Preliminary – Comments Welcome

Reassessing the Impact of IT in the Production Function: A Meta-Analysis

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Abstract

This paper analyzes and extends the growing econometric literature on the economic impact of information technology (IT). I begin with a "meta-analysis" to systematically examine the results of twenty empirical studies and show that much of the observed variation in estimates of the output elasticity of IT is predictable and due to differences in model specification and econometric technique. Using a single dataset for U.S. industries, I then find similar variation across alternative specifications and estimation methods. Most results show a productivity effect from IT-use, but the point estimate of the elasticity is fragile and depends on the details of the estimation.

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I. Introduction

It is now fifteen years since Robert Solow introduced the "computer productivity paradox" to the economics profession with his observation that productivity growth remained sluggish despite the computer revolution. In recent years, however, U.S. productivity has improved dramatically and the perception of information technology (IT) has reversed – IT is now seen by many as the driving force behind the resurgence of U.S. productivity growth after 1995.

This nearly unanimous viewpoint reflects a flood of diverse empirical work on the output and productivity effects of IT. Aggregate growth accounting studies, for example, report large productivity contributions from both IT-producing and IT-using industries, while industry-level comparisons show that IT-intensive industries enjoyed the largest productivity gains after 1995. Similarly, production function estimates using firm or industry data typically report a significant link between IT and output, and industry-specific case studies have documented large benefits from IT in industries as varied as trucking and health care.[1]

This evidence clearly points to a positive productivity effect from IT. But, how large? Are the productivity effects large enough to create "excess returns"? Or is IT a normal piece of capital that earns normal returns? On these questions, there is considerably less agreement. Figure 1 shows a histogram of 41 estimates of the output elasticity of IT (IT-elasticity) from 20 econometric studies.[2] The median estimate is 0.046, but there is obviously considerable variation with estimates ranging from –0.06 to 0.24. This is perhaps not surprising as the studies differ along important dimensions like sample period, level of aggregation, measure of IT, production function specification, estimation technique, and other regressors. Nonetheless, this wide variation obscures our understanding of the impact of IT and highlights methodological questions about estimating output elasticities.

The purpose of this paper is to put some order and structure on this set of divergent results. I begin with a "meta-analysis" that looks for predictable differences in estimates of the IT-elasticity based on study characteristics like sample period, level of aggregation, or econometric specification. The second part of the paper uses U.S. industry data for 1987 to 2000 to estimate IT-elasticities from a variety of plausible specifications and alternative estimation techniques. A single, consistently defined dataset allows one to gauge the sensitivity of the estimates to methodological variation, to identify

[1] Aggregate growth accounting studies for the U.S. include Baily (2002), Council of Economic Advisors (2001), Gordon (2000), Jorgenson, Ho, and Stiroh (2002), Jorgenson (2001), Jorgenson and Stiroh (2000), Oliner and Sichel (2000, 2002). Industry-level studies include Baily and Lawrence (2001) and Stiroh (forthcoming). Many firm-level studies are surveyed by Brynjolfsson and Hitt (2000) and are discussed later. Hubbard (2001) and Athey and Stern (2002) are specific case-study examples.

[2] Section II provides details on these papers and how they were selected.

which factors are the most critical, and to test the predictions of the meta-analysis. Because estimates do vary widely, I take a full-disclosure approach and report estimates from a large number of production function regressions.

The meta-analysis shows that a good deal of the variation in IT-elasticities across studies is predictable and reflects differences in specifications and empirical methods. For example, inclusion of fixed effects or estimation in first differences tends to lower estimates, while more aggregated data or use of later data tends to raise it. These types of study characteristics explain about 35% of the variation in the IT-elasticities across studies and support the idea that there is indeed a productivity effect from IT. If the estimates had been largely unpredictable, idiosyncratic data differences would be driving the results entirely and the case for a pervasive relationship would be weaker.

Results from U.S. industry data support the predictions of the meta-analysis and suggest that IT does matter, although the specific point estimate of the IT-elasticity is fragile. For example, the estimated elasticity of computer capital from a basic log-levels regression with gross output as the dependent variable and year dummy variables is 0.047, while inclusion of industry fixed effects drops the point estimate to 0.012. This variation has very different implications for the role of IT – the first result suggests possible excess returns, while the second appears consistent with normal returns in a neoclassical world. In contrast, weighting industries or estimating a labor productivity regression with constant returns imposed does not change the estimate substantially.

Simultaneity is also an important issue and various instrumental variable (IV) techniques are compared to the more common ordinary least squares (OLS) results. The preferred IV regression that controls for both unobserved industry heterogeneity and simultaneity shows a positive impact from IT, although the point estimate is imprecise and the data just fail to reject the null hypothesis that both computer and telecomm capital have an elasticity of zero. The estimated elasticity of all types of capital are individually insignificant, however, which suggests the results most likely reflect weak instruments, possibly due to the high persistence in capital, or small sample biases rather than a lack of impact from IT.

This new evidence generally supports the view that IT does matter, but the wide variation means that one must be very cautious in putting too much faith in a specific estimate and that observers must remain cognizant of differences across studies. Moreover, this variation raises concerns about publication and specification search biases. Because economic theory makes clear predictions about both the sign and the magnitude of the IT-elasticity, researchers and referees may have a predisposition towards reporting and accepting only those results with the "right" sign and magnitude. The fragility of the estimates under plausible sets of alternative modeling assumptions suggests that this is a real concern in the context of estimating IT-elasticities.

II. A Meta-Analysis of the Impact of IT

Meta-analysis is a "means of combining the numerical results of studies with disparate, even conflicting research methods and findings…to discover the consistencies in a set of seemingly inconsistent findings (Hunt (1997, pg. 1)). The idea behind a meta-analysis is that a systematic, quantitative analysis of the similarities and differences in results and methodologies across related studies can offer new insights into the underlying relationships. More specifically, a meta-regression uses some result (an estimated coefficient or the significance level of some test) from a series of related papers as the dependent variables in a cross-section regression that employs study characteristics (sample period, econometric techniques, assumptions) as independent variables. By identifying the study characteristics most highly correlated with results, one can hope to better understand why studies reach different conclusions and learn something about the underlying relationship.

This approach has gained widespread acceptance in medical and social sciences, and it is becoming increasingly popular as a methodological tool for evaluating the accumulating econometric evidence on a wide variety of topics. Stanley (2001) summarizes this work and shows how meta-analysis has been successfully applied in a variety of economic research areas including studies of minimum wage effects, tests of Ricardian equivalence, the returns to education, and many other empirical topics.

In addition to helping to organize and codify a set of disparate findings, meta-analysis has also been a useful methodological tool to search for potential publication bias and specification search bias (Card and Krueger (1995)). Publication bias reflects the possibility that journals are more likely to publish papers with significant results, while specification bias results if researchers focus on and report only those estimates with the "right" sign and magnitude. Card and Krueger (1995), for example, argue that the published empirical work on the minimum wage with time-series data appears to be biased with statistically significant results over-sampled in the literature. This is a legitimate concern in the current application, and is discussed below.

This section describes a meta-regression analysis for the output elasticity of information technology (IT-elasticity) from econometric estimates of production functions. Figure 1 shows that estimates of the IT-elasticity vary widely across studies and this type of meta-analysis can help explain whether the variation reflects idiosyncratic differences in the underlying data or predictable differences due to alternative methodological choices made by the researchers. I first discuss how IT-elasticities have typically been estimated in the literature, and then describe the meta-analysis methodology and results.

a) A Meta-Regression for the IT-Elasticity

Econometric estimates of production functions have a long history in economics and many recent papers have expanded the set of inputs to explicitly account for IT.[3] In its simplest form, an extended Cobb-Douglas production function can be expressed as:

$$(1)\quad \ln Y = \beta_{IT} \ln K_{IT} + \beta_{NON} \ln K_{NON} + \beta_L \ln L + \beta_M \ln M + \varepsilon$$

where Y is real gross output, K_{IT} is IT capital, K_{NON} is non-IT capital, L is labor, and M is intermediate inputs, all for different firms or industries at different points in time. Firm and time subscripts are suppressed for exposition.

The coefficient of interest is the estimate of β_{IT}, which is the elasticity of output with respect to IT capital (IT-elasticity). There are a number of ways to estimate Equation (1), however. One can estimate it directly in levels, or if one believes there is some unobservable fixed component in ε, it can be estimated in first differences or with a fixed effect. One can allow for shifts in the production function (technological progress) by explicitly including time effects. If constant returns to scale are assumed, variables can be transformed into to per labor units. One can drop intermediate inputs and use a value-added measure of output as the dependent variable. Estimation can be done with ordinary least squares (OLS) or, if one explicitly recognizes the simultaneity issue, with instrumental variables. Data may be for firms or industries, and the time periods may vary.

The purpose of this meta-regression is to relate estimates of β_{IT} to specific study characteristics. To find the relevant research papers, I searched twenty prominent academic journals,[4] National Bureau of Economic Research and Social Science Research Network working papers, and working papers and publications at major economic organizations like the OECD and the Federal Reserve System after 1990 for the following keywords: "productivity," "production function," "labor productivity," "production," "computers," and "information technology." The journals were also searched manually for any relevant work that did not include these keywords. Once candidate papers were identified, reference sections were examined for other cited papers.

