Computing Productivity: Firm-Level Evidence

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Estimating the Contribution of Computers to Productivity Growth

ABSTRACT

In this paper we explore the relationship between computers and productivity growth at the firm level. We apply standard productivity and growth accounting techniques to data from 600 large US firms over 1987-1994. While we find that computer make a positive and significant contribution to output growth in the short term (using 1 year differences), the implied returns to computers are two to five times greater when differences are taken over seven years instead of one year. Our results challenge the conclusions drawn from aggregate data on computers and productivity, but are consistent with case evidence that the combination of computers and organizational co-investments make a substantial contribution to growth.

JEL Categories: O3 Technological Change; D24 Capital and Total Factor Productivity

1. INTRODUCTION

In advanced economies, computers are a promising source of productivity growth. Rapid technological innovation has led to a quality-adjusted price decline of computers of 20% or more per year for several decades (Berndt and Griliches, 1990; Gordon, 1999). Since nominal investment has increased even as prices declined during the past 30 years, the share of computers in capital formation has increased dramatically. Computers may be the modern-day exemplar of technological progress, but the connection between computers to productivity has proven elusive to quantify. What is the relationship between computers and productivity growth?

Computers are a promising area for investigation into the sources of growth in modern economies for several reasons. First, computers are the embodiments of significant investments in technical progress. From 1978 to 1989, the computer industry had the highest level of R&D intensity of any industry in the manufacturing sector (Griliches, 1994) and its products have exhibited unprecedented quality improvements. Second, the value of computers may be substantially attenuated or magnified by complementary investments. Computers are best described as a "general purpose technology" whose primary contribution is to make radically new production methods possible when combined with complementary investments such as work systems, organizational redesign and business processes (Bresnahan and Trajtenberg, 1995; Malone and Rockart, 1991). David (1990) has compared the current computerization of the economy to the historical example of electrification 100 years earlier by noting that new ways to organize work are required to exploit new general purpose technologies. Milgrom and Roberts (1990) argue that computers have been an important driver of the shift from "mass production" to "modern manufacturing". Advocates of organizational "reengineering" have argued that computer-enabled work redesign can lead to vast productivity improvements (see e.g. Hammer and Champy, 1993) while some prominent economists have speculated that synergies with computerization may be leading to significant changes in the economy as a whole (Greenspan, 1999).

Despite these promising elements, how much, and even whether, computers contribute to productivity growth remains a topic of debate. A decade after Solow (1987) quipped "we see the computer age everywhere except in the productivity statistics", aggregate productivity growth in the U.S. began to soar. In the period 1995-2000, U.S. multifactor productivity has grown by 2.7% per year, roughly double the average of the previous 25 years. Nonetheless, others including Gordon (1999), have vigorously argued that while there has been tremendous productivity growth in computer producing industries, there is only limited evidence of any incremental productivity growth in computer using industries.

One explanation for this discrepancy is mismeasurement. Aggregate industry data may not accurately reflect the value of variety, timeliness, customization and other intangibles (Boskin et al., 1997), which may obscure the productivity effects of computers if the benefits of computerization are disproportionately oriented toward intangible value. Firm-level data may better reveal computers' contributions to the extent that consumers consider intangible benefits when they make purchase decisions. Second, there is an issue of adjustment time and learning. Investments in computers may make little direct contribution to overall performance of a firm or the economy until they are combined with complementary investments in work practices, human capital, and firm restructuring (Brynjolfsson and Yang, 1999; Brynjolfsson, Hitt and Yang, 1999; David, 1990; Greenwood and Jovanovich, 1998; Hall, 2000; Hammer, 1992). This may depress the apparent contribution of computers in the short term but result in substantial contributions in the long term.

Research on computers' effects on firm-level productivity has been constrained by data availability and has produced mixed results. Studies by Loveman (1990) and by Barua, Kriebel and Mukhopadhyay (1995) found no evidence that computers contributed positively to output when they examined a data set of 60 business units in the early 1980s. In contrast, studies employing more recent firm-level data have found a correlation between levels of computer investment and productivity level. Brynjolfsson and Hitt (1995, 1996) and Lichtenberg (1995) estimated several production functions using data for approximately 350 large firms from 1988-1992, and found high output elasticities for computers exceeding their capital costs.[1] While several studies have

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[1] The results at the industry level have also been mixed. Morrison (1996) finds a zero or even negative correlation between computers and productivity, while Siegel (1997) found a positive relationship after correcting for

now found a positive correlation between computers and productivity levels, none has examined productivity growth at the firm level. Analyzing the effect of computers on productivity growth is important not only because it implicitly controls for firm heterogeneity, but also because of the importance of productivity growth in determining future living standards.

In this paper our objective is to clarify the relationship between computers and productivity by estimating the contribution of computers to growth and evaluating one possible mechanism that is driving this relationship: the role of organizational co-investments. Using standard growth accounting and productivity measurement approaches we examine the relationship between growth in computer spending and growth in output for 600 large firms over 1987-1994. To the extent that output growth exceeds a "normal" rate implied by economic theory, after accounting for growth in other factors, we can conclude that computers contribute to productivity growth. By performing the estimation at the firm rather than the industry level, we reduce difficulties of mismeasured output and inputs, thus potentially obtaining a more accurate estimate of computers' contributions. We conduct the analysis varying the time horizon (difference length for the growth calculation) to examine how the changes in computers' contribution is affected by longer term investments in complementary factors. Finally, we use multiple econometric approaches to account for different types of biases introduced by firm heterogeneity, endogeneity of factor spending, and slow adjustment of other factors.

We find evidence of a substantial relationship between computers and multifactor productivity growth. Our results indicate that computers' short-run contribution to output is approximately equal to the direct user cost of computer capital. However, in the long run, we find that the implied marginal product and growth contribution of computers rises by an economically and statistically significant margin. Our interpretation is that the long-run contributions rise because

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measurement error in input and output quantity. Other studies showing mixed results in industry data include Berndt, Morrison and Rosenblum (1992), Berndt and Morrison (1995), Morrison and Berndt (1990) and Siegel and Griliches (1991). Even studies which simply assume that computers were earning a normal rate of return have come to contrasting conclusions about what this implies for their overall contribution to the economic growth. See Lau and Tokutsu (1992), Jorgenson and Stiroh (1995), Bresnahan (1986), Brynjolfsson (1996), and Oliner and Sichel (1994). See Brynjolfsson (1993), Brynjolfsson and Yang (1996) and Brynjolfsson and Hitt (2000) for more comprehensive literature reviews.

computers complement productivity-enhancing organizational changes carried out over a period of several years.

The remainder of the paper is organized as follows. Section 2 provides examines the role of computer technology in productivity growth and discusses the measurement problems inherent in analyzing the productivity contribution of computers. Section 3 develops the theoretical framework we employ in estimating productivity effects and introduces our data. The regression results and an analysis of the importance of complementary factors are presented in Section 4. We conclude with some possible interpretations of our results.

2. BACKGROUND

Since the 1960s, semiconductor chipmakers have increased the density of the lines that form transistor circuits by about 10% a year. Combined with numerous other improvements, this has led to a doubling of microprocessor power every 18 months (See Figure 1). These improvements have occurred so consistently that the trend is known in the computer industry as "Moore's Law," after a 1964 prediction by Gordon Moore, a founder of Intel Corporation. Improvements in semiconductors and other components account for the annual 20-30% quality-adjusted price decline for computers (Berndt and Griliches, 1990; Gordon, 1990; Gordon, 1999) and reflect a successful effort to advance the technological frontier for computer production.

Computers are primarily an intermediate good, so their effect on economic welfare depends on how successfully they are used to create other goods and services. Both nominal and real investments in computers have increased substantially over the past several decades (Figure 2), and have further accelerated in the 1990s. Presumably companies perceive a significant potential increase in profit and productivity from exploiting these new technologies. In part, this reflects the substitution of computers for labor or other types of capital along a given production possibility frontier for computer consumers. Users of ever-cheaper computer equipment can thereby achieve greater output for a given cost of inputs. However, after properly accounting for the deflation of computer prices, this type of output growth reflects investment growth, not productivity growth by computer users (Jorgenson and Stiroh, 1995). Griliches (1991) terms this a pecuniary spillover, because the combination of productivity growth and competition in the computer-*producing* sector has allowed computer-*using* industries to purchase computer inputs at prices below their quality-adjusted value. The economic impact of investment and pecuniary spillovers can amount to billions of dollars; a sizable fraction of recent output growth in the United States (Brynjolfsson, 1996; Jorgenson and Stiroh, 1995). Some authors suggest that the entire contribution of computers is in the form of pecuniary spillovers (Gordon, 1999).

