MODELLING TECHNICAL PROGRESS AND TOTAL FACTOR PRODUCTIVITY: A PLANT LEVEL EXAMPLE

by

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Abstract

Shifts in the production frontier occur because of changes in technology. A model of how a firm learns to use the new technology, or how it adapts from the first production frontier to the second, is suggested. Two different adaptation paths are embodied in a translog cost function and its attendant cost share equations. The paths are the traditional linear time trend and a learning curve. The model is estimated using establishment level data from a non-regulated industry that underwent a technological shift in the time period covered by the data. The learning curve resulted in more plausible estimates of technical progress and total factor productivity growth patterns. A significant finding is that, at the establishment level, all inputs appear to be substitutes.

1. Introduction

This paper addresses the problem of modelling how the individual firm learns to exploit a new technology. Technological breakthroughs are often discrete events. Frequently, the only way to incorporate a new technology into the production process is to scrap the technically obsolete equipment and methods, and install new equipment and methods. Once the new technology is installed, the firm must learn how to best exploit it given the demand for its products, input prices, and the existing complementary technology. This learning process often takes considerable time.

In most new installations, there is often a start-up process during which the components of the new capital inputs are tested, the labor force is trained and gains experience, and the "bugs" are worked out of the system. Finally, the newly gained knowledge diffuses through individual establishments and the whole firm. Pilkington (1969) gives ample discourse on this process of learning in the flat glass industry which is the case studied here.

We are interested in breaking down technical change into two parts. The first part can be considered as movements of the technological cost frontier--shifts in the possible. The second would be the movement of the firm toward the possible or optimal--a learning process. We denote shifts in the frontier as the result of the adoption of a new technology. We denote movements toward the new frontier as adaptation. If we can model this adaptation path between frontiers, we may have a better understanding of changes in productivity growth as a new technology comes into use.[1]

A question arises: if the new technology is so much better, why doesn't the firm instantaneously adapt to the new technology? The answer must lie in the costs that are associated with changing the ancillary inputs and training the workers, and the costs that are associated with gaining knowledge on how to efficiently use the new technology. This phenomenon was discussed by Lundberg (1961) in his observation of productivity increases at the Horndal Iron Works in Sweden, the so-called "Horndal effect," by Arrow (1962), in his "learning by doing" concept, and by Johansen (1972) in his idea of "the technique relation." While Arrow was primarily concerned with explaining increases in per capita income and macroeconomic issues, he cited earlier work which observed "The role of experience in increasing productivity." Arrow stated that "technical change in general can be ascribed to experience..."[2]

Consider the production function for a plant with a single input, X, and a single output, Q, operating in period t as

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

or the maximum under the technology F^1. In Figure 1, this situation is represented by point A on the curve F^1.

Now, with the installation of the new technology, the production frontier shifts (assuming technical progress) to F^2 (see

Solow [1957]). We assume that after the firm makes the necessary changes in its machinery and equipment capital to achieve F^2, it must then learn how to efficiently use the new technology.[3] The graphical depiction is the movement from point A, to point B on F2; this is labelled an "Adaptation Path."

The problem of modelling this change has been addressed in previous studies which have included the time trend to account for technical change.[4] Yet, the time trend is probably not a proper proxy for technical change. For one thing, it assumes that technical change moves smoothly through time and ignores the learning process that follows a drastic change in the firm's technology. It also serves as a proxy for both kinds of technical change, adoption and adaptation.[5] Without further technical apparatus, the inclusion of the time trend as a technical change index may also implicitly presume that firms are always at their long-run cost minimization point, (i.e., always on the frontier.) Arrow (1962) condemned trend projections (the use of time to model technical change) as "a confession of ignorance, and, what is worse from a practical viewpoint -- not a policy variable."[6]

In the last decade, flexible functional forms such as the transcendental logarithmic (TL) function have superceded traditional forms such as the Cobb-Douglas function. These newer forms allow for a more general representation of the production technology and have been extensively used in empirical studies of production. Yet these studies have not directly addressed the learning process or adaptation path as technologies shift, but have continued to use the time trend as a proxy for both adoption of and adaptation to technical change.[7]

For example, it is common to model the firm's production function as

$$Q(t) = F(X(t), t), \qquad (2)$$

where $Q(t)$ and $X(t)$ again denote output and input flows in time period t, while F denotes the technology that maps X into Q. Production studies often incorporate one or more parameters associated with time to calculate the rate of technical change, Jp, that can be expressed as

$$Jp = M(\ln F(\cdot))/ Mt. \qquad (3)$$

However, causes of technical change are really quite complex as Solow (1957) has pointed out. The change in productivity may be the result of several phenomena that often occur simultaneously. These include those elements noted as "slowdowns, speedups (in production or inputs), improvements in the education of the labor force"[8] and quality improvements in any input. Thus, with the time trend used as a technological index, Jp would confound technical change, economies of scale and the movement toward the efficient production frontier represented by F.

An alternative to the production approach is to deduce technical change from the firm's dual problem, i.e. the problem of minimizing costs (Diewert 1980). Consider the cost function

$$C(Q, P, t) = \text{minimum } \{P \cdot X: (Q,X) \text{ d } S^t\}, \tag{4}$$

where C denotes total costs, P denotes a vector of input prices, and S^t represents the firm's production possibility set in time t. Then the rate of technical change can be defined as

$$J_c = - M(\ln C)/Mt. \tag{5}$$

Both measures, J_c and J_p, implicitly presume that the firm is always operating on the production or cost frontier and that the time trend adequately measures shifts in the frontier.

