**CAPITAL-ENERGY SUBSTITUTION REVISITED:
NEW EVIDENCE FROM MICRO DATA**

by

Sang V. Nguyen and Mary L. Streitwieser*****
Center for Economic Studies
U. S. Bureau of the Census
Washington D. C., 20233

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ABSTRACT

We use new micro data for 11,520 plants taken from the Census Bureau's 1991 Manufacturing Energy Consumption Survey (MECS) and 1991 Annual Survey of Manufactures (ASM) to estimate elasticities of substitution between energy and capital. We found that energy and capital are substitutes. We also found that estimates of Allen elasticities of substitution -- which have been used as a standard measure of substitution -- are sensitive to varying data sets and levels of aggregation. In contrast, estimates of Morishima elasticities of substitution -- which are theoretically superior to the Allen elasticities -- are more robust (except when two-digit level data are used). The results support the views that (i) the Morishima elasticity is a better measure of factor substitution and (ii) micro data provide more accurate elasticity estimates than those obtained from aggregate data. Our findings appear to resolve the long-standing conflict among the estimates reported in the many previous studies regarding energy-capital substitution/complementarity.

Keywords: Energy-Capital Substitution, Micro Data, Morishima Elasticities of Substitution, and Manufacturing Energy Consumption Survey.

I. INTRODUCTION

Since the 1973 energy crisis, economists and policy analysts have debated about whether energy and capital are substitutes or complements (see e.g., Apostolakis, 1990). The issue has received much attention because of its important policy implications. If capital and energy are substitutes, then an increase in energy prices would lead to an increase in the demand for capital. In this case, energy conservation policies promoting new energy-saving physical capital would be predicted to have the desired effect. However, if they are complements, then rising energy prices would adversely effect capital formation and, hence, such policies would be counterproductive.

Yet, after more than two decades, economists have not come to an agreement as to whether energy and capital are complementary or substitutable. The debate has been fueled by a large number of conflicting econometric estimates of the elasticity of substitution between energy and capital. For example, using time-series data Hudson and Jorgenson (1973) and Berndt and Wood (1975) found that energy and capital are complements. In contrast, Humphrey and Moroney (1975), Griffin and Gregory (1976) and Halvorsen (1977) found energy and capital substitutable based on their cross-section estimates. Other studies, such as those by Field and Grebenstein (1980), Hazilla

and Kopp (1984), Nguyen and Andrews (1989) and Morrison (1993), found mixed results.

Researchers have devoted considerable efforts to reconciling the differences in these results. Griffin and Gregory (1976) and Apostolakis (1990), for example, suggest that cross-section data may capture the long run industry response and result in the estimated substitutable relationship between capital and energy. In contrast, time-series data reflect short run responses to price changes and thereby lead to a complementary relationship between the two inputs. But, this explanation is not entirely satisfactory. Chung (1987) used time-series data and found that capital and energy are substitutes, while Field and Grebenstein (1981) used cross-section data and found mixed results.

Other explanations for the conflicting results have also been offered. Among other things, these include differences (i) in model specifications (three versus four factor model, e.g., Berndt and Wood, 1979), (ii) in the definition of technical change (Griliches, 1967), (iii) in the definition and measurement of capital (e.g., Field and Grebenstein (1980), Wood and Hirsch, 1981 and Morrison, 1993) and (iv) in the aggregation of energy (e.g., Nguyen and Andrews, 1989). But, the intricacies of the relationships have not been clarified, and therefore the controversy surrounding the issue of capital-energy

substitutability/complementary has not yet been resolved (see Apostolakis, 1990).

The above findings are viewed with great skepticism by a number of economists. Solow (1987), for example, discounts previous estimated elasticities of substitution, arguing that these estimates are subject to intractable aggregation biases. He points out that aggregate manufacturing outputs consist of many products that have different energy intensities. Thus, when energy prices vary, changes in the composition of aggregate output will take place concurrently with factor substitution that occurs within the production of each product. As a result, it is not possible for researchers to sort out these effects with aggregate data. Solow concludes that:

> "*[E]stimates of factor substitutability based on aggregate data are misleading because they capture more than simply technological substitution. On this view, none of the various empirical measures of factor substitutability is correct; they are not measuring what they want. Factor substitution is a micro economic phenomenon, and is best examined by looking at microeconomic data.*" (J. Solow, 1987, p. 612)

In a similar vein, Miller (1986) points out that, at aggregate levels (e.g., three- or two-digit industry groups which are mixtures of many industries), as energy prices change product mix substitution effects dominate the true factor substitution effects. Consequently, elasticity of substitution estimates based on aggregate cross-section data are most likely to be biased upward, while those based on aggregate time-series data

are most likely to be biased downward. For cross-section data, product mix differs among states, regions, and countries because of regional comparative advantages: energy prices, for example, are cheaper in some states than others and energy-intensive products are often produced where energy costs are lowest. Thus, cross-section data at high levels of aggregation will overestimate the degree of technical substitution between energy and other inputs. For time-series data, Miller argues that, among other things, as energy prices rise, prices of products (in particular, energy-capital intensive products) also rise. This will reduce the demand for these products, lower their production and hence the demand for factor inputs including capital and energy. Thus energy price changes cause systematic change in output composition between energy-capital intensive industries and other industries, making it appear that energy and capital are complements in the production process.

Perhaps more fundamentally, other economists have contended that the Allen partial elasticity of substitution (AES) -- which has been used as a standard statistic reported in empirical studies on capital-energy substitution -- does not measure the ease of substitution. Blackorby and Russell (1989) formally showed that the Morishima elasticity of substitution (MES) (Morishima, 1967), rather than the AES, is an exact measure of factor substitution, in terms of adjustment along an isoquant.

.   In spite of its theoretical superiority, the MES has been rarely used for measuring factor substitution. Relatively few published studies used the MES in their empirical work. Ball and Chambers (1982) used both the AES and MES to measure factor substitution in the U.S. meat products industry. They found that energy and capital are Allen complements, but Morishima substitutes. Sickles and Streitwieser (1992) estimated elasticities of substitution among inputs in the U.S. interstate natural gas pipeline industry and found that energy and capital (compressors and pipelines) are both Allen and Morishima substitutes. Nguyen and Reznek (1993) also used both the AES and MES to measure factor substitution in five 4-digit industries. They found that capital and materials (including energy) are substitutes by both measures. Recently, Thompson and Taylor (1995) used the estimates of price elasticities of demand reported in eight previous studies to calculate the corresponding MES estimates. They found the mean of the MES between capital and energy equal to 1.01 with a variance of 0.54, whereas the mean of the AES equals 0.17 with a variance of 20.60. They concluded that energy and capital are substitutes. While these studies are useful, their findings are subject to certain limitations. The results of the first three studies are limited to a few individual industries, while Thompson and Taylor's results are simple means of estimates based on data varying

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widely in geography, levels of aggregation, and model
specifications.[1]

In this paper, we revisit the issue of energy-capital
substitution with more appropriate data and a theoretically
correct measure of elasticity of substitution. More
specifically, we use micro (plant level) data with a four factor
translog production model to estimate Morishima elasticities of
substitution among the factor inputs -- with special emphasis on
the elasticity between energy and capital. For comparison, we
also estimate the corresponding cross-price elasticities of
demand, AES, and shadow elasticities. Our model is estimated
using a sample of nearly 12,000 U.S. manufacturing establishments
taken from the newly available 1991 Manufacturing Energy
Consumption Survey (MECS) and the 1991 Annual Survey of
Manufacturers (ASM); both surveys are conducted by the U.S.
Bureau of the Census.