Computers may also affect the multifactor productivity growth of the firms that use them by changing the production process itself and engendering complementary innovations within and among firms. This could lead to an output elasticity that is greater than computers' input share and thus a positive impact on productivity.

Firm-level cases strongly indicate that computers are in fact associated with changes in the composition of both outputs and inputs complicating the problem of estimating their effects. For example, Diewert and Smith (1994) analyzed a wholesaling firm that adopted a computer-based inventory management system. After the system was introduced, the firm restructured the way inventory was handled and realized multifactor productivity growth of over 9% per *quarter*. Interestingly, while inventories per stock-keeping unit declined precipitously, there was virtually no net reduction in total inventories, because the number of products carried increased proportionately. A less careful study would like have missed many of the actual productivity gains if it merely looked at aggregates like inventory or sales. More recently, firms have made large investments in electronic commerce to improve service to customers as well as improve speed and flexibility in their inbound and outbound logistics. This has enabled new types of customer focused strategies to be implemented. For example, several automakers, including Toyota, have announced plans to offer cars on a build-to-order basis with delivery in less than two weeks. Numerous on-line book and music retailers can provide almost any title currently in production delivered within 24 hours, and on-line computer retailers enable consumers to customize their own personal computer on-line which is usually available for shipment within 10 days.

To the extent that aggregate statistics do not reflect the consumer benefits from greater product choice or faster time to market, the effects of computerization will be underestimated. On the other hand, if the sales of individual firms are increased by offering these “intangible” benefits, then firm-level data will detect them.

The above cases also reflect the emerging consensus that substantial investments in “organizational capital” – the built-up knowledge reflected in a firm’s routines, procedures, reporting structures, staff training, work flows, and product positioning– typically also accompany the implementation of the new information systems (See, for example, Cash, Eccles, Nohria and Nolan, 1994; Malone, Rockart, 1991; or Lucas, 1996; Hitt and Brynjolfsson, 1997; Bresnahan, Brynjolfsson and Hitt, 1999). Milgrom and Roberts (1990, 1992) argue that the combination of computers and these complementary investments enable firms to pursue high-productivity strategies that were unprofitable or infeasible in the past.

The long-run increase in output associated with a price decline in an input like computers may be magnified as other complementary organizational factors are adjusted over time (Milgrom and Roberts, 1996). In the short term, output rises because of increased quantities of computer inputs. Over time, firms will adjust quasi-fixed factors, such as physical capital, human capital, business processes, and other organizational characteristics to maximize the contribution of the technology (Berndt and Fuss, 1986).

3. MODEL AND DATA

3.1. Theoretical Framework

We begin by applying the standard growth accounting framework that has been used extensively for studying the productivity of 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 (F) that 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).[2] In addition, we assume that the production function is affected by time (t), and the industry (j) in which a firm (i) operates. Thus:

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

Following common practice, we assume that this relationship can be approximated by a Cobb-Douglas production function and its variants.[3] For most of our analyses, we implement this function 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 on inputs are omitted hereafter):

$$Q = A(i, j, t)K^{b_1}L^{b_2}C^{b_3}\text{, or} \qquad (2a)$$

$$q = a(i, j, t) + b_1 k + b_2 l + b_3 c \qquad (2b)$$

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

$$\dot{q} = \dot{a} + b_1 \dot{k} + b_2 \dot{l} + b_3 \dot{c} \qquad (3)$$

For each firm in each year, the output elasticities of non-computer inputs (b_1, b_2) are set to equal their theoretical value. Under standard assumptions (cost minimization, competitive output and

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[2] Results on the computer elasticity are generally similar whether or not R&D is included in the regression. Because of the large number of missing data points (including almost the entire service sector) we do not show R&D in the main results, but do include R&D in some of the corroborating analyses.

[3] The Cobb-Douglas functional form has the advantage that it is the simplest form that enables calculation of the relevant quantities of interst without introducing so many terms that the estimates are imprecise. More general functional forms such as the transcendental logarithmic (translog) have been utilized in research on the levels of computer investment and productivity (see Brynjolfsson and Hitt, 1995) with similar results.

input markets, and factor quantities in long-run equilibrium), this equals the ratio of the cost of the input to the value of output. Estimating these elasticities by averaging factor input shares over the current and previous years, and rewriting the equation as a function of multifactor productivity growth ($\dot{\lambda}$), where subscripts refer to time period, and r, w, p are the real price of physical units of capital, labor and output respectively, yields:

$$\dot{\lambda} = \dot{q} - \frac{1}{2}\left(\frac{r_t K_t}{p_t Q_t} + \frac{r_{t-1} K_{t-1}}{p_{t-1} Q_{t-1}}\right)\dot{k} - \frac{1}{2}\left(\frac{w_t L_t}{p_t Q_t} + \frac{w_{t-1} L_{t-1}}{p_{t-1} Q_{t-1}}\right)\dot{l} - \beta_3 \dot{c} \qquad (4)$$

The output elasticity of computer capital (β_3) could be calculated using a formula similar to that for ordinary 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 satisfy the standard assumptions necessary for ordinary least squares to be unbiased and efficient):

$$\dot{\lambda}_{\setminus c} = \hat{\lambda} + \hat{\beta}_3 \dot{c} + e \qquad (5)$$

where: $\dot{\lambda}_{\setminus c} \equiv \dot{q} - \frac{1}{2}\left(\frac{r_t K_t}{p_t Q_t} + \frac{r_{t-1} K_{t-1}}{p_{t-1} Q_{t-1}}\right)\dot{k} - \frac{1}{2}\left(\frac{w_t L_t}{p_t Q_t} + \frac{w_{t-1} L_{t-1}}{p_{t-1} Q_{t-1}}\right)\dot{l}$

(Coefficients with hats ^ represent econometric estimates.)

This approach, which was employed by Adams and Jaffe (1996) to study R&D productivity, provides unbiased estimates when all factors are in competitive equilibrium. However, as shown by Berndt and Fuss (1986), it may give biased estimates if a quasi-fixed factor, such as capital, is not in equilibrium. In this case, the value of the service flows from that factor can be adjusted to give accurate estimates of productivity growth. In particular, Berndt and Fuss show that the expected *ex post* shadow rental price of capital should replace the *ex ante* rental price in calculating input shares, and that the expected shadow rental price of capital (z_t) can be approximated by multiplying the traditional Hall-Jorgenson *ex ant*e rental price by Tobin's q (ϕ), which is the market value of the firm divided by the replacement cost of its physical capital stock.

Tobin's q incorporates information on the expectations of investors regarding future input and output prices and thus the shadow price of installed capital. We implement this approach by estimating equation (5) using the expected shadow price of capital ($z_t = \phi_t r_t$) in place of the capital rental price (r_t), where ϕ_t is a normalized value of Tobin's q for each firm in each year.[4]

Evaluating the Contribution of Computers. To interpret these results, 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:

$$MP_c = \frac{\partial pQ}{\partial r^c C} = \hat{\beta}_3 \frac{\overline{pQ}}{\overline{r^c C}} \qquad (7)$$

where: $\overline{pQ}$, $\overline{r^c C}$ represent sample average output and computer (flow) quantities and r^c represents the rental price of computers.

The marginal product should equal 1 if the firms are in a long-run equilibrium; each additional dollar of input (flow) should result in a dollar of output, assuming parameter estimates are unbiased and all relevant costs are measured.

An alternative estimation approach combines the use of marginal product calculations with the productivity estimation framework. Instead of estimating the output elasticity, we can directly estimate the implied rental price of computers by weighting the growth in computer capital by its factor share:

$$\dot{a}_{/c} = \hat{\gamma} + \hat{\psi}\left(\frac{C_{t-d} + C_t}{V_{t-d} + V_t}\right)\dot{c} + controls + e \qquad (8)$$

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4 In addition, the traditional growth accounting framework may also attribute changes in market power and economies of scale to productivity growth. Whether these gains are legitimately part of productivity growth is a matter of interpretation. For example, Morrison (1992) writes "… for some purposes scale economies are appropriate to include as 'productivity growth'."

