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Research Note

Investments in Information Technology: Indirect Effects and Information Technology Intensity

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Many studies measure the value of information technology (IT) by focusing on how much value is added rather than on the mechanisms that drive value addition. We argue that value from IT arises not only directly through changes in the factor input mix but also indirectly through IT-enabled augmentation of non-IT inputs and changes in the underlying production technology. We develop an augmented form of the Cobb-Douglas production function to separate and measure different productivity-enhancing effects of IT. Using industry-level data from the manufacturing sector, we find evidence that both direct and indirect effects of IT are significant. Partitioning industries into IT-intensive and non-IT-intensive, we find that the indirect effects of IT predominate in the IT-intensive sector. In contrast, the direct effects of IT predominate in the non-IT intensive sector. These results indicate structural differences in the role of IT in production between industries that are IT-intensive and those that are not. The implication for decision-makers is that for IT-intensive industries the gains from IT come primarily through indirect effects such as the augmentation of non-IT capital and labor.

Key words: IT productivity; indirect effects; IT investment; output elasticity; technological change; production theory
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1. Introduction

The last few decades have seen a phenomenal rise in information technology (IT) investment, especially during the 1990s. According to Digital Economy, a report of the U.S. Department of Commerce (2002), the level of U.S. real investment in IT grew at 20% per annum from 1995 to 2000. Early studies indicate a complex relationship between IT investment and firm performance (Cron and Sobol 1983, Strassman 1985), pointing to other features within and outside the firm that interact with IT investment.

Since the mid-1990s research using production and process approaches has found positive contributions from IT. The former uses production function specifications to measure IT contributions. Using data from Computerworld and InformationWeek, Lichtenberg (1995) found a positive net marginal product of IT capital. Using firm-level data, Brynjolfsson and Hitt (1996) found positive marginal products of IT capital and IT labor. Using data on manufacturing units, Lee and Barua (1999) concluded that IT capital contribution is positive and that firms underinvested in IT. Using country-level data, Dewan and Kraemer (2000) found positive output elasticities of IT capital for developed countries. These studies complement growth accounting research measuring the contribution of IT in the growth rates of average labor productivity (ALP). Using sector-level data from the U.S., Oliner and Sichel (2000) found high growth rates in ALP and output stemming from growth in IT capital, especially for 1996–1999. Baily and Lawrence (2001) contended that the 1995–2000 growth in ALP from IT was structural as opposed to cyclical.

Crowston and Treacy (1986), Kauffman and Kriebel (1988) and Mukhopadhyay and Cooper (1992) advocated a process approach, proposing that firm-level impacts of IT could be measured through intermediate level contributions. Barua et al. (1995) found that IT explained improvements in capacity utilization and inventory turnover, but not in firm-level performance measures. Nault and Dexter (1995) found that IT-supported fueling commanded higher prices. Mukhopadhyay et al. (1997) found that IT increased output and quality of mail sorting processes. These studies show that firms may see the internal process gains from IT, but that the same gains may not appear in firm-level measures. This can happen, for example, when competition causes firms to pass benefits from IT either upstream or downstream (Cheng and Nault 2007). Indeed, in research using market valuations to estimate the change in firm value from IT investments the results have been equivocal (e.g., Dos Santos et al. 1993, Bharadwaj et al. 1999, Im et al. 2001, Subramani and Walden 2001). Disaggregating IT budgets into elements of IT infrastructure, Rai et al. (1997) found that IT labor, telecommunications, and hardware were positively correlated to firm output and labor productivity, while software was not.

IT also affects the efficiency of other factor inputs. Krueger (1993) suggests that workers using computers earn 10%–15% higher wages. Bresnahan et al. (2002) conclude that higher levels of IT are associated with increased delegation of powers to teams and individuals, and greater levels of skills and education. Autor et al. (2003) found that computerization reduced labor input in routine manual and cognitive tasks, and increased labor input in nonroutine cognitive tasks.

The resource-based view of the firm argues that value of IT may depend on how IT is managed in conjunction with other factors. Clemons and Row (1991) suggest that IT creates competitive advantage by leveraging preexisting complementary human and business resources, and valuable scarce resources. This advantage may survive if the value of a resource is linked to the presence of complementary or cospecialized resources (Rumelt 1984). Brynjolfsson and Hitt (2003) argue that excess contributions of IT are attributable to investments in complementary inputs such as organizational capital. Tippins and Sohi (2003) found that organizational learning mediates the relationship between IT competency and firm performance.

The role of IT has also been found to differ based on the IT intensity of different sectors. Dewan and Min (1997) found IT-intensive firms had a higher output elasticity of IT capital, although non-IT-intensive firms had higher marginal returns to IT. Powell and Dent-Micallef (1997) found that human and business resources yielded highest returns in IT-intensive firms. Dumagan and Gill (2002) found that IT-intensive industries experienced higher output growth than non-IT-intensive industries, and that productivity growth was dispersed across sectors. Oliner and Sichel (2000) report particularly strong growth in total factor productivity (TFP) in the semiconductor and computer producing industries.[1] Gordon (2000) argued that the productivity growth in the 1990s occurred primarily in the sectors producing IT and telecom equipment. Stiroh (2002) concludes that after 1995 growth in Solow residual was concentrated in the high-tech sectors. These results point to potential structural differences in the use of IT and its effects on different sectors.

In this context we argue that IT capital is both different from, and similar to, other factor inputs because of the way IT enables production and interacts with other factor inputs. For example, IT enables information collection, processing and dissemination for decision making, and can transform production and business processes. IT capital is also similar to other factor inputs in that they can be used interchangeably. For example, IT can be used in place of labor in labor-intensive tasks such as payroll or check processing. We classify these effects of IT on output as *direct* and *indirect*. In the *direct effect* IT alters the factor input mix without changing the efficiency of other factor inputs or the underlying production technology. In the *indirect effect* IT augments the efficiency of

[1] TFP is defined as the output contribution not explained by the factor inputs and often interpreted as technological progress. TFP is also known as the Solow residual and as multifactor productivity (MFP).

other factor inputs and modifies the underlying production technology.

Our first research question is whether the direct and indirect effects of IT can be separated and measured, and whether the indirect effect is significant. Our second research question is whether the effects of IT differ between industries that are IT-intensive compared to those that are not. We answer these questions using a production function formulation that explicitly separates a direct effect and an indirect effect of IT capital through augmentation of non-IT capital and labor.