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[3]See Griliches and Mairesse (1998) for a historical view of production function estimates.
[4]*American Economic Review, Brookings Papers on Economic Activity, Canadian Journal of Economics, Econometrica, Economic Journal, Journal of Business, Journal of Economic Literature, Review of Economic Dynamics, Journal of Productivity Analysis, Journal of Economic Growth, Journal of Industrial Economics, Journal of Political Economy, Quarterly Journal of Economics, Review of Economic Studies, Review of Economics and Statistics, RAND Journal of Economics, Journal of Applied Econometrics, Journal of*

This search yielded about 110 published papers and working papers related to IT. Of these, 20 econometrically estimated production functions like Equation (1) with some measure of IT as an explanatory variable. A key point emphasized by Stanley (2001) is that all relevant studies should be included, so I made no attempt to discriminate based on paper quality or result. Each study often reported many estimates, so I identified the authors' most discussed result as the "preferred" result. If several results were emphasized, these were also recorded, which led to 41 estimates of β_{IT} in the "full" meta-regression database. Table 1 shows the author, publication date, journal, and the "preferred" IT-elasticity for each study.[5]

I next identified major differences between studies, which constitute the "moderator" or independent variables for the meta-regression. Because I am focusing on the IT-elasticity, this amounted to differences in the estimation of production function regressions and in data. An initial examination of the papers identified eleven potentially important differences across studies (Table 2). After these variables were created for all studies, four variables (Instruments, Flexible Functional Form, Cross-Section, and Between Effects) had to be dropped, however, due to insufficient variation across studies. This left seven independent variables for the meta-regression.[6] Finally, note that the default specification (all dummy variables set to 0) is a Cobb-Douglas, value-added regression estimated in levels via OLS with firm-level data.

b) Results and Discussions

The first column of Table 3 reports estimates of the meta-regression for the preferred sample. The only significant coefficients are the Aggregate and Average Sample Period dummies, which indicate that firm-level estimates are typically smaller than estimates from more aggregate data and that studies done with more recent data tend to have larger IT-elasticities. Of course, the small sample size makes statistical significance hard to interpret, and the point estimates of the other variables do

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Econometrics, Journal of Economic Perspectives, Journal of Labor Economics, Economics of Innovation and New Technology.

[5]Growth accounting studies or econometric studies that did not explicitly estimate an IT-elasticity were excluded, which led to the exclusion of several well-known papers. For example, Berndt and Morrison (1995) and Greenan et al. (2001) include the ratio of high-tech capital to total capital in a labor productivity regression, but did not estimate IT-elasticities. Morrison (1997) and Gera, Gu, and Lee (1999) estimate the marginal product of IT, rather than the elasticity. Siegel (1997) uses total factor productivity as the dependent variable. Greenan and Mairesse (1996) use data on the share of worker who use a personal computers as their measure of IT intensity, while Licht and Moch (1999) use count variables on the number of IT equipment. All of these studies were excluded from the meta-regression.

[6]Note that I have not included the precise definition of IT as a regressor, i.e., computer hardware or hardware plus software or computers plus telecomm equipment. This obviously effects the magnitude of the estimated elasticity, but wide variation in the measure across studies made it impractical to identify. These differences will show up in the error term, and as long as the definition of IT is not correlated with methodological choices, then this should not be a problem.

seem largely reasonable. For example, estimates from gross output regressions are typically smaller as expected, and inclusion of fixed effects tends to reduce the estimated elasticity.

The second column reports estimates from the full sample. Here, the results are qualitatively similar, and statistical significance increases. The results indicate that first differencing, using firm-level data, focusing on manufacturing, including fixed effects, and using early data all tend to lower the estimated IT-elasticity. A somewhat surprising result is that the conditional difference between gross output and value-added regressions is essentially zero. In the raw data, however, the mean IT-elasticity for the 20 estimates from value-added regressions was 0.068 and the mean IT-elasticity for the 19 estimates from gross output regression was 0.042 (p-value=0.20 for test of difference in means). As a final point, it should be noted that the statistical significance of some of these estimates is not very robust; exclusion of a single observation can sometimes change the significance substantially.

A key result from the meta-analysis is that a good deal of the variation in the estimated IT-elasticity is predictable – the adjusted-R^2 around 0.35 in both regressions – and reflects the researchers' choices of methodology and specification.[7] This suggests that there is some consistency within the wide range of empirical estimates in the literature, which strengthens the belief that there is an underlying relationship between IT and output. If the estimates had appeared totally unpredictable, evidence for a true relationship would be much weaker.

Large variation, whether predictable or not, however, begs the question of what is the best way to estimate an IT-elasticity. Should the output concept be value-added or gross output? Should estimation be done with fixed effects that will likely lower the estimate or in levels, which will likely raise it? Should OLS or an instrumental variable technique be used? Economic and econometric theory provide some guidance, e.g., separability assumptions might inform the choice of a value-added or gross output production function, evidence on unobserved heterogeneity will determine the appropriateness of fixed effects, and beliefs about the nature of productivity shocks might guide suitable instruments. Moreover, the preferred specification is likely to depend on the question at hand. For example, researchers interested in the precise impact of IT might favor fixed effects, while those interested in the broader impact of the IT revolution may not. Nonetheless, researchers must remain cognizant of these differences and recognize that methodological choices matter a great deal and make comparisons across studies quite difficult.

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[7]The remaining variation is due to other characteristics of the study not included here: differences in data, differences in IT definition, specification error in the meta-regression, and random error.

A related issue is publication bias and specification search bias. This is a legitimate concern here because neoclassical production theory makes clear predictions about both the sign and the magnitude of an estimated elasticity: if markets are competitive and returns are constant, elasticities should equal factor shares. Factor shares are relatively easy to measure, so researchers may have strong priors about the expected IT-elasticity and may search specifications and econometric techniques until the "right" coefficient emerges, while journal editors may be more inclined to publish those papers. Indeed, many of the papers explicitly compare the estimated IT-elasticity to the observed factor share to provide supporting evidence for the reasonability of the results. While it is difficult to gauge the magnitude of this concern, the wide range of estimated coefficients suggests that it cannot be ignored.

The remainder of the paper explores these issues more fully by estimating IT-elasticities from a single database for U.S. industries, but with alternative specifications and methodologies. This will provide more direct evidence on the practical effects of different estimation choices and allows a better understanding of the reasons for variation in the IT-elasticities across studies.

III. Data

The primary data are the "Gross Domestic Product by Industry" developed by the Bureau of Economic Analysis (BEA) and described in Lum and Moyer (2001). These data include real output (both gross output and value-added), intermediate purchases, and labor (measured as full-time equivalent employees (FTE)) for 61 detailed industries at roughly the two-digit Standard Industrial Classification (SIC) level. This data is available for 1987-2000 for all industries, and for 1977-2000 for a subset of consolidated industries. For example, Business Services (SIC #73) and Social Services (SIC #83) only have complete data back to 1987, while Electronic and Other Electric Equipment (SIC #36) and Instruments and Related Products (SIC #38) are combined for the early period.

It is useful to be clear about the distinction between the two output concepts used by BEA. Gross output is "sales or receipts and other operating income, commodity taxes, and inventory change," while value-added is industry gross output "minus its intermediate inputs (which consists of energy, raw materials, semifinished goods, and services that are purchased from domestic industries or from foreign sources ((Lum and Moyer (2001, pg. 17))." Both are expressed in real terms based on a Fischer quantity index. For all private industries after 1987, the BEA employs the "double deflation method" to estimate real value-added. This approach essentially subtracts intermediate inputs from gross output in current prices and in base-year prices, and then uses the ratio to construct a real-value-added ratio that can be chained together to form an index series.[8]

Both output concepts are regularly employed in production analysis and have relative advantages and disadvantages. Basu and Fernald (1995) argue that "value added is not a natural measure of output and can in general be interpreted as such only with perfect competition (pg. 251)," but it does have the appealing property that nominal value-added sums to GDP (ignoring the statistical discrepancy). Gross output is more readily available in some cases, e.g., firms are more likely to report sales than payments to primary factors, but one also need details on intermediate inputs for a complete production analysis. In the context of estimating IT-elasticities, about half of the studies use a gross output measure, and this paper examines both.[9]

BEA also produces detailed investment and capital stock data for detailed industries in its "Fixed Reproducible Tangible Wealth" survey described by Herman (2001). These data are available for 62 industries at roughly the two-digit level for 62 distinct reproducible assets including three IT asset categories – computer hardware, computer software, and telecommunications equipment. The BEA capital data, however, is not ideal for productivity analysis. As discussed by Whelan (2002), the BEA capital stock data are "wealth stocks" and not the conceptually more appropriate "productive stocks." In addition, a measure of capital service flows, which accounts for substitution between assets with different marginal products, is preferred to a stock measure.

To avoid these problems, I use the BEA investment data by industry and by asset to construct estimates of capital service flows using the methodology detailed by Jorgenson and Stiroh (2000). In short, I create estimates of real investment by asset by deflating nominal investment across industries by the aggregate price index for each asset.[10] Estimates of real capital stocks are then obtained from the familiar perpetual inventory equation where depreciation rates are taken from Jorgenson and Stiroh (2000), which in turn are largely based on Fraumeni (1997). Important exceptions are the depreciation rate for computer hardware and automobiles, which are estimated as the best geometric approximation to the non-geometric patterns employed by BEA. For the IT assets, the geometric depreciation rates are 0.315 for hardware and software and 0.11 for communications equipment.

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[8]See Yuskavage (1996) for formulas and details.

[9]Several papers in the meta-analysis use gross output (or sales) as the independent variable, but do not have detailed data on intermediate materials (Brynjolfsson and Hitt (1996), Hempell (2002), Lehr and Lichtenberg (1999), and Lichtenberg (1995), Wolff (2002). This suggests a potentially important specification bias, and the common solution is to include industry and time effects and hope that the material ratio does not vary systematically across firms in a given industry at a point in time.

[10]The aggregate price of each asset is the calculated as the sum of nominal investment across industries divided by the sum of real investment. This avoids the noise in the industry-specific deflators.