This analysis (we refer to as a “rate of return” specification) has the advantage that it directly accommodates heterogeneity in computer investment across firms and over time.

3.2. Data Sources and Construction

The data set for this study was created by combining two main data sources: a database of capital stock of computers provided by Computer Intelligence InfoCorp (CII); and public financial information obtained from Compustat II (Compustat). We also employed price deflators from various government and private sources. In some analyses, we also used a data set of computer hardware and related expenses obtained through surveys conducted by International Data Group (IDG), and data from a survey we conducted for this research which asked chief information officers about the benefits they expected from computerization. Appendix A provides additional details on the data sources and construction.

CII conducts a series of surveys that tracks specific pieces of computer equipment in use at approximately 25,000 sites at different locations of the 1000 largest firms in the United States. CII interviews information systems managers to obtain detailed information on each site’s information technology hardware. Site sampling frequency ranges from monthly to annually, depending on the size of the site, and the interview process includes checks on hardware that was reported in previous interviews which makes time series comparisons more accurate. Each piece of hardware is market-valued and aggregated to form a measure of the total hardware value in use at the firm. These data obviate the need to make assumptions about retirement rates or depreciation, which are typically required when constructing capital series.[5] The CII data provide a relatively narrow definition of computers that omits software, information system staff, and telecommunications equipment. The data are available for the Fortune 1000 annually for the period 1987 to 1994.

[5] This methodology may introduce some error in the measurement of computer inputs because different types of computers are aggregated by stock rather than flow values (weighted by rental price). The direction of such a bias is unclear because it depends on assumptions about depreciation rates of various types of computers at each site.

We consulted Standard & Poor's Compustat II database to obtain information on sales, labor expenses, capital stock, industry classification, employment, R&D spending, and other expenses for all the firms in the CII database. These data were supplemented with price deflators from a variety of sources to construct measures of the sample firms' inputs and outputs using procedures consistent with earlier work (Hall, 1990; Brynjolfsson and Hitt, 1995). The procedure for calculating rental prices of computers and other inputs appears in Appendix B.

Sample. Using data from the CII database and Compustat, we constructed a nearly balanced panel of approximately 600 firms in the Fortune 1000 over an 8-year period for a total of 4571 observations.[6] We also have matching estimates of computer stock for 1411 of these observations from IDG, which gathered data from a single officer in each firm and used a somewhat different definition of computer capital. For the overlapping firms, the computer capital data had a correlation of 73% between CII and IDG.

During the sample period, the average factor shares of computers, capital, and labor were .01, .34 and .61 respectively. The firms in the sample are quite large, averaging $1Bn in value-added. The sample consists of 57% manufacturing firms, 41% service firms, and 2% mining, construction and agriculture, and there is at least one firm present from 41 different 2-digit SIC industries. However, some service industries -- banking, insurance -- are largely excluded because many of the firms in these industries do not report ordinary capital stock on Compustat. Because these industries are particularly computer-intensive, the firms in our sample are somewhat less computer-intensive than the economy as a whole. Altogether, our sample appears to be broadly representative of large firms in the U.S. economy and firms in the sample account for about 15% of total U.S. economic output.

4. RESULTS

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[6] The panel is unbalanced because some firms enter or leave the Fortune 1000 each year, merge, or for some other reason fail to have complete or comparable financial data available for all eight years. To prevent the results from being skewed by sample heterogeneity over time, we restrict the sample to firms that participated in at least six of the eight years of our sample.

In this section we estimate the relationship between growth in computers and multifactor productivity growth for the firms in our sample. We begin with a base specification that estimates the relationship between productivity growth and growth in computer input at varying difference lengths, adding additional control variables for time and industry. We then extend this specification by using instrumental variables to address reverse causality and random measurement error and to adjust for disequilibrium effects on capital using *ex-post* rental prices. Finally, to corroborate our productivity results, we take an alternative approach and use a “semi-reduced form” specification that requires fewer assumptions about the ex-post rental price of capital and addresses endogeneity of labor more directly, and replicate and extend previous results concerning the impact of levels of computer investment on levels of output.

4.1. Productivity

Base Estimates. We begin by estimating a conventional multifactor productivity equation that calculates the residual change in output after accounting for changes in ordinary capital and labor. Using equation (5), we calculate multifactor productivity growth (excluding computers from capital), and regress the result against the change in computer capital services varying the length of differencing.

The results of these initial regressions are shown in the first column of Table 1a. We begin by examining first differences (row 1, column 1). We find that the elasticity of computers is about .01, and we cannot reject the hypothesis that the elasticity is equal to the factor share of computers ($t=1.4$). We do find that the elasticity is significantly different from zero ($t=2.2$). When the analysis is repeated with longer difference lengths, we observe a general upward trend in the estimated elasticity with a statistically significant difference between the one-year and the seven-year first difference coefficients ($p<.05$).[7]

[7] We performed the analysis after removing a small number of outliers: those where the one-year multifactor productivity change is greater than 1 (in logarithms), or a multi-year multifactor productivity change is greater than 2. In addition, we require that for all years a 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. This led to the elimination of 12 firms, leaving 599 for analysis. The estimates are similar when outliers are included.

The effect of added control variables on this baseline specification are shown in columns 2-4 in Table 1a, and graphically in Figure 3. When dummy variables for time are included, the elasticity estimates drop in short differences, but are essentially unchanged in longer differences. Industry controls also appear to slightly lower the elasticity estimates across all difference specifications, suggesting that there are some systematic variations in computer input growth and productivity growth across industry. However, the fact that the effects of computers are still significant suggests that firm-level variation is more important than industry-level variation. As a result, it is likely to be difficult to assess the effects of computers on productivity growth using only industry-level data.

Interestingly, regardless of the specification, the elasticity estimates for computers show the same increasing trend as differences are lengthened. We cannot reject the hypothesis that the elasticity estimates are *at least as large* as the computer input share in any of these analyses.[8]

Instrumental Variables. Our earlier results assume that computer investment is determined by exogenous factors and is not correlated with shocks in productivity. However, it may be possible that either time-series or cross-sectional variation in productivity can also influence computer investment. For example, if firms disproportionately increase investments in computers in years where output is unexpectedly high, our short-difference elasticity results will be upward biased.

However, if firms change their other expenses in response to demand shocks more than their investments in computers, or if computer investment is countercyclical for other reasons, then OLS may underestimate the contributions of computers. Similarly, different firms may have different costs of making incremental investments in computers due to the structure of their past

[8] To probe this result further, we estimated regressions using varying difference length for particular years. For example, for 1992 we can examine the 1992-1991, 1992-1990, 1992-1989, 1992-1988 and 1992-1987 differences. The shorter difference results varied depending on the base year chosen, although they are usually positive and close to zero. However, elasticity estimates for fifth, sixth and seventh differences were consistently in the .02 to .03 range.

investments in computers or other factor inputs; if these investments are also associated with higher (lower) productivity, then our estimates will be biased upward (downward) as well.

Regardless of the direction of the bias we can obtain consistent estimates of the contribution of computers using an instrumental variables estimator. This can also correct for the possibility of measurement error in computer inputs.

For instruments, we model computer investment as being driven by the prices of pre-existing complements and substitutes to computers (durable goods, non-durable goods, energy), capital costs (BAA bond yields) and exogenous shocks to investment requirements (defense expenditures) in time series. These are the instruments used for productivity analysis proposed by Hall (1990). To model cross-sectional variation in IT adoption, we build on the idea that different types of computer technologies have different costs of incremental investment. In particular, firms that have already invested heavily in client-server technology may be able to make additional investments much more easily than firms that have relied heavily on mainframe technology and need to undergo a costly (and time consuming) conversion. The adoption of client-server technology is measured as the percentage of personal computers (PCs) connected to local area networks and the ratio of PCs to mainframe terminals. In addition, firms with a newer capital stock may be better able to use computers either because it is likely to be more compatible with computer technology (e.g. uses digital controls), or because newer capital indicates a willingness or ability to use new technologies. Finally, we include measures on the reason the firm is making the investment in computers[9] taken from a survey of IS managers since the indirect cost of computer investment may vary depending on the application.

