On the Relationship of Information Technology with Other Inputs

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Abstract

The ability to take advantage of the economic opportunities that are created by the price adjusted performance improvement in IT depends in part on the ability of IT capital to substitute for other inputs in production. To examine substitution of IT capital for other inputs we adopt a less-well-known measure for the elasticity of substitution, the Morishima Elasticity of Substitution (MES), and calibrate our estimates from regression methods by using Bayesian techniques to impose regularity. Using two industry-level datasets for manufacturing, one 1953-00 at the two-digit SIC level and one 1987-99 at the three-digit SIC level, MES results show that IT capital and non-IT capital are Morishima complements when the price of IT capital changes. IT capital and labor are Morishima complements when the price of labor changes, and over the longer period are also Morishima complements when the price of IT capital changes. These result is at odds with our results for the Allen Elasticity of Substitution (AES), and that of most other studies using the AES that indicate IT capital is a substitute for both non-IT capital and labor. Dividing industries into groups based on IT capital intensity, we find that over the longer period the MES and AES for non-IT intensive industries match the pooled results. Our Bayesian analysis showed the pooled results were remarkably stable. However, we find that our production function estimates for IT intensive industries violate regularity conditions at almost all observations in both datasets, suggesting that production in IT intensive industries may be structurally different. In addition, we find that after the Bayesian analysis the AES results converge to unity from below, suggesting the AES may artificially support production function forms like the Cobb-Douglas.

1 Introduction

Currently, there is consensus that the economic value of the Information Technology (IT) is detectable at the economy (Baily and Lawrence, 2001), industry (Mittal and Nault, 2008; Stiroh, 2002; Dumagan and Gill, 2002; Oliner and Sichel, 2000), supply chain (Cheng and Nault, 2007), firm (Brynjolfsson and Hitt, 1996), and application levels (Mukhopadhyay, Rajiv, and Srinivasan, 1997; Barua, Kriebel, and Mukhopadhyay, 1995).

There is also evidence that industries differ. Dewan and Min (1997) found IT-intensive firms have higher output elasticities, but lower marginal products. Mittal and Nault (2008) found that IT-intensive industries have significant indirect effects of IT and non-IT-intensive industries have significant direct effects of IT. Stiroh (2002) found that industries which use and produce IT account for all the productivity revival attributable to IT, and non-IT industries contributed negatively to the U.S. productivity revival. Dumgan and Gill (2000) also confirmed that the IT sector was the major contributor to recent productivity growth. Using a growth accounting framework, Oliner and Sichel (2000) found strong growth in the Solow residual in the semiconductor and computer producing companies.

Nordhaus (2002) indicates the power of computers has increased at nearly 50% per year since 1940, and Berndt and Rappaport (2001) report that the average annual rate of decline in quality-adjusted PC prices is 25-30%. These continuous improvements in the price/performance ratio of IT and the empirical evidence of a significant IT impact on productivity have motivated increased investment in IT. However, little is known about the impact of the increasing IT investment on the optimal levels of other factors of production. Specifically, whether IT capital is a complement or a substitute to non-IT capital and labor remains an open question (Chwelos, Ramirez, Kraemer, and Melville 2008).

Unlike other factors of production, IT implementations have multiple effects on the production process. Brynjolfsson and Hitt (2000) argue than IT is a general-purpose technology rather than a conventional capital investment because it creates beneficial economical advantages by facilitating complementary technological or organizational innovations that eventually cause dramatic productivity improvements. Hitt and Snir (1999) argue that IT enables some organizational practices such as faster production cycles, flexible machinery, and reduced inventories. Mittal and Nault (2008) find empirical evidence that IT has a direct effect as an effective factor of production, and an indirect effect enhancing the efficiency of non-IT capital and labor. In addition, Farrell (2003) argues that IT increases output because it ehances the efficiency of labor and asset utilization.

Prior IT Capital Substitution Studies Prior studies have examined elasticities of substitution (ESs) between IT capital and other factor inputs. Dewan and Min (1997) used firm-level data for 1988-1992 to estimate Translog and CES-Translog production functions, and then used estimates from these production functions to calculate AESs. They found that IT capital is a substitute for non-IT capital and for labor. They also found that there is no significant difference between the AES for the IT-intensive and the non-IT intensive subsamples. These AES results based on IT intensity prompted the authors to argue that IT-intensive firms have already implemented IT in their business processes, leaving little room for further automation.

Hitt and Snir (1999) employed a cross sectional survey dataset of organizational practices conducted in 1995 and 1996, and matched it with firm-level data on IT spending and output and inputs for 1987-1994. Estimating a Translog production function and using the AES, they also found that IT is an substitute for non-IT capital and for labor. Dividing firms in their sample into modern and traditional organizations, they found that for modern organizations (i.e., firms that employ modern organizational practices such as new capital, decentralized work practices, skilled human capital, and low levels of inventories), IT capital was a substitute for labor and a complement to non-IT capital. On the other hand, for traditional organizations, IT capital was a substitute for non-IT capital and for labor.

In a recent study, Chwelos et al (2008) use firm-level data for 1987-1998 to estimate the Translog, CES-Translog, and SYS-GMM Translog forms. The parameters estimates of the three models were then used to measure the AES. Consistent across the three different functional forms, the authors found that IT capital is a substitute for labor. On the other hand, IT capital and non-IT capital have become complements. The authors also found that the MRTS between IT capital and both non-IT capital and labor are increasing over time, which means that over time more units of IT capital are needed to substitute for a unit of

Labor.

Elasticities of Substitution Hicks (1932) introduced the Hicks Elasticity of Substitution (HES) to examine the substitutability between factor inputs. His purpose was to provide a measure of the curvature of the isoquant or ease of substitution, and information (comparative statics) regarding relative factor shares. Allen (1938) introduced the Allen Elasticity of Substitution (AES) as a measure of factor substitution. For two factor inputs the information properties of the HES are satisfied by the AES. However, for more than two inputs the AES is not a measure of curvature, and provides no information regarding relative factor shares (Blackorby and Russell 1981, 1989).

Fortunately, Blackorby and Russell (1981) discovered a Japanese study by Morishima (1967) that introduces the Morishima Elasticity of Substitution (MES).[1] For an arbitrary number of factor inputs the MES is a measure of the curvature of the isoquant, and provides comparative statics of relative factor shares.

In the only study of IT using the MES, Chun and Mun (2006) used US data from 41 industries for 1984-1999 to measure AESs and MESs. Employing Gross Product Originating (GPO) from the BEA as output, and five inputs - labor, non-IT equipment, structures, IT equipment and software, and intermediate inputs - they estimated the symmetric generalized McFadden cost function, and used these estimates to measure ESs. Their estimates of the AES indicate that IT capital is a substitute for labor, non-IT equipment, and structures whereas IT is a complement to intermediate inputs. On the other hand, their MESs show that IT capital and intermediate inputs are substitutes when the price of IT capital changes, but complements when the price of intermediate inputs changes. They also found that IT substitutability is higher in the manufacturing sector than in the service sector, and that IT substitutability is higher in the less-IT-intensive sector than in the IT-intensive sector. This study differs from ours and prior studies in IT because it uses a cost function rather than a production function, and includes intermediate inputs thereby measuring GPO rather than value added.

[1] To date, Morishima (1967) is not translated into English.

Our Approach Estimating either the AES or the MES requires estimating parameters in a flexible functional form (FFF) representing production or cost functions. The estimated parameters are then used to calculate the elasticities of substitution. However, for the estimated parameters to be reliable and valid, economic theory mandates that an estimated FFF must satisfy so-called regularity conditions. For production functions these include non-negativity, monotonicity, and concavity.

We employ a FFF to estimate a production function with three inputs - non-IT capital, IT capital, and labor - and use the estimated parameters to calculate the AES and MES. We then examine if there are violations of regularity conditions, and when there are we impose regularity conditions using Bayesian methods to re-estimate the FFF and use these newly estimated parameters to recalculate the AES and MES. We find that regularity conditions have some significant impacts on the generated parameters of our Translog model, and consequently on the estimation of ESs.