If we recognize that the firm may not always be operating on the frontier, we must modify the model to incorporate the movement of the firm from one frontier to another: hence J_c, or J_p must be modified. Further, a proper test of such an adaptation path ideally requires plant level data for a period in which a known shift in F from F^1 to F^2 takes place. The recent availability of such data allows us to address this problem.

Ideally, it would be best to apply a dynamic model in this study. However such a model requires time series data for accurate estimation as it uses distributed lags to identify the accelerator coefficient (the rate at which output affects changes in the quasi-fixed input.) Also time-series analysis is needed to formulate price and output expectations which are in turn arguments in the equations to be estimated.[9] Unfortunately, our data covers only a 10 year period that is too short of a time span to fully exploit a dynamic model.

Nevertheless, there is an important feature of our data that should be emphasized. We use microdata at the establishment level extracted from the Census Bureau's Longitudinal Research Database (LRD). These microdata are more suitable than aggregate data for testing hypotheses concerning the production structure and technology of the firm. This is because establishment data would accurately reflect economic activities of individual establishments where production is actually performed. In contrast, aggregate data represent industry totals and therefore would yield aggregation bias in the estimates for production models. The aggregation bias issue is well known and has been discussed in the literature.

For example, Solow (1987) convincingly argued that "estimates of factor substitutability based on aggregate data are misleading because they capture more than simply technological substitution. Factor substitution is a microeconomic phenomenon, and is best examined by looking at microdata" (page 612).

In this paper, we suggest a different approach to allow us to utilize our data set and overcome some of its limitations. We employ a simple comparative static equilibrium model and fit it to pooled cross-section time-series data. As mentioned earlier, because our time span includes only 10 years, distributed lags and time-series analysis are difficult if not virtually precluded. Therefore, instead of modelling the adjustment process, we employ a learning curve to model an adaptation path. We presume that the firm has made its choice of optimal capital (quasi-fixed) stock. What we model is how the firm learns to use the new capital via what we call the adaptation path.

In what follows, we develop two models of the firm, with competing proxies for describing the adaptation path. We estimate the models using plant level data and report the results. Finally, we use the estimated models to generate alternative measures of total factor productivity and compare them.

2. The Model

The plant production function in period t is assumed as

$$Q(t) \# F^1[K(t), L(t), E(t), OF(t), M(t): J(t)]. \quad (6)$$

Here, Q denotes a flow of output, whereas K, L, E, OF, and M respectively denote the service flows from capital stock, production labor, electricity, other fuels, and intermediate materials.[10] If $Q(t) = F^1(\cdot)$, then output is optimal under the given technology, F^1. If $Q(t) < F^1(\cdot)$, then output is less than that obtainable under the existing technology. The symbol J denotes the level of technical competence that the plant has in exploiting the technology under which it operates, the 1-th technology.

At any given level of output, the dual problem is to minimize costs, C, such that

$$C(Q(t), P(t), J) = \text{minimum } \{P(t)\cdot X(t): (Q(t), X(t)) \text{ d } S^1\}. \quad (7)$$

Here, P is a vector of input prices, X is a vector of inputs, and S^1 is the production possibility set.

We denote shifts in the technical frontier by allowing F^1 to move, i.e., 1 = 1, 2. We posit two measures of J below and test them using plant level data. Such a test requires a specific functional form for the cost function. We elected to use the transcendental logarithmic (TL) cost function and assume that it is a precise representation of the firm's costs. Using lower case letters to denote the natural logarithm, the TL cost function is written as

$$C_1 = "_{1o} + E_i \; "_{1i} \; p_i + (1/2) \; E_i \; E_j \; ß_{1ij} \; p_i \; p_j$$
$$+ \; E_i \; "_{1iq} \; p_i \; q + "_{1q} \; q + E_i \; "_{1iJ} \; p_i \; J$$
$$+ \; "_{1qJ} \; q \; J + (1/2) \; "_{1qq} \; q^2 + "_{1J} \; J + 1/2 \; "_{1JJ} \; J^2 \; , \qquad (8)$$

i, j = K, L, E, OF, M and $1 = 1, 2$. Where, the "'s and ß's are coefficients and the p's denote natural logarithms of the input prices. Imposing symmetry and linear homogeneity in factor prices as the maintained hypothesis, implies that

$$ß_{1ij} = ß_{1ij}, \; E_i \; "_{1i} = 1, \; E_i "_{1ik} = 0, \; k = q, \; J, \text{ and } E_i ß_{1ij} = 0,$$

where i, j = K, L, E, OF, M, for $1 = 1, 2$.

Factor share equations are derived in the usual manner via Shephard's Lemma. Thus, factor shares are

$$S_{1i} = "_{1i} + E_j \; ß_{1ij} \; p_j + "_{1iJ} q + "_{1iJ} \; J, \qquad (9)$$

where $(S_{1i}) = \; C_1 / \; p_i$, and i,j = K, L, E, OF, M and $1 = 1, 2$.

Note that the difference between our model and those of previous studies is in the concept of J as something different than the usual shift-through-time concept of the production function, and allowing 1 to take 2 values. We thus must deal with the problem of modelling the adaptation path and the shift of the frontier. We take up the path problem first.

For comparison, we specified the models incorporating two different measures of the time path: (i) a learning process approximated by an inverse circular function designated J_0, and (ii) a linear function designated J_1, the traditional proxy for the technical level. The inverse circular function used is

$$J_0 = \arctan(t-D),\ 0 < D \# 10 \tag{10}$$

The linear function is

$$J_1 = t. \tag{11}$$

In all cases t denotes time and is set equal to 1,2,..., 10.[11] Equation (10) allows J to take the traditional form of a learning curve, a distended S-shaped form with asymptotes of -B/2 and B/2. The value of D allows for variation in the inflection point, the point of fastest approach to the production frontier.