Following Bartelsman, Caballero and Lyons (1994), we lag all our time series instruments by one period, calculate prices as a ratio to the price of energy and allow the effects of the instruments to

[9] The survey contains nine questions about reasons for investing in information technology and asks the respondent to rate the importance of each factor on a ten point scale: increase product variety, quality, customer service, timeliness, provide infrastructure, support business process redesign, reduce costs, improve bargaining position with customers, improve management information. We have data for about half of the firms in our sample on these measures. Where data is unavailable, we include a dummy variable for each question for missing data and the value of the variable itself is set to zero.

vary by industry. The R^2 of first stage regressions ranged from 35% in short differences to 67% in seventh differences. Although this instrument set is clearly less than ideal as it is very difficult to obtain time varying predictors of computers across different firms, we hope to at least directionally compare the results of the instrumental variables analysis with our prior first- and long-difference analysis.

The two-stage least squares (2SLS) estimates are presented in Table 1b and are compared to other analyses in Figure 4. In short differences (first through third), the coefficients are consistently larger in 2SLS than they are in the OLS regressions. This suggests that computer investment may be less cyclical than other investments in the short-run. In fourth and longer differences, the results drop to a level comparable to the OLS results. This is at least partly due to the loss of a time series variation in the data as the difference length increases, reducing the difference between OLS and 2SLS estimates. Although the standard errors are much larger in the 2SLS specification, we can still reject the null hypothesis that computers make no contribution to productivity growth in first through fourth differences, and have no evidence that computers are not at least as productive as other inputs in any specification.

Research and Development. Previous work has found that R&D investment is substantially correlated with productivity level and growth (see e.g., Griliches, 1986; 1994). Because R&D spending is likely to be driven by some of the same factors as information technology spending, such as an overall emphasis on innovativeness, an industry environment or strategy that requires greater speed to market or customer responsiveness, or just a intrinsic capability for innovation within the firm, it is possible that our IT coefficients are biased because we do not account for R&D spending. We explore this possibility in Table 1c where we simultaneously include both computer capital growth and R&D growth in the analysis. In column 1, we replicate our previous analysis without R&D on the subset of firms that have reported R&D expenditure (primarily manufacturing firms). Although the sample size is substantially reduced, we still find positive and, in most cases, significant IT effects. Coefficients on computers rise from about .01 to .05 as the difference length increases with a general upward (but not monotonically increasing) trend. In columns 2 and 4 we show the equivalent coefficients in a regression with R&D included, first with no other control variables (column 2) and then with industry and time controls (column 4). The coefficient estimates are broadly similar to the analysis without R&D, and although tend to be less precisely estimated due to the reduced sample size and multicollinearity between computers and R&D growth, they still are generally positive, significant and show an upward trend as the difference length is increased. Interestingly, the R&D coefficient tends to only be significant in first differences and shows no particular trend as the difference length increases. These results suggest that our analysis is robust to whether or not we explicitly include R&D in the analysis and also that the upward trend in the coefficients is unique to information technology as opposed to applying to investments in innovation more broadly. Moreover, to the extent that sources of reverse causality are similar for computers and R&D, this provides a further indication that these types of specification errors do not appear to be biasing the results (at least in the long run) since the same effects do not appear for R&D.

Adjusting for Input Quasi-Fixity. The fact that time controls and instrumental variables estimates have a substantial effect on short difference elasticity estimates suggests that firms were not always in long-run equilibrium. While the IV estimates correct for the endogeneity of IT with respect to productivity, the do not account for possible biases in the measurement of TFP growth due to quasi-fixity of capital. Because the economic value of capital can deviate from its accounting value depending on short-term economic conditions such as capacity utilization, traditional growth accounting methods will tend to overstate capital inputs in recessions and understate capital inputs in periods of growth. If IT has a systematic relationship to economic cycles as well, this could lead to a biased estimate of the elasticity of computers.

To address the bias in productivity measurement we adjust the rental price of capital to approximate their true shadow values by using Tobin's q (following Berndt and Fuss (1986)). In principal, a q-value greater than 1 implies that the shadow value of the firm's capital is greater than its *ex ante* cost as conventionally measured. However, since many firms have significant intangible assets with zero book value, they may have values for average Tobin's q that are greater than 1 even when the shadow value of capital is below its long-run equilibrium value. One way to correct for this heterogeneity is to normalize all values of q by dividing by each firm's q value in our base year of 1990. Thus, only changes in q relative to 1990 are used to adjust the capital flow weights.

In Table 2, changes in multifactor productivity growth are calculated using firm-specific *ex post* rental prices for capital derived from Tobin's q. When compared to the analysis assuming *ex ante* rental prices, the results are similar to the earlier analysis whether or not industry dummy variables are included and for both OLS and 2SLS estimates. In particular, the coefficients rise as the period of differencing is increased. This would suggest that the previous estimates are not driven by assumptions about whether firms are using equilibrium levels of quasi-fixed inputs.

4.2 Estimating Production Functions instead of Productivity

To examine the possibility that our results are unique to this data set or the modeling approach we employ, we now analyze the data using production functions instead of directly examining productivity and compare results from our data to an alternate dataset from IDG.

All previous firm-level studies have focused on estimating production functions, in which the elasticity of other factors (capital and labor) are estimated from the data, but are constrained to be the same across firms. The results from a 4-input (computers, capital, labor, R&D) production function estimation are shown in Table 3 using both our new data set, and the data set from International Data Group (IDG) used in earlier research by Brynjolfsson and Hitt, and by Lichtenberg. Overall, we find consistency both within this study and between this study and previous work.

The first column shows the results when we average output and all factor inputs across the time dimension for the same firm and estimate a "between" regression by weighted least squares (weights are the inverse of the square root of the number of observations per firm). In the cross-sectional dimension of the data alone, the estimated elasticity is .035 for computers. When we pool the data, as done in previous work, we find that the computer elasticity estimates in levels are around .03 for computers in both data sets. In a more demanding first difference specification, evidence of the contribution of computers is lost in statistical noise in the IDG sample, but not in the broader and longer CII data series. Altogether, when combined with the productivity analyses, we find strong evidence that computers are a productive investment in both cross-section and time-series analyses.

For the CII sample, the estimated elasticity of ordinary capital and labor are near what would be expected in the levels estimates, but the ordinary capital elasticity appears substantially biased downward in first differences. This is possibly the result of labor endogeneity, which can result in lower capital elasticity estimates. In fact, a Hausman test for the production function estimated in levels suggests that labor is endogenous (but not capital or computers) when we used lagged values of the independent variables as instruments. As a result, first difference estimates of a production function with all the factors included may be unreliable.

4.3 Semi-Reduced Form Estimates

By dropping labor from the equation, we can remove potential biases from endogeneity of labor (Griliches and Mairesse, 1984). In this formulation, labor is treated as endogenously determined by the quasi-fixed choices of computers and ordinary capital, thus reducing the possibility that labor endogeneity introduces biases in other coefficients. This results in a system of equations that allows the estimation of the ratio of capital and computer elasticities to the labor elasticities (see the derivation in Griliches and Mairesse, 1984):

$$\begin{aligned} q &= \hat{\delta}_q + \frac{\hat{\alpha}}{1-\beta}k + \frac{\hat{\gamma}}{1-\beta}c + e_q \\ l &= \hat{\delta}_l + \frac{\hat{\alpha}}{1-\beta}k + \frac{\hat{\gamma}}{1-\beta}c + e_l \end{aligned} \qquad (8)$$

This formulation can be estimated in levels or differences. Table 4 reports the estimates of this each equation separately in first differences. We cannot reject equality of coefficient across the two equations, so in the third column we estimate the equations simultaneously, imposing the restriction that elasticities are the same in both equations to improve efficiency. In Table 5, we allow the difference length to vary from 1 to 7 years. After adjusting for the 62% factor share for labor, the coefficient estimates imply that the output elasticity of computers is monotonically increasing from .009 to .044 as the difference length is increased. Similar results are obtained using instrumental variables estimates with the same instrument set as before (not shown), although most of the increase in coefficient estimates occurs between the first and third differences. In addition, the IV estimates are consistently higher than the OLS estimates. This corroborates our earlier results using the productivity formulation, and it also suggests that, *ceteris paribus*, OLS may underestimate the coefficient on computers in production functions estimated in first or long-differences.