Our principal finding is that energy and capital are
substitutes. Our analysis indicates that the MES, rather than
the standard AES, is a correct measure of factor substitution.
Moreover, estimates for the AES are sensitive to varying data
samples and levels of aggregation. In contrast, MES estimates
are more stable across the different data sets -- except when 2-

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[1] The eight studies considered by Thompson and Taylor are: Anderson
(1981), Denny, et al. (1981), Griffin and Gregory (1976), Hudson and
Jorgenson (1974), Berndt and Wood (1975), Berndt and Khaled (1979), Walton
(1981) and Turnovsky, et al. (1982).

digit data are used and estimation problems associated with the small sample become overwhelming. Thus, our results support the views that (i) the MES is a better measure of factor substitution than the AES and (ii) micro data provide more accurate estimates of elasticities of substitution than those obtained from highly aggregated data.

The remainder of the paper is organized as follows. Section II discusses the empirical model and elasticity measurement. Data and estimation methods are described in Section III. Section IV reports and discusses the results. Section V contains concluding remarks and a plan for future research. Finally, the Data Appendix describes in more details the data set and variable construction.

II. MEASURING FACTOR SUBSTITUTION

A. Production Function Model

Elasticities of substitution among production inputs can be obtained from estimating either a production function or its dual cost function. While previous studies on capital-energy substitution often derived their elasticities of substitution from a cost function, we choose to apply a production function in our analysis. This is because data on input prices -- required

for the estimation of a cost function -- are not available at the
plant level.[2]

We assume that there exists a production function that
relates output and input such that

$$Q = F(X, Z), \tag{1}$$

where Q represent output, X is a vector of inputs, and Z is a
vector of other relevant explanatory variables.

If Q is homogeneous of degree λ, then

$$F(X, Z)r^{\lambda} = F(rX, Z), \tag{2}$$

where λ is a constant and r is any positive real number.
Assuming cost minimization and using the generalized Euler's
theorem, we can derive the following cost share equation system:

$$\begin{aligned} S_i &= f_i / \lambda F, \\ &= (1/\lambda)(\partial lnQ/\partial lnX_i), \end{aligned} \tag{3}$$

where $f_i = \partial F/\partial X_i$.

For estimation we need a specific functional form for F.
Because we are interested in factor substitution in production,
it is most appropriate to use a functional form that does not
impose unnecessary restriction on the substitution relationship

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[2] There is no **a priori** reason for preferring the production function over
the cost function or vice versa. Empirically, however, Burgess (1975) found
that the translog production function specification is superior to the
translog cost function in terms of goodness of fit and smaller standard errors
of the parameter estimates.

among the factor inputs.   Following previous studies, we specify
the following four-factor translog production function

$$lnQ = \alpha_o + \sum_{i=1}^{4} \alpha_i lnX_i + \frac{1}{2}\sum_{i=1}^{4} \sum_{i=1}^{4} \beta_{ij} lnX_i lnX_j +$$

$$\alpha_{MU}MU + \sum_{k=1}^{140} \alpha_k IND + \sum_{r=1}^{9} \alpha_r REG,$$

(4)

where ln is the natural logarithm, Q is output, and X_i are the
factor inputs capital, labor, energy, and materials.   MU is a
dummy variable to identify whether the plant is owned by a
single- or multi plant firm.   Industry and geographic region are
represented by the class dummy variables IND and REG,
respectively.   Industry dummies are included in the model to
account for industry specific effects, including industry
specific energy price variations.   Geographic region is included
to accommodate region specific effects, particularly regional
differences in energy prices.

   Differentiating equation (4) with respect to each factor
input and assuming competitive input markets and cost
minimization, we derive the logarithmic marginal productivity
conditions, or cost share equations, of the following form:

$$S_i = \frac{1}{\lambda}(\alpha_i + \sum_{j=1}^{4} \beta_{ij} lnX_j),$$

(5)

where λ is the degree of homogeneity, or returns to scale, of the production function F.

B.   Elasticities of Substitution

Conventionally, the Allen partial elasticity of substitution (AES) and the cross-price elasticity of factor demand (CPE) are used to measure the substitution relationships among inputs in production.   The AES between input X_i and X_j is defined as[3]

$$\sigma_{ij} = \frac{\left|\bar{F}_{ij}\right|}{\left|\bar{F}\right|} \frac{\sum_{i=1}^{4} f_i X_i}{X_i X_j} \qquad \textit{for all i, j,} \tag{6}$$

where X_i is the ith input and f_i is the partial derivative of the production function F, with respect to X_i. $\left|\bar{F}\right|$ is the determinant of the bordered Hessian matrix $\bar{F}$ and $\left|\bar{F}_{ij}\right|$ is the cofactor associated with element f_{ij} in $\bar{F}$.   Within the context of a four-factor translog production function, the AES from equation (1) can be estimated using the formula

$$\sigma_{ij} = \lambda \frac{\left|G_{ij}\right|}{\left|G\right|}, \tag{7}$$

where λ is the returns to scale and $|G|$ is the determinant of the bordered Hessian matrix:

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[3] See Allen, 1938, p. 504.

$$G = \begin{bmatrix} 0 & \lambda S_K & \lambda S_L & \lambda S_E & \lambda S_M \\ \lambda S_K & \left(\beta_{KL}+\lambda^2 S_K^2-\lambda S_K\right) & \left(\beta_{KL}+\lambda^2 S_K S_L\right) & \left(\beta_{KE}+\lambda^2 S_K S_E\right) & \left(\beta_{KM}+\lambda^2 S_K S_M\right) \\ \lambda S_L & \left(\beta_{KL}+\lambda^2 S_K S_L\right) & \left(\beta_{LL}+\lambda^2 S_L^2-\lambda S_L\right) & \left(\beta_{LE}+\lambda 2 S_L S_E\right) & \left(\beta_{LM}+\lambda 2 S_L S_M\right) \\ \lambda S_E & \left(\beta_{KE}+\lambda 2 S_K S_E\right) & \left(\beta_{LE}+\lambda^2 S_L S_E\right) & \left(\beta_{EE}+\lambda^2 S_E^2-\lambda S_E\right) & \left(\beta_{EM}+\lambda^2 S_E S_M\right) \\ \lambda S_M & \left(\beta_{KM}+\lambda^2 S_K S_M\right) & \left(\beta_{LM}+\lambda^2 S_L S_M\right) & \left(\beta_{EM}+\lambda^2 S_E S_M\right) & \left(\beta_{MM}+\lambda^2 S_M^2-\lambda S_M\right) \end{bmatrix} \quad (8)$$

$\left|G_{ij}\right|$ is the cofactor associated with element g_{ij} in G, S_i is the actual factor input cost share, β_{ij} and λ are the estimated parameters of the production function (4).

Allen (1938) has shown that the price elasticities of factor demand (CPE) are related to the AES as follows

$$\eta_{ij} = \frac{\partial X_i}{\partial w_j} \cdot \frac{w_j}{X_i} = S_j \sigma_{ij}, \qquad \textit{for all } i, j, \qquad (9)$$

where $\acute{\eta}_{ii}$ and $\acute{\eta}_{ij}$ are the own and cross-price factor demand elasticities, and w_i and S_i are the ith factor's input price and cost share.

Before proceeding, some important properties of the above elasticities should be noted. First, both the AES and CPE are one-price-one-factor (OPOF) elasticities. That is, both elasticities measure the responsiveness of input i to a one percent change in the price of input j, all other prices and output held constant. Second, the cross AESs are symmetric (i.e., $\sigma_{ij} = \sigma_{ji}$), but the CPEs are generally not symmetric (i.e., $\acute{\eta}_{ij} \neq \acute{\eta}_{ji}$). Lastly, both the AES and CPE must have the same sign. A positive value of σ_{ij} or $\acute{\eta}_{ij}$ indicates that an increase in the

price of input *j* will lead to an increase in the demand for input *i*, indicating that the inputs are substitutes. Conversely, a negative value of the elasticities indicates the two inputs are complements.

