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Substitution of Imports for Domestic Labor, Capital and Materials in U.S. Manufacturing

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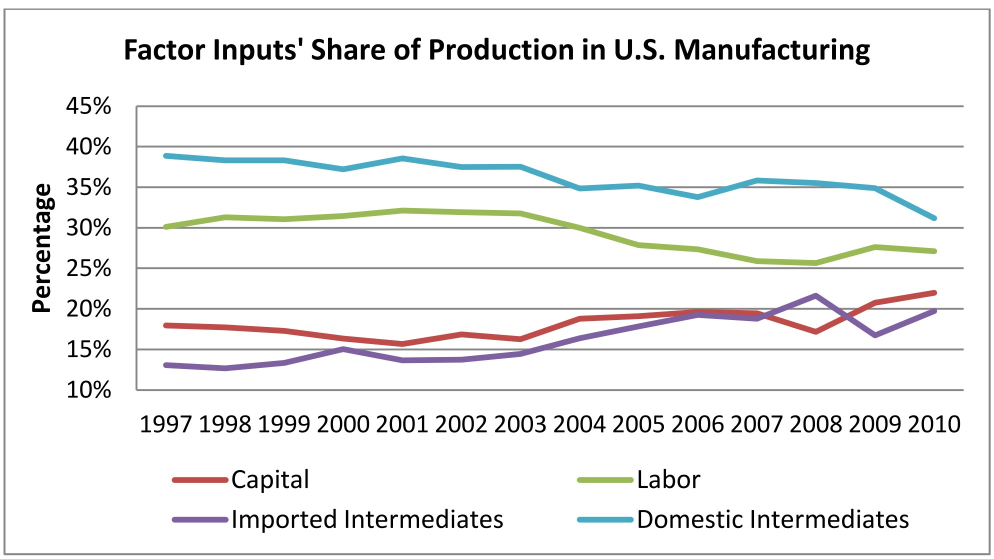
Section I. Introduction

Over the past few decades there has been rapid growth in the purchase of imported goods and services by U.S. manufacturing industries. Imported inputs as a share of the value of manufacturing production grew from 13.1 percent in 1997 to a peak of 21.6 percent in 2008. At the same time, domestic inputs' share of production declined from 38.9 percent to 35.5 percent, and labor's share also declined from 30.1 percent to 25.7 percent. Imports' share of production dipped to 16.7 percent in 2009, likely a consequence of the global recession, and then has begun to show growth, 19.7 percent in 2010. Labor and capital also seem to be showing signs of recovery, while domestic intermediate inputs continue to decline as a share of output coming out of the recession. This shift to imported, rather than domestic, inputs is most likely due to the fact that imported goods and services are often cheaper than their domestic counterparts. In an earlier article we found import penetration in US Manufacturing using a Solow [1958] residual-type growth accounting framework (Eldridge-Harper, 2010). From 1997-2006, we found that imported inputs accounted for about one-quarter of the labor productivity growth in the manufacturing sector. The current study estimates price elasticities of demand across factor inputs using a Translog cost function approach.



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A study by Houseman, Kurz, Lengermann, and Mandel [2010] discussed the often large "discount" enjoyed by firms as they shift to imported inputs and highlighted a possible measurement problem with price and productivity measures. Essentially the U.S. statistical agency measurement processes treat imported inputs in a separate category from domestic inputs, even in cases where the goods in question are similar or identical. Agencies neglect to "link in" any input price declines coinciding with such substitutions. Since price indexes are used to construct measures of intermediate inputs, these undetected price declines may have led to understatement of input growth and hence overstatement of productivity growth in manufacturing. Diewert and Nakamura [2010] developed formulas which can be used to adjust input prices and quantities for import price "discounts" with data on the size of the discount. Alterman [2010] proposed a survey of establishment purchasing agents, with the idea of collecting data on inputs source substitutions and any associated discounts in order to construct an input price index.[2]

The issue at hand is price-driven substitution. The point of departure for this paper is to note that, while there are not yet good data to measure and adjust official data for discounts associated with explicit substitution toward imports, it is possible that substitution has left a fingerprint in the official data. For example, cheaper imports should induce domestic producers to price their products more competitively. This, in turn, should offset some of the incentive to substitute toward imports. To the extent that this type of effect varies by commodity or by year, existing input price and quantity data may contain information about the elasticities of substitution, even though we may be missing some of the price change.

Translog production and cost function models, developed during the 1970s through the 1980s, are especially good tools for studying substitution. By estimating the parameters of such functions we can study how price changes drive factor substitution. The key feature of the Translog specification is that it includes a sufficient number of parameters to permit the estimation of elasticities of substitution. In effect, the Translog significantly relaxes the strong assumptions about the structure of production built into the Cobb-Douglas specification.

We use "factor augmenting" versions of the Translog model (models that include a time counter among explanatory variables) , which allow that part of substitution that is not explainable by price changes to be identified as "technical change bias". An apparent technology bias favoring imports could reflect data measurement errors, such as the unmeasured Houseman-type discounts. On the other hand, a bias favoring imports may reflect bona fide phenomena. For example, firms may have been learning how to take advantage of foreign resources, which would represent true technological advances enjoyed more by firms who adopt imports quickly than those who do not. Our prior expectation was that we would detect an import-using technical change bias, likely reflecting both measurement error and actual rapid advance in import-using know-how. While we do detect such a bias, and it is statistically significant, its magnitude is quite small.

[2] The BLS Office of Prices and Living Conditions is conducting research on the feasibility of such an index.

The main empirical challenge facing us in estimating Translog models was the short length of the annual time series data available to us on imported intermediates – only 14 observations from 1997-2010. In the literature, Translog models are typically estimated with 25-30 years of time series data. What we did have to help increase the number of observations was complete data for 18 manufacturing industries. In order to take advantage of these data to increase statistical degrees of freedom and reduce standard errors, we needed to find an effective way to utilize this detail.

We report two main sets of results in this paper – one for the total manufacturing sector and one for a panel of pooled industry data. We also attach several appendix tables with results for some alternative model specifications.

Section II. Factor-Augmenting Translog Unit Cost Function

The Translog production function was first estimated empirically by Christensen, Jorgenson and Lau [1973]. The Translog specification is a second-order Taylor series expansion of any continuous twice differentiable function of the given set of inputs. This function can be estimated using a set of share equations and quantities, that are derived by assuming constant returns to scale and that firms are perfectly competitive price takers in input markets. It follows that each input is paid the value of its marginal product and that each input's "output elasticity" will equal its share in revenue (the value of output.) Jorgenson subsequently used the Translog production model in many studies with various co-authors. Among the most important findings was that capital and energy were complements in production.[3]

Diewert [1976] demonstrated that there was a close relationship between Translog functions and the Tornqvist indexes used in growth accounting. The Tornqvist growth accounting aggregation tools, which are used by the Bureau of Labor Statistics (BLS) to produce multifactor productivity (MFP) statistics, make the same assumptions about input price-taking behavior and constant returns to scale as do the econometric Translog production and cost models. However, the Translog econometric models differ in that they permit the stochastic estimation of the parameters of the underlying production function. In the 1970's the index-based measures of MFP assumed that technological change was "neutral", that is, that it occurred at the same rate regardless of factor prices or factor proportions. However, Caves, Christensen and Diewert [1982] demonstrated that Tornqvist aggregation does not necessarily assume neutral technical change. Paralleling this, Jorgenson [1984] moved to a "factor augmenting" Translog production model which included a time counter among the explanatory variables, and also a "multifactor productivity" equation. This modeling effort sought to detect "factor biases" which could be present in the index-based MFP trends.[4] Jorgenson's earlier capital-energy complementarity finding was supplanted in his own research by a strong finding that slower productivity growth was closely associated with higher energy prices. Technological change was thus said to be "biased" toward energy or was said to be "energy using" (Jorgenson [1984]). The themes

[3] See for example Hudson and Jorgenson [1978].
[4] The factor augmenting model is described in the volume by Jorgenson, Gollop and Fraumeni [1987].

of substitution and technical change bias come up in our present work with a model that isolates imports, rather than energy, among intermediate inputs.