3. Data

Data for an industry where a shift in technology has occurred are required to test our model. The flat glass industry experienced a technical revolution in the late 1960s and early 1970s when the Pilkington float glass process was commercialized.[12] Therefore we used panel data at the plant level for this industry covering the period 1972-1981. The details on the data construction are discussed in the appendix.

4. The Estimates

Equations (8) and (9) were estimated under the previously discussed specifications of J, the adaptation path proxy, and 1, the frontier shift proxy.[13] The frontier shift proxy was applied on a plant by plant basis. We first determined the year when each plant incorporated the Pilkington process. We then assigned 1 = 0 for prior years when the plant had a stable process and 1 = 1 for the year of the technology shift and afterwards. We estimated the cost and share equations adjusted for the first-order autocorrelation.[14] Initial work involved investigating the three variants of the adaptation path.[15] The path denoted J_1 is straightforward. The optimal path for J_0 was J_0 = arctan(t-5.05). Equations (8) and (9) were then estimated using the switching values of 1 versus a naive model in which 1 is set equal to zero. Because we had only 150 observations (135 after allowing for first order serial correlation) while there are 33 parameters being estimated, we allowed 1 to vary (take values 0, 1) only in the capital share equation and cost function; that is we used a switching dummy variable for "$_{10}$, "$_{1k}$, and for "$_{1KK}$, and thus brought the total number of parameters to 34. A likelihood ratio test showed that the switching dummy was statistically significant in both models with J_0 and J_1 (See Table A.2).[16]

The results in Table 1 suggest that the learning curve, J_0 = arctan (t-5.05), is a better technological index than the linear time trend, J_1 = t. The learning curve results in a statistically significant estimate of "$_J$ with the expected negative sign for technical progress. That is, ceteris paribus, costs decrease with technical progress. In contrast, the traditional linear time trend yields an unexpected statistically significant positive estimate for "$_J$, contradicting economic theory. We note, however, that the two models perform equally well on the basis of the log of the likelihood function, the sums of squared residuals and the Durbin-Watson statistics.[17] Also, both models satisfy the concavity condition of the cost function at approximately ninety percent of the data points.

The detailed parameter estimates for the two models are reported in Table 2. While both models yield similar estimates for the first and second order coefficients associated with output and with input prices, they give significantly different estimates for the coefficients associated with the technical progress variable. Most notably, the learning curve model yields the estimates for "$_J$ that are more consistent with economic theory than those obtained from the traditional linear time trend model, as already mentioned. Also, it is important to note that this model gives the estimated biased technical change parameters, "$_{iJ}$, that have exactly the same signs with those found by Jorgenson (1984) for the Stone, Clay, and Glass (2-digit) industry group.

The Allen-Uzawa elasticities of substitution and the price elasticities of demand for factor inputs are reported in Tables 3 and 4. In general, the elasticities are small, implying a semi-fixed technology except for those associated with intermediate materials inputs. All the own elasticities have the correct negative sign.

[18]

Most strikingly, except for the elasticity of substitution between electricity and fuels in the J_0 model, all point estimates of the cross-elasticities of substitution are positive, indicating that most inputs are substitutes in the long-run even though they could be complements in the short-run. These results are important and consistent with the literature on the substitutability among the conventional inputs in the production process. We emphasize the importance of this finding especially because of the well-known controversy surrounding the energy-capital complementary issue [e.g., Berndt-Wood (1975, 1979) and Griffin and Gregory (1976)] that has not been quite settled by aggregate studies. In this regard, our results, based on micro-data, provide an additional piece of evidence regarding the issue of energy-capital complementarity.[19]

5. Resulting Estimates of Productivity

We used the measure suggested by Ohata (1974) and employed by Berndt (1980), to analyze total factor productivity (TFP) in the flat glass industry.[20] Here, under the proper assumptions regarding duality, curvature, and markets, [see Berndt (1980)], it can be shown that

$$TFP = [1/(\ \ln C/\ \ln Q)]\cdot[-\ \ln C/\ J]. \tag{12}$$

We calculated TFP using the estimated models incorporating J_0 and J_1 and report them in Table 5.[21] The mean TFP plus or minus one standard deviation for J_1 is -1.242 to -.420, whereas that for J_0 is -.447 to +.121.

When technical progress is specified as J_0, the calculated TFP for all 15 establishments is negative (i.e., there are losses in productivity) in the earlier years of the sample period; however, they become positive starting in 1977 and are all positive by 1981. This turn-around in TFP is consistent with the adaptation process postulated above. In contrast, with the conventional specification of technical change, J_1, TFP remains negative for all establishments for the entire period. Thus, the two measures of adaptation to the new production process yield substantially different indexes of TFP and consequently lead to different economic inferences.

6. Conclusion

We have proposed a model of the firm's adaptation to new technology that broadly follows the suggestions of Arrow (1962) and the standard learning curve literature. The model is applied to panel data at the establishment level for the flat glass industry. It is found to be better than the conventional model of linear technical change in terms of the expected signs on the technical progress coefficients, and its ability to generate meaningful patterns in total factor productivity growth. We caution the reader that we have so far demonstrated these results only for this particular data and model and that they are expected to be limited to those cases in which firms must learn adaptively after a large technical change has taken place. Future work should also address the issue of integrating the paradigm offered here with the adjustment cost literature, tying the model more formally to that of Arrow's work, and estimating the costs of learning that determine the adaptation process.