We begin by describing and classifying the different ways IT produces value, and conceptually separating the direct effects of IT from its indirect effects, recognizing that any IT deployment produces both effects. Subsequently, we develop an augmented form of the simple Cobb-Douglas production function that separates the direct effects of IT from its indirect effects, capturing part of the indirect effects through augmentation of non-IT capital and labor by IT. We analytically compare the way IT affects production in this augmented form versus the simple Cobb-Douglas, and discuss how our form compares to the Translog.

Next, we derive an estimation equation and estimate our augmented Cobb-Douglas using a cross-sectional time series on U.S. manufacturing industries, and compare our estimates to those from the simple Cobb-Douglas and Translog forms. We find that both direct and indirect effects of IT are significant and positive, demonstrating the advantage of the augmented Cobb-Douglas. We also find that indirect effects have become increasingly significant over time. This answers our first question: The direct and indirect effects of IT can be separated and measured, and the indirect effect through augmentation is significant.

We then partition our data on the U.S. manufacturing industries into IT intensive and non-IT-intensive sectors and find that in the IT-intensive sector the indirect effects of IT are significant and predominate. In contrast, we find that in the non-IT-intensive sector the direct effects of IT are significant and predominate. This answers our second question, pointing to structural differences in the source of IT contribution based on IT intensity.

The remainder of the paper proceeds as follows. In §2 we describe the direct and indirect effects of IT. In §3 we derive our augmented Cobb-Douglas and explore its properties. Section 4 describes the data and presents estimates of our augmented Cobb-Douglas, comparing them with the results from other forms. We also describe our partition of industries into IT-intensive and non-IT intensive sectors, and estimate our augmented and simple Cobb-Douglas forms for these two sectors. Section 5 concludes with comments, and a discussion of limitations and directions for future research.

2. The Different Effects of IT

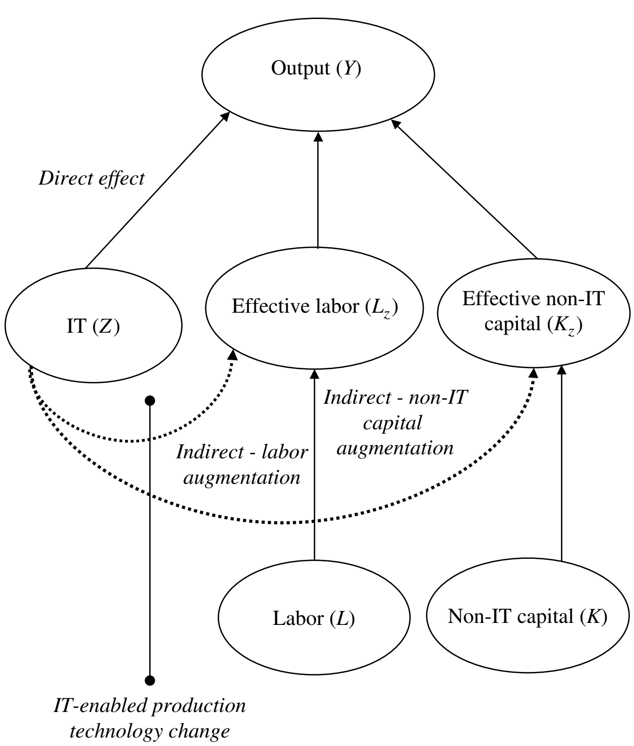
IT invariably and inseparably works with business strategies, processes, and incentive systems. As such, IT is widespread and embedded in many parts of the firm, making it difficult to pinpoint and measure its contribution. For example, IT enabled coordination and uncertainty reduction mitigates the bullwhip effect in a supply chain, but it is difficult to identify the contribution of IT accruing to a particular firm. The problem is partly because of the difficulty in recognizing, quantifying, and accurately measuring the benefits of IT, and partly because of the interactions of IT with other components of a firm.

This suggests that IT is a multifaceted factor input enabling the capture, processing, dissemination, and use of information within and outside the firm, as well as fundamental transformations of business processes. Farrell (2003) indicates that increases in output because of IT originate from increases in labor efficiency and asset utilization, and from adding value to existing goods and creating new goods. Dehning et al. (2003) examine returns to IT in industries classified by the roles IT assumes: automate, informate, and transform. The automate role stems from IT being a more efficient factor input. For example, IT automates data storage, retrieval, and routine transactions, eliminating the need for staff. The informate role is where IT empowers management/employees, or customers. For example, supply chain management software improves coordination by sharing information. The transform role alters ways of doing business and/or business processes and relationships, changing the way a market operates, providing new services or entering into strategic alliances. They find abnormal returns to firms investing in IT with a transform role. Brynjolfsson and Hitt (2000) suggest that the transform role of IT impacts internal and external business processes.

Conceptually, IT has two effects on production. The first is similar to the impact of other factor inputs where IT alters the factor input mix without changing the efficiency of other factor inputs or the underlying production technology. We define this impact as the *direct effect* of IT. The second is where the use of IT alters the efficiency of other factor inputs—effectively augmenting them—and modifies the underlying production technology. We define this second impact as the *indirect effect* and depict these effects in Figure 1. Unless explicitly accounted for, the indirect effect remains embedded in TFP.

There are many examples of how IT augments non-IT capital and labor. Plant and machinery utilization improves through the use of Material Requirement Planning and Enterprise Resource Planning systems as IT seamlessly integrates business processes. Computer-Aided Design/Manufacturing together with computer numerically controlled machines revolutionizes the production process, increasing the utilization of non-IT capital. IT-driven scheduling reduces the time aircrafts spend on the ground and maximizes gate utilization at airports, increasing the availability of both aircraft and gates. The same holds for IT-driven scheduling of vehicle fleets.

Figure 1 Direct and Indirect Effects of IT



One way in which IT augments labor input is through decision support systems (DSS), which enable individuals and groups to organize, collate, share, analyze, recall and communicate data, lowering the cognitive cost (Beach and Mitchell 1978), and broadening what is cognitively feasible (Simon 1955). For example, DSS has been shown to improve performance (Benbasat et al. 1991). Computerized airlines reservation systems enable individuals to efficiently search for routes and connections across various airlines. Patient history tracking systems in hospitals improve the recall and diagnostic ability of doctors, increasing throughput. IT enables changes in job design, providing accurate and timely information to employees, and an auditable trail of employee actions. This allows firms to shift decision rights downward, reducing response time. For example, Black and Lynch (2001) found productivity gains associated with employee voice in decision making, and Brynjolfsson and Hitt (2000) describe IT-enabled flexible jobs as an omitted factor input.

