Computers and Productivity: Are Aggregation Effects Important?

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Abstract

This paper examines the empirical implications of aggregation bias when measuring the productive impact of computers. To isolate two specific aggregation problems relating to "aggregation in variables" and "aggregation in relations," we compare various production function estimates across a range of specifications, econometric estimators, and data levels. The results show that both sources of bias are important, especially as one moves from the sector to the economy level, and when the elasticity of all types of non-computer capital are incorrectly restricted to be equal. In terms of computers, however, the estimated elasticity is surprisingly stable between industry and sector regressions and does not appear to be biased by the incorporation of a restrictive measure of non-computer capital. The data consistently show that computers have a large impact on output.

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I. Introduction

Economic research relies heavily on aggregated data and there are good reasons for this. Aggregation combines details to give a clearer picture of performance. It also simplifies analysis because it is much easier to work with a small set of aggregate variables than to try to model the myriad of details that lie beneath. A third reason is that aggregation enables survey organizations to collect data in broad categories, which limits processing and collection costs. Finally, aggregation protects confidential micro-data, although this is becoming less important as new institutions are developed to maintain secrecy while still allowing access by researchers.

Aggregation, however, also has important problems and the possibility of systematic bias from the use of aggregate data has long been recognized. In an early paper, Theil (1954) formally examined the possibilities for biased estimates of economic relationships when aggregates were used in place of information on individuals or firms. Similarly, the long debate over the "existence" of an aggregate production function or an aggregate measure of capital is essentially about the difficulties when using aggregate data and relationships to represent the underlying microeconomic production relationships.[1] While much has been learned about how aggregation should be done and what conditions are required for meaningful aggregates, e.g., Diewert (1976), aggregation remains an important issue.

The recent availability of micro-data, for example, has led to a host of studies documenting widespread differences in the characteristics of economic units within seemingly homogeneous groups or industries, e.g., Baily, Hulten, and Campbell (1992), Jensen and McGuckin (1996), and Haltiwanger (1997). Arguably, the common practice of using a "representative firm" model to justify use of aggregates is not appropriate in these situations and recent empirical work supports this in a wide variety of situations, e.g., productivity growth, investment dynamics, and employment movements as surveyed in Haltiwanger (1997). As a concrete example of how aggregation may be misleading, McGuckin and Nguyen (1999) find an impact of ownership change on productivity in plant-level data, but the relationship becomes obscured when firm-level observations are used.

This paper examines the empirical implications of using different types of aggregate data in a specific context – measuring the productive impact of computers. This application is of particular interest in light of the widespread discussion and controversy concerning the so-called "computer productivity paradox." This puzzle can be traced to the 1987 observation by Robert Solow that, although computers were becoming ubiquitous, aggregate productivity remained sluggish. One potential explanation was presented by Oliner and Sichel (1994) and Sichel (1997), who emphasized that computers represent a relatively small portion of economy-wide capital. Since computer capital was small, it is not surprising that it did not have a large impact on aggregate productivity or growth in earlier years.[2]

While certainly true in an aggregate growth accounting framework, this doesn't explain the disparity of findings at lower levels of aggregation that analyzed data for same period of the 1980s and early 1990s. Berndt and Morrison (1995), for example, found that computers were having little impact on productivity in the 1980s, while Morrison (1997) reports evidence of over-investment in high-tech capital. In contrast, Brynjolfsson and Hitt (1995), Lehr and Lichtenberg (1999), and Lichtenberg (1995), Siegel (1997), and Steindel (1992) found that computers had a significant impact on productivity and output.

One factor that may be contributing to this divergence is the different degree of aggregation across studies. The purpose of this paper, therefore, is to use a common econometric approach and dataset to isolate the impact of aggregation effects. By comparing econometric results using the same specification at three distinct levels of aggregation – the private business economy, 10 major sector groups, and 55 detailed industries – we can quantify the importance of bias from "aggregation of relations" problems.[3] Similarly, by comparing estimates from different decompositions of capital, we can quantify the importance of bias from "aggregation of variables" problems.

We begin by documenting widespread differences in computer intensity across business sectors and component industries. We then use a continuous measure of computer intensity – measured either as the stock of computer capital or the share of equipment capital in the form of computers – in various production function specifications. Comparison of the estimated

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[1]Fisher (1992) provides details on both capital and production function aggregation and Jorgenson (1990) discusses the stringent assumptions needed to move from a sectoral production function to an aggregate production function.
[2]More recent estimates for the late 1990s in Jorgenson and Stiroh (2000b) and Oliner and Sichel (2000) show that information technology played an important role in the U.S. productivity revival.
[3]Note, however, that data limitations prevent us from extending this comparison to include analysis of aggregation effects that move from the firm or plant level to the industry level. Micro-data is available for manufacturing industries from the Longitudinal Research Database (LRD), but is not available outside of manufacturing.

elasticity from the different regressions provides important insights about the relationship between computers, productivity, and output and the importance of aggregation effects.

Our results suggest that both sources of bias are important in general, although the estimated computer elasticity is surprisingly robust across different levels of data and alternative specifications. The level of aggregation has a direct impact on the estimated elasticity of certain types of capital, most notably structures, while the decomposition of non-computer capital matters because the marginal products of different types of capital are clearly not equal.

In terms of computers, the estimated elasticity is quite large and stable, typically in the range of 0.15 to 0.20, across both the industry and the sector regressions and does not appear to be biased by the use of a restrictive measure of non-computer capital. Since computers experience rapid depreciation and large capital losses due to obsolescence, they must earn a large gross rate of return to cover these costs; this explains the relatively large output elasticity for computers. We conclude that despite the presence of aggregation bias, previous estimates of a large elasticity of computers appear reasonable and are entirely consistent with economic theory.

II. General Approach

Research on computers and productivity has generally followed two empirical traditions. Jorgenson and Stiroh (2000b, 1999, 1995), Sichel (1999), Haimowitz (1998), Stiroh (1998), and Oliner and Sichel (2000, 1994) use growth accounting techniques to compare the growth rate of output to the share-weighted growth rates of inputs and estimate the contribution of each input to economic growth. In contrast, Gera, Gu, and Lee (1999), Lehr and Lichtenberg (1999), Morrison (1997), Siegel (1997), Berndt and Morrison (1995), Brynjolffson and Hitt (1995), Lichtenberg (1995), and Steindel (1992) estimate production or cost functions for firms or industries that explicitly include some measure of computer capital or computer-related labor.[4]

The empirical work typically begins with a production function such as:

$$(1)\ \ Y_{i,t} = A_t \cdot f(K_{i,t}^{computer}, K_{i,t}^{other}, L_{i,t}, i)$$

where $Y_{i,t}$ is output, $K_{i,t}^{computer}$ is capital in the form of computers, $K_{i,t}^{other}$ is other capital, and $L_{i,t}$ is labor for firm, industry, or sector i at time t. A_t represents total factor productivity (TFP) or disembodied technical change that depends solely on time.

[4]Brynjolfsson and Yang (1996) survey this field.