4.3 Rate of Return Specification

To further examine the contributions of computers and gauge the reliability of our earlier results, we also estimate the effects of computers in a rate of return specification, where the coefficient estimate represents the implied rental price – the rental price at which computers contributions equal their costs (Table 6). The numbers that appear in the table are the implied rental price of computers. When the estimates exceed our rental price estimate of 42% per year, it suggests that computers have excess returns or a positive contribution to measured MFP. While this table shows somewhat lower contributions of computers in longer differences (on the order of 1.5 – 2.5 times the rental price), the returns consistently rise from first to third differences and are substantially above theoretical value of the rental price.

4.3 Interpretation of Elasticity Estimates

Across various specifications we find that the elasticity of computers starts at about .01 in first differences and rises to as much as .04 in long differences. The long-difference estimates are up to 8 times as large as would be expected if computers had "normal" returns. In this section, we evaluate several alternative explanations for the large and increasing coefficient estimates, with a focus on the mismeasurement of computer inputs and complementary factors.

Random Measurement Error. One potential explanation is that the results are a product of random measurement error. Because our productivity analyses only have a single regressor, we would expect that random input mismeasurement would bias down the computer elasticity estimates. This bias should be most pronounced in shorter differences since the amount of "signal" (e.g. the true change in computer investment) is likely to be reduced by differencing more than the "noise", because noise is less likely to be correlated over time. Thus, the signal-to-noise ratio, which is inversely proportional to the bias, is likely to increase as longer differences are taken (Griliches and Hausman, 1986).[10] The fact that the coefficients rise as longer differences are taken is consistent with a measurement error explanation. However, an upward trend in the coefficients still appears in the instrumental variables regressions and furthermore, this explanation implies that the true elasticity of computers is actually equal to or greater than our long difference estimate.

If the long-run elasticity estimates are correct, then either the true returns to computer investment are dramatically higher than the returns to other investments or there is some "missing mass" of inputs to the production function that is correlated with computer stock. Only the latter explanation is consistent with long-run equilibrium. We can determine how large any missing mass must be in order to bring the marginal product of computers down to normal levels and how this missing mass relates to factors we do observe.

Miscounted Technological Complements. One component of this missing mass may simply be miscounted computer inputs that are counted as ordinary capital or labor. The analysis of this bias is similar to the analysis of "double counting" of R&D expenditure investigated by Griliches (1988, Ch. 15) and Schankermann (1981). On the one hand, the marginal product of computers is biased upward because the factor input quantity is understated. On the other hand, the estimate of the computer elasticity is biased downward because other factors are absorbing some of the effect that should be attributed to computers. Under some minor assumptions, the measured effect

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[10] In addition, because changes in different inputs for the same firm are nearly uncorrelated in our sample, the same downward bias should be evident in our specifications that have multiple regressors, such as the semi-reduced form estimates. This is a straightforward calculation from the standard results on the effects of errors in variables with multiple regressors (see e.g. Greene, 1993).

of computers represents a weighted average of the marginal products of computers and other inputs, with the weights proportional the amount of misallocation (see Appendix C.2).

The reported stock of computers from CII that we use in our estimation probably does not include all the computers actually at the sample firms. Because ordinary capital is calculated as a residual after subtracting measured computer capital, any "missing" computers will be misclassified as ordinary capital. In addition, a study by IDG (1996) suggests that for a typical information systems installation based on client-server technology, the lifecycle software and operating costs (including computer labor) can be as much as five times the hardware costs.

To assess the approximate impact of such misclassification, assume that for every computer detected by CII, there is an equivalent amount of unmeasured computer capital that is erroneously treated as ordinary capital. Using an annual capital computer capital of 42% (see Appendix B) and multiplying this by five (as per the IDG study) to account for potential unmeasured computer labor, implies that the annual flow of misclassified labor is up to 2.1 times the computer capital stock for any given year. Finally, assume conservatively that the misclassified capital and labor is perfectly correlated with the observed computer capital estimates.[11] Using the equations in Appendix C.2 and assuming normal returns to ordinary capital or labor, this yields a revised marginal product estimate of computers of 1.2 in the short run and 1.8 in the long run. This is closer to the predicted value of 1.0, but it remains somewhat greater than what would be expected in equilibrium. Thus, a correction of this type alone does not fully account for the high long-run elasticity of computer capital.

Our data may also miss some of the technical complements to computers that do not appear in other inputs. For instance, software is a long-lived asset that is often charged as an expense in the year of acquisition or development by standard accounting practices. Regression estimates in subsequent years will reflect the value of the overall system (hardware plus software), not just the measured input quantity (hardware).

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[11] If the correlation with computer capital is less than perfect, then the bias on the computer elasticity estimated will be correspondingly smaller.

As shown in Appendix C, the extent of the bias depends on the value of the omitted technical complements and their correlation with measured computers. Assuming that they have the same marginal product as other computer investments and are perfectly correlated with the observed computer inputs, their cost would have to be approximately $6.50 per dollar of measured computer input after the miscounting correction for computers to have "normal" returns.[12] The magnitude of this number is implausibly large, suggesting that omitted factors are not the sole explanation for excess returns. Furthermore, it does not explain the rise in the coefficients as the length of differencing increases.

Miscounted Organizational Complements. As argued in the introduction, effective use of computers often requires additional organizational adaptations to the use of computers. However, these adjustments may not be instantaneous. For example, a firm may not immediately be able to optimize their organizational characteristics such as work systems, incentives or human capital levels to take full advantage of new production possibilities enabled by computers. As a result, if there are other factors that are complementary to computers, comparing short-term changes in output or productivity growth to short-term changes in computer investment may miss the impact of these other complementary factors. However, if we analyze changes over long time periods the impact of these complements may be more apparent. Thus, as argued by Bartelsman, Caballero and Lyons (1994) in the context of production externalities, it may be possible to observe the effects of slow-changing complementary factors by examining the change in elasticity coefficients at various difference lengths (see further discussion in Appendix C.1).

This explanation is similar to but distinct from models based on “learning.” For example, a firm may experiment with a new computer technology and over time learn the most effective uses of computers. In one interpretation, this is just a variant of our organizational complementarities story – the learning is the “complementary asset”, just one that arises over time rather than through explicit investment. While this is certainly a component of the overall story it is unlikely that learning without deliberate investment is the only component. There are numerous examples (see a survey in Hitt and Brynjolfsson, 2000) of explicit investments in complementary assets such as supply chain redesign, organizational restructuring or human capital. Moreover, there is a very large computer services and consulting industry which exists primarily to transfer (at a cost!) the "learning" on the use of computers from firm to firm. Finally, some of these hypothesized organizational complements can and have been measured directly, such as changes in the structure of the firm in the form of vertical de-integration (Hitt, 1999) or changes in organizational design to utilize greater levels of human capital (Bresnahan, Brynjolfsson and Hitt, 1999).

4.4 What Can the Results Tell Us about Aggregate Productivity Growth?

Using our elasticity estimates for computers and the annual growth rate of computer capital of about 25% per year, computers have added approximately .25% to .5% to output and productivity growth at the firm level over this period. As the factor share of computers grows, so will the productivity contribution, *ceteris paribus*. Because our productivity calculation reflects private returns, including rent stealing but not productivity spillovers, we cannot know whether the aggregate impact on the economy is smaller or larger than the private returns.

If computers were more likely than other inputs to be used to capture rents from competitors, then the aggregate returns to the economy would be less than the sum of the private returns we measure. Because redistributing rents is a zero-sum game, but computer expenditures are costly, the net effect would be to lower aggregate profits. However, aggregate corporate profits do not appear to be any lower in recent years and there is some evidence that they have risen (Poterba, 1997).

