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Dynamic factor demand equations in U.S. and Canadian agriculture

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ABSTRACT

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This research provides one of the first empirical estimates of a data-based dynamic factor demand model for American and Canadian agriculture. Models such as these deserve more widespread use in the empirical analysis of agriculture. These models have the advantage that they do not impose inappropriate dynamics on the data. Rather they permit the data to select the appropriate dynamics.

We use a model originally developed by Anderson and Blundell. This model is a general first-order dynamic model which contains as testable hypothesis several simpler models. This model permits us to estimate the long-run agricultural production structure as a subset of the dynamic parameter estimates. We will test this long-run structure for symmetry, homotheticity and neutral technical change.

The estimated models may be used to test for three alternative dynamic structures. In the limit, dynamics may not be needed and we can test for the static long-run equilibrium model. Two intermediate cases are the *autoregressive* and the *partial adjustment* models which are simpler than the general model but still include dynamics.

Our results suggest that the long-run equilibrium model is unsatisfactory in both countries. A dynamic model is needed. In both countries, the two more restricted dynamic models are rejected. The general dynamic model is required. In Canada, the long-run equilibrium structure is homothetic with neutral technical change. In the United States, homotheticity is also accepted but neutral technical change is rejected.

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1. INTRODUCTION

The estimation of disequilibrium factor demand models has become more common in recent years. In agricultural economics, many researchers have adopted a short-run model in which some factors are fixed, in the short-run. This type of model was originally used in agriculture by Brown and Christensen (1981). More recently it has been used by Hertle (1987), Moschini (1988), Shumway and Alexander (1988), Chambers and Just (1989). Other authors, Kuroda (1987), Huffman and Evenson (1989) and Lopez (1984) have continued to use a long-run equilibrium model as the basis for their estimation.

In this paper, we develop and estimate a set of data-based dynamic factor demand models for U.S. Canadian agriculture. Dynamic factor demand models arise because it is unlikely that the observed production data represent equilibrium prices and quantities. Roughly classified, there are two important streams of work. These streams overlap and in the long-run should converge or at least become more tightly linked. One stream is relatively theory based and introduces dynamics via explicit theoretical modelling of the dynamics. In most cases, the dynamic theory rests on the concept of adjustment costs. A large empirical literature is based on cost of adjustment models. [1] Recent agricultural studies by Vasavada and Chambers (1986), Vasavada and Ball (1988) and Tsigas and Hertel (1989) adopt this approach. The other research stream is relatively data based and lets the data choose the form of the dynamics. Our models are of this type. The extensive work by Sargan, Hendry and others [2], is relatively data based. We do not know of any agricultural studies using exactly this methodology although the preferred model in Tsigas and Hertel (1989) [3] has many of the characteristics of this type of work.

This paper uses annual data from American and Canadian agriculture to investigate the usefulness of a general data-based dynamic model of the demand for agricultural inputs in both these countries. We use a dynamic model originally estimated by Anderson and Blundell (1982, 1983).

Section 2 discusses the equilibrium production model and the theoretical restrictions on the most general equilibrium model that we will test.

Section 3 develops the alternative dynamic model and the tests that will be used to assess the dynamic structure of the factor demand equations.

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[1] Early work was done by Nadiri and Rosen (1969) and two of the many later examples would be Pindyck and Rotemberg (1983) and Epstein and Denny (1983).

[2] See the articles in Hendry and Wallis (1984) and Hendry et. al. (1984).

[3] We would like to thank a referee for bringing this interesting paper to our attention.

Section four briefly discusses the data used in the research and the estimation procedures.

Section 5 presents the results for both the evaluation of the long-run equilibrium models and the investigation of alternative dynamic models. Some brief concluding remarks are contained in the last section.

2. EQUILIBRIUM PRODUCTION MODEL

Suppose we have a production process, $Q=f(X)$, which uses a vector of inputs, X, to produce output, Q. An equivalent representation of the technology by the cost function is $\text{TC}=g(w, Q, t)$, where total cost, TC, is a function of an input price vector, $w=(w_i)$, $i=1, 2, 3$, the level output, Q and a time trend, t.

