the organizational change variables are constant across the time period considered). This feature, combined with the sample size reduction, should result in generally higher standard errors. We repeat the key analyses in this section in both full and partial (labor elasticity fixed) productivity form. We use weighted least squares (weights are the square root of the number of cross sectional units averaged) to account for the slightly unbalanced nature of this panel. The results shown in table B1 below are consistent with the earlier findings, and in all cases are significant at p<.1 or better on the key coefficients.

TABLE B1 Variable	Baseline	IT x System	Baseline Partial Prod.	IT x System
α_c (IT Elasticity)	.0513** (.0220)	.0522** (.0223)	.0749*** (.0182)	.0733*** (.0181)
α_k (Capital Elasticity)	.176*** (.0227)	.178*** (.0227)	.199*** (.0212)	.197*** (.0208)
α_l (Labor Elasticity)	.679*** (.0339)	.672*** (.0342)	.61 (fixed)	.61 (fixed)
System		.00340 (.0149)		.00381 (.0152)
IT x System		.0300* (.0162)		.0356** (.0161)
Controls	Sector***	Sector***	Sector***	Sector***
R^2 (weighted) (unweighted)	97.9% 95.1%	98.0% 95.2%	88.8% 73.6%	89.1% 74.0%

Key: ^ -p<.2, * - p<.1, **- p<.05, *** - p<.01, Heteroscedasticity-consistent (White) Standard Errors in parenthesis.

Appendix C: Previous studies of work systems

Table C1: Relationship of our measures to previous research

Work Practice	This Study	Osterman	Ichniowski et. al.	Huselid	Lawler et. al.	MacDuffie
Job Rotation/Cross-training	✓	✓	✓		✓	✓
Self-Directed Teams	✓	✓	✓		✓	✓
Quality Circles/Emp. Inv.	✓	✓		✓	✓	✓
Pre-Employment Screening	✓			✓		✓
Training	✓		✓	✓	✓	✓
"Alternative" Incentives	✓		✓	✓	✓	
No Layoffs	✓		✓			
Team Building Activities	✓		✓		✓	
Individual Decision Auth.	✓					✓
Promote on Skill	✓			✓		

Appendix D: Derivation of Two Signal Multitask Model

The program for this model appears in the text. The first order conditions for the objective function are given by:

$$B_1 - \alpha_1(1 + rC_{11}\sigma_1^2) - r\alpha_2 C_{12}\sigma_2^2 = 0$$
$$B_2 - \alpha_2(1 + rC_{22}\sigma_2^2) - r\alpha_1 C_{12}\sigma_1^2 = 0$$

[technical note: these equations are obtained by first substituting the IC constraint into the objective function (changing α_i to C_i), differentiating to obtain the first order conditions, and then using the IC constraints again to express the equation in terms of the αs]

From these equations it is clear that as long as there are positive incentives on both activities, in the optimal solution, there are tradeoffs between the incentive intensities on the two activities.

Solving these equations simultaneously yields the following equation for α_1:

$$\alpha_1 = \frac{B_1 + rC_{22}\sigma_2^2(B_1 - \frac{C_{12}}{C_{11}}B_2)}{(1 + rC_{11}\sigma_1^2)(1 + rC_{22}\sigma_2^2) - r^2C_{12}^2\sigma_1^2\sigma_2^2}$$

Because of the symmetry of the problem, the equation for α_2 is the same form (simply swap 1 with 2 and 2 with 1 in all subscripts). The relationship to the case where sharing is unmeasurable ($\sigma_2^2 = \infty$) is more apparent when this equation is rewritten:

$$\alpha_1 = \frac{B_1 + rC_{22}\sigma_2^2(B_1 - \frac{C_{12}}{C_{11}}B_2)}{rC_{22}\sigma_2^2\{1 + (r\sigma_1^2)(\frac{C_{11}}{rC_{22}\sigma_2^2} + C_{11} - \frac{C_{12}^2}{C_{22}})\}}$$

Taking the limit as $\sigma_2^2 \rightarrow \infty$ yields the equation in the text.

Appendix E: Survey Instrument

<u>Organizational Practices Survey</u>
(questions used for this analysis)

A. Production Workers

A1. Where is your firm's most typical establishment located?
(City, State):____

A1a. To the nearest 10%, what percentage of your firm's employees are production workers?
_____%

A1b. About how long has the average production worker been with the firm?
_____ YEARS

A2. In terms of the whole firm, please estimate to the nearest 20% the percentage of all production employees covered by the same human resource practices as those at your most typical establishment? Would you say 20%, 40%, 60%, 80% of 100%?
______%

A3. Can you name two or three high volume products produced at your most typical establishment:

____

A4. Can you name three titles of employees you consider to be production workers at that establishment:

____

A5. Now I'd like you to rate the working conditions for production workers at your most typical establishment. First, would you rate...

	Very High	Moderately High	Medium	Moderately Low	Very Low
a. the average level of individual control and decision making that workers have in conducting their own work?	☐	☐	☐	☐	☐
b. How would you rate the average level of skill required to perform production work?	☐	☐	☐	☐	☐
c. How would you rate the average level of physical activity required?	☐	☐	☐	☐	☐
d. How would you rate the amount of diversity associated with the production work itself?	☐	☐	☐	☐	☐

e. How would you rate the level of computerization of the work tasks?	☐	☐	☐	☐	☐

A6. Next I want to know about the arrangement between workers and managers in the conduct of the work.

	Exclusively Workers	Mostly Workers	Equally	Mostly Managers	Exclusively Managers
a. Who sets the pace of work?	☐	☐	☐	☐	☐
b. Who schedules production work?	☐	☐	☐	☐	☐
c. Who distributes this work among the workers?	☐	☐	☐	☐	☐
d. Who decides how the tasks should be accomplished?	☐	☐	☐	☐	☐
e. Who deals with difficult situations in production?	☐	☐	☐	☐	☐
f. Who deals with customers in routine situations?	☐	☐	☐	☐	☐
g. Who deals with customers over problems or complaints?	☐	☐	☐	☐	☐

A7. Next I would like you to tell me about how computerization has affected production workers?

	Greatly Increased	Slightly Increased	Slightly Decreased	Greatly Decreased	No Effect
a. Would you say that computerization has greatly increased, slightly increased, slightly decreased, greatly decreased or had no effect on the skill requirements of production jobs?	☐	☐	☐	☐	☐
b. Would you say that computerization has greatly increased, slightly increased, slightly decreased, greatly decreased or had no effect on the repetitiveness of work?	☐	☐	☐	☐	☐
c. Using the same categories, has computerization affected the need to monitor work?	☐	☐	☐	☐	☐
d. Has computerization affected the ability to monitor work?	☐	☐	☐	☐	☐
e. Has computerization affected worker autonomy?	☐	☐	☐	☐	☐
f. What about its effect on the ability of supervisors to manage	☐	☐	☐	☐	☐

workers?

g. What about its effect of the number of workers needed to do the work?	☐	☐	☐	☐	☐

The next set of questions is about the extent to which workers are provided with decision making and training opportunities.

A8. Does your firm use "self-managing teams"?
____ (yes, no) [If no, skip to question A9]

A8a. Would you say your firm uses self-managing teams very heavily, heavily, moderately or slightly?
___ Very heavily
___ Heavily
___ Moderately
___ Slightly

A9. Does your firm use any other form of team-based organization different from self-managing teams?
____ (yes, no) [If no, skip to question A10]

A9a. Would you say your firm uses this other team approach very heavily, heavily, moderately or slightly?
___ Very heavily
___ Heavily
___ Moderately
___ Slightly

A10. Does your firm use "employee involvement groups"?
____ (yes, no) [If no, skip to question A11]

A10a. Would you say your firm uses employee involvement groups very heavily, heavily, moderately or slightly?
___ Very heavily
___ Heavily
___ Moderately
___ Slightly

A11. Does your firm use team-building or group cohesion techniques?
____ (yes, no) [If no, skip to question A12]

A11a. Would you say your firm uses these techniques very heavily, heavily, moderately or slightly?
___ Very heavily
___ Heavily

___ Moderately
___ Slightly

A12. Does your firm cross-train workers?
____ (yes, no) [If no, skip to question A13]

A12a. Would you say your firm cross-trains very heavily, heavily, moderately or slightly?
___ Very heavily
___ Heavily
___ Moderately
___ Slightly

A13. Does your firm use temporary production workers for specialized activities?
_____ (yes, no) [If no, skip to question A14]

A13a. Would you say your firm hires temporary workers very often, often, sometimes, or rarely?
___ Very often
___ Often
___ Sometimes
___ Rarely

A14. Does your firm have any kind of incentive plan for production workers?
____ (yes, no) [If no, skip to question A21]

A15. What percentage of total compensation for production workers, not including benefits, is based on some form of variable incentive pay?
______%

Different firms manage their incentive pay operation differently. The next questions ask for your best estimates of the basis for your firm's incentive pay for production workers?