There is more evidence for an effect in the opposite direction. Some of the benefits of computers spill over to consumers and other firms. For example, when two or more banks simultaneously invest in an ATM network, consumers get most of the benefit. Similarly, when a firm like

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[12] The calculation of this figure is as follows: 6.5 = 1.8 ("excess marginal product" on total computer stock, including double counting) x 3.6 (ratio of true computer stock - including the undercounted capital and labor - to

Walmart demonstrates new IT-enabled efficiencies in supply chain management, its competitors attempt to copy their innovations with varying degrees of success. This can explain some of the discrepency between the firm-level result and the analyses using aggregate data. Moreover, the outputs of many firms, especially those in the service sector, are not measured well, leading to underestimates of aggregate productivity growth (Baily and Gordon, 1988; Gordon, 1996). Firm-level data may help reduce problems from output mismeasurement because intangible benefits that are invisible to the econometrician are visible, presumably, to a firm's customers. Firms that improve output quality, variety or timeliness through investments in computers will be able to charge a higher price, force competitors to lower their prices, or both. These private benefits will appear as a correlation between the firm's output and its computer investment.[13] In contrast, in industry- or economy-level data, these differences among firms in the same industry would be obscured. However, when two or more competitors simultaneously introduce intangible benefits, some or all of the benefits will be passed on to their customers and elude detection in revenue or output data. Therefore, even regressions using firm-level data may underestimate the computers contributions to intantible output.

To better understand whether computers were disproportionately contributing to unmeasured components of GDP, we conducted a small survey of information systems managers at Fortune 500 firms in 1997. We asked why managers were investing in computers (see Figure 5). In this survey, managers ranked improving product quality and obtaining new customers higher than cost savings, and four of the top five responses represent investments directed at improving intangible aspects of output. When these intangibles are added to the "true" output of the firms and the economy, this suggests that many of the contributions of computers to output go unmeasured, even in firm level data.

5. Conclusion

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measured computer stock). This is also close to the figure if double counting were not taken into effect.

[13] A similar argument suggests that hidden costs computerization imposes on consumers will also be more evident in firm level data.

This paper presents direct evidence that computers contribute to productivity growth in a broad cross-section of firms. Furthermore, as a general-purpose technology, the pattern of growth contribution appears to suggest that computers are part of a larger system of technological and organizational changes that increases productivity over time.

When we examine the data in one-year differences, we find that computers contribute to output an amount roughly equal to their factor share. This implies that computers contribute to output growth but not productivity growth. Over longer time horizons (between three and seven years), computers appear to contribute substantially more than their factor share – between 2 and 8 times as much as the short term impact. This implies a substantial contribution to long-run productivity growth. These results, as well as corroborating institutional evidence, are consistent with a story that the long-term growth contributions of computers represent the combination of computers and complementary organizational investment. Other explanations for our results, such as measurement error (either random or systematic), omitted variables such as R&D, and quasi-fixity or endogeneity of other factor inputs do not fare as well. Our instrumental variables regressions, although limited by the quality of the instrument set, also suggest that reverse causality does not appear lead to upward biases in the estimation of computers' contribution. The fact that the results are consistent when performed in differences, providing some control for time-invariant firm heterogeneity, and robust to a "rate of return" analysis and industry controls, provides evidence against a firm or industry heterogeneity story. It may be that "high performance" firms grow faster and invest more in computers for unrelated reasons (a story which is very hard to examine without a clear description as to what the reason is), but industry effects or a high past level of productivity or computer investment leading to high current productivity would not explain our results.

It is important to note that conducted the analysis over a time period where there was not extraordinary growth in the overall economy. This suggests that our results are not likely to be biased by (although could be predictive of) the recent massive increases in valuation of technology and computer companies. On the contrary, if computers indeed require several years to realize their growth contribution, our current economic performance may at least in part reflect the massive computer investments as well as complementary organizational investments made in the early 1990s.

Table 1a: Regression of Computer Growth on Multifactor Productivity Growth - Varying Difference Length

Difference	OLS No controls	OLS Time Controls	OLS Industry Controls	OLS Time & Ind. Controls	Sample Size
1 year differences	.0104 (.0043)	.00464 (.0046)	.00924 (.0043)	.00319 (.0046)	3936
2 year differences	.0.0138 (.0054)	.00512 (.00564)	.0144 (.0053)	.00227 (.0056)	3364
3 year differences	.000796 (.0066)	.000295 (.0065)	.00332 (.0064)	-.00445 (.0064)	2775
4 year differences	.0227 (.0072)	.0129 (.0075)	.0218 (.0067)	.0117 (.0070)	2190
5 year differences	.0244 (.0084)	.0234 (.0086)	.0186 (.0077)	.0180 (.0079)	1606
6 year differences	.0244 (.010)	.0248 (.010)	.0183 (.0095)	.0193 (.0095)	1020
7 year differences	.0277 (.015)	.0277 (.015)	.0209 (.0014)	.0217 (0.014)	488

Table 1b. Instrumental Variables Estimates

Difference	2SLS No controls	2SLS Industry Controls	Sample Size
1 year differences	.0195 (.0073)	.0161 (.0073)	3449
2 year differences	.0279 (.0091)	.0206 (.0090)	2948
3 year differences	.0343 (.012)	.0231 (.012)	2433
4 year differences	.0225 (.013)	.0216 (.012)	1929
5 year differences	.0194 (.015)	.00484 (.015)	1390
6 year differences	.0229 (.018)	.0109 (.018)	890
7 year differences	.0358 (.022)	.0379 (.023)	435

Sample size reduced for 2SLS because of data availability for instruments.

Table 1c: Productivity Growth Analysis including R&D

	Baseline: OLS No Controls or R&D	With R&D: OLS, No other Controls		With R&D OLS Time & Industry Controls		Sample Size
Coefficient	Computer Growth	Computer Growth	R&D Growth	Computer Growth	R&D Growth	
1 year differences	.00993 (.0068)	.00964 (.0068)	.00964 (.0068)	.00985 (.0074)	.00575 (.0034)	1498
2 year differences	.0217 (.0081)	.0211 (.00814)	.0211 (.00814)	.0186 (.0082)	.00190 (.0032)	1279
3 year differences	.0199 (.0103)	.0194 (.0103)	.0194 (.0103)	.0210 (.0093)	.00116 (.0031)	1058
4 year differences	.0256 (.0117)	.0248 (.0117)	.0248 (.0117)	.0229 (.0102)	.000476 (.0030)	842
5 year differences	.0204 (.0143)	.0193 (.0144)	.0193 (.0144)	.0244 (.0121)	-.000770 (.0037)	625
6 year differences	.0185 (.0184)	.0186 (.018)	.0186 (.018)	.0264 (.0152)	-0.00238 (.0051)	410
7 year differences	.0507 (.0272)	.0545 (.0278)	.0545 (.0278)	.0519 (.0216)	-.00602 (.0076)	195

Sample size substantially reduced because of missing R&D data

Table 2: Regression of Computer Growth on Multifactor Productivity Growth Adjusted for Quasi-fixed Capital with *ex post* Rental Prices - Varying Difference Length

Difference	OLS Quasi-fixed Capital No controls	2SLS Quasi-fixed Capital No controls	OLS Quasi-fixed Capital Ind. controls	2SLS Quasi-fixed Capital Ind. controls	Sample Size
1 year differences	.0115 (.0044)	.0195 (.0073)	.0103 (.0045)	.0153 (.0075)	3661
2 year differences	.0133 (.0053)	.0279 (.0091)	.0109 (.0055)	.0256 (.0097)	3130
3 year differences	.00550 (.0067)	.0343 (.012)	.00200 (.0065)	.0263 (.012)	2583
4 year differences	.0208 (.0075)	.0225 (.013)	.0207 (.0068)	.0224 (.012)	2041
5 year differences	.0245 (.0087)	.0194 (.015)	.0195 (.0081)	.00969 (.015)	1499
6 year differences	.0242 (.011)	.0229 (.018)	.0166 (.010)	.00961 (.017)	956
7 year differences	.0309 (.015)	.0358 (.022)	.0209 (.014)	.0371 (.024)	456

Sample size slightly reduced for 2SLS because of data availability for instruments.