In this paper we use a cost function approach similar to that proposed by Hans Binswanger [1974]. According to Shepherd's lemma and the theory of duality, equivalent information about the production technology can be recovered from a cost function, under assumptions of constant returns to scale and that firms are perfectly competitive price takers in input markets; the cost function is said to be "dual" to the production function. Among reasons to prefer the cost function approach, Binswanger noted that input prices, rather than their quantities, are the explanatory variables in a cost function. This is consistent with the assumption of competitive price-taking behavior; firms react to the prices they face by setting quantities so as to minimize cost. Binswanger [1974] describes a Translog cost function model in which returns to scale and scale biases can be tested. We simplified this model by imposing constant returns to scale (CRTS) (as in the Jorgenson models) and hence confining ourselves to a "unit cost function". In addition, we enhanced the Binswanger formulation with time terms and time interactions, similar to the terms added by Jorgenson, Gollop, and Fraumeni [1987] in their "factor augmenting" production function.

Given our interest in imported intermediate inputs (I), we partition the set of inputs into labor (L), capital (K), intermediate from domestic sources (D) as well as "I". Our Translog cost function can be written as:

$$\begin{aligned} C_i = \exp(&a_0 + a_L \ln P_L + a_D \ln P_D + a_I \ln P_I + a_K \ln P^i_K + a_t t + \tfrac{1}{2} B_{LL} (\ln P_L)^2 + B_{LD} \ln P_L \ln P_D + \\ &+ B_{LI} \ln P_L \ln P_I + B_{LK} \ln P_L \ln P_K + B_{Lt} \ln P_L t + \tfrac{1}{2} B_{DD} (\ln P_D)^2 + B_{DI} \ln P_D \ln P_I + B_{DK} \ln P_D \ln P_K + \\ &+ B_{Dt} \ln P_D t + \tfrac{1}{2} B_{II} (\ln P_I)^2 + B_{IK} \ln P_I \ln P_K + B_{Lt} \ln P_{It} t + \tfrac{1}{2} B_{KK} (\ln P_K)^2 + B_{Kt} \ln P_{Kt} t + \tfrac{1}{2} B_{tt} t^2 \;) \end{aligned} \qquad (1)$$

Note that this specification imposes symmetry of the second-order parameters ($B_{ij} = B_{ji}\ \forall\ i,j$) as these represent 2^{nd} order partial derivatives which should be symmetric for a well behaved function. This model can be estimated in its first derivatives, which by Sheppard's Lemma are factor cost shares (S_j). The addition of the time interactive term, as used by Jorgenson, results in an additional multifactor-productivity change (dMFP) equation.[5] Assuming constant returns to scale (CRTS) and that factors are paid their marginal products, the model is estimated as:

$$S_L = a_L + B_{LL} (\ln P_L - \ln P_K) + B_{LD} (\ln P_D - \ln P_K) + B_{LI} (\ln P_I - \ln P_K) + B_{Lt}\, t + e_L \qquad (2)$$

$$S_D = a_D + B_{LD} (\ln P_L - \ln P_K) + B_{DD} (\ln P_D - \ln P_K) + B_{DI} (\ln P_I - \ln P_K) + B_{Dt}\, t + e_L \qquad (3)$$

$$S_I = a_I + B_{LI} (\ln P_L - \ln P_K) + B^i_{DI} (\ln P_D - \ln P_K) + B_{II} (\ln P_I - \ln P_K) + B_{It}\, t + e_L \qquad (4)$$

$$-dMFP = a_t + B_{Lt} (\ln P_L - \ln P_K) + B_{Dt} (\ln P_D - \ln P_K) + B_{It} (\ln P_I - \ln P_K) + B_{tt}\, t + e_L \qquad (5)$$

[5] Note that the explanatory variable in the last equation is the *negative* of the rate of growth of MFP. This specification preserves the correct signs when imposing symmetry of the second-order parameters involving time in the MFP equation with those in the share equations. For example B_{It} having a positive sign implies that import's share tends to increase over time, while also implying that MFP rises more quickly when imports become less expensive relative to other inputs.

Note that the CRTS assumption implies the following restrictions on the parameters: $\Sigma_i a_i = 1 \;\; \forall \;\; i \neq t$ and $\Sigma_i B_{ij} = 0 \;\; \forall \;\; i \neq t$ and for all j, including t. These parameter restrictions lead to our omission of a share equation for capital (S_K), as its parameters would be fully determined by the other equations. Also, the second restriction leads to the explanatory variables being expressed as differences in logs of each input's price and the log of capital's price. (The capital parameters and their standard errors are later recovered and used in calculating price elasticities. The results are invariant to which input is omitted in the estimation system.)

Binswanger [1974] demonstrated that elasticities of substitution among factor inputs can be calculated from the parameters of the Translog cost function. The Binswanger elasticity formulas were generalized slightly by Berndt and Wood [1975] to be functions of the second-order Translog-proper parameters (those not involving time) and the input factor shares[6].

The Allen partial elasticities of substitution (AES) for our factor augmenting Translog unit cost function are given by:

$$\sigma_{ii} = (B_{ii} + s_i^2 - s_i) / s_i^2 \qquad \text{for } i = L,D,I,K \quad \text{(Allen own elasticities of demand)} \tag{6}$$

$$\sigma_{ij} = (B_{ii} + s_i s_j) / s_i s_j \qquad \text{for } i \neq j \qquad \text{(Allen elasticities of substitution)} \tag{7}$$

While the AES are symmetric, due to the symmetry of the Translog parameters, the price elasticities of demand, ϵ_{ij}, are not. The rate of response of the ith factor to the change in price of the jth input is given by:

$$\epsilon_{ij} = \partial \ln x_i / \partial \ln p_i = s_j \, \sigma_{ij} \tag{8}$$

Section III. Estimation and Data Sources

We estimated our Translog system of linear equations with Zellner's [1962] technique of "Seemingly Unrelated Regressions" (SUR), which is a special case of the Generalized Linear Model.[7] This technique improves the efficiency of parameter estimates, relative to the ordinary least squares estimators, by taking account of, and eliminating, any covariances among the residuals of the four equations. The presence of any residual covariance would be evidence that the individual equations contain unspecified explanatory information about the other equations. The SUR method takes advantage of this by estimating the equations as a single system and arriving at more efficient parameter estimates that remove the covariances among the equation residuals. Importantly, for our model, the SUR simultaneous estimation allows the imposition of the cross equation parameter

[6] The Berndt-Wood formulation eliminates the need to recover the first-order translog parameters in order to calculate elasticities. This independence turned out to be a key to our paneling technique.