Table 1. A Comparison of Models of the Adaptation Path

OVERALL STATISTICS	J_0 = arctan(t-5.05)	J_1 = t
Log of Likelihood	1571.58	1570.57
Sum of Sq. Residuals		
C	2.303	2.374
K	.394	.404
L	.167	.169
E	.002	.002
F	.032	.030
Durbin-Watson Statistic		
C	1.56	1.59
K	1.51	1.45
L	2.29	2.27
E	1.64	1.60
F	1.73	1.72
Number of Failures of Concavity	13	14
Estimated coefficient on "$_J$	-.463	.670
(Standard Error)	(.222)	(.312)
Estimated Coefficient on "$_{JJ}$	-.095	-.059
(Standard Error)	(.048)	(.024)

Table 2. Estimated Parameters of TL Models Under J_o and J_1
(Standard Errors in Parentheses)

Parameter	J_0 = arctan(t-5.05)	J_1 = t
"$_0$	12.785[a] (1.617)	7. 26 (2.559)
D$_c$	.905[a] (.019)	.887[a] (.019)
"$_q$	-.911[a] (.310)	-1.231[a] (.374)
"$_{qq}$	.068[b] (.031)	.096[a] (.035)
"$_K$	1.331[a] (.136)	1.333[a] (.148)
"$_L$	-.119 (.112)	.002 (.129)
"$_E$	.068[a] (.018)	.006 (.036)
"$_F$	.068 (.075)	-.066 (.091)
ß$_{KK}$	-.015 (.009)	-.016 (.010)
ß$_{LL}$	.037[c] (.018)	.033[c] (.018)
ß$_{EE}$	.003[a] (.001)	.003[a] (.001)
ß$_{FF}$	.010 (.008)	.018[b] (.008)
ß$_{KL}$	.007 (.006)	.007 (.006)
ß$_{KE}$	.001 (.001)	.0004 (.0006)
ß$_{KF}$	.001 (.003)	-.0007 (.0028)
ß$_{LE}$	.001 (.002)	-.00001 (.0019)

Table 2 (cont'd)

Parameter	J_0 = arctan (t-5.05)	J_1 = t
ß$_{LF}$	-.006 (.007)	-.008 (.007)
ß$_{EF}$	-.002 (.002)	-.001 (.002)
"$_{Kq}$	-.143[a] (.012)	-.141[a] (.012)
"$_{Lq}$	.068[a] (.010)	.061[a] (.009)
"$_{Eq}$	.001 (.001)	.001 (.001)
"$_{Fq}$	.006 (.004)	.002 (.004)
"$_{J}$	-.463[b] (.223)	.670[b] (.312)
"$_{JJ}$	-.095[c] (.048)	-.059[b] (.024)
"$_{KJ}$	-.011 (.013)	.001 (.007)
"$_{LJ}$	-.029[a] (.009)	-.013[b] (.005)
"$_{EJ}$	-.001 (.001)	.002 (.001)
"$_{FJ}$	.004 (.005)	.011[b] (.004)
"$_{qJ}$	.043[b] (.020)	.009 (.009)
p_s	.952[a] (.010)	.938[a] (.013)
Switching Dummy	.068[a] (.021)	.096[a] (.033)

a Denotes statistically significant at the 99% confidence level, (t=2.756)
b at the 95% confidence level, (t=2.045) and
c at the 90% confidence level, (t=1.699).

Table 3. Estimated Allen-Uzawa Partial Elasticities

F	J_0 = arctan (t-5.05)	J_1 = t
KK	-.240	-.241
KL	.058	.057
KE	.0004	.0004
KOF	.005	.005
KM	.075	.077
LL	-.129	-.133
LE	.0004	.0004
LOF	.003	.003
LM	.024	.032
EE	-.014	-.014
EOF	-.002	.00007
EM	.017	.038
OFOF	-.050	-.042
OFM	.056	.034
MM	-2.646	-2.792

Note: For standard errors of the elasticities, see endnote 18.

Table 4. Estimated Price Elasticities

n	J_0 = arctan (t-5.05)	J_1 = t
KK	-.1109	-.1112
KL	.0157	.0154
KE	small	small
KOF	.0005	.0005
KM	.0234	.0239
LK	.0216	.0215
LL	-.0310	-.0316
LE	small	small
LOF	.0003	.0003
LM	.0092	.0112
EK	.0002	.0001
EL	.0001	.0001
EE	-.0003	-.0003
EOF	-small	.0001
EM	.0069	.0128
OFK	.0020	.0019
OFL	.0007	.0006
OFE	-small	small
OFOF	-.0040	-.0036
OFM	.0181	.0119
MK	.0270	.0277
ML	.0070	.0085
ME	.0006	.0009
MOF	.0046	.0034
MM	-.5738	-.6003

Note: For standard errors, see endnote 18.