Assume that the long-run cost function may be approximated by a translog functional form. Production requires the use of three inputs to produce one output. The total cost function is:

$$\begin{aligned}\ln \text{TC} = a_0 &+ \sum_i b_i \ln w_i + b_Q \ln Q + b_t \ln t + \tfrac{1}{2} b_{QQ}(\ln Q)^2 \\ &+ \tfrac{1}{2} b_{tt}(\ln t)^2 + \tfrac{1}{2}\sum_i \sum_j b_{ij} \ln w_j + \sum_i b_{iQ} \ln w_i \ln Q \\ &+ \sum_i b_{it} \ln w_i \ln t + b_{Qt} \ln Q \ln t \qquad i, j=1, 2, 3 \qquad (1)\end{aligned}$$

and the input share equations are:

$$S_i = b_i + \sum_j b_{ij} \ln w_j + b_{iQ} \ln Q + b_{it} \ln t \qquad \text{for all } i \qquad (2)$$

These factor share equations can be estimated to provide evidence on the characteristics of the cost function. Factor cost shares must 'add up' to one and this will imply a number of parameter restrictions. For the translog functional form (2), the 'adding up' restrictions are:

$$\sum_i b_i = 1 \qquad \sum_i b_{ij} = 0 \qquad \sum_i b_{iQ} = 0 \qquad \sum_i b_{it} = 0 \qquad \text{for all } j \qquad (3)$$

These restrictions are required for the estimation of the share equations and consequently are maintained throughout the empirical estimation.

There are a number of restrictions on the technology that will be tested in this paper. Symmetry, homotheticity and neutral technical change are tested. For the translog model, the parameter restrictions are:

$$\begin{aligned}\text{Symmetry:}\quad & b_{ij} = b_{ji} && \text{for all } i, j, i \neq j \\ \text{Homotheticity:}\quad & b_{iQ} = 0 && \text{for all } i \\ \text{Neutral technical change:}\quad & b_{it} = 0 && \text{for all } i \qquad (4)\end{aligned}$$

These are not imposed because our tests of the dynamic structure may be sensitive to the nature of the equilibrium technology. Thus we will test the dynamic structure under a variety of alternative maintained hypotheses about the technology.

The first hypothesis, symmetry, has a different theoretical status than the other two hypotheses in (4). If symmetry does not hold, then the estimated long-run share equations are not derived from an aggregate cost function. However, there may still exist aggregate share equations that are consistent with underlying disaggregated share equations and consequently technology.

The other two hypotheses relate to the shifting and twisting of the isoquants due to change in the output level and in the technology.

3. DATA-BASED DYNAMICS

In this section, we will introduce and discuss the particular form of the data-based dynamics that we will consider. At this stage, in the development of dynamic production models, there is no definitive model with wide empirical support. The model that we use was originally developed by Anderson and Blundell (1982, 1983) for the analysis of consumer behaviour. More recently, it has been used by Friesen (1988) and by Nakamura (1986) to analyze production. The model has roots in the work of Hendry, Sargan and others on data-based dynamic models. These models are extensively discussed in Hendry and Wallis (1984), Hendry et al. (1984) and the many references contained in these works.

Economic theory has two conflicting roles in relation to empirical economic analysis. Theory may be used to impose structure on the estimation and to reduce the number of estimated parameters. The imposition of homogeneity of degree zero in prices on a factor demand equation is an example. This use presupposes that the theory is correct. Alternatively, the empirical analysis can be undertaken in order to directly test the theory, i.e. do the data reject homogeneity in prices.

The theory of dynamic production models is less fully developed than the static theory of production. As a consequence, there is less guidance from and less compulsion to use dynamic production theory to restrict empirical models. Data-based models attempt to let the data described the dynamic process underlying the observed time series data. Dynamic theory is not imposed in the estimation because that theory is not sufficiently well developed or tested. Imposing relatively ad hoc models of costs of adjustment will force the estimates to conform to a theory that may not be true. The alternative is a looser theoretical structure. We have chosen the looser structure but it does imply extra costs. These costs are the likely increase in the number of parameters required to permit the data to describe the dynamics.