Table 3: Production Function Approach

Coefficient	CII Between	CII Pooled Levels	CII 1st Diff.	IDG Pooled Levels	IDG 1st Diff.
Computer Elasticity	.0358 (.011)	.0304 (.0040)	.0117 (.0041)	.0248 (.0068)	-.0015 (.0041)
Ordinary Capital Elasticity	.201 (.015)	.188 (.0058)	.0608 (.012)	.187 (.010)	.0574 (.017)
Labor Elasticity	.706 (.016)	.720 (.0064)	.743 (.0139)	.734 (.012)	.719 (.025)
R&D Dummy (1=not present)	.274 (.062)	.287 (.025)	.00383 (.0041)	.304 (.044)	.278 (.078)
R&D Elasticity	.0436 (.0112)	.0464 (.0045)	.0102 (.0057)	.0550 (.0075)	.0205 (.0070)
Controls	Industry	Year Industry		Year Industry	
R^2	97.0%	95.9%	50.3%	97.1%	56.9%
N	599	4571	3946	1411	934

Table 4: Semi-Reduced Form Estimates - First Differences

Coefficient	Single Eqn.: VA	Single Eqn.: Labor	System
ΔComputer Capital	.0219 (.0055)	.0251 (.0050)	.0240 (.0047)
ΔOrdinary Capital	.373 (.013)	.400 (.012)	.391 (.011)
Controls	Year	Year	Year
R^2	20.5%	24.4%	19.5%/24.3%
N	3936	3936	3936

Table 5: Semi-Reduced Form Specification Varying Lag Length - ISUR Estimates

Difference	ΔComputer Capital	ΔOrdinary Capital	Sample Size
1 year differences	.0247 (.0048)	.395 (.011)	3936
2 year differences	.0525 (.0058)	.432 (.012)	3364
3 year differences	.0680 (.0069)	.486 (.013)	2775
4 year differences	.0775 (.0083)	.519 (.014)	2190
5 year differences	.0890 (.010)	.549 (.016)	1606
6 year differences	.0910 (.013)	.590 (.020)	1020
7 year differences	.115 (.019)	.580 (.028)	488

Table 6: Rate of Return Analysis

Difference Length	No Controls	Time Only	Industry Only	Industry and Time
1 year differences	.168 (.175)	-.0111 (.035)	.0552 (.0329)	.0160 (.035)
2 year differences	.474 (.151)	.189 (.159)	.341 (.153)	.0100 (.061)
3 year differences	.810 (.179)	.533 (.184)	.606 (.181)	.278 (.185)
4 year differences	1.14 (.183)	.982 (.190)	.861 (.177)	.659 (.184)
5 year differences	.889 (.196)	.915 (.201)	.521 (.187)	.540 (.193)
6 year differences	.932 (.235)	.972 (.236)	.613 (.219)	.662 (.220)
7 year differences	.877 (.329)	.877 (.329)	.623 (.309)	.623 (.309)

Figure 1: Trends in Semiconductor Manufacturing

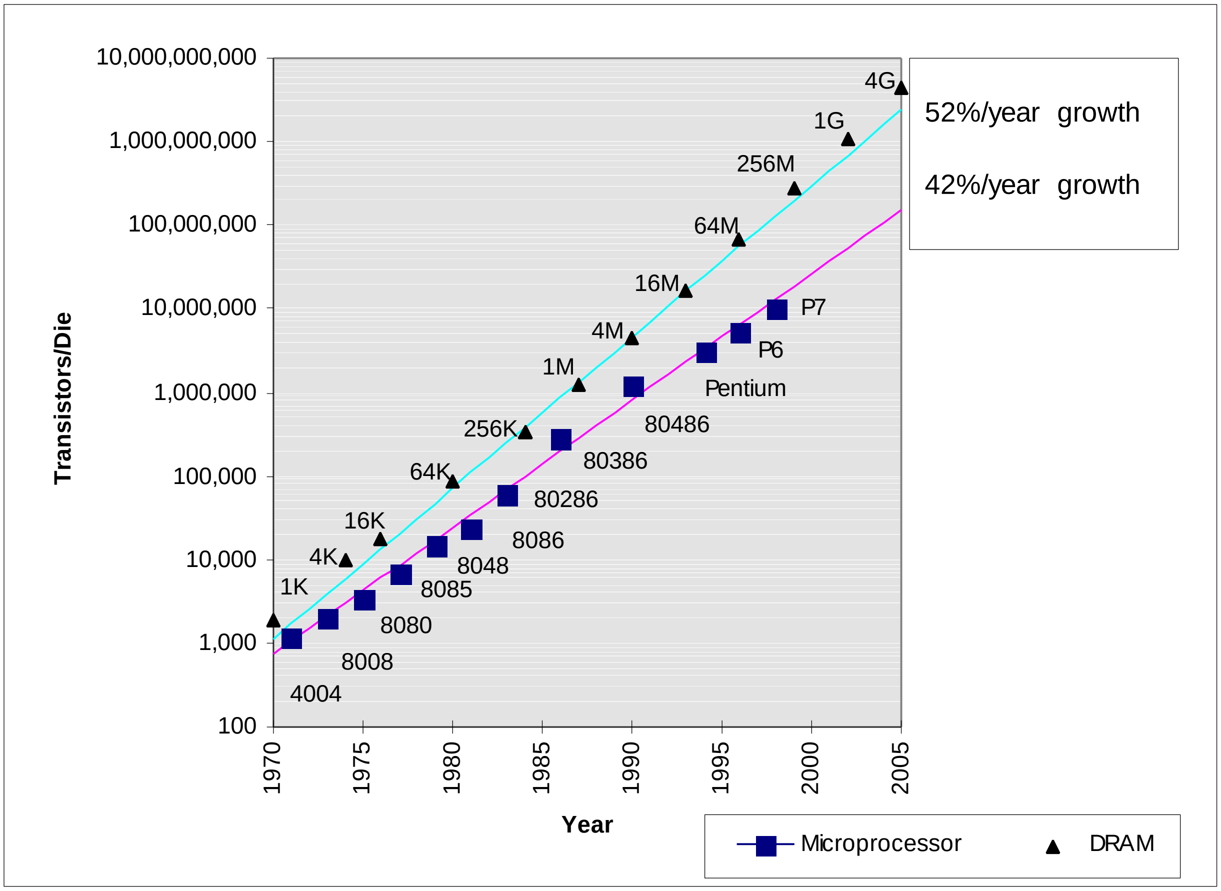
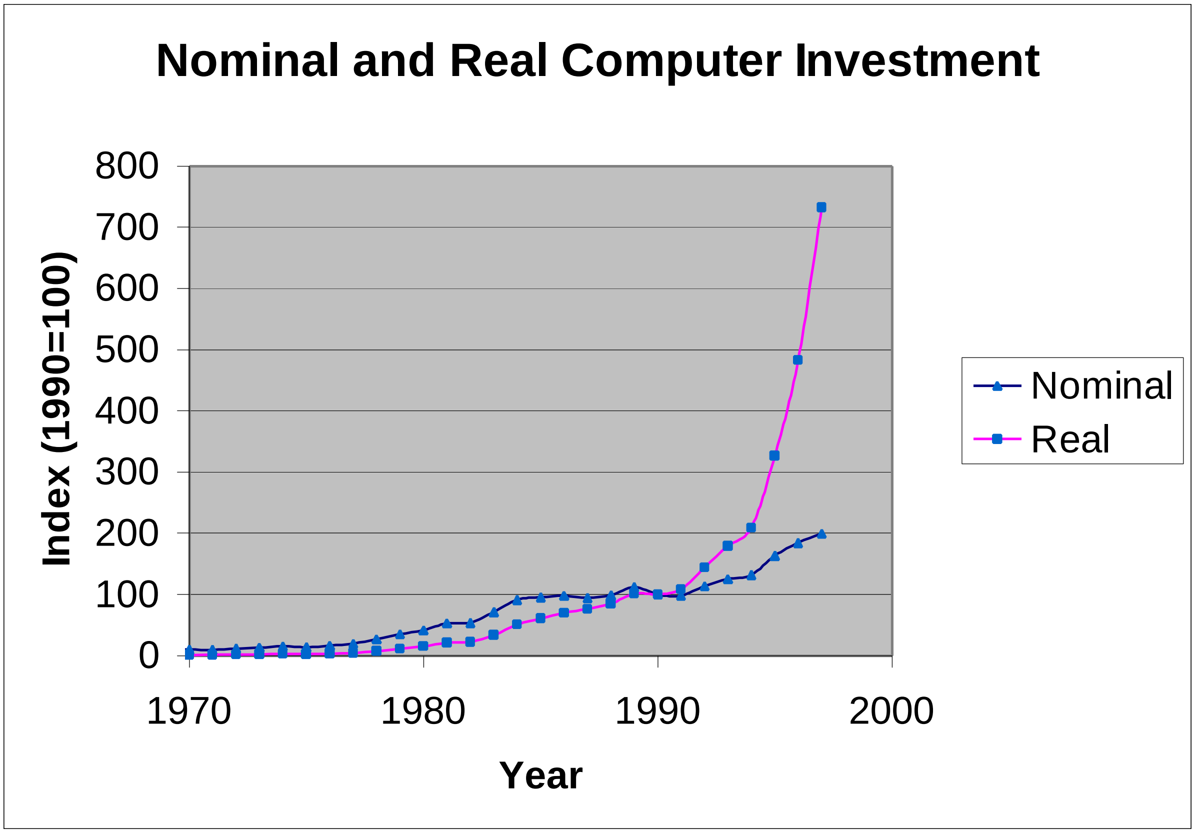