Thus, it is clear that the AES is inferior to the CPE because the AES is more restrictive, due to the symmetry property, and it is less informative. Indeed, from (9) it is clear that the AES is simply a disguised CPE obtained by dividing the CPE by a cost share. Therefore, it does not have a clear interpretation. In spite of its shortcomings, the AES has been used as a standard statistic reported in empirical studies of factor substitution in production (e.g., see Berndt and Wood, 1975, Magnus 1979, and Turnovsky and Donnelly, 1984). Recently, researchers have begun to highlight the weaknesses of the AES. In particular, Blackorby and Russell (1989) show that the AES is uninformative: it does not measure the ease of substitution and provides no new information about factor shares. More important, they show that an alternative, the Morishima elasticity of substitution (MES), is an appropriate measure of factor substitution (or complementarity) because it is an exact measure of the curvature of the isoquant (or the ease of substitution). Thompson and Taylor (1995) argue that the MES is the preferred elasticity to measure the capital-energy substitutability for two reasons. First, the energy cost share is small relative to the

other input cost shares and "... *relatively small variations in energy utilization will induce sizable variations in estimates of the Allen elasticity of substitution.*"   Second, they argue that from a policy perspective, an elasticity which measures the response of the capital/energy ratio, rather than the change in capital, to price is more relevant.

Blackorby and Russell (1989) show that the MES can be defined as

$$\sigma_{ij}^{m} = \eta_{ij} - \eta_{jj}, \qquad \text{for all } i, j; \ i \neq j. \tag{10}$$

Substituting (9) into (10), we can define the MES in terms of the AES, as

$$\sigma_{ij}^{m} = S_{j}(\sigma_{ij} - \sigma_{jj}), \qquad \text{for all } i, j; \ i \neq j. \tag{11}$$

Unlike the AES which is symmetric, the MES is not necessarily symmetric, in absolute value, or in sign. Consequently, in the case of more than two inputs, the classification of one input as a complement or substitute for another input will depend on which input price changes. From (11) it can be seen that because the own AES elasticity (σ_{jj}) is always negative, two inputs which are AES substitutes are also Morishima substitutes. However, the converse does not hold. A pair of Morishima substitutes may be complements by the AES measure.

Note that the MES (σ_{ij}^m) is a one-price-two-factor (OPTF)
elasticity, measuring the percentage change in the ratio of input
j to input *i* when the price of input *i* changes one percent.
Chambers (1988) shows that the MES can be modified to measure the
technical substitution between two inputs in response to changes
in their relative prices. He derives the following shadow
elasticity of substitution (SES):

$$\sigma_{ij}^s = \frac{S_i}{S_i + S_j}\sigma_{ij}^m + \frac{S_j}{S_i + S_j}\sigma_{ij}^m \tag{12}$$

where S_i and S_j are cost shares of input *i* and input *j*. Thus,
the two-price-two-factor σ^s is a weighted average of two MESs
where the weights are given by the relative cost shares of the
two inputs under consideration. An advantage of this elasticity
over the un-weighted MES, σ^m, is that it is symmetric and
measures the technical substitution between the two inputs to
changes in their relative prices.

III. DATA AND ESTIMATION PROCEDURES

A. Data

We utilized a new micro database recently available: the
1991 Manufacturing Energy Consumption Survey (MECS) conducted by
the U.S. Bureau of the Census. We use these cross-section data
simply because plant level time-series data are not available.

The 1991 MECS is a unique data set which provides, for the first
time, an excellent opportunity for examining energy-capital
substitution at the production unit (plant) level. While cross-
section data are subject to some limitations, they have certain
advantages for the purpose of this study. In particular, cross-
section data reflect technology and market conditions at a single
time period and thereby allow us to avoid the problem of
separating the effects of factor substitution from those of
technological change and changes in market conditions on
production. The data also eliminate other effects that time-
series data may capture such as dynamic adjustment due to changes
in relative prices and external shocks. Finally, our cross-
section data set, containing a large number of observations,
allows us avoid the problems and biases associated with small
samples used in most previous studies .

     The 1991 MECS is a plant level survey of over 14,000
manufacturing plants, collecting information on quantities and
expenditures of energy consumed in production for 37 energy
sources. The data on energy are exactly what we need for
estimating production function that includes energy as a factor
of production (see Solow, 1987). Although the MECS surveys less
than 10 percent of the manufacturing establishment universe, the
sample accounts for approximately 35 percent of total employment
and 55 percent of shipments of the manufacturing universe. On a

weighted basis, the survey covers 80 percent of total employment and 90 percent of shipments of the U.S. manufacturing sector.

The 1991 MECS was designed to generate estimates on energy consumption for all the 20 two-digit major groups in manufacturing and 42 three- and four-digit industry groups which meet one of the following criteria: i)   energy-intensive production; or ii) high-growth industries such as computers and medical instruments; or iii) industries with identifiable policy interest or conservation opportunities, as listed in Table A1 of the Appendix.   Thus the SIC category is the single most important classification variable in the MECS data.   The probability of selection is proportional to an energy measure of size. Therefore large plants have a greater probability of being in the sample than small plants.

While the MECS provides excellent data for energy analysis, it does not collect data on outputs and non-energy inputs such as capital, labor and materials that are required for estimating a production function.   Fortunately, data on outputs and non-energy inputs and related variables at the plant level can be obtained from the 1991 Annual Survey of Manufacturers (ASM).   Among other things, the ASM contains data on total value of shipments, inventories, book value of capital assets (buildings and structures, and machinery), employment (numbers of production workers, non-production workers and production worker hours),

total salaries and wages, and expenditures for parts, materials and contract work. These data allow us to construct data on outputs, capital, labor, and material inputs. Data on energy input are taken directly from the MECS.

Both the MECS and the ASM contain common plant and firm identification numbers which facilitate plant level matching of the MECS and the ASM data. After matching the two data sets and omitting plants with missing data or non-positive output and input values, we have 11,520 plant observations in our final data set. (For a more complete data description, see the Data Appendix).

Sample means for the data used in estimation are reported in Table 1. The first three columns show the variable means from the full sample. Weighted and unweighted statistics (columns 1 & 2) differ because of the sample design. The un-weighted mean values in column (2) illustrate the sample selection bias toward larger, energy intensive plants relative to the manufacturing universe, as represented by the weighted means in column (1). Column(3) shows variable means for two-digit industry group aggregates based on the full sample.

Column (4) differs from column (1) in that the latter reports the means based on only 3,637 plants sampled from the 40 selected energy-intensive four-digit industries, whereas the former shows the means based on the full working sample. Column

(5) reports the means from the aggregation of these 40 industries to the four-digit level. The three-digit data in column (5) are derived by aggregating the 40 industries to the three-digit level.

   B.   Estimation Procedures and Hypothesis Tests

   The translog production function (4) is assumed to be symmetric and homogeneous of degree λ. Therefore, the following standard restrictions are imposed in the estimation:

$$\sum_{i=1}^{4} \alpha_i = \lambda, \quad \sum_{i=1}^{4} \beta_{ij} = 0, \quad \sum_{j=1}^{4} \beta_{ij} = 0, \quad and \quad \sum_{i=1}^{4}\sum_{j=1}^{4} \beta_{ij} = 0, \tag{13}$$

Monotonicity and convexity are not imposed, but will be tested for after estimation. We append a random disturbance term u_i to the production function and to each share equation, $i = K, L, E, M$, and assume the resulting disturbance vector $u = \{uk, u_L, u_E, u_m\}$ is multivariate normally distributed with mean vector zero and constant covariance matrix.