Using two industry-level datasets for manufacturing, one 1953-2000 at the two-digit SIC level and one 1987-99 at the three-digit SIC level, we estimate both the MES and the AES using regression and Bayesian analyses. We also estimate the ESs for partitions of each dataset into IT intensive and non-IT intensive industries. MES results show that IT capital and non-IT capital are Morishima complements when the price of IT capital changes. IT capital and labor are Morishima complements when the price of labor changes, and over the longer period are also Morishima complements when the price of IT capital changes. These result is at odds with our results for the Allen Elasticity of Substitution (AES), and that of most other studies (Dewan and Min, 1997; Hitt and Snir, 1999, Chwelos et al, 2008) using the AES which indicate IT capital is a substitute for both non-IT capital and labor. Examining industry groups based on IT capital intensity, we find that over the longer period the MES and AES for non-IT intensive industries qualitatively match the pooled results.

Our Bayesian analysis showed that the pooled MES results were remarkably stable, although the Bayesian results provide some calibration. However, we find that our FFF estimates for IT intensive industries violate regularity conditions at almost all observations in both datasets, suggesting that production in IT intensive industries may be structurally different. In addition, we find that after the Bayesian analysis the AES results for our pooled datasets converge to unity from below. This suggests that findings that show the AES is close to unity (e.g., Dewan and Min, 1997) which support production function forms like the Cobb-Douglas may be the result of artificially imposed regularity conditions in the estimated production function.

The paper is organized as follows. To begin, we review production and measures of ES. We then describe our empirical methodology, providing details of our datasets and estimation methods. In the next section we report the results of our regression-based and Bayesian-based analyses. Subsequently we explain and discuss our results. We finish by summarizing the conclusions from our analyses.

2 Methodology

2.1 Production and Elasticities of Substitution

We define a production function as $Y = f(x)$ where Y is output in units and x is a vector of factor inputs containing non-IT capital K, labor L, and IT capital Z.[2] Generically our inputs are over $i \in \{K, L, Z\}$. We take $f(x)$ to have the usual properties: single valued, non-negative and real for all finite x, monotonic, concave, continuous and twice continuously differentiable. Following Chambers (1988) we can define $V(Y) = x : f(x) \geq Y$, which is closed and non-empty, and the lower boundary of $V(Y)$ is defined by the level set $\tilde{V}(Y) = \{x : f(x) = Y\}$. Consequently, through the implicit function rule we can solve for a given x_i in terms of the remaining x and Y.

For constant output we can obtain the marginal rate of technical substitution (MRTS),

$$\partial x_i/\partial x_j = -\frac{\partial f(x)/\partial x_j}{\partial f(x)/\partial x_i} = -f_j/f_i,$$

where subscripts of f indicate partial derivatives so that f_i is the partial derivative of $f(x)$ with respect to x_i. In a classic work, Hicks (1932) developed an elasticity of substitution between inputs as a percentage change in the input ratio in response to a percentage change

[2]We use capital letters for quantities of Y, K, L, and Z as we use lower case to denote natual logs of these quantities later on.

in the MRTS:

$$\sigma = \frac{d(x_i/x_j)/[x_i/x_j]}{d(f_j/f_i)/[f_j/f_i]}.$$

The HES was originally defined to provide two pieces of information. The first is a measure of the curvature of the isoquant, or ease of substitution. The higher the elasticity, the "easier" is the substitution of one factor for the other - in other words, the lesser the degree of curvature of the isoquant. The second is comparative statics regarding relative factor shares (Blackorby and Russell, 1989).

The HES was generalized for the n-factor case by Uzawa (1962) to the AES. In the context of production functions, the AES is given by

$$\sigma_{ij}^A = \frac{\sum_i x_i f_i}{x_i x_j} \frac{\mathbf{H}_{ji}}{\mathbf{H}} \tag{1}$$

where $\mathbf{H}$ is the bordered Hessian determinant of $f(x)$ and $\mathbf{H}_{ji}$ is the cofactor associated with f_{ij}. In the AES factors i and j are substitutes if $\sigma_{ij}^A > 0$, which means that increasing the price of the j^{th} input increases the optimal quantity demanded of input i. If $\sigma_{ij}^A < 0$, then inputs i and j are complements whereby decreasing the price of input j increases the optimal quantity demanded of input i. From the monotonicity of the production function, own price elasticity is negative, $\sigma_{ii}^A < 0$.

The AES embeds some important restrictions. First, the AES is symmetric so that $\sigma_{ij}^A = \sigma_{ji}^A$. Consequently, the AES does not depend on which price is changing. Second, from the properties of $f(x)$, for a given input x_r at least one σ_{rj}^A must be positive so that a given input must be a substitute for at least one other input. In the context of our production function this latter resriction means that σ_{ZK}^A and σ_{ZL}^A cannot both be negative (Chambers, 1988) so that IT capital must be a substitute for either non-IT capital or labor, or both.

Blackorby and Russell (1989) argue that the AES is not informative beyond the cross-price elasticity of demand. The AES in (1) can be expressed as

$$\sigma_{ij}^A = \epsilon_{ij}/s_j,$$

where $\epsilon_{ij} = \partial \ln x_i / \partial \ln p_j$ is the (constant output) cross-price elasticity of demand and s_j is input j's cost share of the producer's total expenditure, $s_j = x_j p_j / \sum_i x_i p_i$. As such, the AES is not a measure of the curvature of the isoquant. They also argue that the AES does not provide information regarding relative factor shares, concluding that "*absolute income shares is a property of cross-price elasticities and shares; the AES provides no new information about these shares.*"(Blackorby and Russell, 1989: page 884).

In contrast to the AES, the MES can be defined as

$$\sigma_{ij}^{M} = \frac{f_j}{x_i}\frac{\mathbf{H}_{ij}}{\mathbf{H}} - \frac{f_j}{x_j}\frac{\mathbf{H}_{ij}}{\mathbf{H}}. \tag{2}$$

We can rearrange to express the MES in terms of the AES as follows:

$$\sigma_{ij}^{M} = \frac{f_j x_j}{f_i x_i}[\sigma_{ij}^{A} - \sigma_{jj}^{A}].$$

The interpretation of substitutes and complements in the MES relates to the *relative* quantities of inputs, x_i/x_j. In the MES, inputs i and j are substitutes if $\sigma_{ij}^{M} > 0$, which means that increasing the price of the j^{th} input increases the quantity of input i *relative* to the quantity of input j. Inputs i and j are complements if $\sigma_{ij}^{M} < 0$: if an increase in the price of j decreases not only the quantity of input j but also decreases the quantity of input i such that the ratio x_i/x_j decreases.

The MES is not symmetric, which means that in general $\sigma_{ij}^{M} \neq \sigma_{ji}^{M}$. The MES can also classify substitution elasticities differently from the AES. For example, two inputs i and j could be Morishima substitutes, $\sigma_{ij}^{M} > 0$, while being Allen complements, $\sigma_{ij}^{A} < 0$. Hence, "$\cdots$ *the Allen measure has a bias toward treating inputs as complements (or, the Morishima measure has a bias toward treating inputs as substitutes).*" (Mundra and Russell, 2004: 35), reflecting the fact that the AES measures changes in absolute quantities and the MES measures changes in relative quantities.

Blackorby and Russell (1989) make the point that the MES is a measure of curvature of the isoquant, or ease of substitution, and that the MES provides comparative static information about relative factor shares. Using a cost function formulation (which is dual to our production function constant output formulation) they show that

$$\frac{\partial \ln[x_i p_i / x_j p_j]}{\partial \ln[p_i/p_j]} = 1 - \sigma_{ij}^{M}.$$

Thus, for a given increase in the price of input j, the relative share of input j decreases if the $\sigma_{ij}^{M} > 1$, and increases if the $\sigma_{ij}^{M} < 1$.