[7] We used Stata's 3-stage least squares estimation with the specification that all right-hand-side variables are to be treated as exogenous, thus enforcing a seemingly unrelated regression estimation.

restrictions associated with the symmetry of the second-order derivatives of the cost function --- six of our parameters appear in two equations each and we expect to obtain single estimates for each.[8]

Data on domestic factor shares, domestic factor prices and multifactor productivity were obtained from the BLS Productivity Program, while import data were provided by the Bureau of Economic Analysis (BEA). Domestic factor shares were constructed as current dollar value of factor costs divided by the current dollar value of production, as published June 26, 2012. For manufacturing, the BLS measures output for productivity statistics as the deflated value of production shipped to purchasers outside of the sector, including shipments to final users and establishments elsewhere within the private business sector.[9] This is a sectoral output concept, defining output as gross output excluding intra-sectoral transactions (sales or transfers between establishments within the sector or industry) — sales to final demand plus the intermediate goods sent to other industries. The manufacturing multifactor productivity indexes are based on sectoral output in an effort to avoid the problem of double-counting that occurs when one establishment provides materials used by other establishments in the same sector or industry. In the manufacturing sector, inputs include intermediate inputs, as well as capital and labor inputs[10]. Intermediate inputs (energy, materials, and purchased business services) are obtained from BEA's annual input-output tables. Tornqvist indexes of each of these three input classes are derived at the 3-digit NAICS level and then aggregated to total manufacturing. For manufacturing, materials inputs are adjusted to exclude transactions between manufacturing establishments to maintain consistency with the sectoral output concept.[11] [12] For the industry level data, output and intermediate inputs are adjusted to exclude transaction between firms in the industry, but include transaction across other manufacturing industries. All manufacturing data are available at the sector level, as well as for 18 NAICS 3-digit industries.

BEA produces import matrices as supplementary tables to the annual input-output (I-O) accounts. For each commodity, the import-matrix table shows the value of imports of that same commodity used by each industry. Because such information is not available from most businesses, the estimates must be imputed from data available in the annual I-O accounts. The imputed-import values are based on the assumption that each industry uses imports of a commodity in the same proportion as imports-to-domestic supply of the same commodity. (Domestic supply represents the total amount of a commodity available for consumption within the United States; it equals domestic output plus imports less export.) The implication of using this assumption to calculate the estimates is that all variability of

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[8] The SUR technique also assumes that there is no covariance among the explanatory variables in any equation, which is often an issue in Translog models.

[9] These data are constructed by the BLS Industry Productivity Program using data primarily from the economic censuses and annual surveys of the Bureau of the Census, U.S. Department of Commerce, together with information on price changes chiefly from the Bureau of Labor Statistics (BLS).

[10] For a discussion of how inputs are constructed see Technical Information About the BLS Multifactor Productivity Measures for Major Sectors and 18 NAICS 3-digit Manufacturing Industries, http://www.bls.gov/mfp/mprtech.pdf.

[11] Values and prices for energy and services are slightly different than the values published in the BEA GDP-by- industry accounts because they are adjusted for consistency with the manufacturing output data that come from the Bureau of Census

[12] A nonprofit adjustment is made to intermediate inputs, but not to imported intermediates because it is doubtful that nonprofits are using a significant amount of imported intermediates. By not making a nonprofit adjustment to imported intermediates, we may overstate the importance of imports slightly.

import usage across industries reflects the assumption and is not based on industry-specific information.[13]

The BEA provided detailed statistics on imported intermediates for the period 1997-2010 to BLS for this research study in June 2012. These data are not included in BEA published tables because their quality is significantly less than that of the higher level aggregates in which they are included. Compared to these aggregates, the more detailed statistics are more likely to be either based on judgmental trends, on trends in the higher level aggregate, or on less reliable source data.[14]

For this study, nominal values of domestic inputs are constructed as the sum of energy, materials and purchased services less imported inputs. A Tornqvist index is used to construct the price index of domestic inputs. In the model, 2004 was chosen to be the base year because it is in the midst of our sample. All price indexes (prices of L, K, D, and M) are normalized to be 1.00 in 2004 by dividing each price index observation (p_K, p_L, p_I, and p_D) by the 2004 level of that price index. The logarithms of these normalized indexes are thus zero in 2004, as are the differences in logarithms. We also generated a time counter to start at -7 in 1997 so that it would also be zero in 2004. Hence the explanatory variables in the estimation system were all zero in 2004, while the endogenous variables are the levels of the shares of labor, domestic and imported intermediate inputs in the first three equations and the negative of growth rate of the BLS MFP index in the last equation.[15] While Berndt and Wood argued that it is possible to calculate elasticities for each data point using its specific shares using equation (8), our summary tables will show elasticities constructed using 2004 factor shares, near the midpoint of the series. For the industry panel, we use the simple arithmetic average across industries of their 2004 shares. We derived standard errors for all parameters and elasticities, including those involving K, by referencing the variance-covariance matrix of the coefficients; the corresponding t-statistics are presented.

Section IV. Total Manufacturing Estimates

From the outset we knew that data for the aggregate manufacturing sector, with only 14 years of annual data, did not have enough observations to generate statistically significant results. There is not a consensus as to how to calculate degrees of freedom for a system of linear equations with cross equation restrictions.[16] If one awards a degree of freedom for each observation in each equation of the

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[13] Strassner, Yuskavage and Lee [2009] use BEA International Transaction Account (ITA) data to assess the import comparability assumption. They find that real imported materials may be understated in the annual I/O accounts. However, they indicate that the comparability assumption provides reasonable results at the aggregate level. Feenstra and Jensen [2009], prepare alternative Imported intermediates using an alternative method for allocating imported input across industries and compare the results with the BEA import matrix that uses the comparability assumption. Feenstra and Jensen find that there are differences between the two approaches, and identify cells in the I/O table where the differences are greatest. Unfortunately, data limitations prevent them from resolving the differences.

[14] Notes about the imported intermediate input data are from BEA documentation that accompanied the data.

[15] The growth rate of MFP was calculated as the difference between the log of MFP for the year in question and the log of MFP for the previous year. The calculation of MFP change for 1997 required using the 1996 observation which is available from BLS.

[16] A discussion can be found Henningsen and Hamann (2007), p. 11.

stacked regression and subtracts one for each of the 14 parameters estimated, then there are 14*4-14-1=41 degrees of freedom in the system. Now 6 parameters appear in two equations, but the other 8 appear in only one. While there are cross equation effects on the parameters in SUR from eliminating the correlation of the residuals, the 8 parameters estimates reflect, primarily, the information in the single equation they appear in. In that sense, they are estimated with only 14-5-1=8 degrees of freedom. In spite of the known severe limitations, we decided to begin by estimating the total manufacturing model.