The econometric studies take some version of Equation (1), assume a functional form, transform the relationship into a regression, and estimate that regression with the data at hand. Our empirical work follows this tradition and estimates alternative specifications of Equation (1) at different levels of aggregation using several different econometric estimators in order to quantify the importance of two different types of aggregation errors.[5]

(a) Aggregation Issues

Broadly speaking, aggregation bias is a special case of specification error, but ascertaining the bias in any particular application is not straightforward. Maddala (1977) divides the topic of aggregation bias into two broad sets of questions – problems in the "aggregation of variables" and problems in the "aggregation of relations." We examine both issues and, although we do not formally derive or model these aggregation biases here, it is useful to put our comparisons in this context. See Maddala (1977) for details.

Aggregation of variables includes the whole area of index number construction in which an index variable is created to represent the movement of a set of prices or quantities over time. This area has a rich history and we focus on one example relating to incorrectly specifying the production function inputs.

To fix ideas, consider the example in Lichtenberg (1990) where the true structural relationship is $y = b_1 X_1 + b_2 X_2 + u$, but the econometrician incorrectly estimates $y = b(X_1 + X_2) + e$. Lichtenberg shows that the probability limit of the estimate of β is a weighted average of b_1 and b_2, but the weights need not be between zero and one so perverse effects are possible. In his empirical application, Lichtenberg (1990) examines the consequences of using an aggregate measure of research and development (R&D) in place of a disaggregated specification that explicitly includes federal government R&D and private R&D. Since the productivity impact of federal R&D was less than private R&D, the estimated impact of aggregate R&D understated the true impact.[6] Aizcorbe (1990) makes an important contribution to this literature by developing tests of the validity of particular aggregates in the context of generalized production functions that are discussed below.

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[5]Some authors, e.g., Lichtenberg (1995), also decompose labor into a information technology and non-information technology portion. He finds evidence of excess return to labor associated with information technology.

Aggregation of relations includes many issues that deal with the interaction between micro- and macro-relationships. The seminal work of Theil (1954) studied one specific case dealing with the conditions needed for the preservation of the parameters of micro-relations when estimation is carried out using macro-variables.[7] We examine a very specific form of this question and compare differences in the coefficients of the same production function that are estimated at various levels of aggregation. Morrison-Paul and Siegel (1999) undertake a similar exercise in the context of measuring economies of scale in manufacturing and find that the aggregation bias from moving between 4-digit, 2-digit, and total manufacturing data is not substantive.

In the case of computers and productivity, we speculate that both types of aggregation issues are important. Regarding aggregation of variables, the marginal productivity of different forms of capital can be quite varied so aggregating heterogeneous types of capital may be an important source of bias. For example, econometric work that simply includes an aggregate measure of "non-computer capital" as in Equation (1) may generate the exact bias described by Lichtenberg (1990). Regarding aggregation of relations, both production structure and computer intensity vary widely across industries and combining these disparate industries into aggregates may lead to biased coefficient estimates. Thus, the level of aggregation may have a direct impact on the estimated parameters of a production function and create a misleading picture of the productive role of computers.

(b) Econometric Framework

The remainder of this section outlines three related empirical specifications that can be used to examine how production function coefficients vary when they are estimated with different data. In particular, we focus on how the estimated elasticity of computer capital changes across different decompositions of capital (aggregation of variables) and across different levels of aggregation (aggregation of relations).

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[6]The true coefficient of the aggregate variable is a weighted sum (equal to 1.0) of the true coefficients for the individual impacts with the bias depending on the ratio of the variances of each component of aggregate R&D and the correlation between the individual components. See Lichtenberg (1990) for details.

[7]There is a technically similar class of problems that Madalla (1977) includes in aggregation of relations. These problems question whether aggregate or micro based relationships give the "best" prediction or forecast when both types of variables are available. We do not investigate this.

i) Simple Production Function

In the empirical literature on the role of computers, it is standard practice to decompose capital into two parts – computer capital and non-computer capital as in Equation (1) – and econometrically estimate a production function. A common Cobb-Douglas specification, for example, yields the following model:

$$(2)\ \ Y = e^{A(t)} \cdot e^{j\,(i)} \cdot L^{b_0} \cdot K_c^{b_1} \cdot K_n^{b_2} \cdot e^{e}$$

where L is labor, K_c is computer capital, K_n is non-computer capital, $A(t)$ and $j\,(i)$ are general time and industry variables that simply shift the production function, but do not interact with the inputs, and ε is a random error term.[8]

To estimate Equation (2), take logs and include time and industry effects as dummy variables, T and I, to allow flexibility in $A(t)$ and $j\,(i)$, respectively. This implies the following simple production function regression:

$$(3)\qquad \ln Y = a + b_0 \ln L + b_1 \ln K_c + b_2 \ln K_n + q_t T + q_i I + e$$

This regression provides the first way to estimate the impact of computers on output and productivity. Specifications of this type are common in the literature, e.g., Brynjolfsson and Hitt (1995), Lichtenberg (1995), and Steindel (1992).[9]

We emphasize that while Equation (3) isolates computers from other forms of capital, there are still problems relating to aggregation of variables. K_n contains many heterogeneous assets across many vintages, e.g., cars, structures, and machines tools, that likely do not have the same elasticity. Moreover, K_c is an aggregate that includes mainframes, personal computers, displays, printers, storage devices, and other peripheral equipment and these components may have different production characteristics that may make aggregation inappropriate. We do not focus on bias at this level to provide comparability with earlier studies and to maintain tractability of our results.[10]

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[8]Time and industry subscripts have been dropped from the inputs and outputs for ease of exposition.

[9]Under the assumption of constant returns to scale, it is straightforward to transform this output regression to a labor productivity regression and this has been done in several of the studies cited. We estimated these types of labor productivity regressions and found similar results, so we focus on the output level regressions.

[10]There are also important differences across vintages for each detailed asset, e.g., faster processor speed in more recent personal computers. The BEA data, however, account for these vintage differences through constant-quality price deflators that implicitly makes investment across vintages perfect substitutes and allows aggregation across vintages.

ii) Extended Production Function

The implicit assumption in the simple production function of Equation (2) is that all forms of non-computer capital are perfect substitutes and have the same output elasticity. To examine the impact of this assumption, we consider a more general production function that explicitly includes four types of capital – computer capital, K_c, other high-tech equipment, K_h, other equipment, K_o, and structures, K_s – and allows the output elasticity to vary across each asset class. As shown in Lichtenberg (1990), incorrectly imposing a common elasticity can lead to biased estimates due to the aggregation of variables problem.

The extended production function, again in Cobb-Douglas form, is:

$$(4)\ \ Y = e^{A(t)} \cdot e^{j(i)} \cdot L^{b_0} \cdot K_c^{b_1} \cdot K_h^{b_2} \cdot K_o^{b_3} \cdot K_s^{b_4} \cdot e^{e}$$

which implies the following extended production function regression:

$$(5)\ \ \ln Y = a + b_0 \ln L + b_1 \ln K_c + b_2 \ln K_h + b_3 \ln K_o + b_4 \ln K_s + q_t T + q_i I + e$$

The regression in Equation (5) provides a second way to evaluate the impact of computers. By allowing a more general specification that removes a particular form of aggregation error, these regressions may provide better estimates of the impact of computers. Moreover, by comparing the estimated elasticities from Equation (3) to the estimated elasticities from Equations (5), we can directly assess the practical importance of the aggregation of variables bias.

iii) Alternative Production Function

The two approaches described above estimate the impact of computers by explicitly decomposing capital into different types. As an alternative, we also examine a specification similar to Berndt and Morrison (1995) and Lehr and Lichtenberg (1999). This approach uses capital shares to identify differences in the productive impact of equipment capital in general and computer capital in particular.