According to Mundlak (1968), the MES is a *two-factor-one-price* ES because the MES measures relative input adjustment to single-input price changes. On the other hand, the AES measures how a single input adjusts to changes in a single-input price, and thus is a *one-price-one-factor* ES (Chambers, 1988). It is worth noting that the MES does not measure relative input adjustment to relative price changes because the effect on the relative input shares of changing p_i instead of p_j is generally different, as reflected by the asymmetry of the MES.

2.2 Empirical Methodology

Estimation Form Measuring the AES and the MES requires estimating parameters of a functional form that is sufficiently flexible to provide a suitable fit for most datasets. We employ the Translog production function, which is a second order Taylor series expansion. Using lower case letters to represent the natural log of our variables, the Translog production function for three inputs is

$$\begin{aligned} y = \; & \alpha + \beta_z \, z + \beta_k \, k + \beta_l \, l + \beta_{zk} \, z \, k + \beta_{zl} \, z \, l + \beta_{kl} \, k \, l + \beta_{zz} \, z^2 + \beta_{kk} \, k^2 \\ + \; & \beta_{ll} \, l^2 + \epsilon \,, \end{aligned} \tag{3}$$

where the constant α and the βs are the parameters to be estimated, y is value added (as a measure of output), z is IT capital, k is non-IT capital, l is labor, and ϵ is an error term.

Dataset 1: 2-Digit SIC 1953-00 We begin with an industry-level dataset from the Bureau of Labor Statistics (BLS) extracted from the Multifactor Productivity (MFP) database for the two-digit Standard Industrial Classification (SIC) industries of the U.S. manufacturing sector. The dataset is the same as the one used in Mittal and Nault (2008). It covers the period 1953-2000, and captures all the manufacturing industries except Tobacco manufacturing, and descriptions of the two-digit SIC codes are provided in Table **??**. All dollar figures (the annual time series data) provided by the MFP database are in constant 1996 dollars. The database provides times series for labor hours (L), IT capital (Z), and an aggregate measure of five categories of capital stocks: equipment, structures, rental residential capital, inventories, and land. IT capital stock consists of computers and computer peripherals, communication and office accounting machinery and instruments (scientific and engineering), and software. We use the sum of equipment and structures for our measure of productive capital and calculate the time series for non-IT capital (K) by subtracting IT capital from productive capital. The MFP database also provides annual time series for each industry's output that excludes intra-industry transactions, and time series of energy, services, and materials purchased by each two-digit SIC. We calculate real value added (Y) by subtracting the real cost of the purchased energy, services, and materials from real output. We have 19 SIC industries and 48 years of data giving 912 observations.

Dataset 2: 3-Digit SIC 1987-99 Our second dataset consists of the MFP dataset for three-digit SIC code manufacturing industries from 1987 to 1999. We use the same dataset as Cheng and Nault (2007) which contains 85 industries plus 7 industries they dropped because these industries did not supply other industries. The dataset provides the series of output in millions of current dollars and the output deflator to millions of 1987 dollars. The MFP dataset also provides us intermediate purchase compensation in millions of current dollars and the corresponding deflator, and from the output series and the intermediate input series we compute real value-added, Y. The MFP dataset has labor input in millions of hours, L. To calculate IT capital stock we start with a breakdown of 30 asset types for each three-digit SIC code manufacturing industry in 1987 dollars. We aggregated the stock of computers and related equipment, office equipment, communication, instruments, photocopy and related equipment as the IT capital stock in millions of 1987 dollars, Z. From a breakdown of capital stocks we compute the non-IT capital stock from the total of equipment and structures less IT capital stock, giving K. Thus, this dataset has 92 industries over 13 years for 1196 observations. Table 1 contains summary statistics of our two datasets.

Sample Splits Based on IT Intensity In their research on direct and indirect effects of IT, Mittal and Nault (2008) also showed that the direct effect of IT is more significant in non-IT-intensive industries, whereas the indirect effect of IT is more significant in IT-intensive industries. Dumagan and Gill (2002) with industries, and Dewan and Min (1997) with firm-level data, also found differences in their analyses between IT-intensive and non-

IT-intensive partitions. Each of these studies partitioned their datasets based on slightly different definitions of IT intensity. We follow Mittal and Nault (2008) for partitioning our two datasets into IT-intensive and non IT-intensive sub-samples. For each observation (industry, year), we compute the ratio of IT capital stock to value-added to determine IT intensity. We use the overall mean value over industries and years of the IT capital stock to value-added ratio as a break point for separating the different industries based on IT intensity. Industries that fall below the break point are classified as non IT-intensive; otherwise they are classified as IT-intensive. We assume that the ratio of IT capital stock to value-added of an industry is a reasonable indicator of that industry's use and utilization of IT capital, and that our partitioning is an indicative of the structural differences in the utilization of IT. The results of partitioning the different industries in each of our datasets based on IT intensity are reported in the Appendix.

2.3 Estimation

We use two methods to obtain estimates of our Translog form in (3) for each of our datasets. The first is generalized least squares with different econometric specifications as detailed below. The second is a Bayesian approach that allows us to incorporate regularity conditions.

2.3.1 GLS Specifications

Using STATA we estimate the Translog form in (3) using different econometric adjustments for the error term. The estimated parameters are then exported to a custom-made routine to calculate the AES in (1) and the MES in (2).

Econometric adjustments Heteroskadasticity and autocorrelation are the two econometric problems that commonly arise when using panel time series data. Our industries differ in size, production technology, and response to economic shocks. Thus, we expect that our dataset to exhibit heteroskadasticity between industries, and possibly correlated across the industries in our dataset. Besides heteroskadasticity, we also expect that our dataset to exhibit first-order autocorrelation due to the different smoothing procedures used in the derivation of economy-level time series data. Moreover, this autocorrelation may be panel-specific.

Results from both the Breusch-Pagan/Cook-Weisberg test, and the White test indicate the presence of heteroskadasticity in our panel data. Moreover, a significant test statistic for the Wooldridge test rejects the null hypothesis of no first-order autocorrelation in our dataset, hence, confirming the presence of a first-order autocorrelation.

Given the results of these tests we use feasible generalized least squares (FGLS), and run our regressions with econometric adjustments for heteroskadasticity and panel-specific first-order autocorrelation. Because we recognize industries may differ systematically, we also adjust for correlation of the errors between panels with our first dataset. In the second dataset with more industries and fewer years, we have insufficient sample size to adjust for correlation of the errors between panels.

2.3.2 Bayesian Specification

The Impact of Regularity Conditions The Translog form in (3) is a FFF. Many researchers argue that the usefulness of FFF hinges on whether the estimated parameters satisfy regularity conditions implied by economic theory such as non-negativity, monotonicity, and concavity for production functions. Violating any of these conditions causes the second-order conditions for optimizing behavior and duality theory to fail (Barnett, 2002), and inferences obtained from an estimated FFF that violates any regularity condition are unreliable (Barnett and Pasupathy, 2003). Monotonicity violation leads to incorrectly signed elasticities, and curvature violation leads to production possibilities frontiers that are convex to the origin (Caves and Christensen 1980; Diewert and Wales 1987; Morey 1986). To show the impact of violating monotonicity on the sign of an ES, consider our form in (3). Monotonicity is satisfied if $f_i \geq 0$, where $i = \{k, l, z\}$. Clearly, both the AES and the MES given by (1) and (2), respectively are a function of $\mathbf{H}$ and f_i. Thus, by definition, the sign of the ES is influenced by the sign of f_i, which in turn determines if the estimated parameters satisfy monotonicity.

The solution is to impose regularity conditions on the estimated parameters of the FFF.