3. Modeling the Indirect Effects of IT

A production function is a mathematical relationship between quantities of inputs and outputs. Traditionally, studies using the production function approach have fit data to the *simple* Cobb-Douglas to estimate the output elasticity of IT capital. A three-factor input simple Cobb-Douglas is specified as

$$Y = AK^{\alpha}L^{\beta}Z^{\gamma}, \qquad (1)$$

where Y is the quantity of physical output, K is the quantity of non-IT capital, L is the quantity of labor, Z is the quantity of IT capital, and A is factor neutral technological change capturing TFP. Here the indirect effects of IT are unaccounted for and embedded in A. In (1) α, β, and γ are the output elasticities of non-IT capital, labor and IT capital, respectively. Studies such as Brynjolfsson and Hitt (1996) use the simple Cobb-Douglas to estimate the output elasticity of IT capital. Estimates of substitution elasticities close to unity by Dewan and Min (1997) helps validate the use of the simple Cobb-Douglas.

To separate the indirect effects we use a multiplicatively separable but otherwise general form in which we define *augmented* quantities of non-IT capital and labor—that is, non-IT capital and labor augmented by IT capital, K_Z and L_Z, as

$$K_Z = K\zeta(Z) \quad \text{and} \quad L_Z = L\tau(Z).$$

The functions $\zeta(Z)$ and $\tau(Z)$ represent the augmentation of non-IT factor inputs from IT. Each augmentation is increasing in IT capital, $\zeta'(Z) > 0$ and $\tau'(Z) > 0$, and there is no augmentation with no IT capital, $\zeta(0) = \tau(0) = 1$. At this point there is no loss of generality in treating the augmentation as multiplicative because the augmentation functions can always be scaled appropriately. Heathfield and Wibe (1987) used an exponential form of augmentation in a production function to incorporate the effect of technological progress over time. Mefford (1986) found significant augmentation effects of technology on capital, but Loveman (1994) did not find any augmentation from IT.

Using our general multiplicative form we modify the simple Cobb-Douglas to specify the augmented Cobb-Douglas as

$$Y_a = SK_Z^{\bar{\alpha}} L_Z^{\bar{\beta}} Z^{\bar{\gamma}}. \tag{2}$$

In (2) we use the subscript a on output to denote the augmented Cobb-Douglas, and the parameters of this form are denoted with a bar to distinguish them from the parameters of the simple Cobb-Douglas. In capturing TFP, S more accurately reflects factor neutral technological progress in our augmented form as compared to A in (1), that is, S reflects the factor-neutral technological progress devoid of the augmentation effects of IT. Thus, parameters $\bar{\alpha}$, $\bar{\beta}$, and $\bar{\gamma}$ are the output elasticity of non-IT capital, labor, and the direct output elasticity of IT, respectively, in the augmented form corresponding to α, β, and γ of the simple Cobb-Douglas.

To estimate indirect effects we further specify the form for the augmentation of non-IT capital and labor by IT as

$$K_Z = K\zeta(Z) = Ke^{\eta Z} \quad \text{and} \quad L_Z = L\tau(Z) = Le^{\mu Z}, \tag{3}$$

where K and L are the quantities of non-IT capital and labor as defined before. Using these specific functional forms for K_Z and L_Z we can then write the augmented Cobb-Douglas as

$$Y_a = S[Ke^{\eta Z}]^{\bar{\alpha}}[Le^{\mu Z}]^{\bar{\beta}} Z^{\bar{\gamma}} = SK^{\bar{\alpha}} L^{\bar{\beta}} Z^{\bar{\gamma}} e^{\kappa Z}, \tag{4}$$

where the augmentation comes through a weighted average of the direct output elasticities of non-IT capital and labor, $\kappa = \bar{\alpha}\eta + \bar{\beta}\mu$. As firms invest in IT capital, Z increases, leading to increases in the effective non-IT capital, K_Z, and labor, L_Z, through the multiplicative exponential term.

Although there are a variety of forms to model augmentation, we chose the exponential form for four reasons. First, this form allows us to estimate the direct and indirect effects thorough separate parameters, namely $\bar{\gamma}$ and κ. It also lends a natural interpretation to $e^{\kappa Z}$ as indirect effects that are partitioned from the TFP of the simple Cobb-Douglas form. If the output elasticities are equal in both forms (i.e., $\alpha = \bar{\alpha}$, $\beta = \bar{\beta}$, $\gamma = \bar{\gamma}$), then $A = Se^{\kappa Z}$, leaving TFP (S) in our augmented form distinct from the augmentation effects. Second, the simple Cobb-Douglas in (1) is nested in our augmented Cobb-Douglas in (4) so that if $\kappa = 0$, then the two are equivalent. This allows us to empirically test whether augmentation is significant, i.e., whether $\kappa = 0$.

The third reason is related to aggregation. A production function is a firm-level concept wherein inputs are combined to produce outputs at the firm level. However, under certain conditions, the form of an aggregated industry level production function can be the same form as the production function of the underlying firms. Thus, aggregation is a significant requirement that constrains the form of an industry-level production function. Nataf (1950) proved that such an aggregation of individual firm-level to industry-level production functions can be valid if the individual firm production functions are *additively separable*. Both the simple Cobb-Douglas in (1) and the augmented Cobb-Douglas in (4) are additively separable in their log forms (derived below in (7) and (8)), and therefore aggregation from firms to industry is feasible using these forms. Walters (1963) states that "We cannot approximate the basic requirements of sensible aggregation except, perhaps, over firms in the same industry or for narrow sections of the economy" (p. 11). Our data aggregate over firms in the same industry, consistent with his requirements for sensible aggregation. Van Garderen et al. (2000) are a little more pessimistic about aggregation with log-linear forms (such as the Cobb-Douglas). However, their estimates of UK industrial production using more coarsely defined industries than ours showed that "...the simple Cobb-Douglas specification, expressed in differences, provides a very reasonable representation of output movements in the industries of the UK over the sample period" (p. 313). In the IT literature the simple Cobb-Douglas has been used with country-level data (Dewan and Kraemer 2000) and with industry-level data (Cheng and Nault 2007).