Consider the slightly modified Cobb-Douglas production function:

$$(6)\ \ Y = A \cdot L^{b_0} (K^*)^{b_1}$$

where K* is "effective" capital that is measured as:

$$(7)\ \ K^* = K \cdot \left(\frac{K_e}{K}\right)^{d} \cdot \left(\frac{K_c}{K_e}\right)^{g}$$

so that:

$$(8)\ \ln K^{*} = \ln K + d \cdot \ln\left(\frac{K_e}{K}\right) + g \cdot \ln\left(\frac{K_c}{K_e}\right)$$

where K_e is total equipment capital and K_c is computer capital.

Aizcorbe (1990) provides a formal justification and defense of this type of approach. She shows that, under reasonable conditions, a general production function $Y = f(X_1, X_2, \ldots X_K)$ can be restated as $Y = f(X, M_1, M_2, \ldots M_{K-1})$ where X is some aggregate of the individual inputs and $M_i = M_i(X_i, X_K)$ is a "mix function" that relates the two arguments. To test if the aggregate X is valid, one can test if $\frac{\partial Y}{\partial M_i} = 0, \forall i$.

In this framework, δ and γ measure the compositional effects associated with different types of capital. That is, δ>0 implies that a larger proportion of capital in the form of equipment increases the amount of effective capital relative to the measured aggregate. Likewise, γ>0 implies that a larger proportion of equipment in the form of computers increases the effective amount of capital.

Note that this specification only captures composition effects since individual capital stock series are calculated with quality-adjusted price indexes for computers to account for improvement embodied in more recent vintages and all series are aggregated using a Divisia index. Thus, vintage differences and traditional index number problems are eliminated.

Combining Equations (6) and (8) yields the following alternative production function regression:

$$(9)\ \ln Y = a + b_0 \ln L + b_1 \ln K + b_1 d \ln\left(\frac{K_e}{K}\right) + b_1 g\left(\frac{K_c}{K_e}\right) + q_t T + q_i I + e$$

Again, the interpretation of δ and γ is clear. If equipment and computer capital do not have any differential impact and the composition of the capital stock does not matter, then $d=g=0$. If this is true, then $b_1 d = b_1 g = 0$ in Equation (9). Conversely, if composition effects do matter, then the estimated coefficients on the shares will be statistically significant different from zero (assuming the $b_1 {}^{1} 0$ as implied by standard production theory). Of course, the coefficients on the two shares need not be the same and none, either one, or both of the share effects could matter.

The regressions in Equations (3), (5), and (9) provide the means for assessing the practical important of biases from aggregation of variables and aggregation of relations. That is, by comparing estimates from the simple production function to the extended or alternative production functions, we can assess the bias created from a restrictive measure of capital (aggregation of variables). Likewise, by estimating each regression at differ levels of aggregation, e.g., industry, sector, and private business economy, we can assets the bias from incorrectly imposing the same relationship (aggregation of relations).

III. Data Sources and Construction

Data comes from the Bureau of Economic Analysis (BEA) and include gross product originating (GPO) by industry and capital stock by industry and asset.

(a) BEA Gross Product Originating

Gross product originating (GPO) represents each industry's contribution to gross domestic product as calculated by BEA. These data, also called value-added data, equal gross output less intermediate inputs and thus equal payments to labor and capital. The GPO data include current and chain-weighted constant dollar data for 62 detailed private industries. The current dollar GPO is from 1948 to 1996, while the constant dollar GPO is only from 1977-1996. Data on full-time equivalent employees, FTE, is available for the same industries from 1947-1996.[11] Details are provided by Lum and Yuskavage (1997), Lum and Moyer (1998), and Yuskavage (1996).

(b) BEA Tangible Wealth Survey

Investment and capital stock are estimated by the BEA as part of their Tangible Wealth study (BEA (1998)). These data include current dollar net capital stocks and corresponding chain-weighted quantity indexes for 62 private industries and 57 assets from 1947 to 1996. Details on the estimation and data sources can be found in Katz and Herman (1997) and these data correspond to those reported in the September 1997 *Survey of Current Business*.

(c) Creating Consistent Data

The data used in this paper represent consolidated data based on 1987 SIC codes. To focus on the private business economy, we excluded government enterprises, general

[11]As a consistency check, we compared alternative labor series available from the BLS and hours by industry data from Gullickson and Harper (1999) and found very high correlations.

government, real estate, and private households from our econometric analysis. Aggregation of output and capital stocks was done as a Divisia quantity index, which has the desired exact aggregation properties, while labor series are simple sums. This procedure resulted in 55 detailed industries that comprise 10 major sectors with data on gross product originating, labor, and capital stock by asset.

To measure the composition of the capital stock, we created several aggregates from the detailed capital stock series. Computers include mainframes, personal computers, direct access storage devices, printers, terminals, tape drives, and other storage devices. Other high-tech equipment includes communications equipment, instruments, and photocopy equipment. Other equipment includes all other producers' durable equipment. Structures include all non-residential structures. Thus, our capital measure excludes residential structures, land, and inventories and includes only fixed, reproducible tangible assets owned by the business sector.

(d) Descriptive Statistics

Table 1 shows the evolution of computer capital for major sectors and the detailed industries from 1970 to 1996. These data show the rapid accumulation of computers throughout the economy as documented in the aggregate work of Jorgenson and Stiroh (2000b) and Oliner and Sichel (2000).[12]

More important for our purposes, there is wide variation across major sectors and industries. The private business sector shows a nominal computer share in the capital stock of 1.8% in 1996, for example, while only 0.002% of farm capital is computers but more than 20% of business services capital is in the form of computers. Even within major sectors like services or manufacturing, there is substantial variation in computer shares of the total capital stock.

Table 1 also shows wide variation in the accumulation rates of computers across major sectors, ranging from 8.34% in mining to 28.84% in wholesale trade in the 1990s. These growth rates far exceed the growth in other forms of capital, typically by a factor of 10. Again, variation widens significantly at lower levels of aggregation and remains large within major sectors. Since capital stocks are calculated using the same methodology and the same underlying deflators, this reflects enormous differences in investment patterns across industries.

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[12]These studies use a later vintage of capital data and are thus not directly comparable to these industry estimates.

Table 2 presents the distribution of capital by type – computers, other hi-tech, other equipment, and structures – within major sectors and detailed industries. As expected, there is wide variation in all forms of capital since different industries have fundamentally different production techniques. This suggests that the simple production function approach may be quite misleading since it does not account for the wide heterogeneity in capital.