There are two approaches. The first imposes parametric restrictions on the FFF to ensure that certain conditions hold at all data points. For example, global curvature restriction can be achieved by using eigenvalue decomposition techniques and Cholesky factorization methods (Diewert and Wales, 1987). However, these methods undermine the flexibility of most functional forms (Jorgenson and Fraumeni, 1981), and the global imposition of regularity conditions forces many FFFs to exhibit properties not implied by economic theory. For example, imposing global concavity in the inputs of a Translog cost function may lead to an upward bias in the degree of substitutability, and imposing global concavity on a generalised leontief cost function forces all inputs to be substitutes (Diewet and Wales, 1987). Barnett and Pasupathy (2003) argue that imposing regularity conditions globally actually increases the frequency of monotonicity violations.

The second approach imposes regularity conditions locally. Several studies demonstrate that the advantages of local regularity imposition outweigh that of global regularity imposition (Lau, 1978; Diewert and Wales, 1987; Terrell, 1996; O'Donnell and Coelli, 2005). Local imposition of regularity means that constraints are imposed at a single point, at several points, or over a region for which inferences will be drawn (Gallant and Golub, 1984, Salvanes and Tjotta, 1998). Local imposition of regularity conditions can be achieved through sampling theoretic procedures (Jorgenson and Fraumeni, 1981; Ryan and Wales, 1998; Moshini, 1999). More recently, a Bayesian approach has been proposed to locally impose regularity on the parameters of the estimated FFF and the implementation of the Bayesian approach involves the use of Markov Chain Monte Carlo (MCMC) simulation methods. There are many MCMC algorithms; however, the most commonly used are the Gibbs and Metropolis-Hasting (M-H) sampling algorithms.

We examine the compliance of the FGLS parameters estimates with monotonicity by examining the marginal products of the three input factors, and with curvature by checking the signs of the three principle minors of the Hessian matrix. We examine compliance with these two conditions for each observation in our six subsamples and we find that none of the subsamples satisfy both conditions across all their observations. That is, there are some observations in each subsample that violate at least one of the conditions. This violation may render all inferences that are based on the FGLS parameter estimates of the model, such as a variety of elasticities, suspect. Thus, imposing regularity conditions is likely necessary.

Imposing Regularity: A Bayesian Approach Through Bayesian estimation of our Translog model in (3), we have the flexibility and the ability to restrict the sampled parameter estimates (i.e., the generated sample draws, in the context of MCMC simulation) to a sample that satisfies monotonicity and curvature conditions. For our Translog form, we define a vector for the parameters to be estimated, $\beta = [\alpha, \beta_z, \beta_k, \beta_l, \beta_{zk}, \beta_{zl}, \beta_{kl}, \beta_{zz}, \beta_{kk}, \beta_{ll}]^T$. The objective in the Bayesian estimation method is to properly form the posterior probability distribution function, $g(\beta|D)$, from the observed data D - our measures of value added and factor inputs.

Bayes Theorem relates the posterior probability to the prior probability as follows

$$g(\beta|D) \propto L(\beta|D) \times p(\beta), \tag{4}$$

where $L(\beta|D)$ is the likelihood function of the vector of the model parameters β given the observed data D, and $p(\beta)$ is the prior density function of the model parameters vector β. In our analysis we form a posterior density from a noninformative prior. We assume no prior knowledge about the parameters to avoid any bias in the estimation process and we wish to present posterior results that are completely dominated by our sample information.

We take the error term in our Translog form, ϵ, to be multivariate normal, with mean 0 and variance-covariance $\sigma^2 I$, where σ is unknown. We follow Judge, Hill, Griffiths, Lutepohl and Lee (1988) and propose a joint noninformative prior for (β, σ):

$$g(\beta, \sigma) \propto \frac{1}{\sigma}.$$

With this prior the likelihood function can be written as

$$L(\beta, \sigma|D) \propto \sigma^{-T} exp\{-[v\hat{\sigma}^2 + (\beta - b)'X'X(\beta - b)]/2\sigma^2\},$$

where $b = (X'X)^{-1}X'y$ is the least squares estimator of β, $v\hat{\sigma}^2 = (y - Xb)'(y - Xb)$ is the residual sum of squares from the least squares estimator, and v is the degrees of freedom. Notice that although we assume the error term is "well behaved", b is still unbiased as long as the error term is not correlated with the regressors.

Then, continuing to follow Judge et al. (1988), by integrating σ out of the joint posterior p.d.f for (β, σ) we obtain our desired marginal posterior p.d.f for β only:

$$g(\beta|D) \propto [1 + \frac{1}{v\hat{\sigma}^2}(\beta - b)' X' X (\beta - b)]^{-(K+v)/2}. \quad (5)$$

This marginal posterior is actually a multivariate t density, with mean b, variance-covariance matrix $[v/(v-2)]\hat{\sigma}^2(X'X)^{-1}$, and degrees of freedom v.

Implementation The Metropolis-Hasting (M-H) algorithm based Markov Chain Monte Carlo (MCMC) simulation is used to implement the Bayesian approach. The M-H algorithm was originally developed by Metropolis, Rosenbluth, Rosenbluth, Teller, and Teller (1953), and was subsequently generalized by Hastings (1970). The M-H algorithm uses a proposed candidate-generating density function relating the current value of a sequence to a candidate value that is proposed to be included in the generated MCMC sequence. Our purpose in using the M-H based MCMC simulation is to create a Markov Chain that eventually converges to our proposed posterior density function so that the sample observations we get from the simulation are drawn from the posterior density. More importantly, because we reject any observation that violates monotonicity or curvature during the simulation process, each in our set of final observations complies with the necessary regularity conditions.

In order for our Markov Chain to converge to our proposed posterior p.d.f. we set a *burn-in sample*, k, which we discard from our estimation of our Translog parameters $\hat{\beta}$. Our estimation of $\hat{\beta}$ is the mean,

$$\hat{\beta}_{final} = \frac{\sum_{n}^{i=k} \hat{\beta}_i}{n-k},$$

where k is the time before convergence, and n is the MCMC sampe size. The subscript i is an index for the $\hat{\beta}$ estimate in location i in the Markov Chain sequence (array) that the we generated. For each run we generate a $100,000$ MCMC sample size, n, and as a burn-in sample we discarded the first $10,000$ iterations, k, to ensure that the final sample is random and uncorrelated. After executing the Metropolis-Hasting sampling loop, we obtain 9 sample means and standard errors, which are used as point estimates of the β parameters of the Translog production function.

We experimented with different vectors of initial values for $\hat{\beta}$ including a vector of zeros and OLS estimates. Given the size of the burn-in sample, our results do not depend in any meaningful way on the initial values. We use a multinormal candidate-generating function with mean 0 and variance-covariance matrix being the robust variance-covariance estimate from OLS multiplied by a tuning parameter, which is used to control the convergence rate. Notice that although by construction, our posterior density function (5) centers on the OLS estimates, these estimates are still unbiased and consistent as long as all of our regressors are uncorrelated with the error term in our regression model (3).

3 Results

3.1 FGLS-Based Estimates of the AES and MES

In Table 2 we report our parameter estimates for the Translog production function for our two datasets for all industries, and for our IT-intensive and non IT intensive partitions.

Our results of the AES and the MES are based on their definitions using our Translog estimates as the FFF of the production function. The elasticities are calculated using the mean values of the variables in each year for the SIC industries in each of our datasets. We use the same methodology in calculating the AES and MES for each of our dataset partitions into IT-intensive and non IT-intensive industries. Our FGLS-based estimates of the AES for our two datasets and their partitions are reported in Table 4. For easier reading we also provide a qualitative summary of our results in Table 7.

3.1.1 AES Estimates

For the pooled versions of our two datasets, we find that the AES consistently indicates that each pair of factor inputs are substitutes. Thus, if the price of any input increases, there is a corresponding increase in the quantity of each of the other inputs.