   Since the cost shares sum to one, the disturbance covariance matrix of the share equation system (5) is singular. Therefore, the material cost share equation is dropped from the estimation. The resulting estimates are invariant to the equation dropped if a maximum likelihood estimation procedure is used. We use the full information maximum likelihood method (FIML) to jointly

estimate the production equation (4) and three of the four cost

share equations (5).[4]

Our primary focus in this paper is on elasticities of

substitution; however, because these elasticities are derived

from the parameter estimates of the model, it is informative to

test whether or not the production function employed here

adequately describes U.S. manufacturing production technology.

For the purposes of this study, we restrict ourselves to the

following three hypothesis:

(i) The translog function, rather than the Cobb-Douglas

function is an adequate description of U. S. manufacturing

production technology.

(ii) The material input is weakly separable from other

inputs and may be omitted from the production function.

(iii) The U.S. manufacturing production function is

homogeneous of degree 1 (i.e., $\lambda = 1$).

Hypothesis (i) imposes global separability which implies

that the AES between any two inputs in the production equals one.

This is equivalent to testing whether all the second-order terms

of the translog function are equal to zero (i.e., $\beta_{ij} = 0$ for all i and j).

If this restriction is satisfied then the translog production

function reduces to a logarithmic Cobb-Douglas production

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[4] Diewert (1974) suggests that one should include the translog
production function (or cost function) with the cost share equations for
efficient estimation.

function. Hypothesis (ii) is equivalent to requiring $\sigma_{KM} = \sigma_{LM} = \sigma_{EM}$ = 1. If this condition is satisfied then the value-added KLE production model such as the one in Griffin and Gregory (1976) should not be reject as a proper specification. In view of the debate about the gross-output KLEM model versus the value-added KLE model (e.g., see, Berndt and Wood, 1981 and Griffin, 1981), this test is important. Finally, hypothesis (iii) states the production function is characterized by constant returns to scale (CRTS). That is, $\lambda = 1$. This hypothesis test is important because most previous studies of energy-capital substitution were based on the assumption of CRTS.

The above hypotheses can be tested based on the values of the L-statistics which are equal to two times the difference of the logs of the likelihood functions of the restricted and unrestricted models. The L-statistic is asymptotically distributed as a χ^2 variable with degree of freedom equal to the number of restrictions.

To test whether or not the model parameter estimates, and hence the estimated elasticities of substitution, are sensitive to levels of data aggregation, we estimate the model (and the associated elasticities) using plant level data and data aggregated at four-, three-, and two-digit SIC levels and compare the results. If aggregation biases exist, we would expect that estimates of elasticities of substitution between capital and

energy based on data aggregated at higher levels of aggregation would be larger than those based on data aggregated at lower levels of aggregation (see Miller, 1986).

Our model estimation is based on weighted data, using the MECS sample weights, with one exception. We also estimate the model with the unweighted, full sample to illustrate the bias in the sample design.

IV.   EMPIRICAL RESULTS

A.   The Estimated Production Functions:

Before examining the estimates, it is informative to know whether or not the underlying production function is "well-behaved". A well-behaved production function requires that output increases monotonically with all inputs and its isoquants are strictly quasi-concave. Monotonicity implies that all the estimated cost shares of inputs are non-negative. The concavity condition is satisfied if the bordered Hessian of first and second partial derivatives is negative semidefinite. Our base model (weighted plant-level sample) meets the regularity conditions fairly well. In terms of monotonicity, estimated capital, labor, energy, and material factor shares are positive for 99.6, 97.4, 95.9, and 98.9 percent of the observations, respectively. Concavity conditions are met for all but 372 (3.2

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percent) of the 11,520 observations. Except for the production

function estimated using two-digit data, for all other estimated

productions, there are no statistically significant violations of

these conditions when evaluated at the means.[5] When using two-

digit data, the concavity is violated even it is evaluated at the

means of the variables.

We report the parameter estimates (and the associated

standard errors) from the model in Table A2 to illustrate their

statistical significance, although the individual estimates have

little intuitive value because of the complexity of the translog

form. In the Table, columns (1) - (3) present the estimates

based on the full sample (weighted, unweighted and two-digit

aggregate), while columns (4) - (6) show the estimates based on

the 40 industry subsample (weighted, four- and three-digit

aggregates).[6] From the Table, it is clear that the estimates

based on micro data are much more precise than those based on

aggregate data in view of smaller standard errors. Except for

the estimate for β_{LE} in column (3), all the estimates based on

micro data are highly significant, while those based on aggregate

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[5] While we find no statistically significant violation of
regularity conditions when evaluated at the means of the variables,
these conditions are not satisfied at a number of data points (less
than 5 percent of the observations). However, Wales (1977) noted
that the rejection of either the monotonicity or the concavity
condition does not necessarily imply that the elasticity estimates
are incorrect.

[6] When aggregating the 40 industry subsample to the two-digit level,
there are too few observations to estimate the production model.

data are far less significant. In particular, the estimates for $\acute{\alpha}_E$, β_{KL}, β_{KE}, and β_{LE} are insignificant when using data aggregate at all three levels of aggregation. This suggests that the elasticities estimated using micro data are much more robust and hence more reliable than those obtained from aggregate data.

B. Test Results:

Table 2 reports the results of the L-statistics and χ^2 tests for the three hypothesis tests discussed above. The results strongly reject the Cobb-Douglas form in favor of the translog production function as an appropriate description of U.S. manufacturing production technology. The hypothesis that material inputs are separable is also strongly rejected. This result implies that the value-added KLE model is not statistically accepted as the appropriate production model. The KLEM model is a more appropriate one and hence the elasticities of substitution derived from them are more accurate. Finally, even though our estimated returns to scale is very nearly unity (1.004), we statistically reject the hypothesis of constant returns to scale; although, the assumption of constant returns to scale does not impact the resulting elasticities significantly.

C. Factor Substitution

Because our main interest is in the substitution relationship between capital and energy, we report only the estimated elasticities associated with these two inputs in Table

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3. (A complete set of elasticity estimates are reported in Table

A3 of the Appendix.) The Table shows estimates of four types of

elasticities associated with energy and capital: price

elasticities of demand ($\acute{\eta}$), AES (σ), MES (σ^m) and weighted MES (or

shadow elasticity, σ^s). All these elasticity estimates are

evaluated at the sample mean. We use actual cost shares, rather

than estimated shares to evaluate the AES and shadow

elasticities.[7] Columns (1) - (3) of the Table report the

estimated elasticities based on the full sample (weighted,

unweighted, and two-digit aggregates), while columns (4) - (6)

show estimates based on the 40 industry subsample (weighted,

four- and three-digit aggregates).

The estimated elasticities in column (1) are evaluated based

on the model parameters estimated using the full sample in which

individual plants are weighted by their MECS sample weight.

These results suggest that both energy and capital are responsive

to changes in their own prices -- the own price elasticities of

energy and capital ($\acute{\eta}_{EE}$ and $\acute{\eta}_{KK}$) are -3.57 and -1.11. That is,

ceteris paribus, a one percent increase in energy prices leads to

a 3.57 percent decline in energy demand, whereas a one percent

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[7] Most previous studies evaluated elasticities of substitution at the
means of fitted shares.   However, Anderson and Thursby (1986) showed it is
more appropriate to use actual shares.   In particular, they found that "a
normal distribution for the AES (Allen elasticity of substitution) is
appropriate if the estimator uses the <u>means</u> of the <u>actual</u> factor shares." (p.
652)

increase in the price of capital causes a 1.11 percent decrease in the demand for capital input. The cross-price elasticity estimates ($\acute{\eta}_{ij}$) show a weak substitution relationship between energy and capital: a one percent increase in energy prices leads to a 0.02 percent increase in capital demand, while a one percent increase in the price of capital results in a 0.21 percent increase in the demand for energy. With these results one can conclude that energy demand is more elastic than the demand for capital and that capital and energy are weak substitutes. The results on the AES suggest the same conclusion, but as already mentioned above, the AES estimates do not provide any new information beyond what the cross-price elasticity of demand reveals about the substitution relationship between energy and capital. In fact, both of these elasticities are limited because they only measure how one input adjusts in response to a change in an input price.