Table 3 presents the distribution of capital in a different way by reporting the distribution of total computer and hi-tech capital across major sectors. As reported in Triplett (1999) and Stiroh (1998), computers are highly concentrated in service-related sectors with wholesale trade, retail trade, finance insurance and real estate, and services owning over $120 billion dollars of computer equipment, which accounts for over 78% of the U.S. business total. Manufacturing, on the other hand, holds only $26 billion or 17% of the total.

IV. Production Function Estimates

Our empirical results focus on three regressions – Equations (3), (5), and (9) – that are estimated at different levels of aggregation with different econometric methods. The structure of aggregation coincides with Tables 1 and 2 and includes three nested levels. "Aggregate" is the private business economy,[13] which consists of 10 major "sectors," which in turn consist of 55 detailed "industries" at roughly the two-digit SIC level. All aggregation is done with a Divisia index so the 55 detailed industries sum to the 10 major sectors and the 10 major sectors sum to the aggregate in current dollars.[14]

We estimate the production functions in several different ways. We first perform ordinary least squares (OLS) on the aggregate, sector, and industry data. These regressions include year dummy variables for the sector and industry regressions and a linear time trend in the aggregate regression. We then estimate a traditional fixed effect (FE) specification that allows each industry or sector to have a unique intercept to account for unobserved heterogeneity. Since the aggregate data is a single series and cannot be estimated using the panel methods, only an OLS estimate is reported.

While regressions of these types are quite common in the literature, there are important econometric concerns. There is an endogenity problem since output and inputs, particularly

[13]Real estate and private households are not included.
[14]The series do not sum exactly in constant dollars, which is an artifact of Divisia aggregation. A similar property exists in the new chain-weighted indexes in the national accounts. See Landefeld and Parker (1997) for details.

variable inputs such as labor, are likely to be chosen simultaneously. There is also an omitted variable problem since we cannot observe all factors that determine output or productivity, e.g., technology, research and development, efficiency, and input quality. Inclusion of fixed effects in a panel framework can control for unobservable factors that are constant over time, but to the extent that unobservable factors vary and are correlated with particular inputs, those coefficients will be biased. Finally, there are multicollinearity issues since all inputs are likely to be correlated, particularly at higher levels of aggregation with less cross-sectional variation.[15]

To control for both the unobserved heterogeneity and simultaneity problems, we employ more sophisticated econometric tools developed by Arellano and Bover (1995) and Blundell and Bond (1998), and applied to production function estimates by Blundell and Bond (1999). Their system generalized method of moments (SYS-GMM) estimator utilizes a combination of regressions in levels and first-differences with several lagged first-differences as instruments for the equations in levels and several lagged levels as instruments for equations in first-differences. Simulation results in Blundell and Bond (1998) show this estimator offers efficiency gains relative to the basic first-differenced GMM estimator.[16]

A second data limitation forces us to use a measure of capital stock rather than the preferred flow of capital services. This difference has been recognized at least since Solow (1957) and has been an important part of the growth accounting literature. Ho, Jorgenson, and Stiroh (1999) provide details on the conceptual and empirical distinction.

A final issue is our use of gross product originating as the output concept. Ideally, we would prefer to use a measure of gross output, which includes the value of intermediate inputs, but we did not have the corresponding data for intermediate inputs. Such is data is available for manufacturing industries, e.g., the NBER Grey-Bartelsman database, or for relatively high levels of aggregation, e.g., Jorgenson and Stiroh (2000a), but they do not provide the comprehensive

[15]Griliches and Mairesse (1998) provide a detailed review of the econometric difficulties associated with production function estimation and common approaches designed to mitigate the problems.

[16]The SYS-GMM estimator was generated using the DPD98 Gauss software described by Arellano and Bond (1998). All reported SYS-GMM estimates are from the one-step GMM estimator, with standard errors corrected for heteroskedasticity. To avoid over-fitting biases that are possible in our relatively small cross-sectional samples, we report estimates with two lags for the instruments in the sector regressions and three lags in the industry regressions.

coverage of computer-intensive industries or the nested levels of disaggregation required for this exercise.[17] With these caveats in mind, we proceed to the empirical results

(a) Simple Production Function

Table 4 reports estimates of the simple production function in Equation (3) for different levels of aggregation and econometric methods. For the most part, the sector and industry results are reasonable with a large, positive, and significant coefficient on labor in the 0.5 range and capital coefficients that are typically statistically significant.[18] Consistent with Blundell and Bond (1999), the FE (within) estimator produces coefficients that appear to be biased downward, while the SYS-GMM estimators are more reasonable. In both the sector and industry SYS-GMM regression, the coefficient on computer capital is large and statistically significant.

The estimates of the computer elasticity are typically around 0.2 in the OLS and SYS-GMM models, somewhat larger than earlier estimates in Brynjolfsson and Hitt (1995) and Lichtenberg (1995). Those papers estimate a similar regression with firm-level data for earlier periods and report a statistically significant elasticity for computer capital in the range of 0.05-0.12. The larger impact in our data likely reflects the growing importance of computers in our sample relative to their earlier samples.

The large change in coefficients when sector or industry dummy variables are included in the FE estimates suggests that deviations in output over time from the mean for a particular sector or industry are not highly correlated with deviations in computer capital. Similarly, the elasticity of non-computer capital falls and is actually significantly negative at the industry level. This is unexpected, although low and insignificant capital coefficients in FE regressions are common in empirical work and motivated the move to the more sophisticated GMM approaches. Griliches and Mairesse (1998), particularly pg. 178, discuss this phenomenon and suggest that the loss in variance of the right-hand side variables is responsible as other errors like measurement and random noise dominate the remaining information.

In general, there appear to be small differences in the estimated coefficients when the industry and sector level regressions are compared. Consistent with Morrison-Paul and Siegel

[17]We did combine our data with the real gross output series available from the BLS Employment Projections division and estimated the regressions with gross output as the dependent variables and the same explanatory variables. While not the proper specification, the results were similar to those reported.

[18]Not surprisingly, the estimates from the aggregate regression are the least reasonable with a labor coefficient of 1.074 and a negative (though not significant) coefficient on non-computer capital.

(1999), bias from aggregation of relations appears small. When the aggregate regression is compared, however, there are large changes in the estimated coefficients, suggesting the aggregation of relations problem becomes large at the aggregate level.

(b) Extended Production Function

Table 5 reports estimates of the extended production function regressions in Equation (5). The results, again except for the aggregate OLS regression, are generally well-behaved with a coefficient on labor typically in the 0.5 range and mostly reasonable capital coefficients. Again, the SYS-GMM estimates appear the most reasonable, while the FE results appear biased downward.

In terms of comparison across levels of aggregation and biases from aggregation of relations, the computer coefficient is again quite stable across the industry and sector regressions using all estimators. The other capital coefficients show more variability. The estimated elasticity of structures, for example, increases from 0.096 in the OLS sector regression to 0.210 in the OLS industry regression and from 0.048 to 0.194 in the SYS-GMM regression.

To assess the aggregation in variables bias, we compare the results in Table 5 to those in Table 4 and find evidence of an important problem. That is, the estimated elasticities on the different types of non-computer capital are quite different and it is inappropriate to impose a common elasticity on all types of non-computer capital.[19] The point estimates of the computer elasticities, however, typically remain in the range of 0.20. This suggests that any bias introduced by incorrect restrictions on other forms of capital does not substantially change the estimated elasticity of computers.