In Table 8 we show a comparison between our findings and those of previous IT substitutability studies, noting that Chun and Mun (2006) are not comparable because they estimate a cost function and use GPO rather than value added. Our AES results are consistent with previous findings of Dewan and Min (1997), and of Hitt and Snir (1999). Our results are also consistent with the findings of Chwelos et al. (2008) except for the AES between IT capital and non-IT capital. Chwelos et al. (2008) found that IT capital and non-IT capital are complements, whereas results from our study and previous IT substitutability studies indicates that IT capital and non-IT capital are substitutes.

However, when we consider the partitions of our two datsets into IT-intensive and non IT-intensive, we find that in IT-intensive industries the AES continues to indicate labor is a substitute for both types of capital, but IT capital and non-IT capital are complements. This last result is consistent with the Chwelos et al. (2008) overall results. In non IT-intensive industries each pair of inputs are substitutes in our first, longer, dataset. However, in our shorter and finer dataset labor is a complement with both types of capital, while both types of capital are substitutes - the opposite to the results for IT intensive industries. Our AES result whereby labor is a complement with the other two inputs suggests our FFF estimates for non IT-intensive industries in our second dataset may not satisfy regularity conditions as with the AES a given input cannot be a complement with the remainder of the inputs.

3.1.2 MES Estimates

In interpreting the results of our MES estimation, it is helpful to review substitutability and complementarity in the Morishima sense. Consider the relationship between IT capital and non-IT capital. The MES in the case of a change in the price of IT capital is σ_{kz}^M. If $\sigma_{kz}^M < 0$, then IT capital and non-IT capital are complements, and the result of a decrease in the price of IT capital is to increase not only the quantities of IT and non-IT capital, but also to increase the quantity ratio of non-IT capital to IT capital. Moreover, this also increases the ratio of the factor share of non-IT capital to IT capital.

When the MES is positive, then the inputs are substitutes, but the interpretation can be more complex. If $0 < \sigma_{kz}^M < 1$, then the result of an decrease in the price of IT capital is to decrease the quantity ratio of non-IT capital to IT capital. However, the ratio of the factor share of non-IT capital to IT capital increases because the effect of the price decrease in IT capital on the IT capital input cost is greater than the effect of the decrease in the quantity of non-IT capital on the non-IT capital input cost. Thus, in this case, the relative quantity of non-IT capital falls, while the relative factor share does not. However, if $\sigma_{kz}^{M} > 1$, then a price decrease in IT capital decreases both the relative quantity and the relative factor share of non-IT capital to IT capital.

MES: Pooled Industries Table 4 reports the MES estimates. Similar to the AES, the qualitative results are consistent between the two datasets with a single exception. However, what is striking is that in two of three cases there is an asymmetry between MESs depending on which input price is changing.

IT capital and non-IT capital are substitutes when the price of non-IT capital changes, whereas they are complements when the price of IT capital changes. In contrast, IT capital and labor are complements when the price of labor changes, and are substitutes (complements) in our finer (longer) dataset when the price of IT capital changes. The table also shows that non-IT capital and labor are complements when the price of labor changes and are substitutes when the price of non-IT capital changes. All of the MESs are less than unity, meaning the input share change is in the same direction as the input quantity change.

Over the time periods of both datasets the price of IT capital has been decreasing. For the relationship between IT capital and non-IT capital, being Morishima complements when the price of IT capital falls results in not only a greater quantity of IT but also results in an increase in the quantity of non-IT capital relative to IT capital.

The effect of IT capital price decreases on labor depend on the dataset. Over the longer dataset the same result as with non-IT capital obtains: there is an increase in the quantity of IT capital and an increase in labor relative to IT capital. In our finer dataset - a more condensed and recent period - a decrease in the price of IT capital increases the quantity of IT capital, and increases the quantity of IT capital relative to labor. Notice the MES does not indicate whether the quantity of labor increases or decreases.

In general the price of labor and of non-IT capital has been increasing. Labor is a complement to other inputs when the price of labor changes, hence when labor is more expensive not only does the quantity of labor fall, but the quantities of other inputs fall at a greater rate. Non-IT capital is a substitute so when the price of non-IT capital increases the quantity of non-IT capital decreases both net and relative to other inputs.

MES: IT-Intensive and Non IT-Intensive Industries As with the AES and the MES for pooled industries, the qualitative results for IT intensive industies are consistent between our two datasets. What is again strking, and even more so, is that the direction depends on which price is changing.

In line with the concept of "IT intensity", when the price of IT capital changes, both labor and non-IT capital are substitutes. This means that IT capital price declines result in greater quantity of IT capital and a greater quantity of IT capital relative to other inputs. Moreover, because $\sigma_{kz}^{M} > 1$, the input share of IT capital relative to non-IT capital increases in spite of the price decline, leading to greater IT capital deepening.

In addition, labor is a complement of both types of capital so that when the price of labor increases not only does the quantity of labor decrease, but the quantities of both types of capital decrease relative to labor. Non-IT capital is a complement with IT capital and a substitute for labor when the price of non-IT capital changes, meaning an increase in the price of non-IT capital decreases the quantity of IT capital more than proportionally with non-IT capital. As a complement to labor and non-IT capital when the price of the other inputs changes, the effects of such price changes are magnified on the quantity of IT capital - in a sense making IT capital more responsive to price changes in other inputs in IT-intensive industries.

The MES results for the non IT-intensive industries are less consistent across datasets than IT-intensive industries. However, three of four MES measures for IT capital are consistent, and are in contrast with IT-intensive industries. When the price of IT capital changes, IT capital is a complement for other inputs. Thus, when the price of IT capital decreases, not only does the quantity of IT capital increase, but the quantites of labor and non-IT capital increase more than proportionally. In addition, when the price of non-IT capital changes, the two types of IT capital are substitutes so that increases in the price of non-IT capital increase the quantity of IT capital relative to non-IT capital.

For the non-IT intensive industries there is a reversal between the two datasets when the price of labor changes. In our longer dataset when the price of labor changes it is a complement to the other inputs, whereas in our more concentrated dataset labor is a substitute for other inputs and the MES is greater than unity. Thus, in the more concentrated and recent period, increases in the price of labor results in capital deepening in input shares.

3.2 Bayesian-Based Estimates of the AES and MES

In Table 3 we report our parameter estimates from our Bayesian analyses for our two datasets for all industries, and for our non IT-intensive partitions. These parameter estimates reflect our controls for monotonicity and curvature. The procedure we use to calculate AES and MES are the same as before, except we use our Bayesian parameter estimates. We did not obtain Bayesian analysis results for our IT-intensive industries, and issue we discuss later.

3.2.1 AES Estimates

Strikingly, for all our datasets except IT-Intensive, the AES are close to but less than unity. This means every input is a substitute with other inputs; What is more, the fact that the AES from our Bayesian approach are close to unity confirms that for the 3-input case the AES cannot measure the curvature of the isoquant. That is, we suspect that there may be an underlying problem with using the AES in applied research whereby over large samples it tends to unity, and therefore its magnitude does not have any meaning. If so, the AES is "biased" towards confirming Cobb-Douglas forms of production functions for which the elasticity of substitution is always unity, and the AES may be inappropriate to justify any specific production function form.

3.2.2 MES Estimates

Both qualitative results and magnitudes of the MES based on Baysesian estimates are consistent across our four different datasets with only a single exception in the MES between labor and IT capital when the price of IT capital changes. Also, qualitative results and magnitudes of the MES from both pooled datasets and from the longer non IT-intensive dataset are consistent with FGLS-based counterparts. Even in the finer non IT-intensive dataset, qualitative results between IT capital and non-IT capital are the same with FGLS-based estimates, although the magnitudes of results in this dataset generally differ from the FGLS-based ones.

The Bayesian-based MES results from our two longer datasets confirm the complementarity of IT capital to non-IT capital and labor when the price of IT capital changes we found in our FGLS-based results. In general the price of IT capital has been decreasing over time, so the ratio of labor to IT capital and the ratio of non-IT capital to IT capital increase over time.