In contrast, the MES gives information on relative input adjustments to changes in an input price. Its estimates in column (1) reveal a much stronger substitution relationship between energy and capital: other things being equal, a one percent increase in energy prices leads to a 3.59 percent increase in the capital energy ratio. However, this relationship is not symmetric: a one percent increase in the price of capital causes only a 1.31 percent increase in the energy capital ratio.

This asymmetry is due to the fact that the MES measures the responsiveness of input ratios to changes in different input prices. Finally, the weighted MES (shadow elasticity) shows the percentage adjustment in input ratios to changes in factor price ratios. The estimate for the shadow elasticity of substitution between energy and capital indicates that a one percent increase in the energy/capital price ratio (where both prices are allowed to change) lead to a 3.43 percent increase in the energy-capital ratio. Thus, based on the concept of Morishima elasticity, we conclude that energy and capital are strong substitutes.

Comparing the above results with those based on the unweighted sample reported in column (2), we find that the unweighted sample underestimates elasticities. In particular, the energy own price elasticity of demand and AES estimates are substantially smaller than those in column (1). Moreover, the unweighted estimates for cross-price elasticities and AESs become negative, though larger in magnitudes. This downward bias in the unweighted elasticities is due to the fact that the MECS is designed in such a way that the unweighted sample is biased toward larger and more energy-intensive relative to the manufacturing universe. These results are not surprising in view that energy-intensive plants are not as (energy) price responsive as other less energy-intensive plants. All estimates for the MES and shadow elasticities between energy and capital are positive

and are smaller in magnitude relative to those based on the weighted sample. Again, these estimates suggest that energy and capital are substitutes.

When we aggregate the sample to the two-digit level data, column (3), we find that elasticity estimates become erratic: the energy own elasticity estimates ($\acute{\eta}_{EE}$ and σ_{EE}) have the wrong sign. These results appear to supports Solow's assertion that elasticity estimates based on aggregate data are unreliable and often misleading. In fairness, we note that the erratic estimates obtained from two-digit data are in part due to the small sample size.[8]

Column (4) reports elasticity estimates based on a weighted sample of 3,637 plants sampled from 40 selected energy-intensive four-digit industries. These estimates are quite similar to those of the unweighted full sample, and are equal or smaller in magnitude. However, their magnitudes are consistently smaller than those obtained from the weighted full sample. Again, this reflects the composition of the subsample: drawn from energy-intensive production industries.

We now turn our discussion to the results based on aggregate data from the subsample. Examining the estimates in columns (5) and (6), two important findings emerge with clarity. First,

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[8] We have only 20 observations in the sample of two-digit data. We note that this small sample size is not unique. Turnovsky and Donnelly (1984), for example, also used a sample of 20 observations for the Australian iron and steel industry.

energy and capital are substitutes by any measure at the aggregate level, but are complements according to the cross price demand and AES elasticities from the plant level data in column (4). Second, aggregated data generally yields higher estimates of elasticities of substitution than the micro data do. This finding supports the contention that aggregate cross-section data yield upward biases in the estimates of the substitution between energy and capital (Miller, 1986). This bias appears to be more severe in the estimates for the cross-price elasticity of factor demand and the AES than in the MES and shadow elasticities.

Finally, we note that, relative to the Morishima elasticities, the restricted cross-price elasticity of demand consistently underestimates the degree of substitution between capital and energy regardless of levels of aggregation. For example, with plant level data from the full sample (column 1), the value of $\acute{\eta}_{KE}$ is 0.02, while that of σ^m_{KE} and σ^s_{KE} are 3.59 and 3.43, respectively. Similar differences occur for all other models.

D. DISCUSSION

Our empirical results can be summarized into the following findings. First, we find that the translog, rather than the Cobb-Douglas production function, is the proper description of U.S. manufacturing production technology. Second, the assumption

that the material input is separable from other inputs is
strongly rejected. Third, the assumption of constant returns to
scale is rejected. Fourth, among the four factor inputs, energy
is the most price-responsive, while capital is the least price-
responsive. Fifth, energy and capital are weak Allen substitutes
for the manufacturing sector as a whole (but may be weak
complements for energy intensive plants), but they are strong
Morishima substitutes. Finally, data aggregated at higher levels
introduce larger biases in the estimates of factor substitution
elasticities.

The first finding is not surprising and is consistent with
previous evidence that the translog functional form is superior
to Cobb-Douglas form in describing production technologies. This
is particularly true when one uses a production (or cost)
function to study factor substitution because the Cobb-Douglas
function imposes strong restrictions on the substitution
relationships among factor inputs. Indeed, all studies that
focus on testing for these restrictions have unanimously rejected
the Cobb-Douglas functional form in favor of more flexible
functions, such as the translog. For example, Berndt and Wood
(1975), using times-series U.S. manufacturing data, Norsworthy
and Malmquist (1983), using time-series U.S. and Japanese
manufacturing data, and Turnovsky and Donnelly (1984), using
cross-section Australian iron and steel data, strongly reject the

validity of the Cobb-Douglas functional form. Using U.S. manufacturing plant level data, Nguyen and Reznek (1993) also strongly rejected the Cobb-Douglas specification.

An important implication of the second finding is that the value-added (KLE) model, such as the one used by Griffin and Gregory (1976), is not proper for studying factor substitution. This finding is important because it is a major issue in the capital-energy substitution/ complementarity debate (e.g., see Berndt and Wood, 1981 and Griffin, 1981). More specifically, Hudson and Jorgenson (1974), Berndt and Wood (1975), and Berndt and Khaled (1979), employed the translog KLEM model to estimate the AESs among factor inputs in U.S. manufacturing. They found σ_{KE} negative, having values ranging from -1.39 to -3.32 and concluded that energy and capital are complements. In contrast, Griffin and Gregory (1976) used international pool cross-sectional data to estimate a value-added KLE model. They found σ_{KE} positive with values from 1.02 (Belgium) to 1.07 (U.S.) and concluded that capital and energy are substitutes. This led to the subsequent debate.

In an attempt to reconcile these controversial results, Griffin (1981) argues that studies using time-series data, such as that by Berndt and Wood (1975), capture short run factor substitution relationships, while cross-sectional studies capture long run relationships. While this view is supported by

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estimates of some dynamic models such as the work by Pindyck and Rotenberg (1983), other studies such as those by Stapleton (1981), Morrison and Berndt (1981), and Kulatilaka (1985) found that capital-energy complementarity becomes stronger in the long run.

Berndt and Wood (1979,1981) assert that the condition of weak separability of the material input from other inputs imposed by the value-added KLE model is strongly rejected and therefore the KLE specification is not suitable for studying factor substitution. Further, Berndt and Wood show that even if the KLE model is valid, it essentially estimates "gross elasticities", while the KLEM model estimates "net elasticities" and that "gross" and "net" elasticities of substitution can have opposite signs. Thus, the fact that capital and energy are "gross" substitutes, but "net" complements is not theoretically inconsistent. Our findings that material input is not separable from other inputs and that capital and energy are Allen (weak) complements appears to support Berndt and Wood's view. On the other hand, our results do not support Griffin's long run versus short run argument because our cross-section data do not always show (Allen) substitution relationship between capital and energy. There is a composition effect: when the cross-section micro data are dominated by energy intensive plants, we find capital and energy can be complements.