Tables 1-3 present our results for the total manufacturing sector. In Table 1, the first-order Translog-proper parameters (a_L , a_D , and a_I) are strongly significant, statistically, and reflect the share levels of the respective inputs. The second-order Translog-proper parameters (B parameters with subscripts involving two factors as distinct from one factor and time) are best interpreted by looking at the various elasticities, which we will turn to in a moment. The first-order parameter in the MFP equation, a_t, is an econometric estimate of (the negative of) the MFP growth during 1997-2010. Hence the parameter estimate of -0.019 indicates an MFP growth trend of about 1.9 percent per year and the 2.42 t-statistic surpasses the usual standard for concluding that MFP is indeed growing. The second-order parameters related to time (B_{Lt}, B_{Dt}, and B_{It}) indicate a small MFP bias (.002) toward imports a result which is only marginally significant.[17] The final second-order time parameter, B_{tt} , reflects any deceleration (if positive) in MFP growth detectable over the period. That parameter is zero.

Table 2 contains the Allen elasticities (AES), calculated as described at the end of Section II. The own elasticities of demand of the four factors can be read from the diagonal of the matrix. From economic theory, we expect all to be negative. Two of the four are not, while none of the four is significantly different from zero. From this we conclude that our total manufacturing sector model is not a reliably estimated economic model. This was not surprising given that we had only 14 years of data.

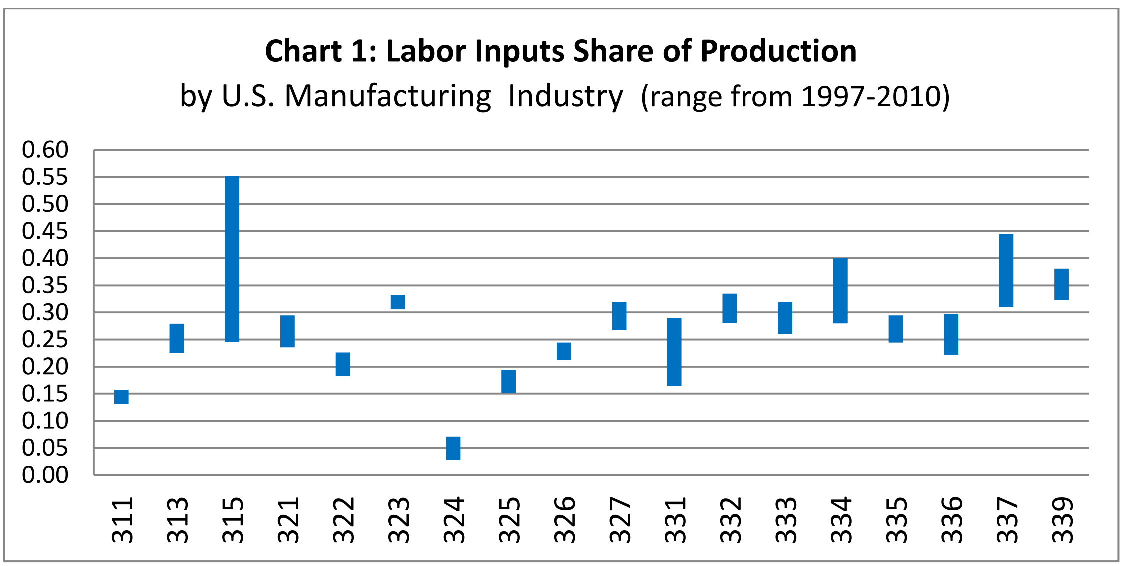
Section V. Manufacturing 18-Industry Panel Estimates

Jorgenson has published numerous studies with Translog estimates for detailed industries. Jorgenson estimates each industry separately, which allows each industry's production function to be independently identified. Jorgenson, Gollop and Fraumeni [1987] estimated factor augmenting Translog production functions for 45 industries using annual data over the period 1948-1979. Jorgenson et al's estimates are based on substantially more than 14 years of data, and for us to estimate separate models for each industry would result in the same limited number of degrees of freedom. Therefore, rather than developing estimates for individual industries, our idea was to use the industry data as representative of behavior by "typical" manufacturing industries. In other words, we wanted to pool

[17] The 0.002 means that for each percent increase in import prices there is a 0.002 percent increase if negative MFP growth, that is, a 0.002 decrease in the MFP growth rate. Higher prices of imports hurt MFP, lower prices help it.

the industry data thereby making each industry-year data point an observation of how a manufacturing industry reacts to relative price change[18].

Our initial attempt to simply pool the industry data improved the model somewhat relative to the total manufacturing dataset, as illustrated in Appendix Tables A.1-A.3. The significance levels of some parameter estimates are slightly higher, while all of the Allen own elasticity estimates are now negative. However, the negative own elasticity for imports is not significantly different from zero. Even with far more data, the model is not able to produce a fully satisfactory set of estimates. The difficulty with the simple-pooling exercise stems from the fact that each industry has a fairly distinctive set of cost shares for L, D, I and K, reflecting their very different technologies, which vary over a fairly narrow range during the 14 year period. For example, labor's factor cost share in the food processing industry ranges from a low of 13.1 percent in 2010 to a high of 15.7 percent in 2002 (Chart 1). By contrast, labor's factor cost share in the fabricated metals industry varies between 28.0 and 33.3 percent. The shares and their variation are illustrated in a set of charts 1-4. Given this, we considered allowing the shares to vary across industries by introducing a set of industry dummies[19]. We expected that each industry-equation dummy estimate would approximate the difference between the average of that industry's share and the share in the reference (18^{th}) industry and improve the estimates of the second-order parameters. Unfortunately, the 17*4=68 dummies did more than explain the industry specific share levels. The sum of an equation's constant term and the industry dummy generally was not particularly close to the share for that factor for that industry. For example some were negative and others were greater than 1.0. Also, the elasticities were not reasonable. Apparently the dummies competed with the Translog parameters in trying to explain variation in the shares as well as the levels of the shares.



[18] While we could find few precedents in the literature for Translog modeling with panels, Binswanger [1974] did face a similar situation to ours, having data for only four years, but for those he had data for 39 states. Binswanger inserted 4 regional dummies to help explain disparities in the patterns of shares.