4 Discussion

The Asymmetry of the Effects of IT Capital In our estimates of the MES for pooled and non IT-intensive industries, we find that for all time periods $\sigma_{zk}^{M} > 0$. This means that these two inputs behave as substitutes when the price of non-IT capital changes. However, even though the amount of IT capital relative to the amount non-IT capital changes, because $\sigma_{zk}^{M} < 1$ (except for the shorter period non IT-intensive dataset) the factor share of IT capital relative to the factor share of non-IT capital does not rise. This is likely because of the scale differences in IT capital versus non-IT capital: the quantity of non-IT capital is about 20 times larger than that of IT capital.

In comparison, because $\sigma_{kz}^{M} < 0$ for all time periods over pooled and non IT-intensive industries, the two inputs behave as complements when the price of IT capital rises. So when the price of IT rises, not only does the amount of non-IT capital fall relative to IT capital, but the factor share of non-IT relative to the factor share of IT capital falls as well. Moreover, because for all time periods the absolute value of σ_{kz}^{M} is greater than the absolute value of σ_{zk}^{M}, a rise in the price of IT capital has a greater impact on relative quantities than does an equivalent rise in the price of non-IT capital.

This asymmetry in our measures of the MES persists for the IT-intensive industries over both time periods – however in a different direction. That is, non-IT capital and IT capital are complements when the price of non-IT capital changes, and are substitutes when the price of IT capital changes. Notice the FGLS based AES indicate that IT capital and non-IT capital are substitutes for our pooled and non IT-intensive industries whereas complements for IT-intensive industries. This is consistent with our Morishima results when the price of non IT capital changes, but in contrast instead when the price of IT capital changes. Hence, it appears that the MES allows us to understand the nature of input substitution more fully.

This remarkable difference in interpretations between the MES and AES persist when considering the relationship between IT capital and labor. Both σ_{zl}^M and σ_{lz}^M from our 1953-2000 datasets for pooled and non IT-intensive industries are negative so that IT capital and labor are Morishima complements. In the latter case, when the price of IT capital falls, quantities of both inputs increase, and the relative amount of labor to IT capital increases. The AES indicates IT capital and labor are substitutes, so that a decrease in the price of IT capital would decrease the quantity of labor.

Finally, we find that throughout the 1953-2000 period the absolute value of σ_{kz}^M is greater than the absolute value of σ_{lz}^M. Thus, a change in the price of IT capital results in greater effects on the relative amounts of non-IT capital than it does on the relative amounts of labor - a result that is also at odds with the AES measures. Of course this supports the Blackorby and Russell (1981, 1989) view that the AES is a scale-free measure.

Effects of IT Capital based on IT Intensity As we mentioned before, effects of IT capital are dramatically different between IT-intensive and non IT-intensive (consistent with pooled in general) datasets. Over 1953-2000 the relationship between IT capital and non IT capital differs between IT-intensive and non IT-intensive industries based on both AES and MES results. In the IT-intensive dataset, IT capital and non-IT capital are complements when the price of non-IT capital changes, and are substitutes when the price of IT capital changes. Moreover, because $\sigma_{kz}^M > 1$, when the price of IT capital increases not only does the quantity of non-IT capital relative to IT capital increase, but the factor share of non-IT capital relative to the factor share of IT capital increases. In the context of a decrease in the price of IT capital, these are reversed: both the quantity and factor share of non-IT capital fall relative to that of IT capital. Besides, the absolute value of $\sigma_{kz}^M > 1$ in non-IT intensive datasets are greater than those in IT-intensive datasets, meaning that the marginal effect of the price of non-IT capital is greater in non-IT intensive industries than IT-intensive industries. At the same time, the AES is negative indicating that non-IT capital and IT capital are complements, so that a decrease in the price of IT capital would increase the quantity of non-IT capital.

Comparing IT-intensive and non IT-intensive results over 1953-2000, the relationship between IT capital and labor is more complicated. They are complements when the price of labor changes in both datasets. However, the absolute value is much greater in the IT-intensive case, meaning that the effect of one unit change in the price of labor on the ratio of IT capital to labor is much larger in the IT-intensive industries than in the non IT-intensive industries. IT capital and labor remain as complements when the price of IT capital changes for the non IT-intensive industries, whereas they are substitutes for the IT-intensive industries. At the same time, the AES between IT capital and labor is positive, so that the problems that plague the AES as compared to the MES persist.

Interestingly, the relationship between non-IT capital and labor are consistent across our results except for the FGLS-based one for non IT-intensive industries over 1987-1999. Non-IT capital and labor are complements when the price of labor changes and are substitutes when the price of non-IT capital changes. The absolute value of σ_{kl}^{M} is in general much greater compared with other Morishima results, indicating a huge effect of the price of labor on the ratio of non-IT capital to labor over time.

The Different Effects of IT Capital: Results from the MES Mittal and Nault (2008) showed direct effects of IT on production in non-IT-intensive industries, and indirect effects of IT on production - effects through labor and non-IT capital – in IT-intensive industries. Our study of ESs supports these earlier results. As we saw, changes in the price and consequent use of IT capital differ markedly between industries that are IT-intensive and those that are not. For the overall period in the IT-intensive industries a drop in the price of IT capital results in a drop in quantity and factor share of non-IT capital relative to IT capital; a drop in the price of IT capital also leads to a drop in quantity share of non-IT capital relative to IT capital. These results are consistent with the estimates from the shorter estimation period, 1987-1999. Thus, we could argue that the indirect effect of

IT capital makes the remaining non-IT capital and labor more productive.

In contrast, for the overall period in non-IT-intensive industries, a drop in the price of IT capital induces an increase in the quantity of labor relative to IT capital, also an increase in the quantity of non-IT capital relative to IT capital. This is a direct effect of IT, transforming the way work is done by coupling additional labor or non-IT capital together with IT capital to be productive.

Indeed, we found that across most of our subsamples there was a lack of concordance between the AES and the MES when the price of IT capital changes – and this lack of concordance was always the case when examining the relationship between IT capital and non-IT capital when the price of IT capital changes. Thus, unlike other factors of production, IT capital has a multifaceted impact on output through its relationships with other factors, and measurement of this relationship requires an asymmetric measure of substitution such as the MES.

Missing Bayesian Results for IT-Intensive Datasets For both our IT-intensive datasets, parameter estimates of the Translog production function are missing because not a single candidate parameter vector was accepted during the MCMC simulation. A candidate parameter vector is not accepted due to violation of at least one of the 3 conditions: first, the Hastings ratio condition which ensures the candidate parameters are drawn from our target posterior density function; second, the monotonicity condition; third, the curvature condition. Since our acceptance rate for Hastings ratio is quite high (over 85% in general), the regularity condition are responsible for most of the rejections.

We think there are two related reasons for the zero acceptance rate. First, for IT intensive industries IT may enter the production function differently from our Translog specification. Although Translog production function is flexible in the sense that it is a Taylor series expansion, the separation of factor inputs in log-additive form may not reflect the "real way" that IT enters the production functions. Mittal and Nault (2008) found that for IT-intensive industries, IT enters production function only through an indirect effect - by enhancing labor and non IT-intensive capital. Second, the reason might lie in the data itself. For IT-intensive industries, the monotonicity and curvature conditions cannot be satisfied at the same time due to some hidden characteristics, for example, one or more inputs may display increasing returns within a certain range covered by the industries in our dataset.

5 Conclusion and Contribution

We introduced the MES, a measure that preserves the salient properties of the original Hicksian concept of the ES. We showed that the AES is lacking in its ability to provide information for the elasticity of substitution in the 3-factor case. On the other hand, we showed that the MES formulation is a correct measure of the curvature of the isoquant, and provides comparative statics information about income shares.