Our finding that energy is the most price-responsive among the four inputs, while capital is the least price-responsive is expected and is consistent with previous studies.[9] An important policy implication of this finding is that imposing a tax on energy would be an effective policy to conserve energy.

Our last two findings are directly relevant to the capital-energy substitution/ complementarity debate: our robust estimates based on a large sample of 11,520 manufacturing plants show that capital and energy are substitutes. We also find aggregate data and sample selection biases in elasticity estimates. These biases are more severe in the estimates for the cross-price elasticity of demand and the partial AES than in those for the MES. For example, our estimates for σ_{KE} range from -1.15 (column 2) to 3.76 (column 5), while those for σ_{KE}^{s} having values from 2.09 (column 4) to 3.43 (column 1). These result are in agreement with the finding by Thompson and Taylor (1995) that estimates for the AES between capital and energy reported in the literature scattered around zero with values ranging from -22.40 to 18.60. In contrast, using the reported estimates of price elasticities of demand, to calculate values for MES, they found the mean values for σ_{KE}^{m} and σ_{EK}^{m} are 1.01 and 0.76, which are qualitatively consistent with our estimates of 3.59 and 1.31. Thus, our results, together with Thompson and Taylor's survey,

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[9] See Thompson and Taylor (1995) for a survey of previous results.

show that the controversy surrounding the issue of capital-energy
substitution/complementarity is a result of previous studies that
use a wrong measure of elasticity of substitution: the partial
AES does not measure the ease of factor substitution and its
estimates are highly sensitive to varying data sets.

V.   SUMMARY AND CONCLUSIONS

In this paper, we revisit the empirical issue of capital-
energy substitutability-complementarity. Our approach differs
from earlier studies in that we use micro data (rather than
aggregate data) to estimate the theoretically correct Morishima
elasticity of substitution (rather than the partial Allen
elasticity). Plant-level data are unquestionably more
appropriate for measuring technical substitution relationships
among factors of production, while the Morishima elasticity of
substitution has been proven as an exact measure of factor
substitution in terms of adjustments of inputs along an isoquant
in response to factor price changes.

Our principal finding is that capital and energy are
substitutes in U.S. manufacturing production. We also find that
micro data provide more accurate elasticity estimates than those
obtained from aggregate data. Our results appear to resolve the
long standing conflict among the estimates reported in previous

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studies regarding the substitution relationship between capital and energy.

In concluding, we note that our results are based on cross-section data for a single year. It is important to examine the robustness of these results by using time-series micro data. In particular, the data used should include the years in which there were substantial energy price increases such as those in 1973 and 1979.

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TABLE 1
MEAN VARIABLE VALUES

Variable	Full Sample			40 4-Digit Industry Subsample		
	Micro Data		Agg. Data	Micro Data	Aggregate Data	
	Weighted	Unweighted	2-Digit	Weighted	4-Digit	3-Digit
	(1)	(2)	(3)	(4)	(5)	(6)
N	11520	11520	20	3637	40	27
Output ($Million)	19.61	116.42	131,699.26	101.79	16,485.13	27,592.23
Capital ($Million)	7.33	50.40	50,809.54	52.89	8,566.38	14,480.59
Labor (Thousand Hrs)	253.40	1,063.29	1,773,166.43	617.53	100,012.67	174,740.09
Energy (Million Btu)	73.57	635.25	515,583.36	969.71	157,048.89	265,217.69
Materials ($Million)	9.67	59.84	68,373.13	60.24	9,756.42	17,198.89
Capital Cost Share	0.25	0.26	0.27	0.27	0.29	0.25
Labor Cost Share	0.34	0.25	0.22	0.22	0.17	0.18

Energy Cost Share	0.02	0.03	0.02	0.04	0.07	0.07
Material Cost Share	0.39	0.46	0.49	0.46	0.48	0.50
Multi-Unit Firm		0.83		0.74		
Total Employment	106	452	742,029	271	43,921	76,985

TABLE 2
HYPOTHESIS TEST

	Cobb-Douglas	KLE;M	CRTS
Restrictions	$\beta_{ij} = 0$; $i \neq j$	$\sigma_{iM} = 1$; for all i	$\lambda = 1.0$
Critical Value	$\chi^2_{(99,10)} = 23.2$	$\chi^2_{(99,4)} = 13.3$	$\chi^2_{(99,1)} = 6.6$
Test Statistic	41,982.2	31,967.7	13.2

[1] Likelihood Ratio Test: L = -2(log likelihood$_r$ - log likelihood$_u$), where the
    restricted and unrestricted models are estimated on the weighted full sample

TABLE 3
CAPITAL-ENERGY ELASTICITIES[1]

Elasticity	Full Sample			40 4-Digit Subsample		
	Micro Data		Agg Data	MicroData	Aggregate Data	
	Weighted	Unwtd	2-Digit	Weighted	4-Digit	3-Digit
	(1)	(2)	(3)	(4)	(5)	(6)
Price Demand						
η_{KK}	-1.105	-1.122	-0.668	-1.060	-1.742	-1.987
η_{EE}	-3.574	-2.802	14.529	-2.922	-2.079	-2.858
η_{KE}	0.015	-0.040	1.145	-0.014	0.048	0.250
η_{EK}	0.208	-0.301	14.778	-0.087	0.200	0.953
Allen						
σ_{KK}	-4.457	-4.282	-2.514	-3.927	-6.072	-7.838
σ_{EE}	-195.482	-80.744	705.176	-66.124	-30.388	-43.047
σ_{KE}	0.838	-1.149	55.578	-0.321	0.696	3.760
Morishima						
σ^m_{KE}	3.589	2.762	-13.384	2.908	2.126	3.107
σ^m_{EK}	1.313	0.821	15.447	0.973	1.942	2.940
Shadow						
σ^s_{KE}	3.433	2.535	-11.310	2.635	2.091	3.072
Capital Share	0.248	0.262	0.266	0.270	0.287	0.253
Energy Share	0.018	0.035	0.021	0.044	0.068	0.066
N	11520	11520	20	3637	40	27

[1] Based on actual cost shares.

Data Appendix

The Manufacturing Energy Consumption Survey (MECS) collects energy production, consumption, and expenditure data from approximately 14,000 manufacturing plants.[10] The MECS sample is a subset of the ASM, which is a representative sample of over 55,000 manufacturing plants drawn from the approximately 350,000 plants in the manufacturing universe. The 1991 MECS was designed to yield estimates on energy consumption for the entire manufacturing sector of the economy, as well as all the 20 two-digit major groups. In addition, the sampling design supports statistics for two three-digit industry groups, and 40 four-digit industries which meet one of the following criteria: i) energy-intensive production in manufacturing; or ii) high-growth industries such as computers and medical instruments; or iii) industries with identifiable policy interest or conservation opportunities. The probability of selection is proportional to an energy measure of size. Thus, while all 3- and 4-digit manufacturing industries are not sampled sufficiently to generate aggregate statistics, the industries which would be most heavily

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[10]   The basic unit of data collection for the MECS and ASM is the manufacturing establishment. An establishment is defined as a single physical location engaged in one of the categories of industrial activity in the Standard Industrial Classification (SIC) System. Manufacturing establishments are often referred to as plants, factories, or mills. This paper uses the term plants.

impacted by changing energy conditions are well represented.

Table A3 lists the SIC and industry breakdown of the MECS survey.