Table 5. Total Factor Productivity (TFP)

	J_0 = arctan(t-5.05)	J_1 = t
Mean TFP	-.163	-.831
Std. Dev.	.284	.411
Range Minimum	-.710	-2.388
Maximum	.745	-.267

Pattern of Signs on Obs. No.	Year	Negative	Positive	Negative	Positive
2	1973	15	-0-	15	-0-
3	1974	15	-0-	15	-0-
4	1975	15	-0-	15	-0-
5	1976	15	-0-	15	-0-
6	1977	12	3	15	-0-
7	1978	8	7	15	-0-
8	1979	6	9	15	-0-
9	1980	2	13	15	-0-

Figure 1

TECHNICAL CHANGE, THE PRODUCTION FUNCTION
AND THE ADAPTATION PATH

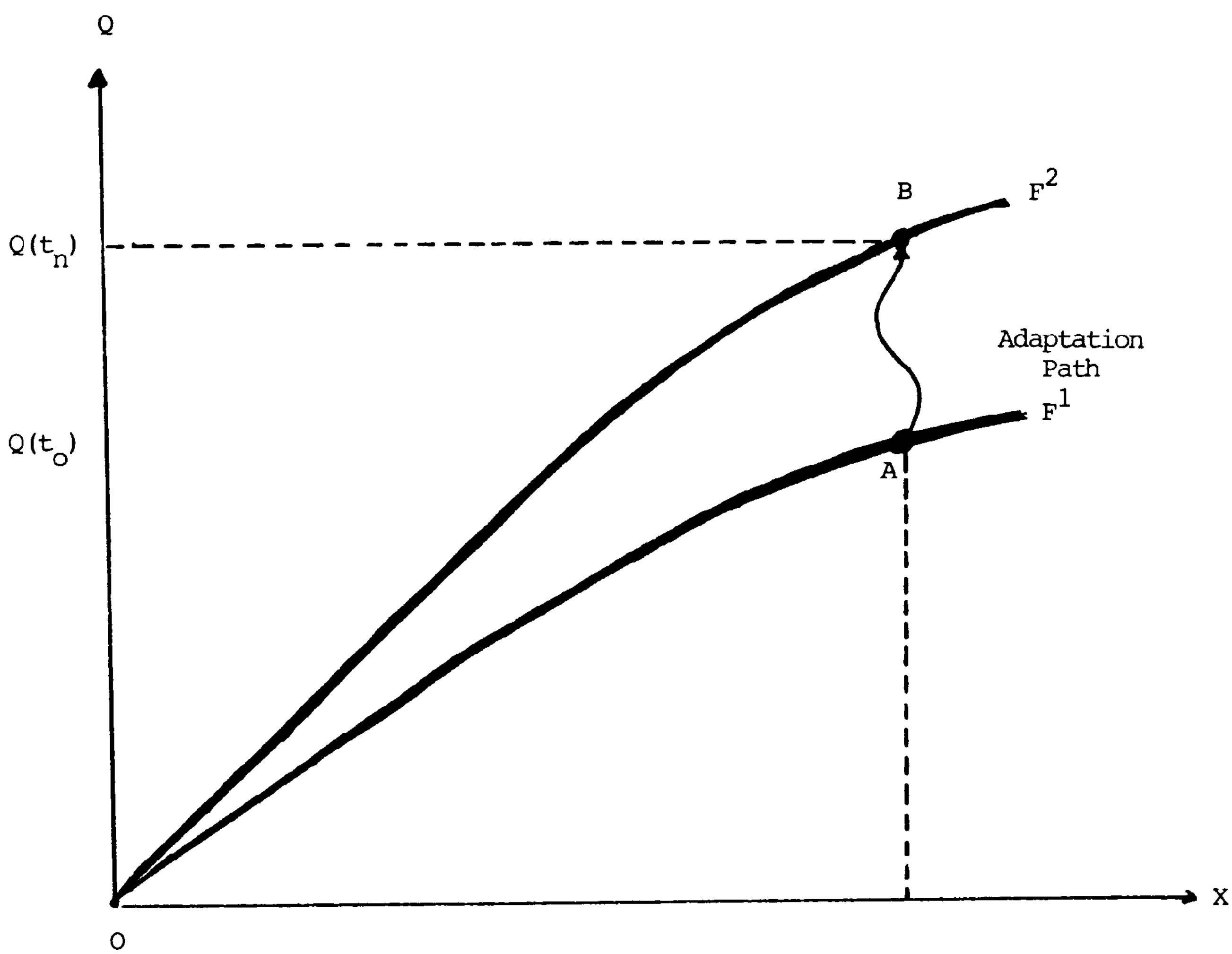

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Table A.1 Log Likelihood Values for Varying Specification of the Adaptation Path

J_0 = arctan (t-D)

D	Log of Likelihood
3.500	1413.95
4.500	1421.93
5.000	1423.96
5.025	1423.97
5.050	1423.97
5.075	1423.97
5.100	1423.97
5.200	1423.94
5.300	1423.90
5.400	1423.87
5.500	1423.84
5.600	1423.79
5.700	1423.69
5.800	1423.52
6.500	1420.77
7.500	1418.81

Note: These first tests were made using an earlier variant of equations (8) and (9).

Table A.2 Log Likelihood Ratio Test for Switching Dummy Variables
(H_0: "$_{1M}$ = "$_{1K}$ = "$_{1KK}$ = 0)

<u>Models</u>	<u>Test Statistics</u> L=2(U-C)[a]	Accept(A)/Reject(R)[b]
Model I (with J_1 = t)	14.96	R
Model II (with J_o = arctan(t-5.05)	13.58	R

[a]The L-statistic is defined as two times the difference of the logs of the likelihood functions of the unconstrained model (U) and the constrained model (C) in which "$_{1M}$, "$_{1K}$ and "$_{1KK}$ are set equal to zero.

[b]The null hypothesis (H_0) is accepted (A) or rejected (R) at the five percent level. The critical value of ^{2}(n=135, k=3) equals 4.61, where n is the number of observations and k is the number of parameter restrictions.

DATA APPENDIX

The data employed in this study were extracted from the Census Bureau's Longitudinal Research Database (LRD). The LRD contains data taken from the Census Bureau's Annual Survey of Manufacturers (ASM) and their quinquennial Census of Manufactures (Census) for over 50,000 establishments in each year (1972-1981). (For a complete description of the LRD, see Monahan, 1983 and McGuckin and Pascoe, 1988.) An establishment is "defined as a single plant or factory in which manufacturing operations are performed . . . (and includes all activities) manufacturing, fabricating, processing, and assembling . . . conducted within the establishment." (Monahan, 1983.)