We derived the expression of the MES from a Translog production function for three factors (IT capital, non-IT capital, and labor). Then, we used the estimated parameters of the Translog model to compute estimates for the AES as well as the MES between IT capital, non-IT capital, and labor. We used two industry-level datasets from the BLS for the U.S. manufacturing sector. The first, used in Mittal and Nault (2008), contained 19 two-digit SIC industries and covered the period of 1953-00. The second, part of which was used in Cheng and Nault (2007), contained 92 three-digit SIS industries and covered the period of 1987-99 In addition to estimates over the pooled dataset, we also examined partitions into IT-intensive and non-IT-intensive industries.

We used two methods to derive our results. First was a least-squares approach using FGLS and appropriate econometric adjustments. Second was a Bayesian approach using a MCMC simulation containing the M-H algorithm. This second approach allowed us to impose regularity conditions – monotonicity and curvature – locally on the parameter estimates of our Translog production function.

Our results from the AES were consistent with those from previous IT substitutability research, which found that IT capital is a substitute for non-IT capital and labor. Unlike the AES, the relationships that are obtained from using the MES depend on which input price changes. Our MES results showed that over both pooled datsets, IT capital and non-IT capital are Morishima complements when the price of IT capital changes. This result is at odds with an AES that indicates IT capital and non-IT capital are substitutes, and at odds with most of the prior research on ESs with IT capital. Therefore, while the AES indicates that a drop in the price of IT capital would result in a higher quantity of IT capital and a lesser quantity of non-IT capital, our MES results indicate that a drop in the price of IT capital would result in not only a greater quantity of IT capital and non-IT capital, but also a greater quantity of non-IT capital relative to IT capital. Over the longer dataset IT capital and labor are complements when the price of IT capital changes, a result that is also at odds with our AES estimates and those in prior research.

We found that the estimated parameters of our Translog model using FGLS violate monotonicity and curvature conditions. Results from our Bayesian analyses indicate that regularity conditions have a significant impact on the generated parameters of our Translog model. Interestingly, the impact on the MES and AES results were not as substantial in the case of our pooled datasets. This confirms the Translog as a FFF – and the fact that ES measures do not depend on individual parameters, but on the FFF as a whole.

The calibration that is evident in the MES estimates from the Bayesian approach is not as evident in the FGLS-based MES estimates. Thus, we argue that the Bayesian approach can add value when the magnitude of the estimate is important. We also found that using the Bayesian approach, the magnitude of the AES converges to unity from below. Therefore, when using large samples the tendency of the AES to converge to unity indicates an underlying problem in the use of the AES because in the 3-factor case (and the more general n-factor case) the magnitude of the AES is not meaningful, and should not be used to justify forms such as the Cobb-Douglas that assumes a unitary elasticity of substitution.

In partitioning our datasets into IT intensive and non-IT intensive industry groups, we found substantial differences. Our FGLS-based estimates of the MES indicate that, in contrast to non-IT intensive industries and our pooled datasets, for IT intensive industries IT capital and non-IT capital are complements when the price of non-IT capital changes, and are substitutes when the price of IT capital changes. Moreover, when the price of IT capital changes, IT capital is a substitute for labor in IT intensive industries and a complement for labor in non-IT intensive industries.

These contrasts between the IT intensity-related industry groups was highlighted in our Bayesian analysis when over our full MCMC simulation none of the parameter draws satisfied regularity conditions. This points to underlying structural differences in the way that IT capital enters as an input into production. Following Mittal and Nault (2008) who found that IT capital entered production in IT intensive industries indirectly through effects on non-IT capital and labor, our Bayesian analysis indicates that the Translog form - and likely many others – cannot capture such effects in spite of being highly flexible.

6 References

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7 Appendix: Elements of the MES and AES

In the context of production functions, the AES and the MES are defined as in (1) and (2), respectively. For inputs IT capital (Z), non-IT captial (K), and labor (L), the determinant of the bordered Hessian, $\mathbf{H}$, is defined as

$$\mathbf{H} = \begin{vmatrix} 0 & f_z & f_k & f_l \\ f_z & f_{zz} & f_{zk} & f_{zl} \\ f_k & f_{kz} & f_{kk} & f_{kl} \\ f_l & f_{lz} & f_{lk} & f_{ll} \end{vmatrix}$$

where the elements are the first and second derivatives of the production function. The first and second derivates of the Translog form in (3) are

$$f_z = \frac{1}{z}[\beta_z+2\beta_{zz}z+\beta_{lz}l+\beta_{kz}k], \quad f_k = \frac{1}{k}[\beta_k+2\beta_{kk}k+\beta_{lk}l+\beta_{kz}z], \quad f_l = \frac{1}{l}[\beta_l+2\beta_{ll}l+\beta_{lk}k+\beta_{lz}z],$$

$$f_{zz} = -\frac{1}{z^2}[\beta_z + 2\beta_{zz}z - 2\beta_{zz} + \beta_{lz}l + \beta_{kz}k], \quad f_{kk} = -\frac{1}{k^2}[\beta_k + 2\beta_{kk}k - 2\beta_{kk} + \beta_{lk}l + \beta_{kz}z],$$

$$f_{ll} = -\frac{1}{l^2}[\beta_l + 2\beta_{ll}l - 2\beta_{ll} + \beta_{lk}k + \beta_{lz}z], \quad f_{zk} = \frac{\beta_{zk}}{zk}, \quad f_{zl} = \frac{\beta_{lz}}{zl}, \quad f_{kl} = \frac{\beta_{lk}}{kl}.$$

By Youngs' theorem, $f_{ij} = f_{ji}$. In the expression of the AES and MES, a cofactor $\mathbf{H}_{ij}$ is defined as $\mathbf{H}_{ij} = (-1)^{i+j}|M_{ij}|$, where $|M_{ij}|$ is the determinant of the minor matrix that is obtained from deleting the i^{th} row and the j^{th} column of the bordered Hessian. The required minor matrices that are needed to form the different cofactors are:

$$\mathbf{M_{kz}} = \begin{vmatrix} 0 & f_k & f_l \\ f_z & f_{zk} & f_{zl} \\ f_l & f_{lk} & f_{ll} \end{vmatrix}, \quad \mathbf{M_{lz}} = \begin{vmatrix} 0 & f_k & f_l \\ f_z & f_{zk} & f_{zl} \\ f_k & f_{kk} & f_{kl} \end{vmatrix}, \quad \mathbf{M_{zk}} = \begin{vmatrix} 0 & f_z & f_l \\ f_k & f_{kz} & f_{kl} \\ f_l & f_{lz} & f_{ll} \end{vmatrix}$$

$$\mathbf{M_{zl}} = \begin{vmatrix} 0 & f_z & f_k \\ f_k & f_{kz} & f_{kk} \\ f_l & f_{lz} & f_{lk} \end{vmatrix}, \quad \mathbf{M_{kl}} = \begin{vmatrix} 0 & f_z & f_k \\ f_z & f_{zz} & f_{zk} \\ f_l & f_{lz} & f_{lk} \end{vmatrix}, \quad \mathbf{M_{lk}} = \begin{vmatrix} 0 & f_z & f_l \\ f_z & f_{zz} & f_{zl} \\ f_k & f_{kz} & f_{kl} \end{vmatrix}$$

Table1: Summary Statistics

Dataset	Industry	Variable	Obs	Mean	Std.Dev.	Min	Max
1953-00 2-Digit SIC	Pooled	Value Added	912	47.4	40.7	1.6	283.0
		Labor	912	1.9	1.1	0.1	4.9
		Non-IT Capital	912	69.2	56.7	3.3	257.0
		IT Capital	912	4.1	7.7	0.002	61.8
	IT-Intensive	Value Added	288	57.0	45.0	5.3	283.0
		Labor	288	2.1	1.2	0.3	4.9
		Non-IT Capital	288	103.0	60.3	5.3	257.0
		IT Capital	288	8.7	11.2	0.1	61.8
	Non IT-Intensive	Value Added	624	42.9	37.7	1.6	180.0
		Labor	624	1.8	1.8	0.1	4.3
		Non-IT Capital	624	53.7	47.6	3.3	208.0
		IT Capital	624	2.0	3.8	0.002	30.3
1987-99 3-Digit SIC	Pooled	Value Added	1196	13	34.2	0.1	679.9
		Labor	1196	0.4	0.4	0.01	2.4
		Non-IT Capital	1196	20.1	22.6	0.5	135.5
		IT Capital	1196	1.8	3.1	0.03	27.7
	IT-Intensive	Value Added	377	9.4	7.6	0.1	28.3
		Labor	377	0.3	0.2	0.01	1.3
		Non-IT Capital	377	21.4	26.8	0.5	117.2
		IT Capital	377	3.4	3.4	0.09	27.7
	Non IT-Intensive	Value Added	819	14.7	40.9	0.6	679.9
		Labor	819	0.5	0.4	0.04	2.4
		Non-IT Capital	819	19.5	20.4	1.5	135.5
		IT Capital	819	1.0	1.9	0.03	17.9

All numbers are in billions of dollars or billions of hours. 1953-00 2-Digit SIC are in 1996 dollars; 1987-99 3-Digit SIC are in 1987 dollars.