The last reason is our chosen form's prior use to measure technological progress. Heathfield and Wibe (1987) used the exponential form to capture technological progress over time—using a convex function of time to model technological progress is common because technological progress accumulates and compounds. We use the exponential form with IT capital for similar reasons: Our augmented Cobb-Douglas is designed to explain part of TFP, and augmentation accumulates and compounds with the amount of IT capital. When our estimation yields significant positive augmentation effects, then these effects have increasing returns to scale. Our augmented Cobb-Douglas can display increasing marginal returns in IT capital. The direct effect represented by $Z^{\bar{\gamma}}$ in our augmented Cobb-Douglas is concave as we expect $\bar{\gamma} < 1$. However, the augmentation term representing part of TFP, $e^{\kappa Z}$, is convex in Z. A negative κ leads to decreasing marginal returns to IT capital. When we have a small augmentation effect the augmented Cobb-Douglas also leads to decreasing marginal returns to IT capital i.e., when $\kappa Z < \sqrt{\bar{\gamma}}(1-\sqrt{\bar{\gamma}})$. For our pooled sample the estimate of $\bar{\gamma}$ is 0.08, which implies we require $\kappa Z < 0.20$ for decreasing marginal returns, and we find that κZ at the mean IT capital is approximately 0.03. Note that Romer (1986) allows for increasing marginal returns of inputs such as knowledge, which is akin to our labor augmenting role of IT. Even with increasing marginal returns to IT, if the cost function is sufficiently convex, an interior solution to profit maximization is achievable.[2]

To show the impacts of our choice of the exponential form for augmentation, we examine the complementarities between factor inputs implicit in the simple and augmented Cobb-Douglas. Taking the cross partial derivative of non-IT capital and IT capital, and of labor and IT capital for the simple Cobb-Douglas in (1) we have

$$\frac{\partial^2 Y}{\partial K \partial Z} = A\alpha K^{1-\alpha} L^{\beta} \gamma Z^{1-\gamma} \quad \text{and} \quad \frac{\partial^2 Y}{\partial L \partial Z} = AK^{\alpha} \beta L^{1-\beta} \gamma Z^{1-\gamma}. \tag{5}$$

Taking the same cross partial derivatives of (4) and rearranging gives

$$\frac{\partial^2 Y_a}{\partial K \partial Z} = S\bar{\alpha} K^{1-\bar{\alpha}} L^{\bar{\beta}} [\bar{\gamma} Z^{1-\bar{\gamma}} + \kappa Z^{\bar{\gamma}}] e^{\kappa Z} \quad \text{and} \quad \frac{\partial^2 Y_a}{\partial L \partial Z} = SK^{\bar{\alpha}} \bar{\beta} L^{1-\bar{\beta}} [\bar{\gamma} Z^{1-\bar{\gamma}} + \kappa Z^{\bar{\gamma}}] e^{\kappa Z}. \tag{6}$$

Comparing (5) with (6) augmentation works through the second term in square brackets and through $e^{\kappa Z}$. Thus, the complementarities in the augmented Cobb-Douglas explicitly include the augmentation effects of IT on other factor inputs. If there is no augmentation, then $\eta = \mu = \kappa = 0$, and (5) and (6) are identical.

The simple and augmented Cobb-Douglas also imply different levels of optimal IT investment. If firms are price takers in input and output markets, and production exhibits decreasing marginal returns in each factor input, then the optimal levels for non-IT capital and labor are when the price of these factor inputs equals their respective marginal returns. The first-order conditions for non-IT capital and labor are the same for the simple and augmented Cobb-Douglas. But in the augmented Cobb-Douglas the marginal returns to IT capital includes the rate of change in augmentation of non-IT capital and labor with respect to IT capital. As we expect the augmentation of non-IT capital and labor to increase as IT

[2] Many functional forms have been used in the information systems literature such as CES-Translog (Dewan and Min 1997) and Translog (Hitt and Snir 1999). Depending on parameter values and factor input levels these functional forms may not satisfy production function regularity conditions. For example, the Translog form did not satisfy regularity conditions for 89% of observations in Dewan and Min (1997) and for 75% of observations in Hitt and Snir (1999). We thank the review team for suggesting we investigate this.

capital accumulates, we take these rates of change as positive. This implies that the optimal level of IT capital is higher when indirect effects are accounted for than when they are not, and if a firm chooses IT investment levels using the simple Cobb-Douglas when its production function is actually the augmented Cobb-Douglas, then it will underinvest in IT.

Estimation Forms. We denote the natural log of the variable by lower case letters. We can then write (1) in log form as

$$y = a + \alpha k + \beta l + \gamma z + \epsilon_1, \tag{7}$$

where ϵ_1 is an independent, identically and normally distributed (i.i.d) error term with mean zero and standard deviation σ_{ϵ_1}. With n observations on the log of output, y, the log of non-IT capital, k, the log of labor, l, and the log of IT capital, z, generalized least squares (GLS) estimates of α, β, γ, and a can be obtained. In this specification, α, β, and γ are the output elasticities of non-IT capital, labor and IT capital, respectively. The factor-neutral technological change in the simple Cobb-Douglas is captured by a.

To get the augmented Cobb-Douglas estimation form we substitute for L_Z and K_Z from (3), take the natural logs of (2), and write the resulting equation with an error term as

$$y = s + \bar{\alpha} k + \bar{\beta} l + \bar{\gamma} z + \kappa Z + \epsilon_2, \tag{8}$$

where ϵ_2 is an i.i.d error term with mean zero and standard deviation σ_{ϵ_2}. We expect that $\kappa > 0$, and the κZ term in (8) represents the augmentation of IT capital on non-IT capital and labor. This augmentation is now separate from factor-neutral technological change s, which is different from a in (7). Substituting $\kappa = \bar{\alpha}\eta + \bar{\beta}\mu$ and rearranging we get

$$y = s + \bar{\alpha}(k + \eta Z) + \bar{\beta}(l + \mu Z) + \bar{\gamma} z + \epsilon_2.$$

Thus, in the augmented Cobb-Douglas, IT capital has a direct effect on y through $\bar{\gamma} z$, and additional augmentation effects $\bar{\alpha}\eta Z$ through non-IT capital and $\bar{\beta}\mu Z$ through labor.

We compare our augmented Cobb-Douglas to the Translog,

$$y = c + \beta_k k + \beta_l l + \beta_z z + \beta_{kk} k^2 + \beta_{ll} l^2 + \beta_{zz} z^2 + \beta_{kl} kl + \beta_{kz} kz + \beta_{lz} lz + \epsilon_3, \tag{9}$$

where c is a constant, and the estimates (βs) are subscripted according to the variables. This form, derived from a Taylor series expansion, is sufficiently flexible to fit most data sets. Comparing our augmented Cobb-Douglas in (8) to the Translog above, the latter only measures generic quadratic and interaction terms, and the resulting parameters are not directly interpretable as economic measures. In addition, the Translog cannot be aggregated unless the interaction terms are zero.[3]

4. Estimation of the Indirect Effects of IT

4.1. Data and Methods

Data Sources. We use the MFP data set of two-digit Standard Industry Classification (SIC) industries for the manufacturing sector dated 12 March 2002 (capital and hours worked) and 29 August 2002 (output tables) obtained from the Bureau of Labor Statistics (BLS), U.S. department of Labor, Office of Productivity and Technology. We chose the manufacturing sector because the output measures are better defined (physical units) and more accurately measured as compared to other sectors. The data set is available for the period 1948–2000 for all twenty two-digit SIC industries in the manufacturing sector. The list of SIC codes available in the data set for the manufacturing sector is given in Table 1.