A16a. First, is some portion of incentive pay for production workers based on individual criteria such as pay for skill acquisition or piecework performance?
____ (yes, no) [If no, skip to A16c]

A16b. Please describe the individual criteria in place at your firm for production worker incentive pay:

____

A16c. Is some portion of incentive pay for production workers based on group performance such as gain sharing?
____ (yes, no)

A16d. Is some portion of incentive pay for production workers based on overall firm performance?

____ (yes, no) [If more than 1 box marked Yes in 16a, 16c and 16d, go to A18]

A17. Then, at your particular firm, all worker incentive pay comes from (Box marked "Yes"), is that right?

____ (yes, no) [Yes - go to A19, No - Re-ask 16a, 16b, 16c]

A18. What is your best guess as to the percentage split in incentive pay between (Read Boxes Marked) for production workers at your firm?

_____% individual ____% group _____% firm

A19. If I looked at the total incentive pay to production workers a different way and asked what percentage of it is based on objective criteria such as pieces produced or number of defects versus subjective criteria such as supervisor review, would you be able to give a meaningful answer?

_____ (yes, no) [If no, skip to A21]

A20. About what percentage of production worker incentive pay would you say is based on objective performance criteria?

_____%

A21. We've talked about incentive pay, now I would like to ask about the promotion of workers. How important are the following factors when promoting production workers?

	Extremely	Very	Somewhat	Not too	Not at all
a. First, seniority, would you say seniority is extremely important, very important, somewhat important, not too important or not at all important?	☐	☐	☐	☐	☐
b. Would you say teamwork is extremely important, very important, somewhat important, not too important or not at all important?	☐	☐	☐	☐	☐
c. How important is skill acquisition?	☐	☐	☐	☐	☐
d. How important is good performance on the job?	☐	☐	☐	☐	☐

A23. How important are the following criteria when conducting pre-employment screens for new production workers?

	Extremely	Very	Somewhat	Not too	Not at all
a. Would you say educational background is extremely important, very important, somewhat important, not too	☐	☐	☐	☐	☐

important or not at all important?					
b. How important is the applicant's score on the formal pre-employment test?	☐	☐	☐	☐	☐
c. How important is prior experience in a similar job or industry?	☐	☐	☐	☐	☐

A24. Please tell me about what percentage of your production workforce has a high school education or less, what percentage has some college or technical school, and what percentage has a college degree?

_____% High school or less
_____% Some college or technical school
_____% College grad

A25. What percentage of production workers received any work-related training off-the-job during the last 12 months? *("Off-the-job" training includes classroom training, or courses or seminars apart from regular work activities.)*

_____ % [if 0%, skip to A27]

A26. Deleted from survey

A27. What is your best estimate of the yearly turnover rate for production workers?

_____% per year

A28. To your knowledge has the production operation of your firm undergone any significant reorganization since you've worked there?

_____ (yes, no) [If no, skip to A31]

A29. When would that have been?

____ Month/Year

A30. Can you briefly describe the nature of the reorganization?

____

A31. How long have you worked at your firm?

_____ Years

B. Firm-Wide Characteristics

Next I want to ask you to estimate how various jobs are distributed across the entire firm, and about any large scale changes that might have happened recently. Some of these questions are quite detailed. If you are not sure of an answer please feel free to give you best guess.

B1. Approximately what percentage of jobs in your firm are in each of the following categories? I will read the categories first and then ask you the percentage of each?

Clerical	______%
Unskilled blue-collar workers	______%
Skilled blue-collar workers	______%
Managers and supervisors	______%
Non-managerial professionals	______%
Total	100%

B1a. Has this distribution been fairly stable over the last 5 years or have there been significant gains or losses in one or another of these categories

______ (stable, gains or losses) [if stable, skip to B2]

B1b. What categories have gained or lost employees?________________________

B2. About what percent per year have wages for clerical workers grown or decreased over the last five years?

______%

B3. About what percent per year have wages for unskilled blue-collar workers grown or decreased over the last five years?

______%

B4. About what percent per year have wages for skilled blue-collar workers grown or decreased over the last five years?

______%

B5. About what percent per year have wages for managers and supervisors grown or decreased over the last five years?

______%

B6. About what percent per year have wages for non-managerial professionals grown or decreased over the last five years?

______%

Now I'd like to know about organizational change within the firm in the last five years.

B7. Have there been mergers or acquisitions in the last five years?

_____ (yes, no)

B8. Have there been divestitures in the last five years?

_____ (yes, no)

B9. Have there been layoffs in the last five years?

_____ (yes, no)

B10. Has there been a downsizing with more than 10% of employees affected in the last five years?

_____ (yes, no)

B11. Have there been a delayering or flattening of the hierarchy in the last five years?

_____ (yes, no)

B12. Have there been a restructuring or internal realignment in the last five years?

_____ (yes, no)

B13. Have there been a major strategy change in the last five years, such as a shift in product lines, an entrance or withdrawal from established markets or shifts away from long-term suppliers?

_____ (yes, no)

B14. Has there been a change in the senior most executive or significant changes in persons answering to this executive in the last five years?

_____ (yes, no)

B15. Have there been a financial restructuring, such as a leveraged buyout or an employee buyout?

_____ (yes, no)

B16. To the nearest 25%, about what percent of production workers in the entire firm are covered by some form of union or collective bargaining agreement?

_____ %

Additional questions on internal firm structure and computerization of work were also included, but not used in this analysis.

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Information Technology and Firm Boundaries: Evidence from Panel Data

Doctoral Dissertation Chapter 3

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Abstract

Previous literature suggested that information technology (IT) has the potential to alter the optimal large scale organizational structure of a firm by changing the relative costs of coordinating economic activity within and between firms (internal and external coordination). This paper examines this hypothesis by determining the empirical relationships among vertical integration, diversification, and information technology use. Because the roles of internal and external coordination differ between vertical integration and diversification, this comparison enables a test of the existence as well as the relative magnitudes of these types of coordination benefits. These tests are performed using an 8 year, near balanced panel data set of information technology spending, firm structure, and relevant control variables.

Overall, there is a consistent positive relationship between IT and diversification and a negative relationship between IT and vertical integration in both cross section and time series. While it is difficult to rule out the influence of specification error, these results are consistent with the idea that both internal and external coordination costs are lowered by IT. In addition, the results imply that coordination cost has decreased sufficiently to cause a net shift away from vertical integration.

1. Introduction

A central issue facing managers and management researchers is the determinants of firm boundaries. Coase (1937) framed the question as a make or buy decision: when should an intermediate input be produced in the firm rather than purchased in the market. More broadly, firms are continually faced with decisions on what products to produce, what markets to enter or exit, and the quantity of resources to commit to any particular product or activity. Understanding the factors that determine the optimal choice and evolution of firm boundaries is crucial for at least three reasons: the costs of changing firm boundaries can be high, any decision requires a long lead time to implement, and the effect on firm performance of these choices is quite large and appears to be increasing, at least in the late 1980s and early 1990s (Wernerfelt and Montgomery, 1988; Lang and Stulz, 1994; Montgomery, 1994).

Recently, there is some evidence that firms are reducing their levels of diversification and substituting market based governance or relational contracting for vertical integration (Milgrom and Roberts, 1992). This is reflected in the managerial literature in the increased interest in outsourcing, partnerships, and "core competencies" (Johnston and Lawrence, 1988; Konsynski and McFarlan, 1990; Prahalad and Hamel, 1990; Quinn and Holner, 1994). Studies have also shown that in recent time periods, firms that target a narrow set of businesses show higher productivity (Lichtenberg, 1992) and increased market valuation (Lang and Stulz, 1994) relative to their diversified counterparts. This is in contrast to earlier research which has showed a positive valuation in the 1960s and a neutral valuation in the 1970s (Matsusaka, 1995).