For each asset in each industry, I then assume that capital services are proportional to the two-period average of the current and lagged stock as in Jorgenson and Stiroh (2000) and Oliner and Sichel (2002). To aggregate assets, I use the capital service prices (rental price) for each asset from the work of Jorgenson, Ho, and Stiroh (2002) and create aggregates as Tornquist indices of the components. While the use of aggregate service prices misses the industry dimension, it captures the most important factors, namely the depreciation rates and revaluation terms. For example, on an economy-wide basis, the service price for computer hardware fell 23.6% per year from 1995 to 2000, while the service prices for software and telecommunications equipment fell only 1.7% and 4.3% per year, respectively. This variation reflects large differences in the BEA investment deflators, which declined by 21.6% per year for hardware from 1995 to 2000, but only 0.5% and 2.9% per year for software and telecommunications, respectively.[11]

This procedure yields estimates of capital service flows from 1960 to 2000 for various categories of assets. Industry total capital (K) includes all 62 fixed reproducible capital assets available in the BEA data, equipment includes 39 types of equipment and software, and structures includes the remaining 23 types of structures. Equipment can be further broken down into IT (K_{IT}) and non-IT components (K_{NON}). IT capital includes computer hardware (mainframes, personal computers, storage devices, printers, terminals, tape drives, and integrated systems), computer software (prepackaged, custom, and own-account), and telecommunications equipment (K_{COMM}). I also create an aggregate of hardware and software, which I call computers (K_{COMP}). Non-IT capital includes non-IT equipment and software (K_{EQU}) and structures (K_{STR}). The structure of the capital data is:

$$\begin{aligned} &K = K(K_{IT}, K_{NON}) \ \textit{where} \\ (2) \qquad &K_{IT} = K_{IT}(K_{COMP}, K_{COMM}) \\ &K_{NON} = K_{NON}(K_{EQU}, K_{STR}) \end{aligned}$$

The two primary datasources are combined to create an internally consistent set of production accounts for 58 industries from 1987 to 2000.[12] These industries account for all private industry output in 2000. To summarize, each industry has data for output (gross output and value-added), capital services and capital stocks (total, structures, equipment, IT, non-IT, computers,

[11]See Jorgenson and Stiroh (2000) and Jorgenson (2001) for more on these relative price differences.

[12]While BEA produces both the output and capital data, the industry lists are not identical, so I aggregated industries to obtain the maximum number of consistently defined industries with data from 1987 to 2000. For the longer period 1977-2000, 49 consistently-defined industries are available, which account for about 71% of 2000 private industry output. The following empirical work focuses on the sample of 58 industries with the longer time series dimension, and results are similar for the 49 industries for 1977-2000.

telecommunications, other equipment), labor (full-time equivalent workers (FTE)), and intermediate inputs. All inputs and outputs are measured in both nominal and real dollars.

Table 4 shows the average revenue shares for each of these inputs; the top panel reports unweighted averages of 58 industries for 1987, 1995, and 2000 and the bottom panel reports FTE-weighted estimates. As mentioned above, neoclassical assumptions about competitive markets and constant returns to scale imply that output elasticities should equal income shares, so these shares are often used to gauge the reasonability of production function estimates. Each input share is calculated as the nominal value of the input divided by the nominal value of gross output for each industry. The value of intermediate inputs is available directly from BEA, the value of labor is defined as all compensation of employees (wages, salaries, and supplements) plus two-thirds of proprietor's income, and the value of capital income is equal to the aggregate asset-specific service price multiplied by the quantity of capital services, summed over all assets in the industry.[13]

The first thing to note is that revenue shares of all inputs do not sum to 1.0. This primarily reflects the exclusion of indirect business taxes (IBT) and the imputed nature of capital income. IBT account for about 9% of private industry GDP, so this suggests that capital income is about right. Second, intermediate inputs are the largest input, accounting for about half of the value of output for the average industry, followed by labor at about 32% and capital at about 16%. Within capital, computers and telecomm each account for only about 1-2% of total revenue.

At face value, these shares provide a benchmark for estimated elasticities. In a gross output regression, one might reasonably expect an elasticity of around 0.50 for intermediate materials, 0.30 for labor, 0.13 for non-IT capital, and 0.02 for IT capital. In a value-added regression, the IT-elasticity should be higher, in the range of 0.03-0.04. Of course, this is a reasonable benchmark only under the neoclassical assumptions. Hall (1988) and Basu and Fernald (1995, 1997) discuss the implications of imperfect competition for estimates of technological change and returns to scale, while Stiroh (2001) discusses reasons why estimated elasticities may differ from factor shares, e.g., production spillovers, excess returns, omitted variables, or measurement error.

As a final point, it is useful to consider the importance of the service price framework. As mentioned above, IT assets, particularly computer hardware, have relatively large depreciation rates and large negative revaluation terms, which means IT has a large service price (user cost) and must provide high marginal products to cover the loss in value as it ages and obsolesces. A high return to

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[13]BEA includes proprietor's income in its "property-type income" category, but some of this is the return to capital owned by small businesses. I arbitrarily include two-thirds of this income as labor income because labor's share of income is traditional thought to be in this range.

IT, therefore, is not necessarily indicative of excess returns, but also reflects the relatively large user cost. At a practical level, large service prices raise the share of IT. For example, in 2000, IT assets accounted for about 10% of the nominal capital stock, but 19% of the nominal capital service flow, which directly reflects the relatively large service prices of IT.

IV. Production Function Estimates

This section examines how estimates of IT-elasticities actually vary across different empirical specifications and methodologies within a single dataset. To this end, I use the industry-level data for 58 industries from 1987 to 2000 for the remaining analysis and systematically vary how the estimation is done. I begin with the most straightforward specification for Equation (1) and gradually incorporate additional features and alternative methods. In particular, I am interested in whether the factors identified in the meta-regression have the predicted effect on the estimate of the IT-elasticity and how much variation one can obtain under plausible specifications. As mentioned above, I take a full-disclosure approach and report estimates from all of these alternative specifications.

a) *Basic Value-Added and Gross Output Estimates*

Table 5 begins with a basic OLS, log-levels regression with real value-added as the dependent variable, total capital and labor as the only inputs, and year dummy variables:

$$(3)\quad \ln V_{i,t} = \beta_K \ln K_{i,t} + \beta_L \ln L_{i,t} + \delta_t D_t + \varepsilon_{i,t}$$

where V is real value-added, K is the industry total capital service flow, L is labor, all for industry $i = 1 \ldots 58$ in year $t = 1958 \ldots 2000$. D_t is a set of year dummy variables, D_t=1 in year t and D_t=0 otherwise.

The results (column 1) look reasonable and show an estimated elasticity for both capital and labor that are near revenue shares; together they imply constant returns to scale. Breaking out capital into the IT and non-IT components (K_{IT} and K_{NON}) yields similar estimates of the labor elasticity, while the estimate of the IT-elasticity (0.096) is much bigger than the revenue share. Again, constant returns cannot be rejected. The final value-added regression includes the full capital breakdown, which breaks out IT capital into computers and telecommunications equipment (K_{COMP}, K_{COMM}) and non-IT capital into other equipment and structures (K_{EQU}, K_{STR}). These estimates show a very large estimate for the computer elasticity (0.13), an insignificant elasticity on telecomm, and continued constant returns.

A first useful comparison is between these value-added estimates and those from a gross output regression. The next three columns of Table 5 use real gross output as the dependent variable and include real intermediate materials as an explanatory variable:

$$(4)\quad \ln Y_{i,t} = \beta_K \ln K_{i,t} + \beta_L \ln L_{i,t} + \beta_M \ln M_{i,t} + \delta_t D_t + \varepsilon_{i,t}$$

where Y is real gross output.

In the basic specification with total capital (column 4), estimated elasticities are close to their revenue shares, although materials appears too large, while labor appears somewhat too small. Estimates of returns to scale have increased, but remain constant. When capital is broken down into the IT and non-IT components (column 5), the estimate of the IT-elasticity remains large and statistically significant. Column 6 includes the full capital breakdown and shows a very large elasticity on computers (0.047), an elasticity for telecomm above its factor shares (0.026), and a surprising negative, although not statistically significant, coefficient on other equipment.

These results show large differences in estimated IT-elasticities between the value-added and gross output specifications. This is not surprising, of course, as the capital and labor elasticities from a gross output production function should equal the elasticity from a value-added production function multiplied by one minus the material share, if the neoclassical assumptions hold. In this data, the average material share is about 0.50, which suggests capital and labor elasticities should be about half as large in the gross output regression. Here, the labor coefficients are about 40% as large as in the value-added regression, while the capital coefficients change considerably. The coefficient on computer capital, for example, falls from 0.129 in the value-added regression to 0.047 in the gross output regression, while the coefficient on communication capital increases from 0.012 to 0.026.

In terms of the meta-regression, about half of the estimated IT-elasticities are based on value-added (mean IT-elasticity of 0.042) and half on gross output (mean IT-elasticity of 0.066), although the conditional difference in the meta-regression is much smaller and not significant. The estimates in Table 5 also show large differences between the gross output and value-added estimates, but the differences do not always match the simple accounting explanations, and suggest some other possible specification bias or failure of key assumptions.

Which to believe? There is reason to have more faith in the gross output regressions. Work by Basu and Fernald (1995, 1997) shows that value-added estimates may suffer from an important omitted variable bias. If there is imperfect competition, the elasticity of materials can exceed its factor share, implying that constructed measures of real value-added fail to account fully for the productive contribution of intermediate inputs. Moreover, if material growth is procyclical, this will tend to bias the estimated elasticities upward. Finally, gross output appears to be the more natural measure of firm output, so the remainder of this paper focuses on the gross output results.

A second issue is estimation in levels or in per unit of labor variables. Under the assumption of constant returns to scale, the specification with the full capital breakdown can be transformed to:

$$\begin{aligned}(5)\quad \ln y_{i,t} = \beta_{COMP} \ln k_{COMP,i,t} + \beta_{COMM} \ln k_{COMM,i,t} + \beta_{EQU} \ln k_{EQU,i,t} + \beta_{STR} \ln k_{STR,i,t} \\ + \beta_M \ln m_{i,t} + \delta_t D_t + \varepsilon_{i,t}\end{aligned}$$

where lower-cases indicate that variables are per unit of labor.