A restriction imposed by the nature of the data is that the Census Bureau collects accounting information, or total dollars, for a specific variable. For example, the total dollars spent on intermediate materials are collected; the prices, however, are not always collected. Quantities must often be imputed from price data, but this is impeded because of the sparse nature of the price data that are reported.

The industry under study is the flat glass industry (SIC 3211). The extract used contains data for 15 separate establishments covering the period 1972-1981. There were 32 establishments that produced flat glass products in 1972, 62 in 1977, and 69 in 1982 respectively. The 15 establishments in our sample accounted for over 70% of total shipments on average for this time period.

Initial work with the complete data set extract involved normalization and plotting to discern outliers. When extreme outliers (greater than 3 standard deviations from the mean of the series in question) became apparent, the particular observation was checked (often back to the original form filled out by the responding establishment). After the editing step, it was apparent that the resulting data is still replete with noise. This arises from occasional legitimate extreme values, intertemporal discontinuities, missing or imputed observations, and most probably from the data reporting and recording process. Thus, a dummy variable was used to accommodate the noise when it was obvious. There were 4 such dummies. The specific variables are discussed below.

Recall the general underlying production function that is assumed is

$$Q = Q(K, L, E, OF, M; J), \tag{A.1}$$

where Q denotes a flow of output, K, L, E, OF, and M respectively denote a capital service flow, labor, electricity, other fuels, and intermediate materials; and where J is a technical change index. Equation (A.1) holds for each year (t) and establishment (j) but these subscripts are noted below only where necessary for clarity.

Output is the deflated sum of the total value of shipments and the net changes in finished goods and in work-in-process inventories during the appropriate calendar year. The deflator is the Producers Price Index (PPI) for Glass Products, 1972 = 100 provided by the Bureau of Labor Statistics. All data on shipments and inventories are available in the LED for each of the establishments with two exceptions. First, for an establishment that started operations in 1972, its initial finished goods and work-in-process inventories were not reported and thus were presumed to be zero. The second, for an establishment that discontinued reporting work-in-process inventories during part of the observation period, it was assumed that this inventory value was subsumed in some other reported inventory asset category, and therefore no adjustment was made.

The flow of capital services was assumed to be proportionate to the depreciated stock of machinery and equipment. The construction of a capital stock series for each establishment was complex, because the Census Bureau collected only part of the information needed for the total time period covered, and does not collect some of the required information at all. The key problem lies in the initial stock of capital assets (structures plus machinery and equipment). The ASM and the Census ask the respondent to provide data on the gross value of structures and of machinery and equipment on the establishment's books for a given year. Data that attempt to recognize the economic worth of the capital assets, such as depreciated assets, are not collected. The ASM reports data on annual depreciation, only since 1977 (similarly for capital retirements). Further, the ASM commenced in 1949, were as some flat glass plant structures date from the late 1800s. Therefore, a perpetual inventory method for the total capital assets of structures, machinery and equipment could not be constructed by working forward from the initial year of the plant's operation. What was done is to rely on the technical breakthrough, the Pilkington process, experienced by the flat glass producers in the late 1960s (See Pilkington [1969]. This innovation led all flat glass producers to change their equipment and machinery including the melting furnace forward along the production line to just short of the warehousing operation. In the U.S., most of the changes occurred in the late 1960s and early 1970s, roughly coincident with the start of the observations in the LED file. This allowed a capital stock series for machinery and equipment to be constructed. Yet, since most of the establishments were housed in structures predating 1970, a related capital stock for structures could not be achieved. The series was constructed by the perpetual inventory method using the reported beginning assets for machinery and equipment (MAB) in 1972. The relevant formula for the dollar value of capital machinery and equipment is,

$$\hat{K}J = MAB + \sum_{i=1972}^{J} [(1/2).(NM_i + UM_i - MRT_i)$$

$$- * \hat{K}_{i-1} + (MR/QK)_i] \quad . \qquad (A.2)$$

Here NM and UM denote new and used machinery and equipment purchases respectively; MRT and * denote machinery and equipment retirements and the depreciation rate; MR represents machinery and equipment rental costs; and QK denotes the user cost of capital. Note that the last term in equation (A.2) is the capitalized value of machinery and equipment rentals. In some cases this was a significant amount of the total capital stock in machinery and equipment (e.g., 6% in one establishment's case).

As mentioned above, retirement data are only available from 1977 forward. Hence, we used the depreciation rate developed by Jorgenson and Stephenson (1967) of 7.53% per year, and retirements were taken at zero for the 1972-76 period. An alternative approach would be to use newer depreciation rates suggested by more recent work. We chose the Jorgenson-Stephenson rate for this study and hope to explore the impact of alternative depreciation rates such as the "best geometric average rate" by asset class suggested by Hulten and Wykoff (1981) in future work.

The cost of capital services, QK, was calculated by a Jorgensonian expression as applied by Mohr (1986).

$$QK = [(1 - T.Z-K)/(1-T)].[PA_{t-1}.r + PA_t.* - (PA_t - PA_{t-1})] \qquad (A.3)$$

Here, PA is the SIC 321 price deflator for capital goods taken from a data file of the Bureau of Industrial Economics (BIE), available at the Center for Economic Studies. The rates of return are approximated by the interest rates obtained for each firm from Moodys (see Kokkelenberg and Hall [1985]). The corporate tax rate and the investment tax credit are denoted by T and K respectively, while Z denotes the present value of the tax effects of accelerated depreciation. These data were taken from a data file maintained at the Center for Economic Studies. Finally, the total cost of capital services, SSK, was calculated by multiplying deflated capital stock, K, by QK, for each establishment in each time period.