One possible explanation for this trend is the facilitating role played by information technology (IT). Theoretical studies (Malone, Yates and Benjamin, 1987; Gurbaxani and Whang, 1991) have argued that IT can potentially alter the cost of coordinating activity within firms (internal coordination) as well as between firms (external coordination). As suggested by Malone and Rockart (1991), the long run impact of this change may be a shift in the economics of organization to favor more coordination intensive firm structures. This relationship between coordination technologies and firm structure also has historical precedent. The technological ability to coordinate activity over long distances provided by the telegraph may partially explain the rapid shift from locally-based to national (and global) firms between 1850 and 1900 (Milgrom and Roberts, 1992). The rapid quality adjusted price decline of computers, the rise of desktop computing, the emergence of interorganizational networks (e.g. the internet), and the diffusion of software-based collaborative tools such as groupware, computer-aided design (CAD), and electronic data interchange (EDI) all facilitate a decline in the unit cost of coordination and enable or necessitate different types of firm structures.

The effect of information technology on firm structure is highly dependent on the relative changes in internal and external coordination costs. As internal coordination costs are decreased, firms may be able to expand in size (vertically, horizontally, or by holding relative boundaries constant). Decreases in external coordination costs will tend to favor market contracting over vertical integration but have little impact on diversification. Furthermore, a proportional change in both types of coordination costs will tend to favor market contracting over vertical integration because the quantity of coordination is greater for markets (Malone, Yates and Benjamin, 1987). Therefore, while it is not possible to compare directly the magnitude of the changes in coordination costs because of differences in the "quantity" of coordination, it is possible to test for the existence of both internal and external coordination benefits and determine which type of benefit dominates in terms of economic significance.

This paper empirically examines the relationship among information technology, vertical integration, and diversification using an 8 year, near-balanced panel of about 600 large firms. The goal is twofold: to provide some general results on the relationship between IT and firm structure and to empirically distinguish IT's effects on internal coordination and external coordination costs. These relationships are examined in both cross section and time series and are carefully controlled for various exogenous factors that might affect firm structure independent from any impact of IT.

The results extend earlier empirical work on the relationship between IT and firm size (Brynjolfsson, Malone, Gurbaxani, and Kambil, 1994) by moving the analysis to the firm level, considering a broader array of firm structure measures, and focusing specifically on the behavior of large firms rather than aggregate movements of industry averages. This analysis also has some similarities to earlier work on the IT-diversification link (Brynjolfsson, Hitt and Viswanathan, 1995), although the dataset employed in this study is much more comprehensive both in terms of sample size and the use of more detailed measures of firm structure and relevant control variables.

The remainder of the paper is structured as follows: section II reviews previous empirical literature on diversification and vertical integration and the theoretical basis for a relationship between IT and firm boundaries, section III discusses the methods and data, section IV contains the results, and the paper concludes with a summary and discussion in section V.

2. Literature Review

The reasons why firms choose to participate in multiple industries has been examined in an extensive literature that includes economics, management science, and sociology. Under assumptions of complete markets and zero transactions costs, any supply arrangement conducted within a firm should be replicable by markets. Similarly, in efficient capital markets, any pattern of firm ownership can be recreated in investors' portfolios as well or better than it can be performed by managers through acquisitions. Thus, researchers have had to look beyond the neoclassical theories of the firm to explain these changes, examining such factors as how information asymmetry leads to market inefficiencies and the relationship between ownership and the nature of economic exchange.

2.1 Diversification Literature

The broader diversification literature was recently surveyed by Montgomery (1994). She identified three sets of explanations for why firms would choose to diversify into multiple businesses: 1) the *agency view* which examines how diversification can arise as managers pursue private benefits at the expense of other parties (e.g. shareholders), 2) the *resource view* which examines whether certain unmarketable scarce resources can be leveraged across multiple markets, and 3) the *market power view* which argues that size can be used to promote collusion through multi-market contact or deter predation through "deep pocket" financial commitments. In addition to these groupings, the empirical literature can be broadly subdivided into two further categories: those studies which examine the relationship between diversification and financial performance and those that attempt to explain the pattern of diversification.

In the diversification-performance literature, most studies done from the economic perspective have generally argued that strategies of de-diversification or focus appear to be more successful. Wernerfelt and Montgomery (1988) found that focused firms appear to show higher performance in cross section. Lang and Stulz (1994) found a substantial discount in market value attributable to diversification over the 1980s as well as evidence that the discount appeared to be increasing using both time series and cross sectional analyses. Matsusaka (1995) examined the 1961-1974 time period, and his results, taken together with studies that have covered the 1980s, led him to conclude that there has been "a major reversal in investor sentiment toward diversification - positive in the 1960s, neutral in the 1970s, and negative in the 1980s." However, while the economics literature is generally in favor of a focus-performance link, other literatures, such as those related to strategic management, tend to emphasize market power effects or internal synergies which give rise to a *positive* diversification-performance link (see the literature review in Grant, Jammine and Thomas, 1988).

There have also been a few studies that have focused on the determinants of diversification without an explicit performance consideration. These studies have examined product market competition (Caves, 1981), intangible resources such as R&D (MacDonald, 1985), and type of human capital (Farjoun, 1994). Overall, these studies find little support for the market power view but some evidence for the resource view. Recently, increases in the efficiency of financial markets may have led to the decreases in diversification found by some authors, consistent with the *agency view*.

2.2 Vertical Integration

While vertical integration is different in practice from diversification, many of the theories apply to both types of industry dispersion. In addition, the constructs used to measure diversification (such as counts of SIC codes) are often unable to make a distinction between vertical and horizontal integration or related and unrelated diversification.

Transactions costs theory (Coase, 1937; Williamson, 1975) argues that firms should use vertical integration (unified governance) when transactions in markets are costly either for explicit reasons (e.g. the cost of writing contracts, locating suppliers, etc.) or because of implicit costs arising from uncertainty, infrequency, or asset specificity. The property rights approach (Grossman and Hart, 1986; Hart, 1988) argues that when ex-ante actions of parties to a transaction are not fully contractible, incentives and total surplus can be affected by the allocation of ownership of essential assets.[49] This translates into a prediction about vertical integration (and possibly related diversification) in the sense that firms are more likely to use market-type governance mechanisms when parties to a supply arrangement must make noncontractible investments to maximize surplus. This is because ownership of assets is one of the few instruments available for providing incentives when contracts are inadequate.

The general predictions of transactions cost theory have been tested in a number of settings. Most studies have found that determinants of contracting costs, such as asset specificity, uncertainty or infrequency of interaction, generally favor long term contracting or unified governance. However, the studies themselves tend to be very situation specific, such as Joskow's (1985; 1987) analysis of coal-supply agreements for electric utilities or Anderson and Schmittlein's (1984) analysis of the tradeoff between the use of independent sales agents and captive company representatives. There is little

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49 The structure of the argument is that in order to get parties to the transaction to make non-contractible investments ex-ante, they must have ex-post bargaining power to ensure that they obtain sufficient ex-post surplus. Because ownership of essential assets confers bargaining power, this develops a link between ownership, incentives, and surplus.

broad-based work on transactions costs across industries and almost no empirical work on incomplete contracts theory.

2.3 IT and Firm Structure

In examining the relationship between information technology and firm structure, it is important to distinguish effects that are likely to act at the economy-wide level and those more specific to firms or industries. For example, the *agency view* links decreases in diversification to increased ability of financial markets to prevent managerial rent seeking. While increased efficiency of financial markets may be associated with the use of IT (see e.g. Clemons and Weber, 1990), the overall effects are not likely to differentially impact firms. However, this would be consistent with IT being responsible for an overall decline in diversification over time (Brynjolfsson, Hitt and Viswanathan, 1995) or decreasing firm size (Brynjolfsson et al., 1994).

More relevant for this analysis are perspectives that address why IT could lead to a variation in firm structure at an industry-specific or firm-specific level. Two plausible candidates are the effects of IT on internal coordination and the effects of IT on external coordination.