Conceptually, if returns are constant, there is no difference in estimating elasticities with a level regression (column 6) or with a per unit of labor regression (column 7). The estimates, in fact, are quite close. This supports the meta-regression, which found no systematic difference in IT-elasticities estimated from levels or per unit of labor regressions.

A third observation from these regressions is the importance of decomposing capital into its constituent parts. In the gross output levels specification, for example, computers have a large positive elasticity of 0.047, while telecomm has a smaller elasticity of 0.026. Similarly, within non-IT capital, structures capital appear highly productive with an estimated of 0.115, while other equipment shows an elasticity of –0.018. The point about aggregation effects has been made in the R&D context by Lichtenberg (1990) and in the IT context by McGuckin and Stiroh (2002), and these results support the notion that aggregation can obscure considerable heterogeneity across types of capital.[14]

Overall, these regressions show large and statistically significant estimates of IT-elasticities. In fact, the estimates, particularly for computer capital, appear to be "too large," at least with respect to their factor shares. One interpretation is that this reflects true "excess returns" in the sense that the marginal returns to computers outweigh marginal costs (Lichtenberg (1995) and Lehr and Lictenberg (1999)). In this case, IT investment, particularly computers, is highly profitable, which raises the question of why there is not even more investment.

Alternatively, there could be a standard omitted variable bias; if IT is correlated with productivity-enhancing inputs that are excluded from the regression, it would be biased upward. Bresnahan, Brynjolfsson and Hitt (2002), for example, report a strong correlation and productive complementarities between IT and human capital, which is not accounted for in these regressions. Similarly, Black and Lynch (2001a, 2001b) document the importance of complementary workplace practices and Hempell (2002) finds strong complementarity between process innovation and IT. In this interpretation, the elasticity of computer elasticity is a "marker" of omitted attributes and is simply picking up the productive effects of the missing inputs (Brynjolfsson and Hitt (1995)). If these unobserved variables are fixed over time, then inclusion of an industry fixed effect should help.

A related explanation centers on adjustment costs (Brynjolfsson and Hitt (1996), Brynjolfsson and Yang (2001), and Kiley (2001)). Here, computers must have high returns to cover the large

[14]Aizcorbe (1990) develops econometric tests for the appropriateness of certain types of aggregation.

adjustment costs that accompany their successful deployment. Brynjolfsson and Yang (2001), for example, estimate computer hardware and software costs account for only about 20% of the total start-up costs for a typical enterprise resource planning (ERP) system. These additional costs are rightly thought of as investment, and it may appear that computers have excess returns if they go unmeasured.

A final explanation is econometric. If output and inputs respond to the same shocks, the coefficients suffer from an upward simultaneity bias. The potential for simultaneity bias is a well-known concern in the production function literature and is addressed later.

To summarize, these alternative OLS regressions yield three conclusions about estimating an IT-elasticity. One, estimates differ between value-added and gross output production functions, although the differences are not always as expected. Two, it is important to disaggregate capital, particularly computers from telecomm equipment. Three, estimates vary very little between level and per unit of labor regressions. The remainder of the paper, therefore, uses gross output as the dependent variable with four distinct types of capital as explanatory variables as the benchmark and varies other dimensions of the estimation procedure to examine the effect on the IT-elasticity.

b) Alternative Gross Output Estimates

Table 6 presents alternative estimates of the benchmark gross output specification:

$$\begin{aligned} \ln Y_{i,t} = {} & \beta_{COMP} \ln K_{COMP,i,t} + \beta_{COMM} \ln K_{COMM,i,t} + \beta_{EQU} \ln K_{EQU,i,t} + \beta_{STR} \ln K_{STR,i,t} \\ & + \beta_L \ln L_{i,t} + \beta_M \ln M_{i,t} + \delta_t D_t + \varepsilon_{i,t} \end{aligned} \tag{6}$$

where column 1 repeats the OLS estimates for reference.

The first question is whether or not to include time trends. It is well known that IT investment and capital has steadily grown in importance. BEA, for example, reports that the real growth rates of computer capital, software capital, and telecomm capital were 24.5%, 12.3%, and 6.7% per year for 1990-2000, respectively, which is much faster than the 2.5% annual growth of aggregate private fixed assets. The previous regressions have all included year dummy variables, which take out the average variation over time and identify the production function parameters primarily through the cross-sectional variation. This, however, may be removing an important part of the IT story. When year dummy variables are excluded (column 2), the coefficient on computer capital rises by about one-third, while the other coefficients remain roughly constant. Because one wants to control for overall technological progress, it seems reasonable to leave the year dummy variables in, but it should be pointed out that coefficients are typically larger when they are excluded.

A second issue is the definition of capital. As discussed earlier, the flow of capital services is the appropriate measure for productivity analysis, but it is more difficult to construct and most studies use the stock of capital. When the capital stock is substituted for the capital service flow (column 3), the results are virtually identical. In this context, this is not too surprising because capital service flows differ from capital stocks due to aggregation effects when there are large differences between service and asset prices. The assets where this likely matters are computers and telecomm, but these assets are already isolated in the benchmark specification. Thus, there is little aggregation effect from different asset weights, which suggests that earlier studies that have used capital stocks rather than capital services are not likely to be materially biased.

The next two columns report weighted least squares (WLS) rather than OLS; column 4 uses labor weights and column 5 uses output weights. In a related context, Kahn and Lim (1998) argue that WLS is appropriate because the variance of residuals is inversely related to industry size, perhaps because data is noisier in smaller industries. Moreover, this might provide a better historical view of the U.S. economy as a whole because industries vary enormously in size and the classifications are somewhat arbitrary. Empirically, the residuals from the base specification do in fact have a higher standard deviation in small industries, suggesting that some weighting is desirable.[15] A more formal test of cross-sectional heteroskedasticity across industries decisively rejects the null of equal variances across industries.[16] In this application, therefore, weights seem appropriate, but they have only a small effect on the results. The remainder of the paper uses labor weights (log of full-time equivalent employees) where possible.

The bottom line from these regressions is that computer capital in particular appears highly productive. The estimated elasticity varies little from 0.047 in the benchmark OLS regression to 0.045 in the labor-weighted regression but does increase when year dummy variables are dropped, while the estimated elasticity of communications equipment varies from 0.026 in the OLS regression to 0.023 in the labor-weighted regression. The next section performs several robustness tests to further examine the strength and stability of the estimated IT-elasticity.

c) Split Sample Estimates

Table 7 presents estimates of the benchmark gross output specification from Equation (6) with labor weights for various sub-samples to serve as robustness checks. Column 1 repeats the benchmark WLS results for all 58 industries from 1987 to 2000. The next column drops the two industries that actually produce most IT hardware, Industrial Machinery and Equipment (SIC #35) and Electronic and Other Electric Equipment (SIC #36). There has been some discussion that much of the productivity gains from IT are concentrated in those industries that actually produce IT hardware, but these results

[15]I calculated the simple correlation between the standard deviation of the residuals from the base specification (Table 6, column 1) and average log output and average log labor; the correlations were –0.32 for the 58 industries.

show that the elasticities of computers and telecomm equipment are both slightly higher outside of these industries. This suggests that the productive benefits from IT-use are not concentrated in these two high-tech producing industries. The other elasticities and estimate of scale economies are virtually unchanged.

One can take this split even farther and allow the estimated coefficients to vary between manufacturing and non-manufacturing industries. I do this by allowing all coefficients (including year dummy variables) in Equation (7) to vary between manufacturing and non-manufacturing industries as:

(7)

$$
\begin{aligned}
\ln Y_{i,t} = {} & (\beta_{COMP} + \gamma_{COMP} \cdot MFG_i)\ln K_{COMP,i,t} + (\beta_{COMM} + \gamma_{COMM} \cdot MFG_i)\ln K_{COMM,i,t} + \\
& (\beta_{EQU} + \gamma_{EQU} \cdot MFG_i)\ln K_{EQU,i,t} + (\beta_{STR} + \gamma_{STR} \cdot MFG_i)\ln K_{STR,i,t} \\
& + (\beta_L + \gamma_L \cdot MFG_i)\ln L_{i,t} + (\beta_M + \gamma_M \cdot MFG_i)\ln M_{i,t} \\
& + (\delta_t + \gamma_t \cdot MFG_i)D_t + \varepsilon_{i,t}
\end{aligned}
$$

where MFG_i is a dummy variable set equal to 1 for manufacturing industries and zero otherwise.[17]

Columns 3 and 4 report results from this regression; column 3 shows the uninteracted coefficients for non-manufacturing industries (e.g., β_{COMP}) and column 4 shows the sum of the uninteracted and interacted coefficient for manufacturing industries (e.g., $\beta_{COMP}+\gamma_{COMP}$). First, the data overwhelmingly reject the null hypothesis that the non-manufacturing and manufacturing coefficients are equal, i.e., that the interaction terms are jointly zero, which suggests different production functions across broad sectors. Second, returns to scale appear different, with decreasing returns in manufacturing. This is similar to Basu et al. (2001) who find the largest decreasing returns in non-durable manufacturing.[18]

Both the computer and telecomm capital coefficient are slightly larger in manufacturing, although not statistically different. Brynjolfsson and Hitt (1995) also found little differences in estimated elasticities for computer capital and labor between manufacturing and services. Thus, it

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[16]Greene (1990, pg. 467).
[17]This set of complete interactions is identical to separate OLS regressions and this joint estimation was done simply to allow for easier hypothesis testing.
[18]Basu and Fernald (1997) report conflicting evidence; two-stage least squares estimates of returns to scale are larger in the private economy than in manufacturing, while OLS estimates show slightly larger returns to scale in manufacturing.

appears there is little variation between these broad sectors. Note that this counters the meta-analysis, which showed that manufacturing studies typically had smaller estimates of the IT-elasticity.