We use two types of information from the MECS. For quantity
of energy, we use the "quantity produced offsite and consumed as
fuel" measure, as this is designed to be the equivalent to "cost
of fuels" collected in the ASM. For energy prices, we use the
"total expenditures, including delivery charges", divided by the
"quantity purchased by and delivered to". Quantity of fuel is
reported in a variety of measures, such as Btu, tons, cubic feet,
gallons, or barrels, depending on the type of fuel. We convert
the various physical units to millions of Btu in order to sum
over types of fuel. Table A4 lists the reported units and
conversion formulas, by type of fuel, used in this paper.

Data for all non energy inputs, output, plant location and
primary industry are from the 1991 Annual Survey of Manufacturers
(ASM). The ASM is conducted during non census years to provide
information of economic characteristics for the manufacturing
sector.[11] Approximately 55,000 establishments from the universe
of over 350,000 are surveyed. A new ASM panel is drawn every
five years. The probability of being selected for the ASM is
based on payroll and shipments size. Generally, only companies
with more than 20 employees are selected for the ASM sampling
frame. Large plants are surveyed every years with certainty.

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[11]   A complete census is conducted in years ending in "2" or "7".

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The MECS and ASM data sets have two common plant identifiers which are used to link the two data sets: identification number and tab number. The identification number is a 10 digit number. For plants which are part of a multi-unit firm, the first six digits identifies the parent firm; the remaining four digits identifies the specific plant. For single-unit firms (plants), the entire ten digit number is unique to that plant. When a plant is sold, or its status from single to multi-unit firm ownership (or the reverse) changes, the identification number changes also. Linking the MECS with the ASM via the identification number fails in a small number of cases because of changes in ownership or firm status which are reflected in one data set, but not in the other, due to differences in the timing of processing and updating. When no match is found using the identification number, we rely on the six digit tabulation number, which for ASM plants, is assigned to a specific physical location. We are able to link over 99 percent of the MECS plant to the ASM.

The nature of the data collected in the ASM places some constraints on the measurement of production inputs and outputs. Economic information in the ASM is generally reported in thousands of dollars. Physical quantities of outputs and non labor inputs and prices are not collected. Output is defined as the total value of shipments, adjusted for changes in inventories

of finished goods and work in progress. One advantage of using cross-section data is that we do not need individual plant prices or deflators.

As information on capital services, vintage, and intensity of use are unavailable, capital is measured by the sum of book value of capital equipment and structures, as information on physical capital is unavailable. Concerns about the obvious capital measurement problem are offset by Doms' (1996) and Dwyer's (1997) work with the Bureau's Longitudinal Research Database (LRD), which indicates book value is a reasonable proxy for physical capital.[12] In determining the expenditure share for capital, we assume zero economic profits and calculate the residual of value of shipments minus labor, energy, and materials expenditures.

Ideally, labor input would be measured by total number of employee hours. While the ASM includes data on number of production and nonproduction employees and production and nonproduction salaries and wages, it collects only total production workers' hours. Rather than assume all employees work a 2,000 hour year, we assume that relative wages are proportional to marginal productivity and calculate production worker

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[12] Doms (1996) constructed capital based on the perpetual-inventory method and compares this series with the book value series. The correlation between the two series for his sample of plants is above 0.90. Thus, the reported book value should be a reasonable proxy for the physical capital stock. Dwyer (1997) found that measures of productivity constructed from different measures of capital are highly correlated and that their association with alternative measures of economic performance is approximately the same.

equivalent hours for all employees. Total labor expenditures is equal to total salary and wages. Lastly, materials are measured by dollar expenditures for parts and materials and contract work.

20   Food and Kindred Products
 2011 Meat Packing Plants
 2033 Canned Fruits and Vegetables
 2037 Frozen Fruits and Vegetables
 2046 Wet Corn Milling
 2051 Bread, Cake, and Related Products
 2063 Beet Sugars
 2075 Soybean Oil Mills
 2082 Malt Beverages
21   Tobacco Products
22   Textile Mill Products
23   Apparel and Other Textile Products
24   Lumber and Wood Products
25   Furniture and Fixtures
26   Paper and Allied Products
 2611 Pulp Mills
 2621 Paper Mills
 2631 Paperboard Mills
27   Printing and Publishing
28   Chemicals and Allied Products
 2812 Alkalies and Chlorine
 2813 Industrial Gases
 2819 Industrial Inorganic Chemicals, nec
 2821 Plastics Materials and Resins
 2822 Synthetic Rubber
 2823 Cellulosic Manmade Fibers
 2824 Organic Fibers, Noncellulosic
 2865 Cyclic Crudes and Intermediates
 2869 Industrial Organic Chemicals, nec
 2873 Nitrogenous Fertilizers
 2874 Phosphatic Fertilizers
29   Petroleum and Coal Products
 2911 Petroleum Refining
30   Rubber and Misc. Plastics Products
 3011 Tires and Inner Tubes
 308 Miscellaneous Plastic Products, nec
31   Leather and Leather Products
32   Stone, Clay and Glass Products
 3211 Flat Glass
 3221 Glass Containers
 3229 Pressed and Blown Glass, nec
 3241 Cement, Hydraulic
 3274 Lime
 3296 Mineral Wool