Internal Coordination. Internal coordination refers to the ability of firms to manage internal production activities and information flow and can be reduced by IT in a number of ways. First, firms can invest in systems that allow increased monitoring and measurement of individual behaviors (Gurbaxani and Whang, 1991) leading to a reduction in "agency costs". Advances in IT have allowed an increasingly fine grain measurement systems to be implemented down to an individual employee. As production operations are increasingly automated, the capacity for performance measurement has been greatly increased (see Zuboff, 1988). This is particularly true for occupations where computers are a key production technology such as telephone customer service or sales of financial products. However, at the same time, IT may be related to a shift toward increased amounts of knowledge work which may make work more difficult to measure (see Chapter 2). Thus, the ability of IT to decrease internal coordination costs may be limited by other types of changes in work organization enabled by IT.

Second, IT can be used to leverage internal resources across areas of a firm or between different markets. Recent technological developments such as groupware are specifically targeted at facilitating coordination of knowledge and expertise across a firm. There has also been a tremendous automation of research and development (R&D) which may have natural economies of scale or scope.

Finally, although not directly related to internal coordination costs, information technology may be a direct correlate of the existence of internal intangible resources. Information technology is disproportionately used in "information processing" industries and for knowledge work in general (Roach, 1988). One would therefore expect that IT is related to the stock of knowledge or information assets (Brynjolfsson, 1994). Because this type of asset is likely to have value in multiple industries, this implies a link between information technology and diversification.

Taken together, the effect of IT on internal coordination costs would suggest an overall positive correlation between firm-level IT spending and firm size. Depending on other conditions, this size may be manifest either by vertical or horizontal expansion or expansion of scale without changing industry participation.

External Coordination. Just as IT can reduce the costs of coordinating activity within the firm, the transactions cost of coordinating across firms are likely to be lowered. Interorganizational systems such as electronic data interchange are specifically targeted at lowering the costs of external coordination on a simple unit cost basis. This has enabled new types of structures, such as continual replenishment, to appear in high transaction industries (e.g. Proctor and Gamble in consumer packaged goods retailing).

In addition, IT may alter the various indirect factors that determine transactions costs such as asset specificity, frequency, or uncertainty (Williamson, 1989). By enabling mutual monitoring of market transactions or increased forecasting and planning, IT can reduce uncertainty and risk (Clemons, Reddi and Row, 1992). IT can help firms to develop reputations and behavior histories thus making infrequency of transacting less of a constraint. Finally, IT may make equipment more flexible thus reducing asset specificity (Malone, Yates and Benjamin, 1987). All of these factors lower market transactions costs and, therefore, favor market or intermediate governance structures over unified governance (see additional arguments to this effect in Brynjolfsson et al., 1994).

These arguments suggest that when market transactions can substitute for internal activities, a reduction of external coordination costs will lead to increased use of markets. In practice, this should appear as decreased vertical integration and firm size. This may be true even if there is a proportional decrease in internal coordination costs. However, it is less likely to impact diversification, because a firm has little need to replace internal production of diversified products with an outside supplier.

Theory Summary. Depending on the relationship between IT and the two measures of firm structure, we may be able to identify the existence of the various coordination costs effects and examine their relative magnitude of the total effects of both. This is summarized in the following table:

Table a. Summary of theoretical arguments of IT and firm structure

Relationship between IT and Diversification	Relationship between IT and Vertical Integration	
	-	+
+	Internal Coordination (✓) External Coordination (✓)	Internal Coordination (✓) External Coordination (?)
-	Internal Coordination (?) External Coordination (✓)	?

Notation: (✓) indicates that there is evidence that IT lowers this type of coordination cost
(?) indicates that no conclusions can be drawn for this type of coordination cost

In three of the quadrants we can make predictions about the relationship of the two types of coordination costs based on the relationships among IT, vertical integration and diversification. Broadly speaking, the effect of IT on external coordination would manifest itself as decreased vertical integration, while improvements in internal coordination facilitate firm expansion along either dimension. Because the demand for the different types of coordination may be different between vertical integration and diversification (see Malone, Yates and Benjamin, 1987) and the analysis only reveals a reduced form relationship between IT and structure, we cannot make any conclusions about the actual magnitude of changes in marginal cost of coordination. However, depending on where the outcome lies in each of the four quadrants, we may be able to determine the existence of one or both of these effects and possibly the relationship between them.

3. Empirical Implementation

Because there is no off-the-shelf model or standard approach to conducting analyses on the determinants of firm structure, a number of technical issues need to be addressed. This section outlines the various components of the problem and how they were addressed in this paper.

3.1 Measuring Firm Structure

There is an area of the strategic management literature that has been devoted to various measures of firm structure starting with Rumelt (1974). There are more than a dozen measures that have been employed for the study of firm structure ranging from subjective classification schemes (Rumelt, 1974) to various types of objective numerical measures derived from industry percentages. The vast majority of objective measures capture industry dispersion in various ways but do not easily address the vertical integration-diversification distinction. A solution to this problem is to develop an accurate measure of vertical integration and then partial the effect of this variable out of the diversification measure. The "residual" diversification, not accounted for by vertical integration, is then a more accurate measure of true diversification. This is most easily accomplished by entering both variables in a regression simultaneously as independent variables.

We employ three measures of diversification in this analysis. The first is the concentric index used by Wernerfelt and Montgomery (Montgomery and Wernerfelt, 1988; Wernerfelt and Montgomery, 1988) for the study of the performance effects of firm focus. This index captures the "relatedness" of diversification using the following formula:

$$Concentric = \sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_i \alpha_j W_{ij}$$

where: i,j = 1... N where N is the number of 4-digit industries a firm participates in
α_i is the share of industry i in the firms' total employment or sales
W_{ij} is a weighting function:
0 if the industries share the same 3-digit SICs
1 if the industries have different 3-digit SICs but the same 2-digit SIC
2 if the industries have different 2-digit SICs

A higher value of the concentric index indicates a greater dispersion of industries and, therefore, a less "focused" firm. This index can be computed for any dataset where we have revenue or employment shares by industry (or suitable industry related aggregates such as segments - see below). Unfortunately, the weights are based on the SIC system which may or may not capture the right sense of "relatedness". For example, a firm may have advantages in logistics leading them to participate in wholesaling, trucking, and air transport, all of which are in different 2-digit (and in some cases 1-digit) SIC categories. While by one interpretation this represents related diversification, the concentric index would treat it as unrelated. Thus, we can only capture related diversification to the extent it follows the distinctions in the SIC system.

A second measure that captures industry participation but not the relatedness of these industries is a Herfindahl index of industry shares (at the 2-digit level). This is computed by (using above notation):

$$Herfindahl = 1 - \sum_{i=1}^{N} \alpha_i^2$$

As a firm spreads its activities over more 2-digit SIC codes this index will rise. A firm in a single industry will have a value of zero. While this measure doesn't require any judgments about relatedness of SIC codes, it still has the difficulty that it requires industry share information which may be subject to measurement error.

Third, we also include a measure of overall industry dispersion as the count of the number of business segments[50] or SIC codes in which a firm participates (Lichtenberg, 1992; Lang and Stulz, 1994). While these counts do not capture the relatedness or distribution of activities across SIC codes, these measures have the advantage that they require substantially less data to compute and, thus, expand the range of possible sources available. They are also insensitive to errors in measuring revenue or employment shares and can only change when a firm makes a major decision to enter or exit a business line.

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50 The segment data is reported on Compustat.

The segment data also has another unique feature. The number of segments directly represents the way a firm views the relatedness of its product lines and, therefore, already incorporates some judgment about the level a firm has diversified (at least from the perspective of the management of the firm).