Table 1: Summary Statistics

Table 2: FGLS Parameter Estimates of the Translog Production Function.

	Pooled		IT-Intensive		Non IT-Intensive	
	1953-00 2-Digit SIC	1987-99 3-Digit SIC	1953-00 2-Digit SIC	1987-99 3-Digit SIC	1953-00 2-Digit SIC	1987-99 3-Digit SIC
β_l	-5.11^{***}	0.37	-15.54^{***}	0.55^{*}	0.13	0.64
β_k	-1.28	1.29^{***}	-6.29^{**}	0.32	-3.16^{***}	1.55^{***}
β_z	-0.31	-0.07	0.80	0.43	0.79^{**}	-0.25
β_{lk}	-0.07^{*}	0.08	0.04	0.16^{**}	0.11^{*}	-0.04
β_{lz}	0.004	-0.06^{**}	-0.03	-0.26^{***}	-0.04^{*}	-0.18^{***}
β_{kz}	-0.0004	0.03	-0.22^{***}	0.26^{***}	-0.01	0.05
β_{ll}	0.18^{***}	-0.004	0.37^{***}	0.05	-0.03	0.12^{***}
β_{kk}	0.064^{***}	-0.09^{***}	0.22^{***}	-0.16^{***}	0.03	-0.08^{*}
β_{zz}	0.009^{*}	0.03^{***}	0.12^{***}	-0.07^{**}	0.01^{*}	0.09^{***}

$* \, p < .01, \; ** \; p < .025, \; *** \, p < .01.$

Table 3: Bayesian Parameter Estimates of the Translog Production Function.

	Pooled		IT-Intensive		Non IT-Intensive	
	1953-00 2-Digit SIC	1987-99 3-Digit SIC	1953-00 2-Digit SIC	1987-99 3-Digit SIC	1953-00 2-Digit SIC	1987-99 3-Digit SIC
β_l	19.70	12.12			13.98	9.89
β_k	8.51	12.26			7.08	21.87
β_z	2.93	8.92			2.70	3.00
β_{lk}	0.23	15.37			0.25	0.42
β_{lz}	-0.02	0.13			-0.05	0.59
β_{kz}	0.08	0.57			0.04	0.84
β_{ll}	-0.47	-0.74			-0.38	-0.72
β_{kk}	-0.24	-0.45			$-.023$	-0.89
β_{zz}	-0.07	-0.16			-0.03	-0.28

Table 4: The AES and MES based on FGLS Estimates.

Elasticities	Pooled		IT-Intensive		Non IT-Intensive	
	1953-00 2-Digit SIC	1987-99 3-Digit SIC	1953-00 2-Digit SIC	1987-99 3-Digit SIC	1953-00 2-Digit SIC	1987-99 3-Digit SIC
σ_{zk}^A	0.87	0.47	−23.58	−1.11	2.20	9.78
σ_{zl}^A	1.31	1.55	3.04	1.96	1.19	−32.16
σ_{kl}^A	2.54	0.43	2.10	0.94	0.86	−7.79
σ_{zk}^M	0.22	0.06	−7.85	−0.04	0.45	1.76
σ_{kz}^M	−3.91	−1.23	16.66	2.42	−18.09	−66.81
σ_{zl}^M	−0.81	−3.10	−8.42	−11.61	−0.01	17.04
σ_{lz}^M	−0.07	0.28	0.33	0.64	−0.32	−6.28
σ_{kl}^M	−51.55	−12.62	−38.86	−37.56	−16.54	143.89
σ_{lk}^M	0.67	0.06	1.66	0.06	0.17	−1.48

Table 5: The AES and MES based on Bayesian Estimates.

Elasticities	Pooled		IT-Intensive		Non IT-Intensive	
	1953-00 2-Digit SIC	1987-99 3-Digit SIC	1953-00 2-Digit SIC	1987-99 3-Digit SIC	1953-00 2-Digit SIC	1987-99 3-Digit SIC
σ_{zk}^A	0.87	0.95			0.90	0.86
σ_{zl}^A	0.93	0.99			0.96	0.87
σ_{kl}^A	0.79	0.88			0.70	0.83
σ_{zk}^M	0.27	0.32			0.28	0.31
σ_{kz}^M	−6.51	−0.51			−15.69	−5.78
σ_{zl}^M	−0.54	−1.92			−0.06	−0.31
σ_{lz}^M	−0.11	0.04			−0.60	0.15
σ_{kl}^M	−13.93	−24.55			−9.80	−9.70
σ_{lk}^M	0.25	0.32			0.21	0.31

Table 6: Qualitative Results of the FGLS-Based AES and MES.

Dataset	Industries	AES			MES when p_j Δ					
		σ_{zk}^A	σ_{zl}^A	σ_{kl}^A	σ_{zk}^M	σ_{kz}^M	σ_{zl}^M	σ_{lz}^M	σ_{kl}^M	σ_{lk}^M
1953-00 2-Digit SIC	Pooled	S	S	S	S	C	C	C	C	S
	IT-Intensive	C	S	S	C	S	C	S	C	S
	Non IT-Intensive	S	S	S	S	C	C	C	C	S
1987-99 3-Digit SIC	Pooled	S	S	S	S	C	C	S	C	S
	IT-Intensive	C	S	S	C	S	C	S	C	S
	Non IT-Intensive	S	C	C	S	C	S	C	S	C

S indicates substitutes, C indicates complements

Table 7: Qualitative Results of the Bayesian-Based AES and MES.

Dataset	Industries	AES			MES when p_j Δ					
		σ^A_{zk}	σ^A_{zl}	σ^A_{kl}	σ^M_{zk}	σ^M_{kz}	σ^M_{zl}	σ^M_{lz}	σ^M_{kl}	σ^M_{lk}
1953-00 2-Digit SIC	Pooled	S	S	S	S	C	C	C	C	S
	IT-Intensive									
	Non IT-Intensive	S	S	S	S	C	C	C	C	S
1987-99 3-Digit SIC	Pooled	S	S	S	S	C	C	S	C	S
	IT-Intensive									
	Non IT-Intensive	S	S	S	S	C	C	S	C	S

S indicates substitutes, C indicates complements

Table 8: A Comparison of our AES Results and Previous IT Substitutability Studies.

Study	Data Year	σ^A_{zk}	σ^A_{zl}	σ^A_{kl}
Dewan and Min (1997)	1988-1992: Firms	1.006	1.063	1.005
Hitt and Snir (1999)	1987-1994: Firms	0.945	0.688	NA
Chwelos et al. (2008)	1987-1999: Firms	-2.569	2.601	2.138
Our study	1953-2000: 2-Digit SIC	0.865	1.313	2.541
	1987-1999: 3-Digit SIC	0.470	1.553	0.434