Columns 5 and 6 report a second split sample regression, this time along the time dimension. Recall that one of the more robust results from the meta-regression was that the IT-elasticity was generally larger for studies of later periods. This seems intuitive as IT has become an increasingly important input, and one can examine this by allowing the coefficients to vary over time. I do this by estimating a regression similar to Equation (7), except that I replace the manufacturing dummy with a time dummy set equal to 1 for years 1996-2000 and 0 for years 1987-1995.

Overall, the data reject the equality of the coefficients between the two periods, primarily due to large differences in the intermediate inputs, telecomm capital, and structure capital coefficients. There is a decline in the computer elasticity, but the difference is not statistically significant. Telecomm capital, however, show a much larger elasticity in the later period, which suggests that this asset has had important productivity effects in recent years.

d) Unobservable Industry Heterogeneity Estimates

All of the regressions reported so far have ignored any unobservable, industry-specific differences in the production process. Given the enormous differences in fundamental production issues like the pace of technological progress, regulatory issues that impact competitive forces, or industry life-cycle factors, etc., it may be more reasonable to specifically allow for unobserved heterogeneity across industries. To do this, one can decompose the error term into an industry-specific component and a classical error term:

$$\begin{aligned}(8)\quad \ln Y_{i,t} = {}& \beta_{COMP} \ln K_{COMP,i,t} + \beta_{COMM} \ln K_{COMM,i,t} + \beta_{EQU} \ln K_{EQU,i,t} + \beta_{STR} \ln K_{STR,i,t} \\ & + \beta_L \ln L_{i,t} + \beta_M \ln M_{i,t} + \delta_t D_t + \left(\alpha_i + \nu_{i,t}\right)\end{aligned}$$

where α_i is the industry fixed effect and $\upsilon_{i,t}$ is a disturbance term that reflects measurement error and productivity shocks.

Equation (8) can be estimated in several ways depending on how one views the composite error term. Ignoring potential simultaneity problems for now, the obvious solutions are to estimate Equation (8) as is with OLS (a "within" estimator) or to estimate it in first differences in order to remove the fixed effect. Historically, however, the fixed effect approach has generally led to disappointing results with insignificant capital coefficients and implausibly low returns to scale (Griliches and Mairesse (1998)). In the IT-context, Brynjolfsson and Hitt (1995) report a decline in their computer elasticity from 0.109 in an OLS regression to 0.052 in a fixed effect regression, while Hempell (2002) shows a decline in the IT-elasticity from 0.24 in a pooled levels regression to 0.016 in a within regression. The meta-analysis also shows this: including fixed effects drops the estimated IT-elasticity by 0.066 according to the full sample regression reported in Table 3.

Table 8 reports various estimates of Equation (8). I emphasize that these results ignore the simultaneity problem and the fixed effect results implicitly assume that productivity shocks are uncorrelated with all inputs in all periods (strict exogeneity); this assumption is explored more fully in the following subsection. I report four types estimates – fixed effects, first differences, fixed effects with first differences, and long differences – for the full capital breakdown.

Column 1 again reports the benchmark WLS results. Column 2 with industry-specific fixed effects is quite different from the benchmark. In terms of the IT-components, both fall as predicted by the meta-regression, and neither is statistically different from zero. Estimated elasticities on other equipment rises, however, and the estimate of returns to scale increases dramatically from 1.01in the basic WLS regression to 1.29 in the fixed effect regression. Both of these increases counter the pattern described in Griliches and Mairesse (1998), and reflect the large increase in the other equipment coefficient.

Estimation in first differences (column 3) yields very poor results. The intermediate input elasticity falls far below it's share and the elasticity of labor rises to around 0.7. This likely reflects the relatively high persistence of capital variables, so that changes are primarily noise, and the relative variability of labor, where year-to-year changes are more meaningful. All of the capital coefficients except other equipment are essentially zero, and telecomm and structures are negative, although very imprecisely estimated. Again, this type of decline in the IT-elasticity is consistent with the meta-regression, which shows smaller estimates in first difference regressions. As a concrete example, the IT-elasticity in Brynjolfsson and Hitt (2000) falls from 0.030 in a panel to 0.012 in first differences in one dataset, and from 0.025 to –0.002 in another.

As a final point about the basic fixed effect and first difference regressions, it is interesting to note the differential impact of the year. If the year dummies are excluded from columns 2 and 3 (not shown), the estimated elasticity on computers rises substantially in the fixed effect regression (coefficient = 0.070, s.e.=0.009), but remains roughly constant in the first difference regression (coefficient = 0.027, s.e.=0.027). This suggests that it is quite important to control for the overall time trend, but less so for changes in the time trend.

An even more ambitious specification includes fixed effects in the first difference regression as in Basu et al. (2001). Typically, one either includes fixed effects or uses first differences to remove the unobserved fixed factor, but it may be reasonable to include a fixed effect in a first difference regression ("within differences" in Griliches and Mairesse (1998)). For example, the error terms in

Equation (8) partially reflect productivity shocks and it is plausible to assume that shocks to productivity growth vary systematically across industries. The IT-producing industries, for example, have consistently shown faster total factor productivity growth than other industries. Estimates of a first difference regression with fixed effects (column 4) are also poor, however, with a large estimate of the elasticity of labor and a large negative coefficients on structures. The coefficient on structures, which drives the returns to scale parameter to only 0.53, suggests that there are important cross-industry differences in the time trend of this variable. The estimate of the computer capital coefficient is large, but imprecisely estimated.

The last three columns include "long difference" estimates where the growth rate of each variable is calculated as the average across either a 5, 10, or 13 year period.[19] As in the first difference regressions, this effectively removes the unobserved component. The added advantage is that longer differences help to remove classical measurement error that may be present in first differences, but at the expense of lost information (Griliches and Mairesse (1998)). In the IT-context, Brynjolfsson and Hitt (2000) find that the estimated return to IT increases with the length of their long difference estimates, which they interpret as evidence of complementarity and adjustment costs.

These results do not show any obvious pattern for computer or telecomm coefficients; they are typically small and imprecisely estimated. The coefficients for intermediate inputs and labor seem reasonable and, like the fixed effect and first difference results, the coefficient on other equipment capital is large when the unobserved coefficient is removed. This suggests that within variation in other equipment is important, but gets swamped by cross-industry differences in the levels regressions.

It is difficult to draw specific conclusions about the magnitude of the IT-elasticity from these results and one needs a more fully developed model of unobserved heterogeneity to choose between alternatives. The only clear point is that it matters a great deal for all types of elasticities how one deals with unobserved heterogeneity. This general point is not new, but in the context of understanding the productive impact of IT, these comparisons show that researchers' choices have a considerable impact on the conclusions. As seen earlier in the meta-analysis, inclusion of fixed effects or estimation in first differences substantially lowers the estimated elasticity of IT capital and generates a much more pessimistic view of the IT revolution.

e) Instrumental Variable Estimates

[19] Each long difference regression uses the maximum number of observations available. For example, the 13 year difference regression has only one observation per industry (1987-2000), while the 10 year difference regression has 4 observations per industry (1987-1997, 1988-1998, 1989-1999, 1990-2000), etc.

The final issue relates to the simultaneity problems surrounding the entire production function literature. The key point, discussed at length by Griliches and Mairesse (1998), is that inputs are not really independent variables, but are chosen by the firms in some behavioral fashion. If the factors that determine inputs are fixed, then the fixed effect approach described above can satisfactorily solve the problem if one is willing to assume that all explanatory variables are strictly exogenous. If one believes that there is a fixed component and that shocks are correlated with inputs choices, e.g., firms hire more labor when a positive productivity shock raises the marginal product of labor, then one should use first differences to remove the unobservable component and suitable instruments to account for endogeneity. It is worth noting that despite the well-known nature of this problem only seven of the twenty papers included in the meta-analysis econometrically account for simultaneity through an instrumental variable approach.[20]

Instruments, however, are hard to come by: one needs variables that are correlated with inputs (the right-hand side variables) and uncorrelated with productivity shocks (the error term in Equation (8)) and the production function literature has pursued several alternatives. The micro-econometric literature developed by Arellano and Bond (1991), Arellano and Bover (1995), Blundell and Bond (1998a, 1998b), and others has focused on "internal" instruments such as lagged independent variables, while macro work by Hall (1988), Basu and Fernald (1995, 1997) and Basu et al. (2001) has used demand-side instruments like oil prices, defense spending shocks, and monetary policy shocks. This section will pursue both approaches.[21]

Table 9 compares instrumental variables (IV) approaches with the more common OLS approach. Column 1 reports OLS estimates for the levels specification in Equation (6). The results are similar to the weighted regressions in Table 8, and the two IT coefficients are large, and statistically significant both individually and jointly (p-value=0.003 for the null that both are equal to zero).[22] Column 2 then reports the fixed effect estimates as in Equation (8) and again the results are similar to the weighted estimates with insignificant IT coefficients (p-value=0.80 for the same null).

Column 3 reports IV estimates of the fixed effect specification where estimation is via the generalized method of moments (GMM) framework developed by Arellano and Bover (1995) and

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[20]These papers are Dewan and Kramer (2000), Hempell (2002), Brynjolfsson and Hitt (1996, 2000), McGuckin and Stiroh (2002), and Stiroh (2001, 2002).

[21]A third approach using input-output data has been developed by Shea (1993a, 1993b). This approach, however, is not applicable for many non-manufacturing industries that do not produce intermediate inputs. Even within manufacturing, Shea (2002b) finds that less than half of the industries have plausible instruments from input-output data.