[19] We ran the industry-dummy model on an earlier data set 1997-2006. Because the results were not informative, we have not yet reproduced the results with the most recent data

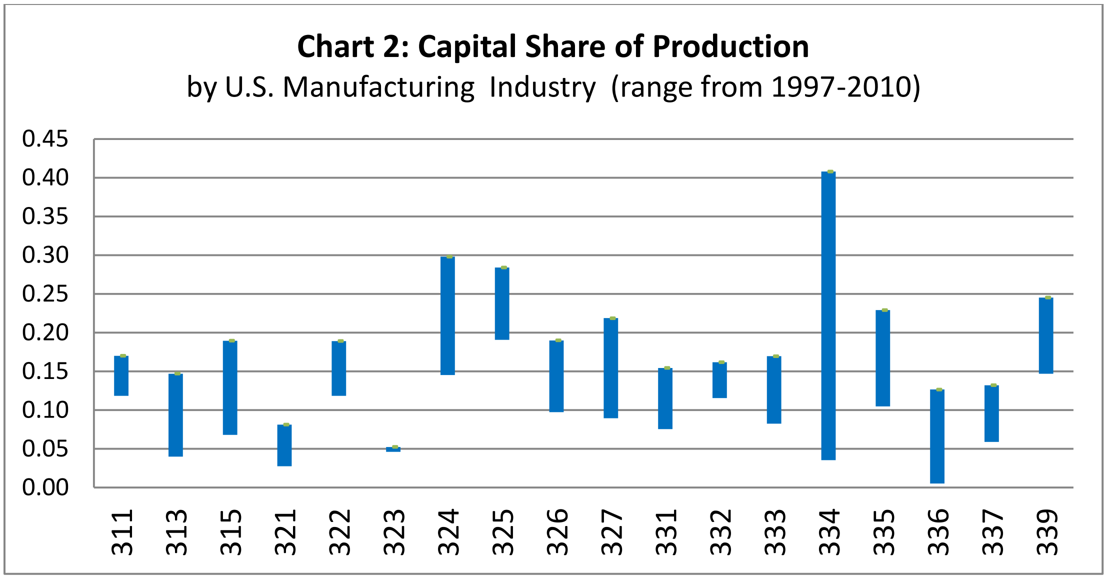


Chart 2: Capital Share of Production
by U.S. Manufacturing Industry (range from 1997-2010)
0.45
0.40
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
311
313
315
321
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323
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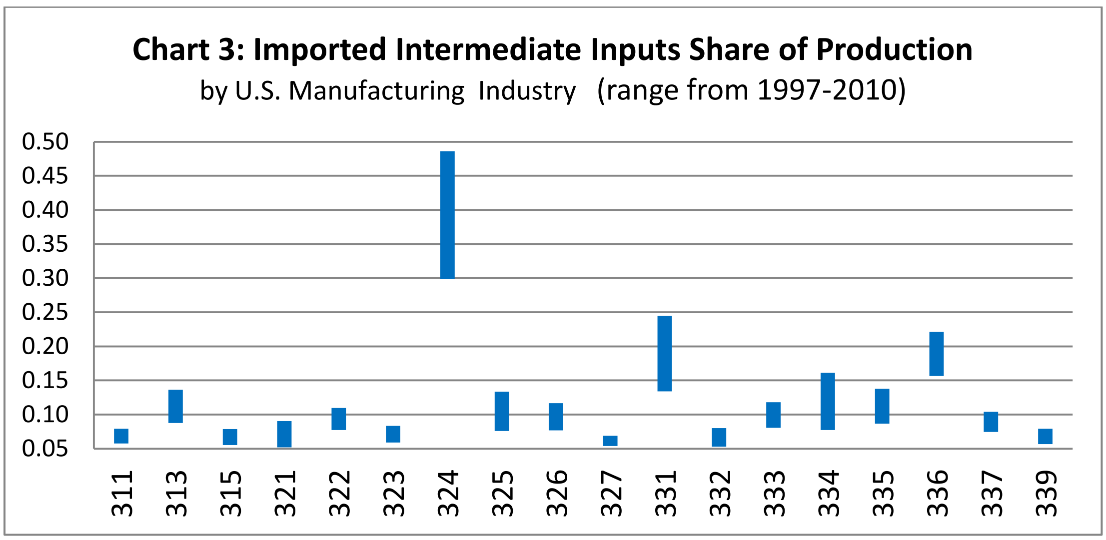
Chart 3: Imported Intermediate Inputs Share of Production
by U.S. Manufacturing Industry (range from 1997-2010)
0.50
0.45
0.40
0.35
0.30
0.25
0.20
0.15
0.10
0.05
311
313
315
321
322
323
324
325
326
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337
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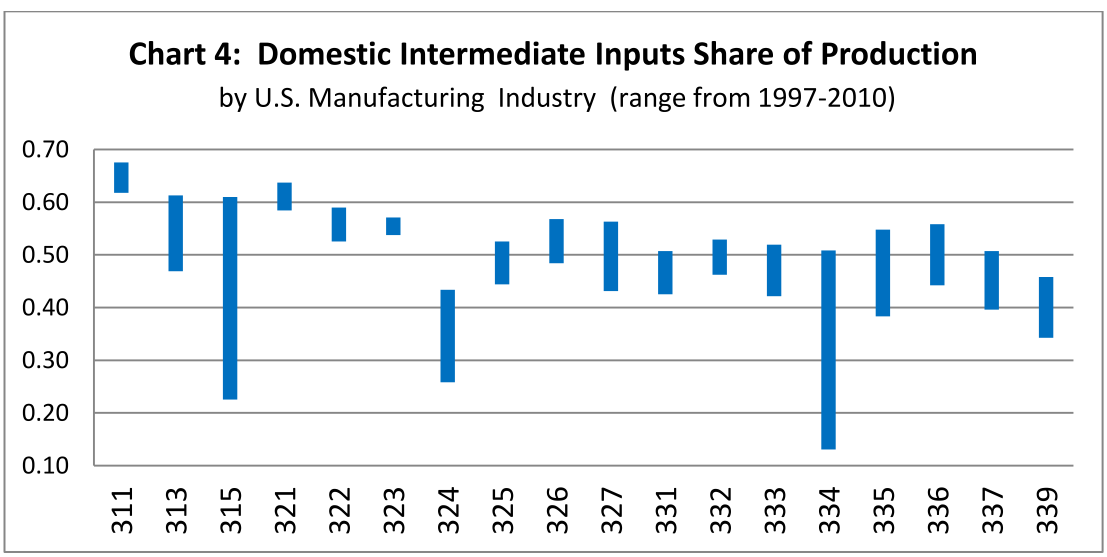
Chart 4: Domestic Intermediate Inputs Share of Production
by U.S. Manufacturing Industry (range from 1997-2010)
0.70
0.60
0.50
0.40
0.30
0.20
0.10
311
313
315
321
322
323
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Rather than remove the large industry share variations econometrically, we decided to "realign" the shares and represent them as deviations from the industry specific shares for a given year. This approach was intended to prevent the regression from reconciling cross-industry *share level differences*, while enabling it to identify *year-to-year share changes* in terms of relative price changes and time. From each industry-year factor share observation we subtracted the 2004 level of that industry's share for that factor input, rendering all 2004 observations of the three "aligned share" endogenous variables as zero. We expected that the first-order Translog-proper parameters (a_L, a_D, a_I) would be different as a result of this linear adjustment, but were hopeful that the second-order parameters would be unaffected. In addition, because the elasticity formulas of Berndt and Wood are independent of the first order parameters, the elasticity estimates also should be unaffected by adjusting the shares by a constant in the estimation system[20] We tested our share alignment approach by rerunning the total manufacturing sector model of Table 1 with its shares adjusted to zero in 2004. The results are in Appendix Table A.4. Note that all second-order Translog-proper parameters and all parameters with time subscripts were exactly the same the same as in our original total manufacturing model, while the first-order Translog-proper parameters (a_L, a_D, a_I) differ, these now being close to zero rather than close to the average factor shares. Therefore it seems reasonable to align the industry shares to zero in 2004 in order to obtain estimates of second-order parameters. We assume that the second-order parameters are the same for all industries and that each industry-year data point is a statistically separate observation of how a typical manufacturing industry share responds to a given relative price change . While factor prices are strongly correlated across industries, there is some variation due to the fact that the four category prices (for L, D, I and K) are aggregates from finer input categories whose prices are measured separately. Aside from that, we are assuming that each industry's response to a given price change is observed with some statistical error.