This data set provides annual industry output (excluding intraindustry transactions), and the cost of energy, materials, and services purchased, all in current dollars. In addition, it provides the price deflators indexes (1996 = 100.00) for each of these series (output, energy, materials, and services). This enables calculation of the output and inputs in constant 1996 dollars. Subtracting the real cost of energy, materials, and services from the real output provides the real value added (in constant 1996 dollars). We use this as our measure of output Y. In addition, it provides aggregate productive capital stock in five categories, namely, equipment, structures, rental residential capital, inventories and land (in constant 1996

[3] A further extension of the Translog is the CES-Translog. But as Dewan and Min (1997) found, this extension often causes the interaction terms to be individually insignificant.

Table 1 **Description of SIC codes**

SIC code	Description of the industry	IT intensive
20	Food and kindred products	No
21	Tobacco manufacturing (excluded from study)	No
22	Textile manufacturing	No
23	Apparel and related products	No
24	Lumber and woods	No
25	Furniture and fixtures	No
26	Paper and allied products	No
27	Printing and publishing	No
28	Chemicals and allied	Yes
29	Petroleum and related	Yes
30	Rubber and miscellaneous	No
31	Leather and its products	No
32	Stone, clay, glass, and concrete	No
33	Primary metal	Yes
34	Fabricated metal	No
35	Industrial/commercial machinery and computer equipment	Yes
36	Electrical and electronic equipment	Yes
37	Transportation	No
38	Measuring, analyzing, and controlling equipment	Yes
39	Miscellaneous manufacturing	No

dollars). It also provides the series for the IT capital stock (in constant 1996 dollars), which we use for Z. Included in this series of IT capital are computers (including computer peripheral equipment), software, communications, and others (office and accounting machinery, instruments: scientific and engineering, photocopy, and related equipment). To calculate the non-IT capital stock we total the equipment and structures components of the aggregate productive capital stock and subtract the IT capital stock to give the series for non-IT capital, K. For the labor series, L, we use labor hours available in this data set.

From the annual time series of Y, K, L, and Z we calculate the annual log time series y, k, l, and z. We exclude SIC 21 (Tobacco) from our data set as its deflator for output is abnormally high for 1999 and 2000, leading to negative real value added.[4] The price deflator series does not provide data for 1948, 1950, 1951, and 1952; hence, we use the data only for 1953–2000. As a result our data is a cross-sectional time series with 19 SIC codes and 48 years yielding 912 observations. Our data set does not incorporate changes in labor quality and in the quality of most of the capital categories, although there is some quality adjustment for IT capital embedded in the price deflator. At this time the BLS does not have quality adjusted series or indices available for our variables. Therefore, to the degree that it affects our measurement of output and input variables, the quality changes are omitted variables.

[4] Our conclusions do not change by excluding this SIC code from our data set. Details are available on the *Information Systems Research* website (http://isr.pubs.informs.org/ecompanion.html).

Methodology. To enable comparison with prior studies we estimate the log form of the simple Cobb-Douglas in (7), our augmented Cobb-Douglas using the log form in (8), and the Translog form given in (9), all using the pooled data. Subsequently, we estimate our augmented Cobb-Douglas for two 30-year and one 31-year rolling time windows for the pooled data. Finally, we use a partitioned data set for IT-intensive and non-IT intensive sectors and estimate the simple and augmented Cobb-Douglas in log forms as above.

Econometric Adjustments. Being a cross-sectional time series data set, there is both autocorrelation and heteroskedasticity between industries when data is pooled. Autocorrelation arises from smoothing procedures used in the derivation of economy level time series data, and from a response to economy level shocks. If the smoothing procedures or responses are not uniform across industries, which we expect, each industry would differ in its magnitude of autocorrelation. Heteroskedasticity arises because industries differ in size, production technology, and in their response to macroeconomic shocks. In the latter case the heteroskedastic errors may also be correlated across industries.

The Wooldridge test for autocorrelation shows that first-order autocorrelation (AR1) cannot be ruled out for each of our data sets (overall, IT-intensive, and non-IT-intensive) using both the simple and augmented Cobb-Douglas specifications. The presence of AR1 invalidates use of iterated GLS to get the maximum likelihood estimates and therefore prevents the use of the standard tests of heteroskedasticity such as the likelihood ratio test (Greene 2000). As we a priori expect heteroskedasticity, we correct for both correlated heteroskedasticity and industry specific autocorrelation. To estimate the parameters of our regressions we use the GLS procedures implemented as XTGLS in STATA with adjustments to

Table 2 Elasticity Estimates from Past Studies

Description	Data granularity	Production function form	Labor elasticity	Capital elasticity	IT labor elasticity	IT elasticity
Lichtenberg (1995) Computerworld data set	Firm level	Cobb-Douglas	0.507	0.333		0.10
Lichtenberg (1995) Info-week data set	Firm level	Cobb-Douglas	0.489	0.390		0.122
Brynjolfsson and Hitt (1995)	Firm level	Cobb-Douglas	0.472	0.242		0.0522
Brynjolfsson and Hitt (1996a)	Firm level	Cobb-Douglas	0.883	0.0608	0.0178	0.0169
Dewan and Min (1997)	Firm level	CES-Translog	0.601	0.281		0.104
Dewan and Kraemer (2000) overall sample	Country level	Cobb-Douglas	0.723	0.492		−0.013
Dewan and Kraemer (2000) developed countries	Country level	Cobb-Douglas	0.955	0.176		0.051

account for industry specific AR1 and correlated heteroskedasticity. Compared to fixed effects, the industry differences are controlled for in a general manner by our two econometric adjustments: Industry specific AR1 allows for a separate autocorrelation function for each industry; heteroskedasticity adjustments allow for heteroskedastic errors correlated between industries.