The Anderson and Blundell model assumes that only first-order dynamic effects are important. This model can be characterized by the label 'general first-order data-based dynamics'. It is general because there are no restrictions on the type of first-order dynamics. The restriction to first-order dynamics is a practical matter. With a relatively short annual time series, more complex general second-order dynamics would be impossible to estimate. The dynamics are data-based because there are no restrictions arising from dynamic economic theory. We permit the data to choose the form of the dynamics.

It may be easier to understand the dynamic model [4] by restating it in the form of a single equation error correction model (ECM). Suppose the long-run equilibrium model is $Y=\beta X$. However, for a variety of possible reasons, the actual observations are not the long-run equilibrium values of the Y and X variables. Two broad processes are used to describe the disequilibrium. First, producers may make errors in earlier periods. Current changes in Y will partially reflect responses to these past errors. Second, current changes in Y will reflect current changes in X and the response to these current X changes may not be complete within the period of observation. Taking into account these two adjustments, the ECM may be written:

$$\Delta Y_t = \alpha \, \Delta X_t + \gamma[\beta X_{t-1} - Y_{t-1}] \tag{5}$$

Changes in the endogenous variable, Y, occur because of changes in the exogenous variables, X, and due to adjustment from previous errors [5]. The adjustment parameters, α and γ, represent the responses to new information about the exogenous variables, X and error correction, respectively.

For the share equations in our translog model, the first-order dynamic model may be written in vector form:

$$\Delta S_t = A \, \Delta X_t - C[S_{t-1} - BX_{t-1}] \tag{6}$$

where all the capitalized variables are vectors or matrices. The variables are the vector of first differences of the variable factor shares, ΔS_t, the vector of the first differences of the regressors, ΔX_t, and a vector of lagged values of all regressors, X_{t-1}.

[4] This discussion follows Hendry et al. (1984) closely.

[5] EC models are not simply adjustments to current and past information. Nickell (1985) discusses the links between forward looking optimization and the ECM model. Further discussion of this issue is contained in Hendry et al. (1984).

There are three parameter matrices, A, B and C. The B matrix contains the long-run cost function parameters. These parameters are the parameters of the translog cost function (1) or share equations (2) above [6]. The elements of the other two matrices are short-run adjustment parameters. The A matrix contains parameters that correspond to α in the single equation model, (6). These are the responses to new information about the regressors. The C matrix contains parameters that are the 'error correction' parameters reflecting the adjustment to last period's disequilibrium. They are equivalent to the γ parameter in (6).

The system of share equations in (6) must be modified in two ways before estimation. Adding up requires that the shares add to one in each time period. Since the lagged shares appear in (6), adding up requires that one of the lagged shares be deleted from the model. Suppose the third lagged share is deleted. This will introduce new parameter constraints [7] on the C matrix:

$$c_{ij}^{*} = c_{ij} - c_{i3} \qquad i = 1, 2, 3 \qquad j = 1, 2 \tag{7}$$

in addition to the usual adding up constraints in (3). It will not be possible to retrieve the original c_{ij} parameters. This is because we can not estimate the c_{i3} parameters. Deleting the third lagged share also requires deleting the row of the B matrix that corresponds to the third share equation. The parameters that are deleted from the B matrix can be recovered from the adding up constraints in (3).

There is an additional set of adding up constraints. The first difference in the shares, i.e. the dependent variables, must sum to zero. Consequently, one equation must be deleted from the model. This implies that the column sums of A and C^{*} must sum to zero. From these column sum constraints, one can recover all the a_{ij} and c_{ij}^{*} parameters. The parameters in B can be recovered from the constraints imposed in (3).