Figure 2: Nominal and Real Computer Investment



Source: NIPA Historical Cost Investment Table and Chain-Weighted Quantity Index Table for Fixed Private Capital (1998)

Figure 3: Baseline Estimates of Computer Elasticity with Different Controls

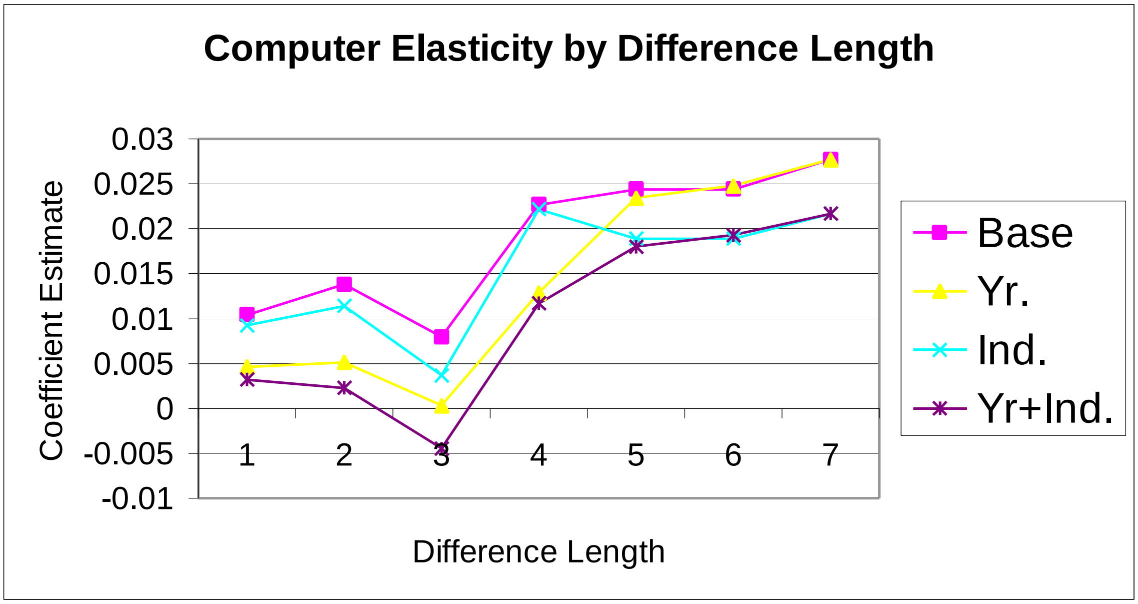


Figure 4: Computer Elasticity Estimates Under Different Specifications

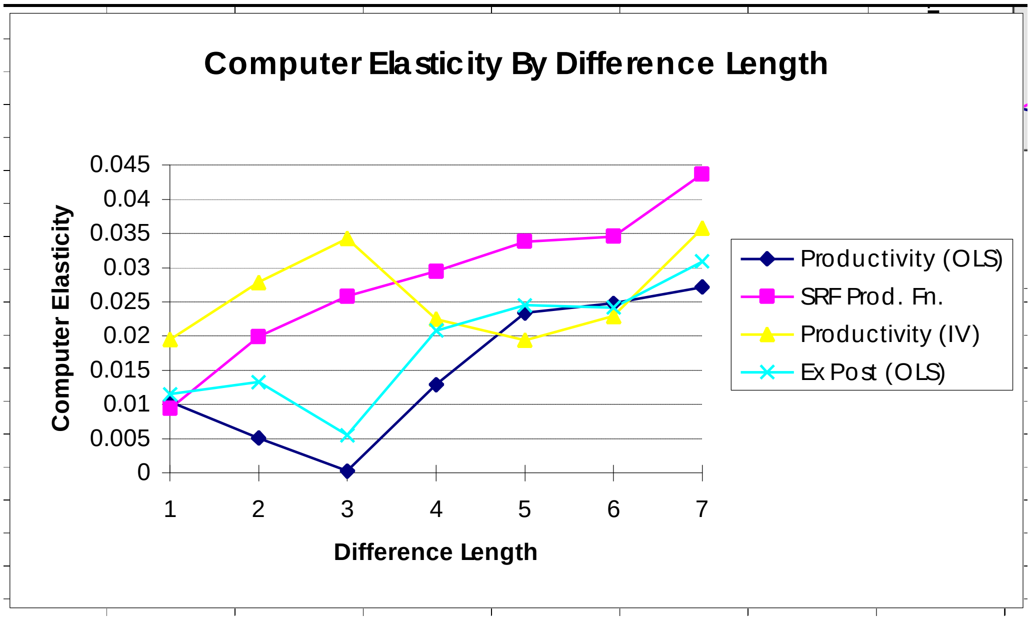


Figure 5: Reasons for Investing in IT

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 1987-1993, and estimated for 1994 using the five-year average inflation rate by industry.

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 (CII). Total market value of all equipment tracked by CII for the firm at all sites. Market valuation is performed by a proprietary algorithm developed by CII 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 (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% for PCs and 42% for terminals, which was the average ratio reported in 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, 1992).

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 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). The figure for 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 fewer 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. 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.

Tobin's q. Computed by adding the market value of all stock equity (from Compustat) to the book value of all outstanding debt (from Compustat) and dividing by total assets (from Compustat).

Appendix B: User Cost of Computers and Ordinary Capital

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):

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

where

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

r_t = investor's required nominal rate of return (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 (1993), 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%.[14] Using a slightly different formula, Lau and Tokutsu (1992) and Lichtenberg (1994) 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 = .01.[15] This

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[14] 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.

[15] Jorgenson and Stiroh (1993) do not report aggregate values for these variables. However, Lau and Tokutsu, (1992) report that reasonable values are δ_τ = .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

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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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 C: Omitted Variable Bias

C.1 Omitted Factors Not Counted Elsewhere

Suppose there is an overall technical system that includes computers as well as other factors that are not otherwise accounted for elsewhere in the productivity analysis such as software or past training investments. Assume that this system (S) has a contribution (θ) to output (O). For exposition, let C and S have unit variance in the data. Let output be composed of the output contribution of all other factors ($\hat{O}$), the impact of S and random error:

$$O = \hat{O} + qS + e$$

In a regression of computers on output, the estimated coefficient on computers (d_c) can be given by the bivariate regression formula (note $\mathrm{cov}(C,\hat{O}) = \mathrm{cov}(C,e) = 0$ by definition):

$$d_c = \frac{\mathrm{cov}(C,qS)}{\mathrm{var}(C)} = qr_{CS}$$ where r_{CS} is the correlation coefficient between C and S

When this estimate is then used to calculate marginal product, the estimate is biased upward because the measured marginal product ($MP^{measured}$) includes the contribution of the entire system, but only the input quantity C.

$$MP_C^{measured} = \frac{qr_{CS}O}{r_c C}$$

If C and the rest of S have exactly the same marginal product the true marginal product of C is given by:

$$MP_C^{true} = \frac{(q\frac{C}{S})O}{r_c C} = q\frac{O}{r_c(S)}$$

This bias increases as the C and the system become more closely correlated or C becomes a smaller proportion of the overall system. This analysis holds in differences as well, as long as the relationship is stable. However, because changes in S may occur at times different from changes in C, the correlation between the computers and other factors in the system (r_{CS}) may be increasing in difference length leading to an increase the in bias.

C.2 Effect of Misallocation Between Computers and Other Inputs

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):

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

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 the actual and measured marginal products of computers. For this calculation let $K_c= \tau_k C$ and $L_c= \tau_l C$. Then with the above assumptions we have:

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

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

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