The factor augmenting Translog unit cost function was estimated using the pooled industry data with the factor shares "aligned" at 2004.[21]. (See results in Tables 4-6). In Table 4, the first order Translog-proper parameters (a_L, a_D, a_I) are fairly close to zero, reflecting the alignment of the shares to zero in 2004. The first-order parameter in the MFP equation, $a_t = -0.014$, indicates an MFP growth trend of about 1.4 percent per year[22] during 1997-2010 and the t-statistic is quite significant. The second-order parameters that relate to time (B_{Lt}, B_{Dt}, and B_{It}) indicate a small MFP bias (.003) toward imports.

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[20] The Berndt-Wood paper would imply that there is a separate elasticity estimates for each year for each industry. To present a manageable set of elasticity estimates, we use the simple average of shares across industries in 2004 along with the Berndt-Wood formulas.

[21] This estimation system has ample degrees of freedom (14-1)*4*18-14=922 , with (14-1)*18-5=229 degrees of freedom in each equation.

[22] This is smaller than the total manufacturing sector trend of 1.9 percent per year. This reflects the fact that the BLS total manufacturing sector Solow-residual MFP growth rate is similarly larger than the average of industry Solow MFP trends. This, in turn, reflects the BLS "sectoral output" concept. Intra-industry sales between manufacturing industries are included in output and inputs for the individual industries (since they are not double counted from the industry perspective), but these same sales are excluded from total manufacturing output and input (since their inclusion here they would involve double counting). The resulting MFP trends are larger at higher levels of aggregation reflecting a kind of productivity augmentation. For example in transportation equipment, a productivity improvement in engine manufacture augments productivity improvements in auto assembly, leading to even faster productivity gains in overall automobile manufacture.

This magnitude is tiny, though quite significant statistically. B_{tt}, the rate of deceleration of MFP, is essentially zero during 1997-2010.

Using the second-order Translog parameters on factor inputs, we calculate Allen own elasticities and elasticities of substitution among factor pairs (See Table 5). The Allen own elasticities of demand (along the diagonal of Table 5) are all strongly negative and highly significant, indicating a well behaved model from the perspective of economic theory. In the upper triangle of Table 5, five of the six Allen partial elasticities of substitution are positive, and one is negative. All are strongly significant, statistically. Overall, our results indicate that the substitution estimates are relatively important, and the technological bias estimates relatively trivial.[23] The one case where the AES is negative indicates complementarity, and, surprisingly, the complementary pair is labor and imports. The substitution results are quantified in Table 6. For example, a one percent increase in the price of imports causes a 0.253 percent decline in demand for domestic labor. Conversely *cheaper imports actually appear to increase the amount of labor* directly employed by U.S. manufacturing establishments. This result is quite surprising but we would strongly caution that it does not demonstrate that imports have helped U.S. employment. We will ponder what it may reflect in our concluding section.

Before concluding, we present two additional sets of results that used our industry panel with shares aligned in 2004. In Appendix Tables A.7-A.9 we re-estimate a simple Translog unit cost function, omitting the time variable from each equation and the multifactor productivity equation all together. In Table A.8, the Allen own elasticities all come out negative and significant. In fact the entire pattern of substitution, including the L-I complementarity finding, is extremely similar to that of in factor augmenting model, Table 5. Apparently the factor-augmenting aspect does little to perturb a very robust pattern of substitution elasticities. This result is not surprising given the very small magnitude of the technical change biases in Table 4.

We also explore the possibility that these models are being driven by imported oil, a large element of imports with a great deal of price volatility. While we do not have the data to separate out specific import categories by industry, we can reasonably assume the most of the direct buying of imported crude within U.S. manufacturing is by NAICS industry 324, "petroleum and coal products." We take advantage of our industry data and exclude the petroleum and coal products industry from our sample. In Tables A.10-A.12, we find again that our model is well behaved and the pattern of substitution is virtually unaffected. This dismisses our concern that oil is driving our parameter estimates. These two alternative models tend to confirm the robustness of our main model.

Section VI. Summary and Conclusions

[23] This finding contrasts with the experience of Jorgenson [1984] in which technology toward energy supplanted the earlier findings of energy-capital complementarity.

In this paper we have demonstrated a new technique for extracting highly significant estimates of elasticities of substitution and technical change bias for a sector, by using not only time series data but also cross section detail that may be available for subcomponents of the sector.[24] The novel element we have introduced is to "align" the shares of the subcomponents, which correspond to first-order Translog-proper parameters, in order to study substitution without the noise introduced by widely variant levels of subcomponent average shares. These differences are extraneous if we are mainly interested in how relative input price changes tend to drive substitution in input proportions and shares. Estimates of elasticities of substitution and of technical change bias can be calculated from second-order Translog parameters, without reference to the first-order Translog parameters. We believe that fewer studies have used production models during the past two decades due to the limited significance and robustness of their results. We are hopeful that techniques like ours will allow researchers to extract more results from the limited data we have available under tight budget conditions.

We were driven to search for a good paneling technique by our interest in studying substitution of imported intermediate inputs for domestic factors of production. While the BLS MFP data are available from 1987 forward, data on imported intermediate inputs begin in 1997, yielding only 14 annual observations. When we estimated our model pooling the industry data, we found strong statistical significance, and strong conformance with the expectation of economic theory that when a factor's relative price increases, firms tend to shift away from that factor. In terms of cross elasticities, we found that, among our four factors (labor, domestic intermediate inputs, imported inputs and capital), only one of the six possible pairs were not economic substitutes. Our prior expectation was that we would detect an import-using technical change bias, likely reflecting both measurement error and actual rapid advance in import-using know-how. While we do detect such a bias, and it is statistically significant, its magnitude is quite small.

Surprisingly imports appear to be a complement to domestic labor. This means that cheaper imports appear to increase demand for domestic labor by U.S. manufacturing. At first blush, this result flies in the face of the conventional wisdom that cheap imports lead to the loss of U.S. jobs. However, careful consideration of what is in our categories cautions us not to dispute conventional wisdom. First of all, domestic intermediate inputs are a very strong substitute for imports. There are many U.S. jobs outside of manufacturing that produce these domestic intermediate inputs. Our results imply that there must be substantial loss of U.S. jobs in firms that supply parts and other intermediate inputs and that those employed by these firms are suffering the brunt of off-shoring. Secondly, imported *final* goods, including capital goods, are outside the scope of our model. Much of a U.S. manufacturing industry's production of final goods for U.S. and foreign markets may be supplanted by imports, resulting in U.S. manufacturing job loss. This type of shift would not involve an increase in imported intermediate inputs and would not be linked to imports in our elasticities of substitution. A third possibility is that certain industries have technologies that are much more suitable than others for off-shoring. In particular, industries consisting mainly of large sophisticated firms may be especially good at off-shoring, while also employing large domestic labor forces. This would tend to re-enforce the L-I complementarity finding.