For vertical integration, there are very few choices for measures. The most common approach is to use the ratio of value-added to sales. In theory, if sales are held constant and firms purchase more external inputs, value added will be reduced relative to sales and measured vertical integration will be lower. However, in addition to capturing vertical integration, this measure also captures: 1) variations in profitability and, 2) the position of a firm in the value chain (e.g. mining companies will show high value added to sales because there are very few material inputs). As a result, the primary measure used for this study is the vertical industry connection index (VIC) developed by Maddigan (1981). This measure represents how related the industries are in which a firm participates, using the aggregate input-output tables for the U.S. economy (Lawson and Teske, 1994) as a measure of vertical relatedness. While this measure does not incorporate industry shares, it has the advantages that it is motivated by economic theory instead of being ad hoc, requires no subjective judgment, and captures vertical integration uniquely.[51]

3.2 Model and Control Variables

In considering any analysis on the determinants of firms structure, there are two important empirical facts that need to be considered (Montgomery, 1994): 1) large firms in the U.S. economy participate in a substantial number of different industries, and 2) that while

[51] Rumult's measures included subjective classifications for vertical integration. Vertical integration has also been measured by the "specialization ratio" which is the percentage of the firm accounted for by the largest industry. It is not clear how this measure captures vertical integration apart from diversification.

there are changes on the margin over time, on average, the changes are small relative to a large and fairly stable base. It is therefore important to employ a specification that controls for as much of this "natural" variation in firm structure as possible.

Specification. The general specification for this analysis relates the quantity of information technology used by a firm to a measure of vertical integration, a measure of horizontal integration, and a set of appropriate control variables:

$$IT = \beta_0 + \beta_d Diversification + \beta_v Vertical\ Integration + \gamma \log(IT\ Price) \\ + controls + \varepsilon$$

This can be interpreted as a demand equation if IT is measured as a ratio of input quantity to output. The firm structure variables shift the overall demand level for IT but do not change the responsiveness to price changes (price elasticity). To prevent the dependent variable from being influenced by short run economic fluctuations in the level of output, IT is instead measured as the ratio of computer capital stock to total capital stock. It is important to recognize that in this formulation, IT, diversification, and vertical integration are jointly endogenous and the coefficients should not be interpreted as elasticities.[52] Instead, estimates from this equation could best be interpreted as representing conditional correlations between IT and the firm structure measures.

Analytical Approach. As suggested earlier, the approach to controlling for firm heterogeneity is key to this analysis. One strategy is to identify all the relevant variables

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52 A complete model could identify the complete demand system for IT, vertical integration, and diversification. This would involve the specification of (at least) three demand equations (IT, vertical integration and diversification) as a function of each other and unique exogenous variables that are known to affect the levels of these factors but not the others. This system could then be estimated by three stage least squares.

and explicitly include them in the analysis. A second approach is to treat all the unobserved components as a firm effect[53] and use fixed effects, first differences, or long differences for some of the analyses. In this way, firm specific cross-sectional variation can be eliminated retaining only the time series effects. In some cases, this may remove some of the wanted variation and increase other biases due to errors in variables (Griliches and Hausman, 1986) so the analysis will be done in levels, fixed effects, and differences.

Controlling for industry heterogeneity. For cross sectional analyses in firm-level data, it is important to distinguish characteristics that are unique to firms with those that arise because of industry participation. For example, firms which have a substantial presence in financial services industries are likely to have high IT spending relative to other firms even if their core industries are similar. In addition, some measures are only meaningful as an industry weighted average, such as the amount of import competition a firm faces or overall market share. To control for these effects, we use the "chop shop" methodology, originally proposed by LeBaron and Speidell (1987) for other purposes and used by Lang and Stulz (1994) to study the financial effects of diversification. In the context of IT, this would involve the construction of a variable which represents what the firm would have spent on IT if they were at the industry average in all the industries in which they participate. By comparing overall IT to this measure, we can differentiate between firms that have invested extensively in IT and those that are simply in high IT industries.

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[53] A firm effects specification assumes a model of the form:

dependent variable = firm specific constant + independent variables.

If we are not interested in the actual values of the firm constants, we can eliminate them by taking differences over time or subtracting the firm average (for each variable) from the dependent and independent variables. This specification has the advantage that it controls for all factors that are firm specific that do not change over time and therefore eliminates much of the cross sectional heterogeneity in the sample. The firm effects specification has two drawbacks: it requires time series or panel data, and is known to the increase the adverse impact of measurement error (Griliches and Hausman, 1986).

Similarly, it is possible to construct measures of competition or other industry-specific factors that can be used as control variables (Montgomery and Wernerfelt, 1988).

Control Variables. To control for factors that are likely to influence the level of vertical integration or diversification irrespective of the level of IT investments, a number of control variables from prior theoretical and empirical work are incorporated into the analysis. It is important to note that if one assumes profit maximization, we only observe behavior of these firms after they have optimized their firm boundaries. In many cases, it is not clear whether there should be any relationship between firm structure and some of these control variables as a result. However, given that they are included only as controls for sample heterogeneity, lack of any effect makes the statistical analysis less efficient but is unlikely to create any systematic bias.

1) *Time Controls.* As mentioned previously, the agency view is not likely to differentially impact firms, although it can influence broader trends over time. In addition, short run economic effects may influence both the level of diversification as well as the investments in technology. Furthermore, since we do not have good measures available of the IT price, this can also be proxied by a time dummy variable.[54] Therefore, dummy variables are included for each year of the sample to control for these effects.

2) *Market Power Variables.* In cross section, the market power view would suggest that diversified firms have a higher degree of market power in their product markets. This would broadly predict that diversified firms have high levels of market power, but that the level of competition in their markets is relatively low. The same is true for vertical integration but for different reasons Firms that face suppliers with monopoly power

54 The coefficient on the time dummy variable will be a composite of three factors: the price decline of IT, the price elasticity of IT, and other time varying effects on the other variables.

may be more likely to vertically integrate. However, substantial presence in upstream or downstream markets may suggest that these firms have overcome scale barriers rather than having market power per se. This suggests the inclusion of a variable which measures the weighted average market share in all industries as an indicator of own market power (constructed using the chop shop methodology). In addition, for manufacturing industries other variables can also be constructed from industry level data: 1) import competition which is the weighted average share that imports account for as a percentage of gross industry output, 2) export strength which is a similar weighted average for exports as a percentage of domestic product and captures world-wide competitiveness, and 3) industry concentration as measured by the weighted average four firm concentration ratio (or alternatively, a weighted Herfindahl of industry shares in each industry). The import, export, and concentration measures have been previous used by Montgomery and Wernerfelt (1988).

3) *Resources*. By the resource view, firms should be more likely to diversify (and potentially vertically integrate) to leverage resources which cannot be transacted on markets. Research and development investment is likely to represent one of these resources. Therefore, we include the ratio of R&D stock (constructed using the procedures in Hall, 1990) to capital stock to capture these effects.

4) *Other*. There are a number of other variables that arise in the discussion of diversification. Industry growth may be related to diversification (by the *agency view*) if managers choose to diversify when growth opportunities in existing markets are limited. Another argument is that firms diversify to lower variance in returns and are therefore able to use higher leverage. It is unclear whether there is any relationship of these factors to vertical integration. To capture these effects, we include debt to equity ratio and weighted average market growth. In addition, overall firm capital intensity may represent

a firms vulnerability to hold-up in supply arrangements. This would suggest a positive relationship between vertical integration and the capital to output ratio by transactions cost arguments.

The control variables are summarized in the table below. While one cannot claim to have controlled for all sources of variation in firms structure, these variables do capture aspects of the three primary explanations of diversification (agency, market power, resource view), as well as a measure of transactions costs.

Table b. Summary of Expected Influence of Control Variables

	Effect on Vertical Integration	Effect on Diversification
Industry Growth	~	+
Market Share	+	+
Export Intensity	~	+
Import Intensity	-	-
R&D Intensity	+	+
Capital Intensity	+	~
Debt/Equity Ratio	~	+
Concentration	+	+

~ - represents no predicted effect

4. Data

The data for computer spending is identical to that used for IT and productivity analyses described earlier in this thesis (see Chapter 1).

The unique data for this analysis comes from several databases that track industry participation. As part of their surveying process for collecting IT data, Computer Intelligence Infocorp also tracks industry participation for large firms. The core of the data is developed from Dun and Bradstreet's database of firm locations, and is updated during CI's interview process for collecting the IT data. The database is organized by site (approximately 20,000 sites per year are related to the ~600 firms in our analysis) and contains an SIC code, approximate number of employees, and approximate sales. For the early years of the database (1987-1988), there are only size buckets for employment and sales rather than actual numbers (buckets are 1-5, 5-10, 10-50, 50-100...).[55]

The advantage of these data are that they have a complete panel over the 8 years, although the accuracy of some of the size numbers and the overall coverage of sites is unclear. When compared to an alternative source, (TRINET, 1987 only), the CI data in 1987 appears to account for approximately 40% of the sites and 60% of employment (although the employment comparison is suspect because of the use of size buckets in that year by CI). To partially address this error introduced by missing sites, we focus primarily on the percentage distribution across SIC codes for a firm or use SIC counts rather than percentage data. We also compare the various measures of firms structure with other sources to gain additional comfort with the validity of the data.