(c) Alternative Production Function

Table 6 presents estimates of Equation (9), which includes aggregate capital and two share variables, as opposed to each type of capital separately. As discussed above, Aizcorbe (1990) shows this to be an equivalent representation of the production function if aggregation across variables is valid. Again, we report estimates from the OLS, FE, and SYS-GMM estimators.

[19] Econometric tests of the null hypothesis of a common coefficient on all types of non-computer capital are reported at the bottom of Table 5.

The results are consistent with the earlier findings and mostly appear reasonable: labor elasticities are in the 0.5 range, the capital elasticity is between 0.3-0.4 in the OLS and SYS-GMM estimates, and the FE estimates appear biased downward. These estimates are broadly consistent with expected income shares. As in the earlier specifications, the capital elasticity drops in the FE regression and the aggregate regression appears the least reasonable with a large, negative elasticity on capital and a labor elasticity that appears too large.

When comparing the sector and industry regressions, some estimated coefficients seem to vary a great deal, while others do not. For example, labor elasticity in the FE regression was estimated at 0.04 at the sector level and 0.46 at the industry level. In contrast, the computer share coefficient varies little across levels of aggregation, but falls dramatically in the FE regression. This suggests that between industry rather than within industry variation is the primary source of output variation associated with computers.

The results also imply that the composition of the capital stock matters with regard to computers, but not necessarily with regard to equipment in general. That is, a higher share of equipment in the form of computers is typically associated with higher output, while a larger share of capital in the form of equipment is not. More formally, in the sector and industry regressions, ***d*** in Equation (9) is typically small and insignificantly different from zero, while *g* is typically positive and often significant. The implied estimates ***d*** and *g* and the associated p-value are reported in Table 6.[20]

Lehr and Lichtenberg (1999) estimate a similar specification and find results that are broadly consistent. Their coefficient estimates are not directly comparable, however, since they do not include the equipment to capital ratio in their regression and estimate an approximation without taking logs of the computer share. Despite these differences, they also find that the share of computers is positively and significantly related to output across a panel of firms in the late 1980s and early 1990s.

It is important to recognize that our evidence that computers appear more productive than other forms of capital does not necessarily imply that computers earn excess returns. In a neoclassical framework, for example, an asset's output elasticity equals its nominal income share. This income share is typically derived from a user-cost approach that includes tax factors,

[20]The p-value is associated with the null hypothesis that δ or γ is equal to zero.

depreciation, capital gains/losses, and the acquisition price of the asset. In the case of computer equipment, rapid obsolescence and massive price declines yield a high user-cost, which makes a high marginal product necessary simply to make the computer a worthwhile investment

Lichtenberg (1995) explicitly tests the hypothesis that computer equipment has excess returns by comparing the ratio of marginal products to user-costs for different types of capital and finds evidence of excess returns to computers. While we do not perform this type of test, one can get a rough sense by comparing the average income share reported in Jorgenson and Stiroh (2000b) and Oliner and Sichel (2000) to our estimated elasticity. Both studies use aggregate data for the U.S. and report relatively small income shares: about 1.0% in Jorgenson and Stiroh and 1.4% in Oliner and Sichel. Both shares are considerably below our estimated coefficient, although the results are not directly comparable since we do not have detailed capital service data for all assets and the output concepts are not identical.

(d) Robustness Checks

One concern in estimating these types of regressions is measurement error. The recent divergence in productivity growth between manufacturing and non-manufacturing industries, for example, has led some to believe that measurement problems lead output, and therefore productivity, to be understated in certain industries. Dean (1999), for example, concludes, "there are important measurement problems in some service activities (pg. 24)."

These difficulties may reflect inadequate data, conceptual problems in defining service sector output, or an inability to accurately decompose nominal changes into prices and quantities. In the specific context of measuring the impact of computers, Siegel (1997) finds that computers lead to both quality change and productivity growth, after accounting for potential measurement errors. Using a different framework, McGuckin and Stiroh (2000) conclude that measurement error associated with computer investment may be contributing to an underestimate of aggregate productivity growth.

To examine whether our results are robust to such potential problems, we split the industry data into manufacturing and non-manufacturing industries. Table 7 reports OLS results for the simple production function and SYS-GMM estimators for all three specifications. In all cases, the coefficient related to computer capital is larger in the manufacturing regression, but typically less precisely estimated. This is similar to McGuckin and Stiroh (2000), but contrasts Brynjolfsson and Hitt (1995) who report a larger estimated coefficient on computers in the service sector compared to manufacturing. If one believes that manufacturing output is better measured than non-manufacturing, these results suggest that the estimates for all industries and sectors may be understating the productive impact of computers. The pattern of coefficients, however, is similar to that found earlier, suggesting that the qualitative results are not being driven by service sector mismeasurement.

V. Conclusions

The purpose of this paper is to document the empirical importance of aggregation effects in the context of estimating production functions that include computer capital as a distinct asset. Drawing together the results from alternative specifications that were estimated at different levels of aggregation, several conclusions stand out.

It is clear that the economy-wide specification provides very unstable results and gives a misleading picture of computer productivity. The elasticity of labor is often quite large and the impact of computers was typically small and varies considerably across specifications at the aggregate level. In contrast, both the sector and the industry estimates show a very stable estimated elasticity for computers, typically in the 0.15 to 0.20 range, across specifications in OLS and SYS-GMM regressions. Estimates are typically smaller in FE regressions, consistent with previous findings of a downward bias in this type of estimate. These findings also echo the results of our earlier work in McGuckin and Stiroh (1998), which found that because computer use was concentrated in a small number of industries, the impact was obscured at higher levels of analysis.

The stability of the estimated impact of computers between the industry and sector regressions and across specifications was somewhat surprising, but also reassuring. Since these estimates are robust to the specification and aggregation level, it suggests that computers are having a real impact on output. This does not mean, however, that aggregation of relations problems are not important since the estimated elasticities of the non-computer aggregate, particularly structures, varied substantially between the industry and sector regressions. Thus, empirical work must still be careful when choosing the level of aggregation.

The bias from aggregation in variables was also generally found to be important. There is wide variation in the productivity of different types of capital and it is inappropriate to include a single capital index in many cases. When included individually, structures showed a large and significant elasticity, while the impact from other forms of non-computer equipment was harder to find. The estimated computer elasticity, however, did not change when more disaggregated capital variables were included, which suggests that the bias was not transmitted to all coefficients.

These results show a large and robust elasticity of computer capital across a wide range of specifications, estimation techniques, and aggregation levels. Despite the clear presence of other aggregation problems, our results suggest that computers are more productive than other forms of capital. This is entirely consistent with economic theory; computers must earn a high gross rate of return to offset the rapid depreciation and capital losses. These results support the growing body of work at both the micro and the aggregate level that shows computers are indeed an important source of growth and productivity.