[22]Weights are not included to be consistent with the IV estimates.

Blundell and Bond (1998a) where lagged first differences are used as instruments.[23] The estimates for intermediate inputs and labor are similar to the OLS estimates, while none of the capital coefficients are significantly different from zero. This IV estimate provides weak evidence that IT capital matters, although the test that both the computer and telecomm capital coefficients are zero cannot be rejected (p-value=0.17). The lack of precision of all capital coefficients, however, suggests that this may be reflective of weak instruments, rather than a lack of a true underlying relationship. Strictly speaking, however, estimating the GMM levels equation with fixed effects is appropriate only if the correlation between regressors and the fixed effect is constant over time and a stationarity condition is met, so I now turn to the first difference estimates.

To provide a benchmark, column 4 reports the OLS first difference estimates; this removes the unobservable fixed component, but does not account for the simultaneity problem. As in the weighted regressions in Table 8, these estimates are poor with insignificant and often negative capital coefficients. The two IT capital coefficients are far from joint significance (p-value=0.55). Column 5 reports IV estimates where instruments are lagged levels and estimation is via GMM (Arellano and Bond (1991)).[24] The estimates for intermediate input and labor elasticities are somewhat improved, i.e., closer to factor shares, but all capital coefficients remain insignificant.

A third GMM approach, developed by Blundell and Bond (1998a), is a "system GMM estimator (SYS-GMM)" from a stacked system of first difference equations (with lagged levels as instruments) and levels equations (with lagged first differences as instruments). These estimates (column 6) are the most sensible: returns to scale are constant, both intermediate inputs and labor are near their factor shares and are estimated very precisely, and the capital coefficients are mostly plausible.[25] Here, the point estimate of both computer and telecomm capital are near factor shares, but estimated imprecisely. The p-value associated with the null of their joint significance is 0.15. The SYS-GMM estimates reflect state-of-the-art econometric methodology and provide some evidence productive impact from IT, although all the capital coefficients are estimated imprecisely. Finally, note that the SYS-GMM estimates essentially recover the GMM level estimates (column 3). This

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[23]All GMM estimation is done with DPD98 described by Arellano and Bond (1998). Reported GMM estimates are the one-step estimates with robust standard errors.

[24]Due to problems inverting the instrument matrix with a large number of lags, I use a single lag for intermediate inputs and labor and two lags for capital, rather than all available lags as is conceptually feasible. This reduces the efficiency of the estimates, but avoids the possible over-fitting problems from a large number of instruments (Arellano and Bond (1998), pg. 8).

[25]To avoid an overly large instrument matrix, the instrument set included one lag of first differences and one lag of levels for intermediate inputs, labor, and the capital components.

suggests that the input series have relative large auto-regressive components so that identification is coming from the levels and not the differences, which would be mostly noise.

A second IV approach used by Hall (1988), Basu and Fernald (1995, 1997), Basu et al. (2001), and others incorporates demand-side variables as instruments, i.e., variables that are hopefully correlated with inputs, but uncorrelated with technology. In particular, Basu et al. (2001) use oil prices (current and one lag), defense spending shocks (current and one lag), and monetary policy shocks as instruments for industry-level regressions of output growth on input growth, and I follow this approach. [26] One difficulty, however, is that their defense spending shocks are constant after 1980, so I cannot include the full capital breakdown.

Before discussing results, I should point out that Basu et al. (2001) are interested in different questions and focus on estimating returns to scale and utilization parameters. Therefore, they do not decompose input growth into specific components, but rather regress output growth on the growth of an aggregate of all inputs (a Tornquist aggregate of materials, labor, and capital using average input shares as weights), and various adjustments terms for returns to scale, utilization, and adjustment costs. In principle, one can simply include the components rather than the aggregate, but I use the same instrument set with more right-hand side variables, so this is asking a good deal more of these aggregate instruments.

Column 6 of Table 9 reports estimates of an OLS regression in the spirit of Basu et al. (2001), i.e., output growth on input growth. [27] The coefficient of 0.86 implies decreasing returns to scale; Basu and Fernald (1997) estimate 0.83 in a similar regression. The demand-side IV approach (column 7) shows a much larger coefficients (1.16), bigger standard error, and the data reject constant returns to scale. If productivity shocks induce input growth, then one would expect a positive bias in the OLS estimates, but these results show larger estimates of scale economies in the IV regressions. Column 8 uses the same IV approach, but decomposes total input growth into the materials, labor, and two capital components (IT capital and non-IT capital). There appears to be little predictive power from these instruments for capital input growth as the estimates are all far from factors shares and imprecisely estimated. This could reflect the weakness of the instruments (Nelson and Startz (1990)), which may lead to considerable small-sample bias.

To summarize, the most plausible IV estimates are from the SYS-GMM framework that estimates a stacked system of equations in levels and first differences. In this case, labor and material

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[26] I thank John Fernald for providing these data to me.

coefficients are near factor shares and the various capital coefficients have some explanatory power. Other IV estimates are generally disappointing. This divergence highlights both the difficulty and the importance of accounting for simultaneity issues in production function analyses and offers one explanation for why most studies in the meta-analysis did not explicitly deal with the issue. Standard IV techniques do not seem to generate "reasonable" results, and researchers and journals may be less inclined to report results that differ from prior expectations. As econometric techniques continue to improve and become incorporated into standard econometric software packages, researchers interested in the impact of IT will need to address the simultaneity issue more seriously.

V. Conclusions

The large and growing literature on the economic impact of information technology has fueled a surge in optimism surrounding the IT revolution. The estimates reported in this paper do not refute the optimistic view, but both the meta-analysis and the new econometric results suggest caution when trying to precisely quantify the impact of IT. Reasonable differences in econometric techniques yield a wide range of estimates of the output elasticity of IT, which have very different implications for how important IT has been for the U.S. economy.

Estimating production functions in levels is the most common technique in the literature, and virtually all of the level estimates from U.S. data show a large elasticity for IT. This implies either excess returns for IT or some important omitted variable. The omitted variable interpretation seems most sensible as a growing body of microeconomic work stresses the importance of complementary innovations like improved workplace practices and firm reengineering for the successful deployment of IT. If one specifically accounts for unobserved heterogeneity via fixed effects or estimation in first differences, the IT-elasticity falls substantially. A pessimistic interpretation is that IT does not really matter, and has simply been receiving credit for productivity gains more appropriately attributed to other fixed factors. This interpretation seems too strong, however, because all capital coefficients tend to be smaller in these specifications, and it is unlikely that all physical capital is really unproductive.

The most promising IV estimates are from the system-GMM estimator. Here, the point estimates for computer and telecomm capital are consistent with normal returns. Other IV estimates are weaker, but this may be more reflective of weak instruments than of a lack of a productive impact from IT. Future empirical research on IT needs to take this simultaneity issue more seriously and

[27] This is not exactly the Basu et al. (2001) approach because they estimate via three-stage least squares rather than in a panel, allow parameters to vary across broad sectors, include fixed effects, and include terms for adjustment costs and utilization changes.

examine the possible biases that remain from small samples and weak instruments. A Monte Carlo analysis of synthetic production function data, for example, could shed some light on these issues.

An important implication of the variation in the estimated IT-elasticities is the potential for publication and specification search bias. The range of estimates from seemingly plausible specifications raises the possibility that the set of published results is not truly representative of the research performed. This is always a concern in empirical work, of course, but seems especially problematic in this application due to the strong priors about the elasticity from a basic neoclassical framework. The results reported here suggest that researchers have a great deal of discretion in the types of estimates they report. If researchers are more inclined to report only those estimates that conform to prior expectations and journals are more likely to publish the same, then the published literature will over-sample the basic OLS, levels regressions that provide those answers. Indeed, the majority of papers in the IT/productivity literature do focus on estimates of levels regressions without a great deal of attention to unobserved heterogeneity or simultaneity issues.

The bottom line result from this paper is that IT does matter, but one must be careful about putting too much weight on any given estimate. The preferred estimate in this analysis, the system-GMM estimator that accounts for both unobserved heterogeneity and simultaneity, suggests that IT earns normal returns. This is somewhat reassuring, because the existence of either sustained excess returns or large investment in an unproductive asset counters the notion of rational, profit-maximizing firms. Moreover, the existence of normal returns provides empirical grounding for the influential growth accounting literature, which implicitly assumes normal returns to all factors. If this is the case, the emerging consensus that IT played a critical role in the U.S. productivity revival remains intact.