Robustness. We recognize that firms can adjust their levels of factor inputs and therefore labor, non-IT capital, and IT capital could be endogenous variables. Moreover, our data set does not include adjustments for labor quality over time. Although our rolling time window regressions and our adjustments for panel-specific autocorrelation and heteroskedasticity may indirectly adjust for quality, in general the quality of non-IT capital and labor quality are omitted variables. Finally, as our factor inputs are measured at the industry level, there is the potential for measurement errors in these variables. If there is endogeneity, omitted variables or measurement errors in our input variables, then there is the possibility of correlations between these variables and the error term, or serial correlation in the errors, both of which would result in biased estimates. To deal with these issues we could test for endogeneity and serial correlation, or instrument the variables in question. As we do not have suitable alternative industry level variables for instruments, we use endogeneity tests instead with lagged variables.

There are no endogeneity tests available in XTGLS with our econometric adjustments. However, following Baum et al. (2003), we tested for endogeneity in our augmented Cobb-Douglas using generalized methods of moments (GMM) with specifications for autocorrelation and heteroskedasticity. Using lagged versions of our right-hand side variables, both the Hansen J Statistic (a Lagrange multiplier test for excluded instruments) and the C statistic (testing for the exogeneity/orthogonality of excluded instruments) show that labor, IT capital, and non-IT capital variables are exogenous both individually and jointly for our pooled data set. In addition, industry specific AR1 estimation accounts for serial correlation in the residuals, recognizing that cyclical movements in omitted variables could be manifested in serially correlated residuals. This provides confidence that our results are not driven by endogeneity, omitted variables, or measurement errors.[5]

4.2. Results from the Pooled Manufacturing Sector

Estimates from Prior Studies. To compare our results, in Table 2 we report the estmates of prior studies using the simple Cobb-Douglas. In two studies using firm-level data, Brynjolfsson and Hitt (1995, 1996) estimated the output elasticity of IT capital at 0.052 and 0.0169. Using some of the same data, Dewan and Min (1997) estimated the output elasticity of IT capital at 0.104. Lichtenberg (1995) used two different data sources and calculated output elasticities of IT capital of 0.10 and 0.12. Using country-level data, Dewan and Kraemer (2000) estimate the output elasticity of IT at −0.013 for the overall sample and 0.051 for developed countries.

[5] We also ran our augmented Cobb-Douglas using different sets of econometric adjustments: fixed effects for year and industry to control for autocorrelation and industry heterogeneity; first differences to control for autocorrelation; time to capture non-IT technological progress; and fixed effects and adjustments for AR1 to control for industry heterogeneity and autocorrelation. In each case there were problems with insignificant, incorrectly signed, or unrealistic magnitudes in the output elasticity estimates, suggesting incomplete econometric adjustments.

Table 3(a) Cross-Sectional Regression for Pooled Data

No.	Specification	Labor elasticity	Non-IT capital elasticity	Direct IT output elasticity	Indirect IT output elasticity (κ)	Total IT output elasticity (at Z_{mean})	Number of parameters
1.	Simple Cobb-Douglas	0.70*	0.25*	0.12*			213
2.	Augmented Cobb-Douglas	0.69*	0.27*	0.08*	7.36e-12*	0.11*	214

Notes. $Z_{\text{mean}} = \$4.11$ billion, Sample size = 912. For the Augmented Cobb-Douglas form, the total output elasticity is equal to direct IT output elasticity plus ($\kappa^* Z_{\text{mean}}$), as κ is significant.
*Significant at p value = 1%.

Table 3(b) Cross-Sectional Regression for Pooled Data

No.	Specification	β_k	β_l	β_z	β_{kk}	β_{ll}	β_{zz}	β_{kl}	β_{kz}	β_{lz}	Number of parameters
1.	Translog	−1.28	−5.12*	−0.31	0.06*	0.18*	0.009	−0.07	−0.0004	0.004	219

Note. Sample size = 912.
*Significant at p value = 1%.

Estimates from the Simple Cobb-Douglas. We estimate the simple Cobb-Douglas using our data set, and the results are presented in row 1 of Table 3(a). The estimate of the output elasticity of IT capital is 0.12.[6] What is striking is that our results are similar to the earlier studies in Table 2 even though the earlier studies differ in the data sources, the forms specified for estimation, and the econometric adjustments.

Estimates from the Augmented Cobb-Douglas. Our estimates from the augmented Cobb-Douglas are presented in row 2 of Table 3(a). The output elasticities of non-IT capital and labor are similar to those from the simple Cobb-Douglas. The direct output elasticity of IT capital is positive and roughly two-thirds of the magnitude of the output elasticities of IT capital obtained from the simple Cobb-Douglas. The indirect output elasticity of IT capital is positive and significant. This confirms the presence of direct effects of IT, and indirect effects of IT through augmentation of non-IT capital and labor—effects that are indistinguishable in the simple Cobb-Douglas.

The indirect component of the output elasticity of IT capital is κ in (8). This coefficient is 7.36e−12 and is significant. It means that for an additional one billion dollars of IT capital, the indirect output elasticity of IT increases by 0.0074. To estimate the total output elasticity of IT capital we add the estimated direct output elasticity of IT capital to the product of the indirect output elasticity of IT capital and the mean level of IT capital (i.e., $\bar{\gamma} + \kappa Z$ in (8)). For our sample the overall mean level of IT capital is \$4.11e+9. The indirect component of the output elasticity of IT capital and the estimates of the total output elasticity of IT capital are 0.03 and 0.11, respectively. This answers our first question: Indirect effects through IT augmentation can be separated from direct effects; they are positive, can be measured, and are significant. That the augmented Cobb-Douglas explains the effects of IT in greater detail than the simple Cobb-Douglas is clear from the fact that, although simple Cobb-Douglas in (7) is nested in the augmented Cobb-Douglas in (8), κ is significant.

Estimates from the Translog. Our estimates from the Translog specification in (9) are presented in Table 3(b). Both the linear and quadratic coefficients for labor, and the quadratic term for non-IT capital are significant. None of the IT capital coefficients nor the non-IT capital coefficients except for the quadratic term are significant. This is in stark contrast to the indirect effects in Table 3(a), which are significant using the identical data set. Thus, it is clear that the direct and indirect effects that can be separated in our augmented Cobb-Douglas are different from generic interactions between factor inputs as estimated in the Translog, demonstrating the advantage of our augmented Cobb-Douglas in interpretability, parsimony, and the ability to capture the indirect effects.

[6] All the coefficients reported as significant are significant at $p = 0.01$ unless noted otherwise.