[24] In our case we used industries, but the same technique might be applicable to regions within a country.

Fourth, our complementarity finding could be a reflection of measurement problems, such as missing input price discounts or assumptions built into factor shares by the U.S. statistical agencies.

We have not determined exactly what lies behind the finding, and so our conclusion from this study is necessarily modest. The precise mechanisms by which cheaper imports affect U.S. employment need to be better categorized and measured in order to support sound policies on imports.

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TABLE 1. Total Manufacturing Sector: Regression Coefficients

a_L =	**0.299**	B_{LL} =	**0.169**	B_{LD} =	**-0.144**	B_{LI} =	**0.006**	B_{Lt} =	**-0.006**
	165.26		*7.34*		*-2.82*		*0.20*		*-8.61*
a_D =	**0.357**			B_{DD} =	**0.465**	B_{DI} =	**-0.218**	B_{Dt} =	**-0.001**
	129.01				*3.59*		*-2.95*		*-0.60*
a_I =	**0.156**					B_{II} =	**0.226**	B_{It} =	**0.002**
	49.93						*4.59*		*2.19*
a_t =	**-0.019**							B_{tt} =	**0.000**
	-2.42								*0.10*

t-statistics in italics

TABLE 2. Total Manufacturing Sector: Allen Elasticities of Substitution

σ_{LL} =	**-0.459**	σ_{LD} =	**-0.377**	σ_{LI} =	**1.120**	σ_{LK} =	**0.456**
	-1.795		*-0.772*		*1.834*		*1.850*
		σ_{DD} =	**1.959**	σ_{DI} =	**-2.815**	σ_{DK} =	**-0.578**
			1.840		*-2.179*		*-1.573*
				σ_{II} =	**3.311**	σ_{IK} =	**0.548**
					1.805		*0.697*
						σ_{KK} =	**-0.132**
							-0.196

t-statistics in italics

TABLE 3. Total Manufacturing Sector: Price Elasticities of Demand

ϵ_{LD} =	**-0.131**	ϵ_{DL} =	**-0.113**
	-0.77		*-0.77*
ϵ_{LI} =	**0.184**	ϵ_{IL}=	**0.336**
	1.83		*1.83*
ϵ_{LK} =	**0.085**	ϵ_{KL} =	**0.137**
	1.85		*1.85*
ϵ_{DI} =	**-0.461**	ϵ_{ID} =	**-0.981**
	-2.18		*-2.18*
ϵ_{DK} =	**-0.109**	ϵ_{KD} =	**-0.202**
	-1.57		*-1.57*
ϵ_{IK} =	**0.103**	ϵ_{KI} =	**0.090**
	0.70		*0.70*

t-statistics in italics

Table 4. Pooled Manufacturing Industry Data with Shares "Aligned" in 2004: Regression Coefficients

a_L =	-0.004	B_{LL} =	0.010	B_{LD} =	0.111	B_{LI} =	-0.097	B_{Lt} =	-0.001
	-2.57		*0.93*		*9.99*		*-12.94*		*-2.03*
a_D =	0.011			B_{DD} =	-0.126	B_{DI} =	0.065	B_{Dt} =	-0.005
	4.66				*-7.42*		*5.83*		*-9.37*
a_I =	-0.010					B_{II} =	0.037	B_{It} =	0.003
	-6.35						*3.37*		*6.93*
a_t =	-0.014							B_{tt} =	0.000
	-4.58								*-0.54*

t-statistics in italics

Table 5. Pooled Manufacturing Industry Data with Shares "Aligned" in 2004: Allen Elasticities of Substitution

σ_{LL} =	-2.671	σ_{LD} =	1.871	σ_{LI} =	-2.156	σ_{LK} =	0.355
	-17.67		*21.47*		*-8.84*		*3.65*
		σ_{DD} =	-1.602	σ_{DI} =	2.141	σ_{DK} =	0.248
			-22.13		*10.95*		*3.06*
				σ_{II} =	-4.822	σ_{IK} =	0.704
					-6.04		*3.29*
						σ_{KK} =	-2.177
							-8.78

t-statistics in italics

Table 6. Pooled Manufacturing Industry Data with Shares "Aligned" in 2004: Price Elasticities of Demand

ϵ_{LD} =	0.906	ϵ_{DL} =	0.491
	21.47		*21.47*
ϵ_{LI} =	-0.253	ϵ_{IL}=	-0.566
	-8.84		*-8.84*
ϵ_{LK} =	0.048	ϵ_{KL} =	0.093
	3.65		*3.65*
ϵ_{DI} =	0.251	ϵ_{ID} =	1.037
	10.95		*10.95*
ϵ_{DK} =	0.034	ϵ_{KD} =	0.120
	3.06		*3.06*
ϵ_{IK} =	0.096	ϵ_{KI} =	0.083
	3.29		*3.29*

t-statistics in italics

Appendix Table A.1. Pooled Manufacturing Industry Data using Raw Share Levels : Regression Coefficients

$a_L =$	**0.256**	$B_{LL} =$	**-0.060**	$B_{LD} =$	**0.124**	$B_{LI} =$	**-0.071**	$B_{Lt} =$	**0.001**
	46.35		*-1.81*		*4.12*		*-2.54*		*0.66*
$a_D =$	**0.500**			$B_{DD} =$	**-0.141**	$B_{DI} =$	**0.030**	$B_{Dt} =$	**-0.004**
	84.98				*-3.02*		*0.84*		*-3.10*
$a_I =$	**0.105**					$B_{II} =$	**0.096**	$B_{It} =$	**0.001**
	19.95						*2.41*		*0.68*
$a_t =$	**-0.014**							$B_{tt} =$	**0.000**
	-4.60								*-0.63*

t-statistics in italics

Appendix Table A.2. Pooled Manufacturing Industry Data using Raw Share Levels: Allen Elasticities of Substitution

$\sigma_{LL} =$	**-3.686**	$\sigma_{LD} =$	**1.978**	$\sigma_{LI} =$	**-1.296**	$\sigma_{LK} =$	**1.188**
	-7.62		*8.33*		*-1.43*		*3.95*
		$\sigma_{DD} =$	**-1.667**	$\sigma_{DI} =$	**1.526**	$\sigma_{DK} =$	**0.803**
			-8.35		*2.43*		*4.49*
				$\sigma_{II} =$	**-0.547**	$\sigma_{IK} =$	**-2.465**
					-0.19		*-3.63*
						$\sigma_{KK} =$	**-3.025**
							-7.28

t-statistics in italics

Appendix Table A.3. Pooled Manufacturing Industry Data using Raw Share Levels : Price Elasticities of Demand