The resulting share equations may be written:

$$\begin{aligned}
\Delta S_{it} = {} & \sum_j a_{ij} \ln(w_{jt}/w_{jt-1}) + a_{iQ} \ln(Q_t/Q_{t\text{-}1}) + a_{it} \ln(t/t-1) \\
& + \sum_j c_{ij}^{*} S_{jt-1} + \sum_j c_{ij}^{*} b_j + [c_{i1}^{*} b_{11} + c_{i2}^{*} b_{21}] \ln w_{1t-1} \\
& + [c_{i1}^{*} b_{12} + c_{i2}^{*} b_{22}] \ln w_{2t-1} + [c_{i1}^{*} b_{13} + c_{i2}^{*} b_{23}] \ln w_{3t-1} \\
& + [c_{i1}^{*} b_{1Q} + c_{i2}^{*} b_{2Q}] \ln Q_{t-1} + [c_{i1}^{*} b_{1t} + c_{i2}^{*} b_{2t}] \ln (t-1) \\
& i = 1, 2 \qquad j = 1, 2, 3
\end{aligned}$$

[6] EC In our single equation example, equation (5) or (6), the β parameter is replaced by the B matrix in the system of factor demand equations.

[7] These are derived in Anderson and Blundell (1982).

The long-run equilibrium model is a special case of the dynamic model. The parameter restrictions used to test for the long-run equilibrium model are:

$$c_{ii}^* = 1 \qquad c_{ij}^* = 0 \qquad a_{ij} = b_{ij} \qquad a_{iQ} = b_{iQ} \qquad a_{it} = b_{it} \tag{9}$$

With these restrictions, factors adjust completely to the current information on relative factor prices and the quantity of output.

The general dynamic model may be simplified to two common models. Both the partial adjustment model and the autoregressive model have been widely used in economics. In the same notation as the ECM model in (5), the three models are [8]:

$$\begin{aligned} \Delta Y_t &= \alpha\ \Delta X_t + \gamma[\beta X_{t-1} - Y_{t-1}] && \text{ECM} \\ \Delta Y_t &= \gamma\beta\ \Delta X_t + \gamma[\beta X_{t-1} - Y_{t-1}] && \text{Partial adjustment} \\ \Delta Y_t &= \beta\ \Delta X_t + \gamma[\beta X_{t-1} - Y_{t-1}] && \text{Autoregressive} \end{aligned} \tag{10}$$

The partial adjustment and autoregressive models are special cases of the ECM. In the ECM, the parameter, α, is the adjustment parameter for current changes in the exogenous variables, X. This adjustment can be different than the adjustment to past errors which is represented by the parameter, γ. In the *partial adjustment* model, all adjustments are equivalent and their is no distinction between adjustments to current changes in the exogenous variables and adjustments to past errors. The *autoregressive* model imposes the constraint that all adjustments to changes in the current exogenous variables are instantaneous. Adjustments to past errors are permitted. In each of these models, the parameter α, in the ECM must be constrained as follows:

$\alpha = \gamma\beta$ for the partial adjustment model
and
$\alpha = \beta$ for the autoregressive model

For our translog model, these restrictions may be written:

$$\begin{aligned} a_{ij} &= \sum_k c_{ik}^* b_{kj} && \text{partial adjustment} \\ a_{ij} &= b_{ij} && \text{autoregressive} \end{aligned} \tag{11}$$

In Section 5, we will present the results for the tests of these nested dynamic models.

[8] This is not the standard method of writing either the partial adjustment or the autoregressive model but this formulation permits easy comparisons with the ECM, (5).

4. DATA AND ESTIMATION

The agricultural data were originally developed by Capalbo, Vo and Wade (1985) for the United States, and Brinkman and Prentice (1983) for Canada. These data were modified for use in Capalbo and Denny (1986). A brief data appendix to that paper describes the data in more detail. To increase the data comparability between countries, Capalbo and Denny started with the most disaggregated available data in both countries. The data were aggregated consistently in both countries using Divisia indexes. This has the advantage of reducing, but not eliminating, the chance that data procedures are responsible for any variation in the test results for the two countries.