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Table 1: Change in Computer Intensity by Major Sectors and Detailed Industries, 1970-1996

Industry	Nominal Computer Capital Share				Real Computer Capital Growth Rates				Growth in Total Capital
	1970	1980	1990	1996	1970-80	1980-90	1990-96	1970-96	1970-96
AGRICULTURE, FORESTRY & FISHING	0.000	0.011	0.020	0.016	22.77	20.11	15.36	19.93	0.96
Farms	0.000	0.002	0.004	0.002	0.00	20.26	8.13	15.71	0.59
Agricultural services, forestry and fishing	0.000	0.131	0.156	0.099	21.70	20.15	16.50	19.83	4.65
MINING	0.082	0.169	0.233	0.140	36.62	18.83	8.34	23.25	1.77
Metal mining	0.000	0.039	0.041	0.020	22.54	18.14	8.46	16.70	1.50
Coal mining	0.000	0.004	0.016	0.030	0.00	14.48	29.37	17.83	2.98
Oil and gas extraction	0.104	0.203	0.274	0.158	36.99	18.72	7.16	23.08	1.67
Nonmetallic minerals, except fuels	0.000	0.008	0.122	0.241	0.00	30.34	26.41	28.86	1.47
CONSTRUCTION	0.416	0.147	0.238	0.113	16.67	19.52	7.77	15.71	0.90
MANUFACTURING	0.905	0.926	1.758	1.747	27.61	23.58	19.77	24.25	2.27
DURABLE MANUFACTURING	1.146	1.346	2.291	2.097	28.94	22.40	18.17	23.94	2.21
Lumber and wood products	0.311	0.869	0.494	0.899	26.83	10.01	27.94	20.62	1.44
Furniture and fixtures	0.000	0.966	1.893	1.570	29.95	24.98	16.59	24.54	2.54
Stone, clay, and glass products	0.144	1.688	2.353	1.354	37.05	19.78	9.79	24.12	0.77
Primary metal industries	0.420	0.283	0.474	0.492	21.18	19.78	18.49	20.02	-0.15
Fabricated metal products	0.811	0.464	0.986	1.037	23.54	24.50	20.28	23.16	2.15
Industrial machinery and equipment	4.566	3.664	4.557	3.255	27.92	20.49	14.06	21.86	3.50
Electronic and other electric equipment	0.525	2.130	3.200	3.585	40.23	23.68	23.88	30.09	4.96
Transportation equipment	0.779	0.862	1.962	1.801	28.49	25.04	17.90	24.72	2.11
Instruments and related products	1.751	1.324	3.742	3.348	27.39	30.47	18.03	26.41	4.69
Miscellaneous manufacturing industries	0.751	0.685	1.519	2.034	15.15	23.79	24.43	20.61	1.95
NON-DURABLE MANUFACTURING	0.620	0.452	1.170	1.382	24.08	26.76	22.74	24.80	2.35
Food and Kindred Products	0.580	0.360	0.842	1.069	25.21	25.20	23.99	24.93	1.86
Tobacco products	0.000	0.527	1.128	1.318	12.70	24.80	19.14	19.35	3.68
Textile mill products	0.812	0.262	0.517	0.640	13.54	21.98	21.61	18.65	0.15
Apparel and other textile products	2.354	1.191	0.864	1.914	17.40	11.85	31.10	18.43	2.09
Paper and allied products	0.181	0.392	0.982	0.685	25.76	28.05	13.70	23.86	2.61
Printing and publishing	1.436	1.388	4.469	3.943	29.11	31.89	17.12	27.41	3.39
Chemicals and allied products	0.465	0.289	0.854	1.531	25.78	26.82	29.78	27.10	2.93
Petroleum and coal products	0.453	0.385	0.659	0.857	25.54	22.66	24.72	24.24	1.76
Rubber and miscellaneous plastics products	1.123	0.664	1.120	1.376	21.85	23.84	25.75	23.52	3.38
Leather and leather products	0.495	0.851	1.344	1.482	10.88	17.30	19.06	15.24	-0.64
TRANSPORTATION, COMM., & UTILITIES	0.068	0.106	0.332	0.300	24.59	27.77	18.55	24.42	2.07
Railroad transportation	0.012	0.013	0.023	0.009	17.37	20.26	4.92	15.61	-0.83
Local and interurban passenger transit	0.155	0.112	0.170	0.030	9.51	18.44	-10.77	8.27	-1.24
Trucking and warehousing	0.108	0.047	0.060	0.051	9.97	19.90	20.18	16.15	3.20
Water transportation	0.149	0.057	0.098	0.100	5.84	18.15	18.44	13.48	0.26
Transportation by air	0.430	0.438	0.869	0.404	25.16	26.31	10.36	22.19	3.24
Pipelines, except natural gas	0.054	0.050	0.026	0.198	11.16	2.13	51.93	17.09	1.09
Transportation services	0.214	0.163	1.261	0.316	13.49	36.78	2.88	20.00	2.24
Communications	0.141	0.153	0.441	0.575	29.79	28.12	24.73	27.98	4.54
Utilities	0.027	0.112	0.359	0.283	28.52	28.54	15.96	25.63	2.40
WHOLESALE TRADE	2.427	3.113	4.636	6.948	34.17	25.01	28.84	29.42	6.38
RETAIL TRADE	0.406	0.592	1.705	1.853	31.57	29.08	23.48	28.75	3.61

Notes: Shares and growth rates are percentages.
Source: BEA (1998) and authors' calculations.

Table 1-continued: Change in Computer Intensity by Major Sectors and Detailed Industries, 1970-1996

Industry	Nominal Computer Capital Share				Real Computer Capital Growth Rates				Growth in Total Capital
	1970	1980	1990	1996	1970-80	1980-90	1990-96	1970-96	1970-96
FINANCE, INSURANCE & REAL ESTATE	0.977	1.322	2.277	2.285	32.10	27.07	21.33	27.68	4.39
Depository institutions	3.664	4.439	5.314	3.273	35.51	24.94	14.01	26.48	7.40
Non-depository; holding and investment offices	4.388	3.576	5.626	6.981	29.13	28.43	26.67	28.29	7.48
Security and commodity brokers	8.345	9.442	7.411	8.712	28.97	20.70	21.00	23.95	6.77
Insurance carriers	7.732	6.381	7.979	5.170	31.18	32.49	19.42	28.97	11.17
Insurance agents, brokers and services	11.521	8.572	5.062	4.295	29.11	10.41	16.10	18.91	3.24
Real estate	0.174	0.164	0.452	0.928	26.50	29.89	31.00	28.84	3.09
SERVICES	1.361	1.582	4.083	4.966	28.44	28.29	25.22	27.64	4.41
Hotels and other lodging places	0.031	0.236	0.338	0.167	29.10	23.07	8.98	22.14	2.74
Personal services	0.000	0.619	2.979	1.099	37.52	32.84	6.03	27.70	1.77
Business Services		4.408	12.458	20.406	36.25	27.63	29.46	31.37	5.34
Auto repair, services, and garages	0.106	0.970	3.870	0.907	35.51	34.09	3.18	27.50	5.22
Miscellaneous repair shops	0.000	0.986	2.660	2.454	29.54	27.42	20.22	26.33	3.16
Motion pictures	0.000	1.554	3.069	1.868	47.04	28.99	19.37	31.97	6.06
Amusement and recreation services	0.000	0.481	0.841	0.856	35.62	21.08	23.56	26.15	2.37
Health services	0.610	0.600	1.423	1.924	24.75	30.94	27.38	27.74	5.67
Legal services	6.877	2.199	7.869	5.852	19.08	35.82	12.89	24.09	4.74
Educational services	11.940	2.450	1.166	0.685	18.50	13.05	15.80	15.78	8.22
Other	3.636	2.446	4.936	5.849	20.92	25.46	23.96	23.37	4.97
PRIVATE BUSINESS SECTOR	0.550	0.678	1.575	1.847	29.97	26.17	22.96	26.89	2.90

Notes: Shares and growth rates are percentages.