The labor input, L, was constrained to concern production workers only. The inclusion of non-production workers was dropped from the model, because of obvious accounting artifacts. The number of non-production workers reported in the ASM fluctuated widely by establishment, even when normalized by output or production man hours. It is likely that different firms place non-production worker on different payrolls (e.g. plant versus home office). The total production labor cost, SSL, for each establishment in each year is given by

$$SSL = [WW + LC\ @\ (WW/(OW + WW))] \tag{A.4}$$

Here WW is the total salaries and wages in current dollars, LC is the total supplemental labor costs in current dollars (which accrued to both production workers and non-production workers), and OW denotes non-production workers salaries and wages.

The Census Bureau collected the cost of purchased electricity, EE. Cost of other fuels is also complete and similarly treated to obtain, SSOF, the total fuel cost.

The total cost of materials was calculated by

$$SSM = (CP + CR + CW), \qquad (A.5)$$

where CP denotes the costs of materials and parts purchased during the relevant time period, CR denotes the costs of resales, and CW denotes the costs of contract work. As part of this study, field visits were made to several glass establishments. It was noted that they frequently engaged in warehousing and resale operations of significant magnitude to enable them to meet their customer's demands. In this data set, the cost of resale goods varied from zero to over $25 million, with an average value of $2 million or 12.5% of CP.

The estimation of a translog cost function and its elasticities requires factor shares as dependent variables which were calculated in the usual way where total cost is the sum of SSK + SSL + SSE + SSOF + SSM. Prices of the inputs are required as exogenous variables in estimating a translog cost function and these proved to be difficult to obtain for all inputs. The service price of capital is discussed above. The price of labor was generated by dividing SSL by the total production worker man hours which was collected by the Census Bureau in the ASM. Similarly, a price of electricity was generated by dividing the total cost of purchased electricity by the kilowatt hours purchased, both variables collected by the Bureau for the whole sample.

During the sample period, the establishments used a variety of fuels with the major three being natural gas, residual fuel oil, and distillate fuel oil. Over time, as fuel oil prices rose more rapidly, there was a shift out of fuel oil to natural gas for the sample as a whole. Although this varied from establishment to establishment, it is an apparent result of long-term fuel contracts. Thus, the average price of fuel, POF, was calculated as

$$\begin{aligned} POF = [&FCR/(FQR\ @\ 6.285) + FCN/(FQN\ @\ 1.020) \\ &+ FCD/(FQD\ @\ 5.824)]/[FCR + FCN + FCD], \end{aligned} \qquad (A.6)$$

where FCR, FCN, FCD denote residual fuel oil, natural gas and distillate fuel oil total costs respectively. FQR, FQN, and FQD denote the respective quantities (in 42 gallon barrels for the oil and 1000's of cubic feet for the gas). The factors 6.285, 1.020, and 5.824 are the respective millions of British Thermal Units per 42 gallon barrel or 1000 cubic feet. Equation (A.6) results in a Btu weighted fuel cost. These data exist for each establishment for 1974-1981. An appropriately weighted average of the Producers

Price Index for fuels and natural gas, benchmarked to the 1974 btu weighted price for each establishment, was calculated for the two years, 1972 and 1973.

The price of materials was determined for the two Census years, 1972 and 1977, by calculating a delivered price for glass sand and for soda ash for each establishment. Quantity and cost data for a variety of materials are gathered in each Census year but not in the ASM years. The two inputs, glass sand and soda ash account for 50% or more of the intermediate materials costs for each establishment and by far the largest tonnage. Other materials which account for a large share of total costs are packaging products and inorganic minerals which are added to the materials charged to the furnace (e.g. lead). However, the details for the intermediate materials other than glass sand and soda ash were sparse. The price of materials is then calculated by

$$PM = [CGS \cdot (CGS/QGS + CSA \cdot (CSA/QSA)]/[CGS + CSA], \qquad (A.7)$$

where CGS denotes the total cost of glass sand delivered, QGS the quantity of glass sand, CSA the total delivered cost of soda ash, and QSA the quantity of soda ash. This weighted price, PM, was calculated for 1972 and 1976 to establish benchmarks. The 1972 price was then used together with the PPI for intermediate materials in manufacturing (1967=100) to generate 1972, 1973, and 1974 prices for each establishment. Prices for 1975 through 1981 were generated by the 1977 Census year benchmark weighted price and the PPI for intermediate materials.

ENDNOTES

1. This adaptation cost is not to be confused with the Eisner and Strotz (1963) concept of adjustment cost. The latter is a cost accompanying the installation of new quasi-fixed inputs.

2. Arrow, (1962), pg. 156.

3. Theoretically, the stock of capital associated with the new technology may also differ from that of the old technology in another important aspect, that of raw material and work-in-process inventories. In this study, we lack the appropriate data to determine the exact differences in the raw and intermediate material inputs under the old and the new technologies. A perusal of the technical literature suggests that there are no substantive differences in the raw materials required in either process (c.f. the Encyclopedia of Chemical Technology [1977]). Therefore we adopt the usual practice of using the stock of capital and the output of the final product to proxy for this omission. We thank an anonymous referee for pointing out this assumption.