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33   Primary Metal Industries
 3312 Blast Furnaces and Steel Mills
 3313 Electrometalurgical Products
 3321 Gray and Doctile Iron Foundries
 3331 Primary Copper
 3334 Aluminum
 3339 Primary Nonferrous Metals, nec
 3353 Aluminum Sheet, Plate, and Foil
34   Fabricated Metal Products
35   Industrial Machinery and Equipment
 357  Computer and Office Equipment
36   Electronic and Other Electric Equipment
37   Transportation Equipment
38   Instruments and Related Products
 3841 Surgical and Medical Instruments
39   Misc. Manufacturing Industries
```

Parameter	Full Sample			40 4-Digit Subsample		
	Micro Data		Agg Data	MicroData	Aggregate Data	
	Weighted	Unwtd	2-Digit	Weighted	4-Digit	3-Digit
	(1)	(2)	(3)	(4)	(5)	(6)
$\acute\alpha_o$	0.414 (0.007)	0.487 (0.014)	0.602 (0.285)	0.645 (0.017)	0.361 (0.167)	0.217 (0.229)
$\acute\alpha_K$	0.198 (0.001)	0.213 (0.002)	0.209 (0.108)	0.235 (0.002)	0.301 (0.066)	0.272 (0.094)
$\acute\alpha_L$	-0.094 (0.001)	-0.071 (0.002)	-0.046 (0.087)	-0.079 (0.003)	-0.083 (0.038)	-0.076 (0.052)
$\acute\alpha_E$	0.023 (0.0004)	0.010 (0.001)	-0.020 (0.020)	-0.005 (0.001)	-0.038 (0.037)	-0.067 (0.050)
$\acute\alpha_M$	0.876 (0.001)	0.841 (0.001)	0.848 (0.060)	0.839 (0.002)	0.825 (0.029)	0.881 (0.032)
β_{KK}	0.047 (0.0002)	0.053 (0.0002)	0.075 (0.033)	0.052 (0.0004)	0.112 (0.022)	0.111 (0.033)
β_{LL}	0.106 (0.0003)	0.094 (0.0005)	0.080 (0.024)	0.093 (0.001)	0.096 (0.010)	0.091 (0.016)
β_{EE}	0.013 (0.0001)	0.021 (0.0002)	0.019 (0.003)	0.026 (0.0002)	0.034 (0.010)	0.039 (0.014)
β_{MM}	0.169 (0.0001)	0.173 (0.0004)	0.215 (0.020)	0.170 (0.001)	0.197 (0.008)	0.201 (0.013)
β_{KL}	0.007 (0.0002)	0.005 (0.0003)	0.020 (0.027)	0.002 (0.0005)	-0.012 (0.011)	-0.007 (0.020)
β_{KE}	-0.001 (0.0001)	0.0005 (0.0002)	-0.002 (0.007)	-0.002 (0.0003)	-0.008 (0.012)	-0.018 (0.017)
β_{KM}	-0.053 (0.0001)	-0.058 (0.0003)	-0.092 (0.025)	-0.052 (0.0003)	-0.092 (0.010)	-0.085 (0.011)
β_{LE}	-0.004 (0.0001)	-0.003 (0.0002)	0.003 (0.005)	-0.0006 (0.0004)	-0.002 (0.008)	0.005 (0.011)
β_{LM}	-0.109 (0.0002)	-0.096 (0.0003)	-0.103 (0.008)	-0.094 (0.0005)	-0.081 (0.006)	-0.089 (0.005)
β_{EM}	-0.007 (0.0001)	-0.018 (0.0002)	-0.019 (0.006)	-0.024 (0.0003)	-0.024 (0.006)	-0.026 (0.006)

λ	1.004 (0.001)	0.993 (0.001)	0.991 (0.018)	0.991 (0.001)	1.004 (0.010)	1.010 (0.012)
Log Likelihood	51660.3	49383.8	177.3	14492.9	281.7	181.9
N	11,520	11,520	20	3,637	40	27

Standard errors are given in parentheses. All regression include industry and region dummy variables, except 2-digit model. All regressions using unweighted micro data also include a multi-unit dummy variable.

Elasticity	Full Sample			40 4-Digit Subsample		
	Micro Data		Agg Data	MicroData	Aggregate Data	
	Weighted	Unwtd	2-Digit	Weighted	4-Digit	3-Digit
	(1)	(2)	(3)	(4)	(5)	(6)
Price Demand						
η_{KK}	-1.105	-1.122	-0.668	-1.060	-1.742	-1.987
η_{LL}	-1.580	-1.929	0.888	-2.164	-3.426	-3.097
η_{EE}	-3.584	-2.802	14.523	-2.922	-2.079	-2.858
η_{MM}	-2.135	-2.053	4.970	-2.152	-2.815	-2.727
η_{KL}	0.011	-0.045	1.064	-0.010	-0.188	-0.161
η_{KE}	0.015	-0.040	1.145	-0.014	0.048	0.250
η_{KM}	1.079	1.207	-1.541	1.084	1.882	1.899
η_{LK}	0.008	-0.049	1.276	-0.012	-0.321	-0.230
η_{LE}	0.029	-0.065	2.145	-0.185	-0.134	-0.481
η_{LM}	1.543	2.042	-4.310	2.362	3.881	3.808
η_{EK}	0.208	-0.301	14.778	-0.087	0.200	0.953
η_{EL}	0.538	-0.456	23.082	-0.938	-0.329	-1.287
η_{EM}	2.828	3.560	-52.389	3.947	2.208	3.191
η_{MK}	0.678	0.691	-0.833	0.633	1.132	0.958
η_{ML}	1.326	1.093	-1.943	1.142	1.366	1.347
η_{ME}	0.131	0.270	-2.195	0.377	0.317	0.422
Allen						
σ_{KK}	-4.457	-4.282	-2.514	-3.927	-6.072	-7.838
σ_{LL}	-4.660	-7.869	-4.007	-9.678	-20.418	-17.427
σ_{EE}	-195.482	-80.744	705.176	-66.124	-30.388	-43.047
σ_{MM}	-5.412	-4.481	10.106	-4.656	-5.902	-5.428

σ_{KL}	0.034	-0.185	4.800	-0.044	-1.120	-0.909
σ_{KE}	0.838	-1.149	55.578	-0.321	0.696	3.760
σ_{KM}	2.733	2.635	-3.133	2.345	3.947	3.779
σ_{LE}	1.587	-1.862	104.121	-4.195	-1.961	-7.240
σ_{LE}	3.911	4.458	-8.763	5.108	8.139	7.580
σ_{EM}	7.167	7.771	-106.522	8.537	4.629	6.352
Morishima						
σ_{KL}^{m}	1.592	1.883	0.176	2.154	3.238	2.936
σ_{KE}^{m}	3.589	2.762	-13.384	2.908	2.126	3.107
σ_{KM}^{m}	3.214	3.260	-6.511	3.237	4.697	4.626
σ_{LK}^{m}	1.114	1.073	1.945	1.048	1.421	1.757
σ_{LE}^{m}	3.603	2.738	-12.383	2.736	1.945	2.377
σ_{LM}^{m}	3.678	4.095	-9.280	4.514	6.696	6.535
σ_{EK}^{m}	1.313	0.231	15.447	0.973	1.942	2.940
σ_{EL}^{m}	2.119	1.472	22.194	1.226	3.097	1.811
σ_{EM}^{m}	4.963	5.613	-57.359	6.099	5.022	5.918
σ_{MK}^{m}	1.783	1.813	-0.165	1.693	2.874	2.945
σ_{ML}^{m}	2.907	3.022	-2.831	3.307	4.792	4.445
σ_{ME}^{m}	3.705	3.072	-16.723	3.299	2.395	3.279
Shadow						
σ_{KL}^{s}	1.316	1.492	0.982	1.653	2.567	2.450
σ_{KE}^{s}	3.433	2.535	-11.310	2.635	2.091	3.072
σ_{KM}^{s}	2.335	2.234	-2.392	2.262	3.559	3.508
σ_{LE}^{s}	3.527	2.581	-9.443	2.487	2.278	2.223
σ_{LM}^{s}	3.263	3.396	-4.835	3.700	5.287	4.991
σ_{EM}^{s}	3.761	3.251	-18.357	3.543	2.725	3.587
N	11,520	11,520	20	3,637	40	27

[1] Based on actual shares.

TABLE A4
MECS Reporting Units of Quantity and
BTU Conversion, by Fuel Type

Type of Fuel	MECS Reporting Units	Conversion to Million Btu
Noncombustible		
Electricity	Thousand kilowatt hours	x 3.412
Steam	Million Btu	
Industrial Hot Water	Million Btu	
Combustible		
Solids		
Anthracite	Short Tons	x 27.751
Bituminous & Subbituminous Coal	Short Tons	x 22.407
Lignite	Short Tons	x 22.407
Breeze	Short Tons	x 24.800
Coal coke	Short Tons	x 24.800
Fluid Catalytic Cracking Unit Coke	Barrels	x 6.024
Unrefined or Green Petroleum Coke	Barrels	x 6.024
Calcined Petroleum Coke	Barrels	x 6.024
Roundwood	Million Btu	
Wood Chips, Bark, & Waste	Million Btu	
Biomass	Million Btu	
Waste Materials/Scrape	Million Btu	

Other Solids	Million Btu	
Gases		
Natural Gas	Thousand Cubic Feet	x 1.031
Acetylene	Million Btu	
Blast Furnace Gas	Million Btu	
Coke Oven Gas	Million Btu	
Hydrogen	Million Btu	
Waste & Byproduct Gases	Million Btu	
Other Gases	Million Btu	
Liquids		
Butane	Gallons	/42 x 3.821
Ethane	Gallons	/42 x 3.821
Propane	Gallons	/42 x 3.821
Other LPG & NGL Liquids	Gallons	/42 x 3.821
Diesel Fuel	Barrels	x 5.825
Distillate Fuel Oil	Barrels	x 5.825
Kerosene	Barrels	x 5.670
Motor Gasoline	Gallons	/42 x 2.253
Pulping or Black Liquor	Million Btu	
Residual Fuel Oil	Million Btu	
Waste Oils & Tars	Million Btu	
Other Liquids	Million Btu	

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