Table 4 Rolling Window Cross-Sectional Regression for Pooled Data

No.	Period/ specification	Labor elasticity	Non-IT capital elasticity	Direct IT output elasticity	Indirect IT output elasticity (κ)	Total IT output elasticity (at Z_{mean})	Sample size	Number of parameters
				Simple Cobb-Douglas specification				
1.	1953–1982	0.68*	0.36*	0.02*			570	213
2.	1963–1992	0.57*	0.30*	0.10*			570	213
3.	1973–2000	0.59*	0.33*	0.12*			589	213
				Augmented Cobb-Douglas specification				
4.	1953–1982	0.70*	0.35*	0.03*	−1.67e-12	0.03*	570	214
5.	1963–1992	0.59*	0.28*	0.09*	3.43e-12	0.09*	570	214
6.	1973–2000	0.61*	0.32*	0.08*	8.92e-12*	0.14*	589	214

Notes. Z_{mean} for 1973–2000 = \$6.59 billion. For the Augmented Cobb-Douglas form, the total output elasticity equals direct IT output elasticity if κ is insignificant and equals the direct IT output elasticity plus ($\kappa^* Z_{mean}$) if κ is significant.
*Significant at p value = 1%.

Estimates for Rolling Time Windows. Our data set provides the series over 48 years—from 1953 to 2000—for 19 different industry sectors. IT has changed over this period from a regime of mainframe/legacy to relational to client-server to Internet, etc. These regimes are overlapping as IT has diffused over time. To account for differences in these regimes, we consider how the output elasticities change by partitioning our data set into three overlapping time windows of around 30 years each: 1953 1982, 1963 1992, and 1970 to 2000. We chose the 30-year time window to provide sufficient degrees of freedom for estimation of the large number of parameters under a panel specific autocorrelation and correlated heteroskedastic error structure.

The results for both the simple Cobb-Douglas and augmented Cobb-Douglas are presented in Table 4. In each time window all the output elasticity estimates from the simple Cobb-Douglas are significant. The results for the augmented Cobb-Douglas show a progression in the significance of augmentation over time. For the earlier period only direct effects of IT are significant. During the second time window the direct effects are significant and the augmentation effects become significant at $p = 0.07$. During the last time window both the direct and augmentation effects are significant. These results suggest that indirect effects through augmentation from IT become more important in more recent time periods, which in turn causes the total output elasticity of IT to increase in more recent time periods. Given the overlap in our rolling time windows (about 20 of 30 years), that our results for IT capital from each window are considerably different indicates the windows are capturing fundamental changes in IT and in TFP.[7]

4.3. IT-Intensive vs. Non-IT-Intensive

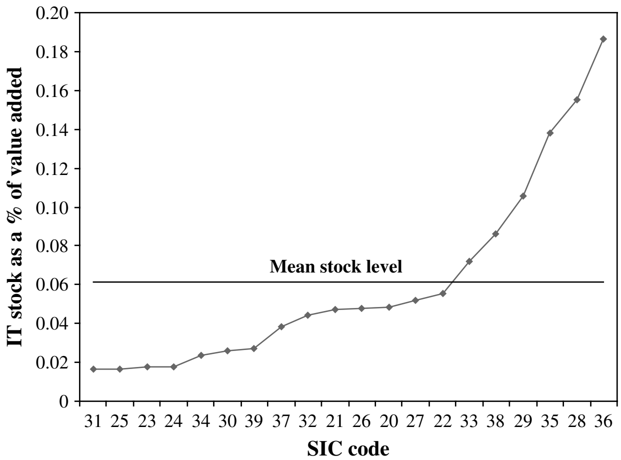
Our data set covers the manufacturing sector of the U.S. economy comprising 19 industries. The estimates obtained by pooling data across industries implicitly assumes that the parameters do not vary over different SIC codes. The parameters may not be the same across sectors as we expect differences in the way IT has been used in different parts of the manufacturing sector. These differences could arise from differences in the age of IT investments, the way IT deployment affects production, different levels of IT investments, or rates of return on the factor inputs—all reflecting structural differences.

To gain insight into the impact of IT in different parts of the economy, we run regressions separately for different sectoral groupings based on IT intensity: an IT-intensive sector and a non-IT-intensive sector. We look for differences in the way IT has affected production. Structural differences would be reflected in the varying significance of the direct and indirect effects of IT between the two sectors.

IT Intensity. Dewan and Min (1997) divided firms in their sample into two groups of roughly equal size based on the factor share of IT capital among the production inputs. Dumagan and Gill (2002) classified industries as IT intensive by ranking them on the ratio of IT capital to number of full time hours of employment relative to the ratio for pooled industries. Rank

[7] We thank the AE and a reviewer for suggesting this analysis.

Figure 2 IT Intensity by SIC Code



ordering the industries by this ratio, an industry was considered IT intensive if it contributed to the top half of the cumulative sum of average shares of nominal GDP. Effectively, Dewan and Min (1997) used the median factor share of IT capital and Dumagan and Gill (2002) used the median of the cumulative sum of average shares of nominal GDP, to separate the IT-intensive from the non-IT-intensive industries.

We use an alternative approach based on levels of IT that might underlie structural differences in IT use. Using the ratio of IT capital stock to value added as a measure of IT intensity for each industry, we rank the industries, and plot this ratio in Figure 2, looking for a natural break in the IT intensity ratio. Our plot shows that the industries represented by SIC codes 28 (Chemical and allied), 29 (Petroleum and related), 33 (Primary metal), 35 (Industrial/commercial machinery and computer equipment), 36 (Electrical and electronic equipment), and 38 (Measuring, analyzing, and controlling equipment) are more IT intensive. The overall mean of IT capital divides the IT-intensive industries from the non-IT-intensive industries at the same point. These six IT-intensive sectors contribute 37% of the value added of the manufacturing sector in the overall sample mean. We create two mutually exclusive data sets—one for the IT-intensive sector and one for the non-IT-intensive sector based on this partition. Table 1 shows industries that are IT-intensive versus those that are not.

Simple Cobb-Douglas and IT Intensity. To compare the IT-intensive and non-IT-intensive sectors we estimate the simple Cobb-Douglas in (7). The results for the IT-intensive sector are in row 1 of Table 5 and those for non-IT-intensive sector are in row 1 of Table 6. The direct output elasticity of IT capital for the IT-intensive sector is 0.004 but insignificant ($p = 0.89$). However, the direct output elasticity of IT capital for the non-IT-intensive sector is 0.15 and significant. This is surprising as we would have expected IT-intensive industries to have greater output elasticities of IT capital than non-IT-intensive industries. This indicates structural differences between the two sectors—differences that are embedded in TFP.

Augmented Cobb-Douglas and IT Intensity. We ran separate regressions for IT-intensive and non-IT-intensive sectors to see the significance of direct and indirect effects using our augmented Cobb-Douglas in (8). The results for the IT-intensive sector are reported in row 2 of Table 5 and those for non-IT-intensive sector are reported in row 2 of Table 6.