$\epsilon_{LD} =$	**0.958**	$\epsilon_{DL} =$	**0.519**
	8.33		*8.33*
$\epsilon_{LI} =$	**-0.152**	$\epsilon_{IL} =$	**-0.340**
	-1.43		*-1.43*
$\epsilon_{LK} =$	**0.161**	$\epsilon_{KL} =$	**0.312**
	3.95		*3.95*
$\epsilon_{DI} =$	**0.179**	$\epsilon_{ID} =$	**0.739**
	2.43		*2.43*
$\epsilon_{DK} =$	**0.109**	$\epsilon_{KD} =$	**0.389**
	4.49		*4.49*
$\epsilon_{IK} =$	**-0.335**	$\epsilon_{KI} =$	**-0.290**
	-3.63		*-3.63*

t-statistics in italics

Appendix Table A.4. Total Manufacturing Sector with Aligned Shares : Regression Coefficients

a_L =	**-0.001**	B_{LL} =	**0.169**	B_{LD} =	**-0.144**	B_{LI} =	**0.006**	B_{Lt} =	**-0.006**
	-0.48		*7.34*		*-2.82*		*0.20*		*-8.61*
a_D =	**0.009**			B_{DD} =	**0.465**	B_{DI} =	**-0.218**	B_{Dt} =	**-0.001**
	3.19				*3.59*		*-2.95*		*-0.60*
a_I =	**-0.007**					B_{II} =	**0.226**	B_{It} =	**0.002**
	-2.34						*4.59*		*2.19*
a_t =	**-0.019**							B_{tt} =	**0.000**
	-2.42								*0.10*

t-statistics in italics

Appendix Table A.5. Total Manufacturing Sector with Aligned Shares : Allen Elasticities of Substitution

σ_{LL} =	**-0.459**	σ_{LD} =	**-0.377**	σ_{LI} =	**1.120**	σ_{LK} =	**0.456**
	-1.80		*-0.77*		*1.83*		*1.85*
		σ_{DD} =	**1.959**	σ_{DI} =	**-2.815**	σ_{DK} =	**-0.578**
			1.84		*-2.18*		*-1.57*
				σ_{II} =	**3.311**	σ_{IK} =	**0.548**
					1.80		*0.70*
						σ_{KK} =	**-0.132**
							-0.20

t-statistics in italics

Appendix Table A.6. Total Manufacturing Sector with Aligned Shares : Price Elasticities of Demand

ϵ_{LD} =	**-0.131**	ϵ_{DL} =	**-0.113**
	-0.77		*-0.77*
ϵ_{LI} =	**0.184**	ϵ_{IL}=	**0.336**
	1.83		*1.83*
ϵ_{LK} =	**0.085**	ϵ_{KL} =	**0.137**
	1.85		*1.85*
ϵ_{DI} =	**-0.461**	ϵ_{ID} =	**-0.981**
	-2.18		*-2.18*
ϵ_{DK} =	**-0.109**	ϵ_{KD} =	**-0.202**
	-1.57		*-1.57*
ϵ_{IK} =	**0.103**	ϵ_{KI} =	**0.090**
	0.70		*0.70*

t-statistics in italics

Appendix Table A.7. Pooled Manufacturing Industry Data– Shares Aligned, Excluding Time and MFP equation: Regression Coefficients

a_L =	**-0.003**	B_{LL} =	**0.014**	B_{LD} =	**0.106**	B_{LI} =	**-0.100**
	-1.93		*1.26*		*9.47*		*-11.21*
a_D =	**0.015**			B_{DD} =	**-0.154**	B_{DI} =	**0.083**
	5.60				*-8.62*		*6.54*
a_I =	**-0.012**					B_{II} =	**0.031**
	-6.88						*2.28*

t-statistics in italics

Appendix Table A.8. Pooled Manufacturing Industry Data– Shares Aligned, Excluding Time and MFP equation: Allen Elasticities of Substitution

σ_{LL} =	**-2.611**	σ_{LD} =	**1.831**	σ_{LI} =	**-2.254**	σ_{LK} =	**0.466**
	-16.48		*20.87*		*-7.77*		*4.86*
		σ_{DD} =	**-1.721**	σ_{DI} =	**2.452**	σ_{DK} =	**0.477**
			-22.63		*11.04*		*5.44*
				σ_{II} =	**-5.275**	σ_{IK} =	**0.173**
					-5.37		*0.75*
						σ_{KK} =	**-2.750**
							-10.54

t-statistics in italics

Appendix Table A.9. Pooled Manufacturing Industry Data– Shares Aligned, Excluding Time and MFP equation: Price Elasticities of Demand

ϵ_{LD} =	**0.887**	ϵ_{DL} =	**0.480**
	20.87		*20.87*
ϵ_{LI} =	**-0.265**	ϵ_{IL}=	**-0.591**
	-7.77		*-7.77*
ϵ_{LK} =	**0.063**	ϵ_{KL} =	**0.122**
	4.86		*4.86*
ϵ_{DI} =	**0.288**	ϵ_{ID} =	**1.187**
	11.04		*11.04*
ϵ_{DK} =	**0.065**	ϵ_{KD} =	**0.231**
	5.44		*5.44*
ϵ_{IK} =	**0.024**	ϵ_{KI} =	**0.020**
	0.75		*0.75*

t-statistics in italics

Appendix Table A.10. Manufacturing Industry Panel – Shares Aligned, Excluding NAICS 324, Petroleum and Coal Products : Regression Coefficients

a_L =	**-0.005**	B_{LL} =	**0.002**	B_{LD} =	**0.118**	B_{LI} =	**-0.098**	B_{Lt} =	**-0.001**
	-2.83		*0.18*		*9.51*		*-11.10*		*-1.84*
a_D =	**0.010**			B_{DD} =	**-0.135**	B_{DI} =	**0.063**	B_{Dt} =	**-0.006**
	3.97				*-7.64*		*5.58*		*-9.29*
a_I =	**-0.010**					B_{II} =	**0.037**	B_{It} =	**0.003**
	-6.49						*3.14*		*6.74*
a_t =	**-0.014**							B_{tt} =	**-0.001**
	-4.74								*-0.70*

t-statistics in italics

Appendix Table A.11. Manufacturing Industry Panel – Shares Aligned, Excluding NAICS 324, Petroleum and Coal Products : Allen Elasticities of Substitution

σ_{LL} =	**-2.602**	σ_{LD} =	**1.859**	σ_{LI} =	**-2.536**	σ_{LK} =	**0.369**
	-15.79		*20.58*		*-7.96*		*3.60*
		σ_{DD} =	**-1.553**	σ_{DI} =	**2.267**	σ_{DK} =	**0.260**
			-21.85		*9.99*		*3.08*
				σ_{II} =	**-5.295**	σ_{IK} =	**0.817**
					-4.56		*3.10*
						σ_{KK} =	**-2.475**
							-9.50

t-statistics in italics

Appendix Table A.12. Manufacturing Industry Panel – Shares Aligned, Excluding NAICS 324, Petroleum and Coal Products: Price Elasticities of Demand

ϵ_{LD} =	**0.925**	ϵ_{DL} =	**0.512**
	20.58		*20.58*
ϵ_{LI} =	**-0.255**	ϵ_{IL}=	**-0.698**
	-7.96		*-7.96*
ϵ_{LK} =	**0.047**	ϵ_{KL} =	**0.102**
	3.60		*3.60*
ϵ_{DI} =	**0.228**	ϵ_{ID} =	**1.128**
	9.99		*9.99*
ϵ_{DK} =	**0.033**	ϵ_{KD} =	**0.129**
	3.08		*3.08*
ϵ_{IK} =	**0.103**	ϵ_{KI} =	**0.082**
	3.10		*3.10*

t-statistics in italics