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Figure 1: Histogram of IT-Elasticities
41 Estimates from 20 Studies

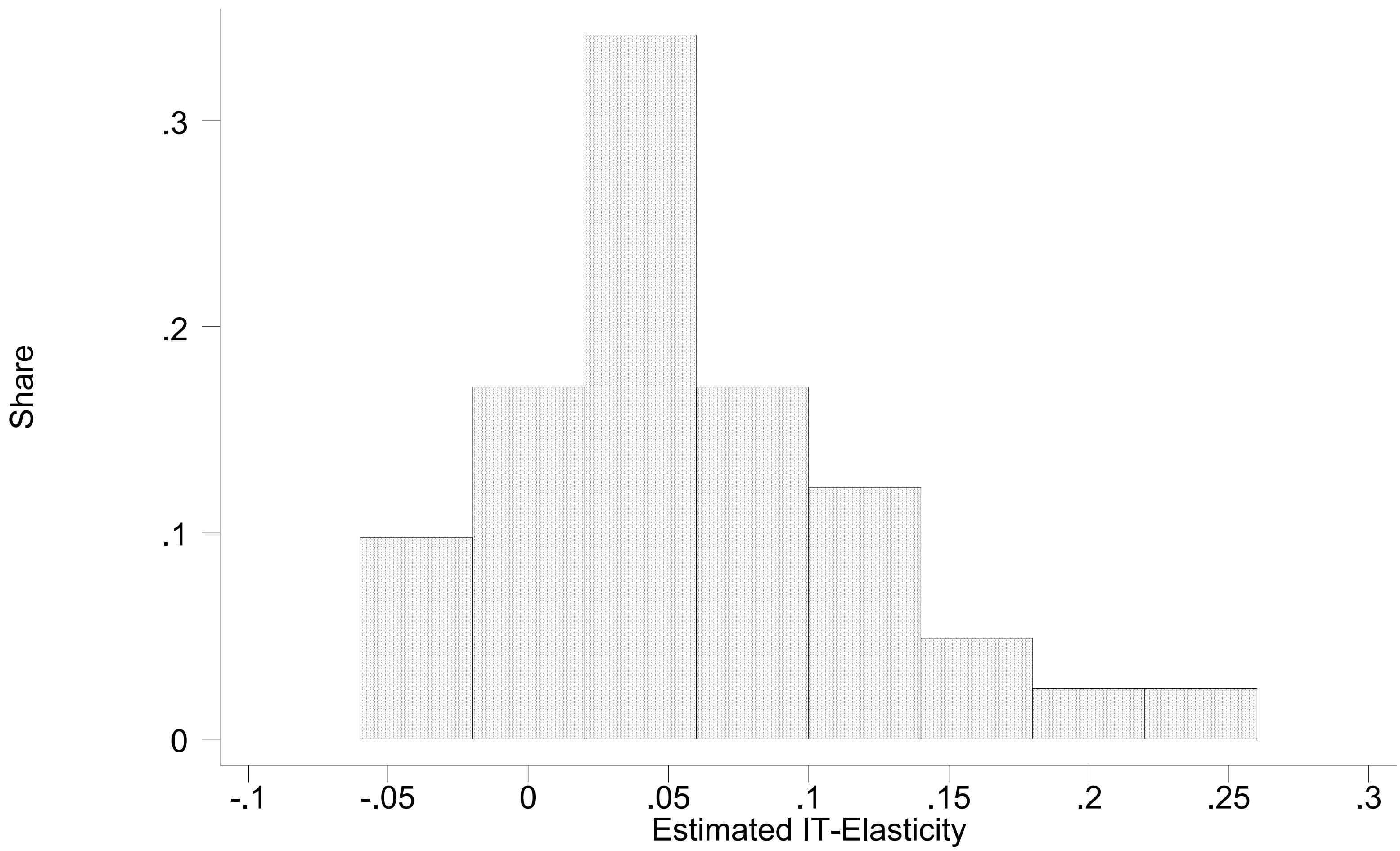

Table 1: Studies Included in Meta-Analysis

#	Authors	Year	Journal	Estimated IT-Elasticity
1	Bresnahan, Brynjolfsson, and Hitt	2002	*Quarterly Journal of Economics*	0.035
2	Brynjolfsson and Hitt	1995	*Economics of Innovation and New Technology*	0.052
3	Brynjolfsson and Hitt	1996	*Management Science*	0.017
4	Brynjolfsson and Hitt	2000	Mimeo	0.030
5	Caselli and Paterno	2001	Bank of Italy, WP #419	0.031
6	Department of Commerce	1997	EA/OPD 97-3	0.105
7	Dewan and Kremer	2000	*Management Science*	0.051
8	Dewan and Min	1997	*Management Science*	0.104
9	Hempell	2002	ZEW, WP	0.075
10	Kiley	2001	*Carnegie-Rochester Conf. Series*	0.060
11	Lee and Barua	1999	*Journal of Productivity Analysis*	0.024
12	Lehr and Lichtenberg	1998	*Journal of Industrial Economics*	0.061
13	Lehr and Lichtenberg	1999	*Canadian Journal of Economics*	0.077
14	Lichtenberg	1995	*Economics of Innovation and New Technology*	0.100
15	Loveman	1994	In "IT and the Corporation of the 1990s: Research Studies"	-0.060
16	McGuckin and Stiroh	2002	*Economic Inquiry*	0.177
17	Steindel	1992	*Quarterly Review, FRBNY*	0.026
18	Stiroh	2001	FRBNY, WP #115	0.045
19	Stiroh	2002	*Review of Income and Wealth*	-0.003
20	Wolff	2002	NBER, WP #8743	-0.006
			Mean	0.050
			Standard Deviation	0.050

Notes: List presents preferred estimate of the IT-elasticity from each paper. Section II describes creation of the database.

Table 2: Variables for IT-Elasticity Meta-Regression

Variable	Definition	Mean: Preferred	Mean: Full
	Dependent Variable		
IT-Elasticity	Estimated elasticity of output with respect to information technology (IT)	0.050	0.054
	Independent Variables		
Labor Productivity	= 1 if dependent variable was labor productivity (output per labor); = 0 if output	0.250	0.220
Gross Output	= 1 if dependent variable was gross output; = 0 if value-added	0.600	0.512
First Differences	= 1 if estimation was done in differences or system of differences & levels; = 0 if levels	0.400	0.317
Instruments	= 1 if estimation used some type of instrumental variables; = 0 if not	0.150	0.098
Flexible	= 1 if estimation employed flexible functional form; = 0 if not	0.050	0.098
Aggregate	= 1 if data were aggregated (industries or countries); = 0 if not (firms or business units)	0.400	0.415
Manufacturing	= 1 if data were only for manufacturing; = 0 if not	0.250	0.244
Cross-Section	= 1 if data were for a single cross-section; = 0 if a panel	0.050	0.024
Fixed Effects	= 1 if a fixed effects model; = 0 if not	0.250	0.268
Between Effects	= 1 if a between effects model; = 0 if not	0.000	0.049
Average Sample Period	= mean of sample period	1987.7	1987.9

Notes: Preferred sample includes 20 observations, one from each study. Full sample includes 41 observations. In the meta-regression, *Average Sample Period* is normalized by the mean average sample period.

Table 3: Meta-Regression Results

Independent Variables	Sample: Preferred	Sample: Full
Labor Productivity	0.011	0.031
	(0.028)	(0.030)
Gross Output	-0.015	0.001
	(0.022)	(0.018)
First Differences	-0.006	-0.041 **
	(0.021)	(0.018)
Aggregate	0.046 *	0.062 ***
	(0.024)	(0.020)
Manufacturing	-0.039	-0.054 *
	(0.028)	(0.027)
Fixed Effect	-0.041	-0.066 ***
	(0.026)	(0.020)
Average Sample Period	0.005 *	0.006 **
	(0.003)	(0.003)
Constant	0.061 ***	0.065 ***
	(0.018)	(0.015)
Adjusted R^2	0.318	0.392
No. Obs.	20	41

Notes: The dependent variables is the estimated IT-elasticity. The preferred sample includes one estimate from each of 20 different studies, while the full sample includes 41 observations, between one and four estimates from each study. Reported coefficients are from OLS regressions. All independent variables are dummy variables, except for *Average Sample Period,* and defined in Table 2.

***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table 4: Average Revenue Shares

	1987	1995	2000
	Unweighted Mean		
Total Revenue Share	96.4	98.4	98.8
Intermediate Inputs	47.6	49.8	50.0
Labor	33.3	32.6	32.1
Capital	15.5	16.0	16.8
Computers	1.3	1.4	1.8
Telecomm	0.9	1.1	1.1
Other Equipment	6.2	6.4	7.2
Structures	7.1	7.0	6.6
Value-Added Share	52.4	50.2	50.0
	Weighted Mean		
Total Revenue Share	92.0	92.0	91.8
Intermediate Inputs	42.6	42.9	41.4
Labor	39.9	39.6	40.6
Capital	9.5	9.5	9.8
Computers	1.6	1.4	1.9
Telecomm	0.5	0.6	0.6
Other Equipment	3.9	4.0	4.3
Structures	3.5	3.4	3.0
Value-Added Share	57.4	57.1	58.6

Notes: All summary statistics are for the 58 industries that are consistently defined from 1987 to 2000. Weighted mean uses full-time equivalent workers as the weights. Each revenue share is defined as nominal input payments divided by nominal gross output. Value-added share is defined as nominal gross product originating (value-added) divided by nominal gross output. All values are percentages.

Table 5: Basic Value-Added and Gross Ouptut Estimates

	Value-Added			Gross Output			Gross Output per Labor
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intermediate Inputs				0.600 ***	0.614 ***	0.612 ***	0.611 ***
				(0.015)	(0.014)	(0.016)	(0.015)
Labor	0.631 ***	0.594 ***	0.550 ***	0.255 ***	0.223 ***	0.220 ***	
	(0.015)	(0.017)	(0.018)	(0.011)	(0.011)	(0.011)	
Capital	0.373 ***			0.160 ***			
	(0.020)			(0.012)			
IT Capital		0.096 ***			0.059 ***		
		(0.013)			(0.007)		
Non-IT Capital		0.305 ***			0.113 ***		
		(0.023)			(0.013)		
Computer Capital			0.129 ***			0.047 ***	0.048 ***
			(0.015)			(0.009)	(0.009)
Telecomm Capital			0.012			0.026 ***	0.026 ***
			(0.009)			(0.006)	(0.006)
Other Equipment Capital			0.044 ***			-0.018	-0.018
			(0.017)			(0.011)	(0.011)
Structure Capital			0.246 ***			0.115 ***	0.114 ***
			(0.020)			(0.011)	(0.010)
Returns to Scale	1.00	0.99	0.98	1.02	1.01	1.00	
CRS p-value	0.830	0.754	0.285	0.145	0.384	0.834	
No. Obs.	812	812	812	812	812	812	812
Adjusted-R^2	0.854	0.860	0.877	0.954	0.957	0.961	0.908

Notes: Estimates are from OLS regressions for 58 industries from 1987 to 2000 and include year dummy variables. Robust standard errors are reported in parentheses. *IT Capital* includes computer hardware, software, and telecommunications equipment. *Computer Capital* includes hardware and software. All variables are measured in logs. *CRS p-value* reports the p-value associated with a test of the null hypothesis that the sum of the input coefficients equals 1.0.