Source: BEA (1998) and authors' calculations.

Table 2: Distribution of Capital within Major Sectors and Detailed Industries, 1996

Industry	Computers	Other Hi-Tech	Other Equipment	Structures	Total Value of Capital Stock
AGRICULTURE, FORESTRY & FISHING	0.02	0.87	41.76	57.38	366,430
Farms	0.00	0.04	38.22	61.69	315,425
Agricultural services, forestry and fishing	0.10	5.95	63.35	30.53	51,276
MINING	0.14	1.89	16.88	81.05	436,641
Metal mining	0.02	0.99	19.78	79.20	35,165
Coal mining	0.03	0.42	33.89	65.67	36,171
Oil and gas extraction	0.16	2.17	13.22	84.45	344,343
Nonmetallic minerals, except fuels	0.24	1.34	43.03	55.42	20,745
CONSTRUCTION	0.11	0.81	59.31	39.80	88,188
MANUFACTURING	1.75	6.30	51.47	40.49	1,480,426
DURABLE MANUFACTURING	2.10	5.98	51.71	40.23	759,300
Lumber and wood products	0.90	2.05	47.03	50.05	29,331
Furniture and fixtures	1.57	1.81	36.76	59.87	13,316
Stone, clay, and glass products	1.35	4.94	51.33	42.41	43,403
Primary metal industries	0.49	2.76	58.89	37.80	127,819
Fabricated metal products	1.04	2.23	62.95	33.76	81,906
Industrial machinery and equipment	3.26	6.61	51.76	38.33	128,598
Electronic and other electric equipment	3.59	12.87	45.54	38.01	128,802
Transportation equipment	1.80	3.23	54.43	40.55	139,315
Instruments and related products	3.35	13.23	33.44	49.98	53,024
Miscellaneous manufacturing industries	2.03	3.28	43.11	51.59	14,001
NON-DURABLE MANUFACTURING	1.38	6.64	51.19	40.77	721,018
Food and Kindred Products	1.07	4.64	49.47	44.86	145,868
Tobacco products	1.32	3.47	46.96	48.27	9,182
Textile mill products	0.64	2.95	52.71	43.74	37,655
Apparel and other textile products	1.91	2.81	39.85	55.41	13,332
Paper and allied products	0.68	4.69	69.13	25.47	98,503
Printing and publishing	3.94	9.66	42.69	43.72	60,044
Chemicals and allied products	1.53	11.13	48.87	38.47	206,387
Petroleum and coal products	0.86	5.16	41.35	52.64	92,578
Rubber and miscellaneous plastics products	1.38	2.07	61.77	34.81	54,711
Leather and leather products	1.48	0.84	31.12	66.51	2,629
TRANSPORTATION, COMM., & UTILITIES	0.30	12.42	23.81	63.51	2,301,741
Railroad transportation	0.01	1.77	11.93	86.24	360,656
Local and interurban passenger transit	0.03	6.56	21.39	72.00	19,912
Trucking and warehousing	0.05	3.61	72.73	23.59	108,208
Water transportation	0.10	4.04	76.74	19.10	36,002
Transportation by air	0.40	7.94	72.31	19.36	110,141
Pipelines, except natural gas	0.20	1.71	8.68	89.38	48,361
Transportation services	0.32	12.16	71.34	16.20	42,660
Communications	0.58	36.83	7.44	55.17	562,226
Utilities	0.28	5.04	23.51	71.15	1,014,044
WHOLESALE TRADE	6.95	10.34	33.21	49.47	402,858
RETAIL TRADE	1.85	1.85	22.68	73.67	540,565

Notes: Shares are percentages and values are millions of current dollars.
Source: BEA (1998) and authors' calculations.

Table 2 - continued: Distribution of Capital within Major Sectors and Detailed Industries, 1996

Industry	Computers	Other Hi-Tech	Other Equipment	Structures	Total Value of Capital Stock
FINANCE, INSURANCE & REAL ESTATE	2.28	5.11	16.95	75.62	1,960,245
Depository institutions	3.27	8.14	30.79	57.81	370,374
Non-depository; holding and investment offices	6.98	11.52	55.51	26.02	151,641
Security and commodity brokers	8.71	5.62	13.89	71.78	11,542
Insurance carriers	5.17	8.79	27.36	58.67	180,296
Insurance agents, brokers and services	4.29	6.79	29.91	59.01	6,449
Real estate	0.93	2.87	6.55	89.64	1,239,803
SERVICES	4.97	8.83	30.19	56.06	754,670
Hotels and other lodging places	0.17	1.28	9.20	89.37	127,093
Personal services	1.10	6.31	28.96	63.63	26,266
Business Services	20.41	14.20	37.01	28.34	126,464
Auto repair, services, and garages	0.91	2.87	83.21	13.01	114,535
Miscellaneous repair shops	2.45	2.13	59.37	36.00	11,987
Motion pictures	1.87	23.21	22.24	52.73	29,366
Amusement and recreation services	0.86	1.29	25.84	71.96	48,536
Health services	1.92	14.30	12.64	71.16	153,883
Legal services	5.85	11.48	26.79	55.87	18,922
Educational services	0.69	1.46	6.93	91.00	18,221
Other	5.85	12.56	18.01	63.60	79,647
PRIVATE BUSINESS SECTOR	1.85	7.32	28.87	61.99	8,328,842

Notes: Shares are percentages and values are millions of current dollars.
Source: BEA (1998) and authors' calculations.

Table 3: Distribution of Computer and High-Tech Capital Across Major Sectors, 1996

Industry	Computer Capital		High-Tech Capital	
	Nominal Value	Percent of Total	Nominal Value	Percent of Total
AGRICULTURE, FORESTRY & FISHING	58	0.04	3,243	0.42
MINING	612	0.40	8,874	1.16
CONSTRUCTION	100	0.06	811	0.11
DURABLE MANUFACTURING	15,919	10.35	61,278	8.02
NON-DURABLE MANUFACTURING	9,965	6.48	57,829	7.57
TRANSPORTATION, COMM., & UTILITIES	6,905	4.49	292,832	38.35
WHOLESALE TRADE	27,991	18.20	69,677	9.12
RETAIL TRADE	10,018	6.51	20,009	2.62
FINANCE, INSURANCE & REAL ESTATE	44,789	29.11	144,988	18.99
SERVICES	37,475	24.36	104,160	13.64
PRIVATE BUSINESS SECTOR	153,833	100.00	763,700	100.01

Notes: Shares are percentages and values are millions of current dollars. High-tech capital includes computers, scientific instruments, photocopy equipment, and communications equipment.
Source: BEA (1998) and authors' calculations.