The two sectors differ substantially in both the sign and statistical significance of the direct and indirect effects. The IT-intensive sector has a positive and statistically significant indirect output elasticity of IT capital (augmentation), but an insignificant ($p = 0.023$) and negative direct output elasticity of IT capital. Compared to the simple Cobb-Douglas where the output elasticity of IT capital is positive but insignificant, the augmented Cobb-Douglas separates

Table 5 Cross-Sectional Regression Results for IT-Intensive Sector

No.	Specification	Labor elasticity	Non-IT capital elasticity	Direct IT output elasticity	Indirect IT output elasticity (κ)	Total IT output elasticity at Z_{mean}	Number of parameters estimated
1.	Simple Cobb-Douglas	0.61*	0.48*	0.004			31
2.	Augmented Cobb-Douglas	0.47*	0.73*	−0.08	1.53e-11*	0.13*	32

Notes. Z_{mean} IT intensive = \$8.66 billion, Sample size for IT intensive = 288. For the Augmented Cobb-Douglas form, the total output elasticity reported is equal to ($\kappa^* Z_{mean}$) as the direct IT output elasticity is insignificant.

*Significant at $p = 1\%$.

Table 6 **Cross-Sectional Regression Results for Non-IT-Intensive Sector**

No.	Conditions of regression	Labor elasticity	Non-IT Capital elasticity	Direct IT output elasticity	Indirect IT output elasticity (κ)	Total IT output elasticity at Z_{mean}	Number of parameters estimated
1.	Simple Cobb-Douglas	0.74*	0.19*	0.15*			108
2.	Augmented Cobb-Douglas	0.74*	0.18*	0.15*	2.72e-12	0.15*	109

Notes. Z_{mean} non-IT intensive = \$2.02 billion, Sample size for non IT intensive = 624. For the Augmented Cobb-Douglas form, the total output elasticity reported is equal to the direct IT output elasticity since κ is insignificant.
*Significant at $p = 1\%$.

the direct and indirect effects in the IT-intensive sector. Here the impact of IT capital is through augmentation, which is positive and significant. In contrast, the non-IT-intensive sector has an insignificant ($p = 0.25$) indirect output elasticity of IT capital, and a positive and statistically significant direct output elasticity. This suggests that the two sectors are structurally different in terms of the role of IT capital. In the IT-intensive sector the role of IT is to augment non-IT capital and labor. In the non-IT-intensive sector IT impacts production by simply changing the mix of factor inputs.

We also calculate the total output elasticity of IT capital using mean values of IT capital, but use separate means for the IT-intensive and non-IT-intensive sectors. The mean IT capital for the IT-intensive sector is more than four times larger than that of the non-IT-intensive sector: \$8.66 B for IT-intensive versus \$2.02 B for non-IT-intensive. The estimates of the total output elasticity of IT capital using the augmented Cobb-Douglas are close to those obtained using the simple Cobb-Douglas for non-IT-intensive industries, and for IT-intensive industries are consistent with our pooled estimates. This adds confidence in the reliability and accuracy of our model and results.[8]

5. Conclusion

Our research focused on two specific questions. The first is whether the augmentation portion of the indirect effect of IT through non-IT capital and labor can be separated and measured, and whether this effect is significant. This is important because strategic decisions about investments in IT depend on how organizations make the case for these investments. The presence of indirect as well as direct effects of IT means that organizations should consider IT capital not only as a usual factor input, but also as an input that can yield improvements with non-IT capital and labor. An answer to this question is also important for research as it separates the different paths of IT value addition.

Our augmented Cobb-Douglas shows that both direct and indirect effects of IT are important: Estimates of both the direct and indirect output elasticities of IT capital were statistically significant and positive. This provides empirical evidence that IT not only adds value directly through changes in the mix of factor inputs, but also adds value through IT-driven augmentation of non-IT capital and labor. In addition, the increasing significance of the indirect effects over time in our rolling time window estimates suggests that IT is increasingly augmenting non-IT capital and labor.

The second question is whether the types of contributions from IT capital, direct versus indirect, differ between IT-intensive and non-IT-intensive sectors. An answer to this question is important for strategic decision making about investments in IT because the type of value addition from IT could depend on whether an organization is in an IT-intensive industry. An answer to this question is of deeper interest to researchers because differences in the type of value addition from IT based on IT intensity point to structural differences in the relationship between factor inputs. We found that estimates from our augmented Cobb-Douglas on the two sectors were strikingly different: In the IT-intensive sector the indirect effects predominate with positive and statistically significant indirect output elasticities of IT capital, and negative and mostly insignificant direct output elasticities of IT capital, whereas in the non-IT-intensive sector the direct output elasticities of IT capital are positive and statistically significant, and the indirect output elasticities of IT are insignificant. These results

[8] We found similar patterns of significant indirect effects and insignificant direct effects for IT-intensive sectors in later time subsets of the data. Details are available from the authors.

indicate structural differences in the role of IT in production: In the IT-intensive sector the role of IT is to augment other factor inputs; in the non-IT-intensive sector the role of IT is similar to the effect of any other factor input.

Thus, there are two critical managerial implications from our research. The first is that IT impacts production both directly and indirectly, and in making IT capital investments managers should account for the indirect effects. As the indirect effects work in part through non-IT capital and labor, investments in these other factor inputs should be considered simultaneously with investments in IT capital. The second is that the value of IT capital arises differently in IT-intensive versus non-IT-intensive industries. Surprisingly, the indirect effects are relatively more important in IT-intensive industries, suggesting that in these industries competitive forces require that IT investments deliver value through augmentation and technological change, and that as the relative stock of IT capital grows in a firm, the contribution of IT shifts from direct effects to indirect effects.

Like all research in IT and productivity, there are limitations because of the available data. Although our study used two-digit SIC industry data, we recognize that technology and factor input choices are made at the firm-level. Thus, firm-level data would considerably enhance our ability to investigate the key distinction between direct and indirect effects. In addition, our data set only covers the manufacturing sector, and the service sector is thought to be a sector where IT has had considerable impact. We speculate that an analysis of the service sector would yield even stronger indirect effects. Furthermore, there are data limitations relating to the limited granularity of our factor input measures. For example, we conjecture that labor quality has increased over time, and that there may be a selection bias in the industries that employ more highly educated labor. A finer breakdown of capital and labor would allow for richer estimation methods that can incorporate quality changes. Finally, our analysis does not explicitly account for learning whereby the effectiveness of IT investments often increase over time. Examining our indirect effects using a distributed lag structure to incorporate learning may be a fruitful avenue for future research.

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