For 1987, we have the equivalent information from another source called TRINET. The core of this database is developed from telephone directories combined with telephone

[55] The size buckets correspond to the minimum of a size range. We therefore use the midpoint in the bucket range as the true value.

interviewing to obtain number of employees, approximate sales, parent company, and SIC codes. Documentation for these data claim about 80% coverage of sites in the U.S. with SIC codes between 20 and 50 and more than 20 employees.

Compustat II provides several additional measures. First, Compustat tracks a complete list of SIC codes for all firms in their database. Unfortunately, this list is updated periodically and the historical data do not appear on the database.[56] However, we are able to get a list of SICs (although no sales figures or employment data) for 1994 using available sources. In addition, Compustat tracks data on business segments, which come from a FASB regulatory reporting requirement for all firms that began in the mid-1980s. Firms are supposed to report all independent lines of business that represent over 10% of sales. The data include an SIC code for each line of business, a count of the total number of segments and, in some cases, sales, employment, and asset data. In practice, the asset and employment data are highly incomplete, but there appears to be some consistency in the sales data. Because these data rarely sum to actual sales, we use the same method of examining industry proportions as we did for the CI data. These data are available from 1988-1994.

Using the CI, TRINET and Compustat segments data, we are able to construct concentric, Herfindahl and count measures. In addition, we also have count measures for the 1994 Compustat industry data. We also compute the Vertical Industry Connection (VIC) index for the CI data. Table c depicts the years available for each of the data sources.

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[56] The custom services group of Compustat was unhelpful in obtaining back data after repeated attempts to enlist their cooperation. In addition, the updates do not appear to correspond to new releases of the data on any regular interval, thus raising questions about its time series accuracy.

Table c: Data Availability from Various Sources

Year	CI	TRINET	Compustat Bus. Segs.	Compustat Ind. List
1987	X	X		
1988	X		X	
1989	X		X	
1990	X		X	
1991	X		X	
1992	X		X	
1993	X		X	
1994	X		X	X

All "chop shop" measures are calculated using CI employment shares (percent employment by 2 or 4 digit SIC). These appear to be more accurate than the revenue data since the number of employees at an establishment requires no estimation on the part of the respondent about the value of products or services produced and is theoretically non-zero even for establishments that do not have external sales. For IT, we use BEA data at the 2-digit level for an estimate of industry level IT stock. The relevant variables are calculated by constructing an equivalent firm for each real firm in our dataset as an industry weighted average value. We use the average current dollar stock of Office, Computing and Accounting Machinery as reported by the Bureau of Economic Analysis (BEA) divided by current dollar output at the 2-digit SIC level taken from the GDP by Industry Tables (Bureau of Economic Analysis, 1994). This ratio is then converted to constant dollars using the computer deflator. The industry weightings are derived from the CI data by aggregating the data to the two-digit SIC level and using revenue shares of each SIC code.

For other measures, a variety of additional sources are used. Industry level competition was computed from the Census Bureau 1987 and 1992 concentration indices by 4-digit manufacturing industries (no equivalent exists for services). The data on the four firm concentration ratio and a Herfindahl index of firm market shares were matched to the closest year (1987-1990 were matched to the 1987 indices and 1991-1994 were matched to the 1992 figures). Industry growth and size was calculated from various releases of the GDP by Industry tables provided by the BEA which covers 1987-1993 (1994 was assumed to be the same as 1993). Growth was defined as the one year change in real output. Average market share was computed by taking overall firm output and dividing by a weighted average of industry size. Imports and exports were calculated from the BEA tables on imports and exports by 4-digit industry, aggregated to the two digit level. The import rations were then computed by dividing total imports by the GDP by industry figures and a similar approach was used for export intensity. These data are only available for manufacturing industries.

5. Results

5.1 Sample Characteristics

While the sample is broadly representative of the Fortune 1000, they are not representative of the economy as a whole. The average firm is very large, with value added of about $1Bn and employment of approximately 16,000. Not surprisingly, these firms are both highly diversified and vertically integrated. In 1990, the average firm participated in 14 4-digit SIC industries and 8 2-digit SIC industries, although the level of industry participation is much larger for manufacturing firms (an average of 18 4-digit SIC industries) than for service firms (averaging 9 4-digit SICs). There is also substantial difference in the vertical industry connection index between manufacturing and services (.25 vs. 07) although the magnitude does not have an easy interpretation.[57]

Both vertical integration and diversification appear to be increasing from 1987 until 1990 and decreasing thereafter according to the CI sample (Table 1, numbered tables appear at the end), although the level of focus as measured by the concentric index appears to be relatively stable over time. When Compustat segment data are used, there appears to be a slow decline in the number of segments over time. However, the rate of decline appears to be substantially larger in the post-1990 period which is consistent with the decline in other measures over this time period. Interestingly the Value-Added to sales (VA/S) ratio does not show the same trend as the VIC index. This is most likely because VA/S includes profits and over time appears to track movements in the economy fairly closely (for example, the lowest levels of VA/S are in 1990 and 1991 at the bottom of the recession). As suggested before, this makes this measure unreliable for the purposes of this analysis. These time trends in all the measures also appear in a fully balanced panel (495 firms) so they do not appear to be driven by sample attrition or year to year heterogeneity.

5.2 Comparison Across Data Sources

In order to make data collection manageable, the Computer Intelligence database is not a full census of every establishment for every firm. Because it has been updated annually or more frequently since the early 1980s, the year to year consistency is believed to be

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[57] The VIC is bounded below by zero (single industry or no vertical linkages) and above by one although the upper bound would not be attainable in our sample given the structure of the I-O matrix. See Maddigan (1981) for more discussion of the properties of this index.

quite good.[58] However, it is important to consider the possibility that there are systematic biases introduced by the use of this dataset. We therefore compare measures on the CI database against the equivalent measures computed from Compustat and TRINET.

The datasets overlap in 1987 for the TRINET and CI and in 1994 for the Compustat industry participation list. Overall, in terms of mean levels of SIC codes reported, the CI and Compustat data agree fairly closely; Compustat reports an average of 10.6 4-digit SICs compared to 12.6 4-digit SICs on the CI database. However, on average, the measures derived from TRINET suggest that firms are more diversified than do the measures derived from CI. TRINET reports roughly twice the number of 2 and 4-digit SICs as does CI, and the values for the concentric and Herfindahl (based on employees) are roughly 25% higher. The impact of CI's undercounting is unclear. If the missing components are random, there should be little impact since the actual and the real values would be highly correlated. This would simply introduce random measurement error in the dependent variables, which often leads to a bias toward zero for econometric estimates. Alternatively, the database may be censoring smaller sites (this is implied by the calculation that shows employment coverage is greater than site coverage). In this case, our measures are broadly reflective of the firm as a whole, but do not capture the full detail of smaller sites.

The correlations between similar measures from different data sources are reported in Table 2. The computations based on employment shares appear to perform better than the computations based on revenue shares, except for the Compustat segments data where the

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58 In any event, there is no equivalent source that was available for this analysis so the time series behavior cannot be verified against a second source. The only other measure that has time series variation is the Compustat segment data which captures a different aspect of firm structure.

employment data is very sparse. Because employment is probably less subject to judgmental biases in the collection of these data, we focus on these measures throughout. Overall, the correlations are reasonably good between CI and TRINET, exceeding 59% in all cases, and over 80% for SIC counts. This provides some confidence in these data, particularly given that both sources are likely to contain some error.[59] The segments data appears to perform somewhat worse. This is probably caused in part by the aggregation already inherent in the segment data (firms may lump multiple SICs into a single segment and only report a "primary" SIC code) and, in part, by the inconsistency in reporting approaches across firms. Given the lack of consistency with other, potentially more accurate measures, we focus only on the number of segments data from the segment file. As before, we have reasonably good agreement between the Compustat 1994 industry listings and the CI data (correlations ~70%). Taking these results in totality, it appears that while there is the potential for some noise in these measures, they are relatively consistent across different data sources. However, care should probably be used in interpreting any calculation based on industry shares given the amount of unique variance in these measures.