Table 4: Simple Production Function Regressions, 1980-96

	OLS			Fixed Effects		SYS-GMM	
	Aggregate	Sector	Industry	Sector	Industry	Sector	Industry
ln(L)	1.074 ***	0.511 ***	0.493 ***	0.051	0.468 ***	0.554 ***	0.340 ***
	(0.104)	(0.025)	(0.020)	(0.075)	(0.062)	(0.053)	(0.114)
ln(K_c)	0.052 **	0.188 ***	0.178 ***	0.046	-0.018	0.171 ***	0.305 ***
	(0.018)	(0.016)	(0.010)	(0.038)	(0.018)	(0.064)	(0.084)
ln(K_n)	-0.227	0.154 ***	0.256 ***	0.030	-0.122 **	0.123	-0.020
	(0.291)	(0.033)	(0.015)	(0.097)	(0.056)	(0.120)	(0.081)
Year	0.003						
	(0.003)						
R^2	0.99	0.89	0.85	0.87	0.50		
No. of Obs.	17	170	935	170	935	160	880

Notes: All regressions include year dummy variables, except for aggregate OLS. Robust standard errors are in parentheses. R^2 is adjusted-R^2 for OLS and within-R^2 for fixed effects. Dependent variable is log of real value-added; L is labor; K_c is computer capital; K_n is non-computer capital. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table 5: Extended Production Function Regressions, 1980-96

	OLS			Fixed Effects		SYS-GMM	
	Aggregate	Sector	Industry	Sector	Industry	Sector	Industry
ln(L)	1.299 ***	0.533 ***	0.505 ***	-0.001	0.465 ***	0.557 ***	0.485 ***
	(0.126)	(0.028)	(0.021)	(0.089)	(0.060)	(0.072)	(0.102)
$\ln(K_c)$	0.073 *	0.161 ***	0.142 ***	0.069 *	0.001	0.132 *	0.177 **
	(0.034)	(0.024)	(0.013)	(0.037)	(0.019)	(0.073)	(0.076)
$\ln(K_h)$	-0.028	0.057	0.070 ***	0.122 ***	0.071 ***	0.123	0.105 *
	(0.388)	(0.044)	(0.012)	(0.041)	(0.023)	(0.098)	(0.061)
$\ln(K_o)$	-0.752 ***	-0.050	-0.015	-0.190 **	-0.223 ***	-0.105	-0.170 **
	(0.184)	(0.051)	(0.013)	(0.088)	(0.060)	(0.105)	(0.078)
$\ln(K_s)$	-0.441	0.096 *	0.210 ***	0.246 **	0.059	0.048	0.194 **
	(0.609)	(0.056)	(0.017)	(0.115)	(0.070)	(0.203)	(0.075)
Year	0.011 **						
	(0.004)						
R^2	0.99	0.88	0.86	0.89	0.52		
No. of Obs.	17	170	935	170	935	160	880
p-value	0.013	0.116	0.000	0.019	0.000		

Notes: All regressions include year dummy variables, except for aggregate OLS. Robust standard errors are in parentheses. R^2 is adjusted-R^2 for OLS and within-R^2 for fixed effects. Dependent variable is log of real value-added; L is labor; K_c is computer capital; K_h is other high-tech capital; K_o is other equipment capital; and K_s is structures. p-value is associated with null hypothesis of equal elasticities for all types of non-computer capital. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table 6: Alternative Production Function Regressions, 1980-96

	OLS			Fixed Effects		SYS-GMM	
	Aggregate	Sectors	Industry	Sectors	Industry	Sectors	Industry
ln(L)	1.342 ***	0.539 ***	0.512 ***	0.040	0.463 ***	0.577 ***	0.484 ***
	(0.094)	(0.032)	(0.021)	(0.078)	(0.061)	(0.102)	(0.086)
ln(K)	-1.056 ***	0.318 ***	0.417 ***	0.217 **	-0.035	0.344 ***	0.281 ***
	(0.235)	(0.031)	(0.013)	(0.098)	(0.057)	(0.116)	(0.085)
$\ln(K_e/K)$	-0.503 ***	0.061	0.006	-0.256 **	-0.313 ***	-0.007	-0.063
	(0.134)	(0.082)	(0.032)	(0.103)	(0.086)	(0.273)	(0.121)
$\ln(K_c/K_e)$	0.092 ***	0.181 ***	0.182 ***	0.066 *	0.003	0.141 **	0.231 ***
	(0.015)	(0.016)	(0.010)	(0.039)	(0.020)	(0.058)	(0.056)
Year	0.015 ***						
	(0.004)						
Implied δ	0.476	0.191	0.015	-1.179	8.921	-0.020	-0.224
p-value	0.001	0.454	0.841	0.009	0.570		
Implied γ	-0.087	0.568	0.437	0.303	-0.078	0.410	0.821
p-value	0.000	0.000	0.000	0.128	0.901		
R^2	0.99	0.89	0.86	0.88	0.51		
No. of Obs.	17	170	935	170	935	160	880

Notes: All regressions include year dummy variables, except for aggregate OLS. Robust standard errors are in parentheses. R^2 is adjusted-R^2 for OLS and within-R^2 for fixed effects. Dependent variable is log of real value-added; L is labor; K is total capital; K_e is equiptment capital; K_c is computer capital. Implied d and implied g are from Equation (9) and p-value is associated with the null hypothesis that the implied coefficient equals zero. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level.

Table 7: Comparison of Manufacturing and Non-Manufacturing Results, 1980-96

	Simple - OLS		Simple - SYS-GMM		Extended - SYS-GMM		Alternative - SYS-GMM	
	Mfg	Non-Mfg	Mfg	Non-Mfg	Mfg	Non-Mfg	Mfg	Non-Mfg
ln(L)	0.128	0.565 ***	0.178	0.412 ***	0.197	0.582 ***	0.127	0.602 ***
	(0.205)	(0.058)	(0.195)	(0.085)	(0.155)	(0.085)	(0.152)	(0.089)
ln(K)							0.384 ***	0.265 ***
							(0.082)	(0.085)
ln(K_c)	0.262 **	0.164 ***	0.458 **	0.228 ***	0.191	0.143 **		
	(0.112)	(0.032)	(0.232)	(0.066)	(0.126)	(0.061)		
ln(K_n)	0.299 ***	0.261 ***	0.038	0.098				
	(0.108)	(0.066)	(0.231)	(0.082)				
ln(K_h)					0.365 ***	0.054		
					(0.140)	(0.069)		
ln(K_o)					0.147	-0.135 *		
					(0.209)	(0.073)		
ln(K_s)					-0.398	0.231 ***		
					(0.328)	(0.066)		
ln(K_e/K)							1.512 ***	-0.266 **
							(0.528)	(0.132)
ln(K_c/K_e)							0.358 **	0.169 ***
							(0.159)	(0.046)

Notes: All regressions includes year dummy variables. Robust standard errors are in parentheses. Variables are defined in Tables 4-6. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level.