The Canadian data cover the period 1961-80 and the U.S. data the period 1948–79 [9]. Due to the short time series for Canada, we have aggregated the data to the level of one output and three inputs. The inputs are capital, labour and materials.

The share equations (8) for the variable factors are estimated after defining an error structure. It is assumed that the errors, ϵ_t, have a distribution that is singular and independent and identical over time. The equations are estimated using maximum likelihood methods and the results are independent of which equation is deleted prior to estimation [10].

5. EMPIRICAL RESULTS

Our focus is on the testing of the estimated production structure rather than any particular properties, e.g. elasticities, of the estimated models.

The test results are organized into three parts. First, we will test for the rapid adjustment of the factors. Second, test are performed on the theoretical structure of the equilibrium cost function. Third, the testing evaluates alternative simpler dynamic models. With classical testing procedures, there is no test structure that is best. We have tried to provide a degree of sensitivity analysis in each part and are reasonably confident that the testing structure is not determining the results.

We want to test the restrictions, given equation (9), that are required for the hypothesis that the equilibrium model is appropriate. On the other hand, we do not want a single test based on a particular maintained

[9] In Canada, there are problems in extending the data into the eighties. Government budget reductions have reduced the basic data collection which underlies parts of the current data sets.

[10] Anderson and Blundell (1982) show that this follows directly by an argument that is analogous to that given in Berndt and Savin (1975).

TABLE 1

Tests of long-run equilibrium with alternative maintained hypothesis

Maintained hypotheses	D.F.	Unrestricted ln L	Restricted ln L	χ^2	c.v.
A. Canada					
unrestricted	14	172.38	148.59	47.58 *	29.14
symmetry $b_{ij} = b_{ji}$	11	163.07	128.93	68.29 *	24.73
neutral technical change $b_{it} = 0$	12	170.31	137.30	66.03 *	26.22
homotheticity $b_{iy} = 0$	12	167.84	147.44	40.80 *	26.22
B. United States					
unrestricted	14	262.21	217.41	89.59 *	29.14
symmetry $b_{ij} = b_{ji}$	11	251.34	199.39	103.90 *	24.73
neutral technical change $b_{it} = 0$	12	255.92	210.16	91.51 *	26.22
homotheticity $b_{iy} = 0$	12	258.88	217.38	82.99 *	26.22

Notes:
* rejection at 1% significance level.
D.F., degrees of freedom; c.v., critical value of test statistic;
χ^2, Chi-squared test statistic; ln L, log of the likelihood function.

hypothesis about the technology, see equation (4). In Table 1, we test the equilibrium model restrictions, (9), relative to a number of different maintained hypotheses [11] based on (4). The exact restrictions are included in the Table rows and in the discussion of the results.

A likelihood ratio test is used to test these restrictions. The results for Canada and the United States are shown in Table 1. Column 1 describes the maintained hypothesis for each test with the associated parameter restrictions, from equation (4), below. Columns 2, 3 and 4 present the

[11] This sensitivity analysis provides evidence on the consequences of imposing theoretical restrictions for the test of instantaneous adjustment.

degrees of freedom, D.F., and the values of the log of the likelihood function, ln L, in the unrestricted and restricted cases, respectively. Columns 4 and 5 contain the value of the χ^2 test statistic and its critical value, c.v..

Panel A of the table contains the results for Canada and panel B the results for the U.S. Each row contains the test results for a different maintained hypothesis. In the first row of each panel, only 'adding up' parameter restrictions are imposed. There are no additional theoretical constraints. The next three rows, in each panel, independently impose symmetry, neutral technical change and homotheticity on the maintained hypothesis used in the test for instantaneous adjustment.

The hypothesis that the all factors adjust instantaneously is rejected in all cases for both the U.S. and Canada. There is no support for the long-run static equilibrium model under a wide variety of maintained hypotheses. The results may be extended in two directions.

First, we can test a number of theoretical restrictions on the technology. Second, there are simpler dynamic models that are nested in the general case. Investigating the model in these two directions will permit us to test for a more parsimonious model.