5. 3 Comparison across measures

For the remainder of the analysis, the focus will be on the various measures computed from the CI database, as well as the segment count for Compustat. To better understand the interrelationship between these measures, we compute the correlations among the various measures used in our analysis. The results are reported in Table 3. While all the measures have substantial correlation and they share 63% of common variance in a principal components analysis, there appears to be some differences between the different

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[59] In general, the Dun and Bradstreet data that the CI dataset is based on is generally believed to be more accurate than the Trinet. However, it is not clear how they compare after censoring by CI.

measures. The Herfindahl and concentric measures are closely related, as are the two SIC count measures. All the other correlations are on the order of 50%. This suggests that it may be important to consider multiple measures of industry dispersion in the analysis. Interestingly, value-added to sales does not appear to be significantly correlated (<10%) with any of these measures which is implausible; this provides additional support for the use of alternative measures of vertical integration such as the VIC index.

5.4 Information Technology and Firm Structure

We begin by estimating a baseline regression of IT intensity (IT stock/capital stock) on measures of firm structure (vertical integration, diversification, firm size), IT price and time controls. The analysis is repeated for each of the four measures of diversification: the count of 4-digit SICs, the concentric index, the Herfindahl index, and the number of Compustat business segments. The results (Table 4) suggest that across the different measures, diversification appears to be positively related to IT use, and vertical integration is negatively related to IT use. Both firm structure measures are strongly significant in almost all cases except for the number of segments. After controlling for the other variables, firm size appears to be neutral to negative. This is consistent with earlier results on IT and firm size (Brynjolfsson, et. al., 1994). The results are similar when the analysis is restricted to manufacturing firms only, except the Herfindahl diversification measure is no longer significant and the number of segments is negatively related to IT demand.

To account for heterogeneity of firms, we reestimate these base equations using additional controls for various determinants of diversification and vertical integration. For all firms the control variables include: industry IT intensity, industry growth, average market share, capital intensity, debt/equity ratio, and a set of industry controls that represent the percentage of the firm in each of 10 industry areas[60] to account for differences in scale and scope related to core production processes. These sectors roughly correspond to 1-digit SICs with a few additional subdivisions: mining/construction, process manufacturing (paper, chemicals), other non-durable manufacturing, "high tech" manufacturing (aerospace, electronics, instruments, computers), other durable manufacturing, transport, utilities, trade, finance and other services. For the manufacturing firms in our sample, we can also include measures of R&D as well as industry weighted averages of import intensity, export intensity, and industry concentration.[61] We report the results of these regression separately for the full sample and manufacturing using the number of SICs measure of diversification (Table 5).

The results are fairly similar across measures so we will focus on the "number of SICs" measure of diversification since it is likely to have the least measurement error.[62] The coefficients on the measures of firm structure are similar to those before, although the magnitudes have been reduced somewhat. The vertical integration measure remains strongly significant, while the diversification measure is strongly significant in the full sample but somewhat less strong in the manufacturing subsample ($t=2.1$, $p<.05$). The coefficient on industry IT is always positive and significant in the manufacturing regression, which suggests that there is some effect of industry participation on the overall level of IT, irrespective of firm structure or other factors.

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60 This is a generalization of the standard approach of including an industry dummy variable. These two approaches are equivalent if the firm participates in only one sector.

61 In principle, since manufacturing firms often participate in many non-manufacturing industries, these variables should be considered as relating to their core business only. However, the differences among firms in industry participation is already accounted for in the industry controls.

62 The results are directionally consistent with the Compustat segments measures as well: the vertical integration coefficient is consistently negative and significant, and the diversification measure is consistently positive and significant in many of the analyses.

The signs of the control variables are difficult to interpret in these specifications because they mix the effects on vertical integration and diversification as well as a direct effect of IT. To determine whether the effects of these controls is as predicted, we run auxiliary regressions of the firm structure variables against the control variables (after partialling out the effect of the firm structure measures on each other). In these regressions, capital intensity is positively (and significantly) related to vertical integration and not significantly related to diversification as predicted. Market share has a positive sign and is significant for both measures, suggesting that larger firms tend to focus their size on a few industries. Import intensity is positively related to both vertical integration and diversification, which is unexpected. R&D intensity is negatively related to both measures of firm structure. This may be due to two opposing effects: a *resource view* effect which would lead to a positive correlation and a dominant negative effect due to the need for focus in R&D activities. Finally, diversification is negatively related to export strength and concentration; again, this does not have a clear interpretation.[63] Overall, these regressions are consistent with some, but not all, predictions from previous work. This may be due to the problem of observing only a reduced form, where firms have already optimized their structures. This may also arise because many of the theoretical predictions about diversification or vertical integration lack empirical support. It may be more important, therefore, to focus on analyses which control for all firm specific effects (such as fixed effects or differences) rather than trying to model them explicitly.

5.5 Changes in Firm Structure and IT

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63 Unlike the analysis of Brynjolfsson et. al. (1994), there is no discernable lag structure in the data. The current year effect appears to be the strongest. However, in these firm-level panels, identification of a lag structure tends to be difficult (Brynjolfsson and Hitt, 1996).

While evidence that firms that have a particular firm structure use more IT is consistent with the predictions that these two factors are related, the theoretical argument is certainly much stronger in terms of changes in IT use and changes in firm structure. For example, the original argument in Malone et. al. (1987) was not about cross sectional variation but changes in the cost of IT enabling a shift toward more coordination intensive structures. In addition, no matter how carefully the control variables are selected, there will always be factors that managers use in making decisions that will be unobserved to the researcher. Examining time series variation may remove at least some of the effect of these unobserved factors, at least to the extent that they remain constant over time.

One approach is to use a fixed effects model, treating unobserved variables as firm specific constants which are removed by the regression procedure. The difficulty is that this approach increases biases from errors in variables, particularly for variables which may be changing slowly. An alternative approach is to use long difference estimates which remove the firm specific component but can accommodate slow changing factors. Because firm structure is not likely to adapt instantaneously to exogenous trends, we might expect that long difference results would perform better. In addition, because the vertical integration measure and the SIC count measures only change when a firm enters or exits a two digit industry entirely, the changes in these measures are likely to be slow.

The base and extended regressions are reestimated using fixed effects and then long differences. Because there was a small methodology change in the way the data in the CI dataset was collected in the early years, the long differences analyses are repeated with the maximum seven year difference and a five year difference that requires no data before the change.[64] Again, the focus is on the SIC count measure because the results tend to be

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64 This impact of this measurement change is reduced because the effect of the dataset change is partially captured by the time industry dummies. As mentioned in the data description, CI changed from reporting

slightly stronger, although directionally consistent with the other measures. Table 6 shows the results of the baseline and extended controls in fixed effects and the 1989-1994 difference. The effect of diversification is approximately the same magnitude as before and significant, but the previously robust vertical integration coefficient is now positive and near zero (t=1.1). Similar results are found in the fixed effects analysis with controls in both the full sample (shown in column 2) and in manufacturing only, although the vertical integration coefficient is even closer to zero (estimate=.04, t=0.2). Signs on the controls are also similar to the cross sectional analysis.

The change in the vertical integration coefficient may be a result of the relatively slow changing nature of this measure. To increase the "signal" in this measure relative to the noise, we repeat the analysis by using five and seven year differences with 1994 as the end year. The five year difference results (Table 6, column 3-4) show similar results to much of the previous analyses, despite the substantial sample size reduction (from N=4440 to N~400). Without controls, the magnitudes are almost comparable to the results in levels and both vertical integration and diversification measures are significant at p<.01. With additional controls the magnitude is slightly lowered along with the significance level (now p<.05) for the analysis in the full sample. The analysis on the manufacturing sample with full controls (not shown) shows the right signs, but neither of the firm structure coefficients are significant, probably in part because of the relatively small sample size for this analysis (N=294).

6. Summary and Discussion

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size buckets to reporting the actual sales and employees for each site. This will not influence the "number of SICs" measure, but may affect the calculation of the Herfindahl and concentric indices. However, even for these, the direction of the bias is not clear.