4. See, e.g., Binswanger (1974) or Helliwell (1976).

5. See Ross (1986).

6. Arrow, op. cit., pg. 155.

7. The possible exception is that of Brown and Christensen (1981) who developed a flexible functional paradigm which considered short-run costs only, holding the technology as represented by the quasi-fixed inputs constant. The next step was to estimate a series of such short-run cost models and then estimate the long-run model. This has been done by Morrison (1985) among others. Yet the problem of modelling the learning or adaptation path is still not directly addressed by this approach.

8. Solow (1957), page 312.

9. See Bischoff (1971) or Kokkelenberg and Bischoff (1986) for examples.

10. Two important but omitted inputs are non-production workers and certain intermediate material inputs. Both are omitted because usable data are lacking. We recognize that in the absence of explicit treatment of these omitted inputs and of non-separability, there are biases in the parameter estimates.

11. Note that while equation (11) is traditional, it would allow costs to decrease without limit. This failing is seldom mentioned in the literature. In the short-run this may not appear to be a problem, but only equation (10) is consistent with the idea of approaching a frontier. We also investigated a model using $J_{,} = t^a$, $0 < a < 1$. This exponential model, which allows for a monotonic but decreasing impact of J, proved to be inferior to either J_0 or J_e and was dropped from further work.

12. Pilkington (1969). See also The Encyclopedia of Chemical Technology (1977) volume 7, which includes a large number of references on the float glass process.

13. Equations (8) and (9) were estimated using the iterative Zellner (1962) seemingly unrelated nonlinear estimation procedure in T.S.P. 4.0. This estimation procedure is asymptotically equivalent to the full information maximum likelihood method. The regressions were carried out on the Hewlett Packard 9000 at the Center for Economic Studies, U.S. Bureau of the Census.

14. A more complex lagged structure may be more appropriate because the phenomenon being considered has an underlying dynamic property. A dynamic model may help to distinguish between short and long run phenomena. We were constrained from incorporating longer lags, however, by degrees of freedom considerations.

15. See Table A.1 for the results of an initial screening of J_0. In addition a number of rational functions were tried; for example $J = t/(t^2+t+1)$ or $J = t/(t+1)$ or $J = (t+1)/t$. While all of these showed some slight improvements over $J = t$ in terms of coefficients that were statistically significant, they failed to improve the overall fit of the system of equations.

16. We attempted to include the switching dummy variable in each share equation for each parameter, but the added cross equation constraints were beyond the capabilities of our software. Because the new technology is associated with capital stock, we then limited the switching dummy to the cost intercept, "$_{10}$, the capital intercept "$_{1K}$ and the coefficient, "$_{1KK}$. Note that we are making an assumption about the switching dummy. Specifically we are assuming that this dummy is a proxy for shifts in technology rather than the effects of the adaptation to the existing technology, or a proxy for other changes that may be occurring in the industry.

17. The Durbin-Watson statistics are all such that the hypothesis of first order serial correlation among the residuals after the correction must be either indeterminate or rejected. The problem of the non-normality of this data set is evidenced by a Lagrange

multiplier test (Jarque and Bera, 1980). This, of course, should be borne in mind when evaluating the overall results of those statistics that presume an underlying normally distributed disturbance term. The number of sign changes after the inclusion of a first order auto-regressive correction showed no serial correlation as did a regression of residuals on lagged residuals. A Park test for heteroscedasticity (Park, 1967) and a plot of the squared residuals versus scaling variables showed no signs of heteroscedasticity for any model of J.

18. These elasticities were calculated using the formulas given below.

$$\hat{F}_{ii} = (\hat{ß}_{ii} + \hat{S}_i^2 - \hat{S}_i)/\hat{S}_i^2$$

$$\hat{F}_{ij} = (\hat{ß}_{ij} + \hat{S}_i\hat{S}_j)/\hat{S}_i\hat{S}_j$$

$$\hat{n}_{ij} = \hat{S}_j \cdot \hat{F}_{ij}$$

$$\hat{n}_{ii} = \hat{S}_i \cdot \hat{F}_{ii}$$

where i,j = K, L, E, OF, M. Calculations were made at each observation and Tables 3 and 4 report mean values of the elasticities. We do not report the standard errors of the elasticities because proper estimates for such statistics are difficult to obtain. In fact, we can calculate standard errors for these elasticities over the sample, but then they only show the variance in the factor shares, the $\hat{S}_i$. They can also be calculated at a point and the mean fitted or actual factor share used together with the variance on the $\hat{ß}_{ij}$. Anderson and Thursby (1986) investigated this issue and concluded that "a trade off between the use of highly-disaggregate data and the width of the confidence intervals surrounding elasticity estimates [exists]" (page 656). We calculated the standard error over the sample and found that the own Allen-Uzawa elasticities are more than two standard errors different from zero. However, all of the cross elasticities are not. We used the Anderson-Thursby preferred method in a further test and found the same results with 95% confidence, but results consistent in regards to sign for cross elasticities with 80% confidence.

19. As mentioned earlier, J. Solow (1987) argued convincingly that it is impossible to resolve the controversy surrounding the energy-capital complementarity without the use of microdata.

20. The advantage of this measure of TFP is that it does not require neutrality of technical change. Equally important, it is better than the Gollop-Jorgenson approach because it does not impose the restriction of constant returns to scale.

Kokkelenberg (1987) showed that this restriction does not hold for this data.

21. Note that an index of total factor productivity in stone, glass and clay products for the period covered was as follows (1977=100)

1972	99.0
1973	103.8
1974	102.8
1975	93.2
1976	96.3
1977	100.0
1978	104.8
1979	107.0
1980	102.0
1981	99.5

Source: American Productivity Center (1982)