***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table 6: Alternative Gross Ouptut Estimates

	Benchmark (1)	No Year Dummies (2)	Capital Stock (3)	Labor Weights (4)	Gross Output Weights (5)
Intermediate Inputs	0.612 ***	0.628 ***	0.614 ***	0.607 ***	0.617 ***
	(0.016)	(0.017)	(0.016)	(0.015)	(0.016)
Labor	0.220 ***	0.203 ***	0.220 ***	0.235 ***	0.219 ***
	(0.011)	(0.010)	(0.011)	(0.011)	(0.011)
Computer Capital	0.047 ***	0.061 ***	0.046 ***	0.045 ***	0.048 ***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Telecomm Capital	0.026 ***	0.025 ***	0.027 ***	0.023 ***	0.025 ***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Other Equipment Capital	-0.018	-0.022 *	-0.020 *	-0.010	-0.020 *
	(0.011)	(0.012)	(0.011)	(0.011)	(0.011)
Structure Capital	0.115 ***	0.108 ***	0.115 ***	0.113 ***	0.120 ***
	(0.011)	(0.011)	(0.011)	(0.010)	(0.011)
Returns to Scale	1.00	1.00	1.00	1.01	1.008
CRS p-value	0.834	0.744	0.801	0.132	0.413
No. Obs.	812	812	812	812	812
Adjusted-R^2	0.961	0.960	0.961	0.961	0.961

Notes: Estimates are from OLS or WLS regressions for 58 industries from 1987 to 2000 with gross output as the dependent variable. All regressions except column 2 include year dummy variables. Robust standard errors are reported in parentheses. Weights are either the log of full-time equivalent employees (labor weights) or log of gross output (gross output weights). *Computer Capital* includes hardware and software. All variables are measured in logs. *CRS p-value* reports the p-value associated with a test of the null hypothesis that the sum of the input coefficients equals 1.0.

***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table 7: Split Sample Regressions

	Benchmark	Drop IT-Producing	Industry Split: Non-Mfg	Industry Split: Mfg	Time Split: 1987-1995	Time Split: 1996-2000
	(1)	(2)	(3)	(4)	(5)	(6)
Intermediate Inputs	0.607 ***	0.603 ***	0.607 ***	0.787 ***	0.507 ***	0.630 ***
	(0.015)	(0.016)	(0.026)	(0.018)	(0.040)	(0.015)
Labor	0.235 ***	0.236 ***	0.245 ***	0.061 ***	0.230 ***	0.231 ***
	(0.011)	(0.011)	(0.017)	(0.011)	(0.035)	(0.011)
Computer Capital	0.045 ***	0.050 ***	0.056 ***	0.071 ***	0.064 ***	0.042 ***
	(0.009)	(0.009)	(0.010)	(0.018)	(0.020)	(0.010)
Telecomm Capital	0.023 ***	0.024 ***	0.015 ***	0.020	-0.017	0.031 ***
	(0.006)	(0.006)	(0.006)	(0.015)	(0.015)	(0.005)
Other Equipment Capital	-0.010	-0.005	0.000	0.026 **	0.007	-0.014
	(0.011)	(0.011)	(0.013)	(0.013)	(0.037)	(0.011)
Structure Capital	0.113 ***	0.109 ***	0.096 ***	-0.030	0.158 ***	0.106 ***
	(0.010)	(0.010)	(0.011)	(0.019)	(0.035)	(0.011)
Returns to Scale	1.01	1.02	1.02	0.94	0.95	1.02
CRS p-value	0.132	0.067	0.136	0.000	0.094	0.008
Split p-value			0.000		0.005	
No. Obs.	812	784	812		812	
Adjusted-R^2	0.961	0.962	0.965		0.962	

Notes: Estimates are from WLS regressions for 58 industries from 1987 to 2000 with gross output as the dependent variable and include year dummy variables. Robust standard errors are reported in parentheses. Weights are the log of full-time equivalent employees. IT-producing industries include SIC #35 and #36. Industry split sample regression allows all coefficients (including year dummy variables) to vary between manufacturing and non-manufacturing industries; see text for details. Time split sample regression allows all elasticities to vary between the two time periods; see text for details. *Computer Capital* includes hardware and software. All variables are in logs. *CRS p-value* reports the p-value associated with a test of the null hypothesis that the sum of the input coefficients equals 1.0.

***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table 8: Unobserved Industry Heterogeneity Estimates

	Benchmark	Fixed Effects	First Differences	Fixed Effects and First Differences	Long Differences 5 Years	Long Differences 10 Years	Long Differences 13 Years
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intermediate Inputs	0.607 ***	0.506 ***	0.323 ***	0.297 ***	0.487 ***	0.553 ***	0.558 ***
	(0.015)	(0.027)	(0.023)	(0.023)	(0.028)	(0.037)	(0.078)
Labor	0.235 ***	0.497 ***	0.743 ***	0.655 ***	0.552 ***	0.394 ***	0.490 **
	(0.011)	(0.065)	(0.093)	(0.112)	(0.059)	(0.096)	(0.234)
Computer Capital	0.045 ***	0.012	0.021	0.065	0.025 *	0.009	-0.011
	(0.009)	(0.011)	(0.027)	(0.046)	(0.013)	(0.013)	(0.024)
Telecomm Capital	0.023 ***	-0.001	-0.019	-0.027	0.001	-0.001	0.015
	(0.006)	(0.012)	(0.027)	(0.057)	(0.014)	(0.015)	(0.032)
Other Equipment Capital	-0.010	0.210 ***	0.182 *	0.017	0.186 ***	0.214 ***	0.244 *
	(0.011)	(0.052)	(0.095)	(0.131)	(0.055)	(0.072)	(0.145)
Structure Capital	0.113 ***	0.062	-0.142	-0.471 ***	0.091	0.087	-0.206
	(0.010)	(0.147)	(0.251)	(0.146)	(0.105)	(0.181)	(0.437)
Returns to Scale	1.01	1.29	1.11	0.53	1.34	1.26	1.091
CRS p-value	0.13	0.00	0.57	0.02	0.00	0.01	0.671
No. Obs.	812	812	754	754	522	232	58
Adjusted-R^2	0.961	0.990	0.459	0.482	0.791	0.842	0.789

Notes: Estimates are from WLS regressions for 58 industries from 1987 to 2000 with gross output as the dependent variable and include year dummy variables. Robust standard errors are reported in parentheses. Weights are the log of full-time equivalent employees. Fixed effect regression includes an industry-specific dummy and first difference regression one-period differences all input and output variables. Long differences include rolling n-period growth rates of each variable; the number of observations varies with the number of n-period observations. *Computer Capital* includes hardware and software. All variables are in logs. *CRS p-value* reports the p-value associated with a test of the null hypothesis that the sum of the input coefficients equals 1.0.

***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table 9: Instrumental Variable Estimates

	Internal Instruments						Demand-side Instruments		
	Levels			First Differences		Stacked	First Differences		
	OLS	OLS-FE	GMM-FE	OLS	GMM	SYS-GMM	OLS	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intermediate Inputs	0.611 ***	0.480 ***	0.633 ***	0.302 ***	0.540 ***	0.630 ***			0.292
	(0.045)	(0.058)	(0.060)	(0.036)	(0.051)	(0.054)			(0.572)
Labor	0.220 ***	0.537 ***	0.239 ***	0.762 ***	0.398 **	0.239 ***			0.878
	(0.036)	(0.124)	(0.047)	(0.099)	(0.156)	(0.044)			(0.629)
Computer Capital	0.047 *	0.012	0.014	0.027	0.025	0.021			
	(0.026)	(0.020)	(0.026)	(0.025)	(0.023)	(0.022)			
Telecomm Capital	0.026 *	0.000	0.025	-0.016	-0.015	0.018			
	(0.015)	(0.027)	(0.022)	(0.036)	(0.032)	(0.020)			
Other Equipment Capital	-0.018	0.238 **	-0.015	0.194 **	0.192	-0.010			
	(0.034)	(0.100)	(0.054)	(0.090)	(0.130)	(0.055)			
Structure Capital	0.115 ***	0.042	0.077	-0.157	0.060	0.079			
	(0.034)	(0.153)	(0.049)	(0.232)	(0.166)	(0.049)			
Total Inputs							0.856 ***	1.156 ***	
							(0.065)	(0.158)	
IT Capital									0.034
									(0.167)
Non-IT Capital									0.863
									(4.093)
Returns to Scale	1.00	1.31	0.97	1.11	1.20	0.98	0.86	1.16	2.07
Jt. Sig. of IT Variables	0.00	0.80	0.17	0.55	0.54	0.15			
Sargan Statistic			40.5		42.7	40.8			
Sargan p-value			0.99		1.00	1.00			
No. Obs.	812	754	812	754	754	812	754	754	754

Notes: Estimates are for 58 industries from 1987 to 2000 and include year dummy variables. Robust standard errors are reported in parentheses. All variables are in logs. OLS-FE includes an industry fixed effect. GMM-FE in levels includes an industry fixed effect and uses lagged first differences as instruments. GMM first difference estimates use lagged levels as instruments. SYS-GMM estimates are from a stacked system of levels equations (with lagged first differences as instruments) and first difference equations (with lagged levels as instruments). Demand-side instruments include growth in relative price of oil (current and lagged), relative price of oil (current and lagged), and monetary policy shocks (one lag). *Jt. Sig. of IT Variables* reports p-value associated with Wald test of the joint significance of the Computer and Telecommm coefficients. *Sargan Statistic* is a test of overidentifying restrictions (null of valid instruments) and *Sargan p-value* is the associated p-value.

***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.