Overall, across models and measurement approaches we find consistent evidence that information technology is related to increased diversification but less vertical integration. This effect is consistent across various conceptions of diversification, including measures of "relatedness", although it appears to be strongest for the most general measure (the count of SIC codes a firm participates in). When controls are added for exogenous factors that are likely to influence the relationship, the control variables often have the predicted signs and the large increases in explained variance suggest that there is substantial heterogeneity in firm structure apart from any effects of IT. Possibly the most powerful result is that the effect is similar in both cross section and time series; firms that have made more substantial changes in their structure are increasing IT stocks more rapidly. While it is quite possible that the observed trends in firm structure and information technology are a result of an unmeasured "third force", this factor would have to be unique to individual firms but also changing over time.

One original conjecture in this paper is that information technology was related to an industrial de-diversification and de-integration that had been documented in the late 1980s. While there is evidence of a de-integration, this relationship with diversification is not supported by this analysis. Part of the problem is a measurement issue; very few time series measures of firm structure are available and the ones that are appear to show conflicting results (Montgomery, 1994). In addition, the lack of an appropriate metric for "closeness" in the economy other than the SIC system may add additional confusion in addition to the general problem that most measures of firm structure confound vertical integration and diversification.

Nonetheless, the results in this study are remarkably consistent with earlier predictions about the influence of IT on organizations and markets (Malone, Yates and Benjamin, 1987; Gurbaxani and Whang, 1991; Malone and Rockart, 1991). The negative relationship between information technology and vertical integration is consistent with the notion that information technology has an influence on external coordination costs. This relates to and extends previous time series that found that IT was associated with decreased industry average firm size (Brynjolfsson et al., 1994). However, this earlier result could be due to small firms entering IT intensive markets, large firms shrinking outright, or larger firms spinning off smaller firms. This study provides an additional piece to this puzzle: large firms are getting smaller in vertical size. What has not been empirically demonstrated is the type of governance structures which are emerging to fill this space: is it simply markets or some type of coordination intensive hybrid such as partnerships or "virtual corporations"? This is a potentially interesting line of future inquiry.

The results are also consistent with the idea that information technology facilitates the management of larger enterprises through reduction in internal coordination costs. This finding is interesting in its own right because it suggests that the tremendous recent investment in coordination technologies within the firm such as networks and groupware are having an impact. This can also add to the emerging collection of results that suggest that changes in information technology often support or require changes in internal organization.

These types of large sample results should always be interpreted carefully. Despite the long tradition of research into the determinants of firm structure, a complete theoretical understanding and a comprehensive set of empirical tools are lacking. There are also very few time series results with which to compare this analysis. The results in this paper are quite consistent across approaches, but it is always difficult to rule out the influences of measurement error, reverse causality, or omitted variables. Attempts to address these factors included estimating the effect in cross section and time series, validating the data against similar sources, and using the most accurate constructs possible. However, the data analytic approach (rather than explicit modeling) clearly abstracts away many important factors such as the role of other inputs, complementary organizational factors, and historical or institutional issues. As researchers and practitioners once again become interested in the determinants of firm structure and, particularly, the role of advanced technology, more detailed theory is needed.

The general approach employed in this paper can be extended to examine other related issues, such as how the combination of different IT strategies and different organizational strategies affect long run and short run economic performance. In addition, while the focus was on linkages within firms, it may also be interesting to consider how external linkages are changing.

This paper represents a first step in understanding empirically the relationship between large scale firms structure and IT to complement earlier theoretical work. As the technology evolves to allow greater levels of within firm and interfirm coordination to occur, the types of changes documented in this paper are likely to become more pronounced over time. From a managerial perspective, it is important to understand that organizational structure and technology are related, and that this relationship may affect the evolution of organizations and markets. Because large scale organizational change in necessarily slow and expensive, managers need as many tools and empirical facts at their disposal as possible to understand what types of structures are likely to appear in the future and the role of technology in supporting change in their own firms.

Table 1: Firms structure measures over time

Year	Conc.	Herf.	# 4-digit SICs	# 2-digit SICs	Segment	VA/S	VIC
1987	.92	.50	11.3	5.7	n/a	.43	.15
1988	.91	.54	12.8	6.7	2.62	.43	.17
1989	.90	.55	13.3	7.2	2.60	.42	.18
1990	.93	.58	13.9	7.5	2.61	.40	.18
1991	.94	.59	13.9	7.7	2.65	.40	.18
1992	.94	.59	14.2	7.2	2.51	.41	.17
1993	.92	.57	12.8	6.9	2.45	.43	.16
1994	.94	.57	12.6	6.7	2.40	.43	.16

All measures computed from CI data except "Segments" which is from Compustat.

Table 2: Correlations between CI measures and other sources

Comparison	Concentric	Herfindahl	# 4-digit SICs	# 2-digit SICs
Trinet vs. CI (1987)	.61	.59	.85	.83
Segments vs. CI (1988-94)	.47	.51	.53	.27
Compustat - CI (1994)	x	x	.71	.68

Table 3: Correlations between firm structure measures

Measures	Herf.	4-digit SICs	2-digit SICs	Segment	VIC	VA/S
Concentric	.88	.59	.50	.46	.47	-.01
Herfindahl		.61	.55	.43	.43	.01
4-digit SICs			.97	.52	.43	.07
2-digit SICs				.45	.57	.08
Segments					.43	-.05
VIC						-.11

All measures computed from CI except segments and VA/S

Table 4: Information technology demand as a function of firm structure

Coefficient	Divers. as 4-digit SIC	Divers. as Herfindahl	Divers. as Concentric	Divers. as Segments
Diversification Number of SICs	.043** (.0036)			
Diversification Herfindahl		.521** (.11)		
Diversification Concentric			.302** (.064)	
Diversification # of Segments				.0151 (.0022)
Vertical Integration VIC	-2.33** (.15)	-1.37** (.13)	-1.43** (.13)	-1.26** (.15)
Size - log(Employment)	-.150** (.027)	-.017 (.024)	-.012 (.025)	-.0005 (.029)
Other Controls	Time (DV)**	Time (DV)**	Time (DV)**	Time (DV)**
R^2	12.5%	9.96%	10.2%	7.87%
N	4440	4439	4370	3491

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

Table 5: Information technology demand with additional control variables

Coefficient	Full Sample	Manufacturing Only
Diversification Number of SICs	.0147** (.0036)	.00741* (.0036)
Vertical Integration VIC	-.754** (.16)	-.547** (.17)
Firm Size log (Employment)	-.192** (.035)	.0170 (.045)
Industry IT	1.43 (.88)	8.06** (.15)
Capital Intensity	-.376** (.032)	-.464** (.053)
Debt-Equity Ratio	-.0007 (.001)	.0018 (.0018)
Industry Growth	.0335** (.0061)	.0112 (.0075)
Market Share	-.154 (.091)	-.312** (.098)
Additional Controls	Sector % ** Time (DV)**	Sector (%) ** Time (DV)**
R&D Intensity (R&D Stock/Capital)		1.66** (.13)
Import Intensity		-.018** (.0027)
Export Intensity		.014** (.0012)
Concentration		-.000625 (.0029)
R^2	26.8%	37.4%
N	4416	2630

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

Table 6: Time series analysis with and without additional controls

Coefficient	Fixed Effects Full Sample	Fixed Effects Full Sample	Fifth Difference Full Sample	Fifth Difference Full Sample
Diversification Number of SICs	.0195** (.0065)	.0214** (.0065)	.047** (.015)	.033* (.016)
Vertical Integration VIC	.220 (.22)	.22 (.20)	-2.30** (.75)	-1.48* (.0075)
Firm Size log (Employment)	-.304** (.0085)	-.356** (.0091)	-.0228 (.14)	.244 (.17)
Industry IT		1.79 (1.05)		8.82 (5.8)
Capital Intensity		-.252** (.051)		-.594** (.124)
Debt-Equity Ratio		.0007 (.0009)		.00426 (.0060)
Industry Growth		.0128** (.0045)		.139** (.044)
Market Share		.044 (.12)		-.1.11* (.46)
Additional Controls	Firm** Time (DV)**	Firm** Time (DV)**		
R^2	72.7%	73.2%	2.8%	12.9%
N	4440	4416	415	405

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

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