In our maintained hypothesis, technical change is non-neutral, the function is non-homothetic in output and we do not impose any symmetry constraints. These technical characteristics can be tightened by imposing symmetry, neutral technical change and homotheticity in output.

The parameter restrictions for the three hypotheses were given above in equation (4). Since these hypotheses are not nested, a sequential testing procedure is followed. There are three sequences which begin with one of the three hypotheses. If a hypotheses is accepted at the first stage, the second stage tests another hypothesis, conditional on the first stage non-rejection. This continues to a third stage. For any sequence, testing is halted at the first rejection. The significance level changes at each stage to control for the total significance level [12]. The results of the sequential tests are contained in Fig. 1 for the United States and Fig. 2 for Canada.

Consider the results for the United States in Fig. 1. At the first stage of the sequences, neutral technical change and symmetry are rejected but homotheticity is not rejected.

Conditional on homotheticity, the tests reject neutrality and symmetry. The most parsimonious U.S. model is homothetic and nonsymmetric but exhibits non-neutral technical change.

[12] These procedures may lead to conflicts in which a hypothesis is rejected in one sequence and not rejected in another. This possibility can not be avoided with classical testing techniques.

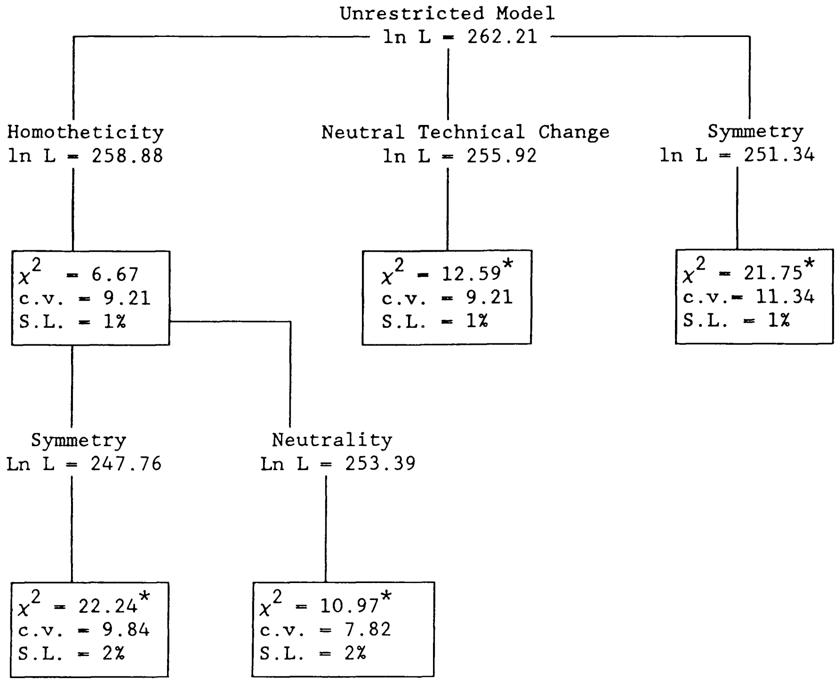

Fig. 1. Tests for theoretical restrictions, dynamic long-run model: United States.

The results for Canada, in Fig. 2, are more complex. Consider the first row of boxes in Fig. 2 for Canada. Of the three hypotheses, symmetry is rejected but homotheticity and neutral technical change are not rejected. Testing continues only for the sequences that begin with neutral technical change and homotheticity.

In the second row of boxes in Fig. 2, conditional on homotheticity, the hypothesis of neutral technical change is not rejected while the hypothesis of symmetry is rejected. Conditional on neutral technical change, homotheticity is not rejected but the test rejects symmetry.

Finally, the third row indicates that symmetry is rejected conditional on homotheticity and neutral technical change no matter what the ordering of the latter two hypotheses. The final Canadian model is a non-symmetric model with homotheticity and neutral technical change.

In both countries [13], homotheticity is accepted and symmetry is rejected but the results are opposite for neutral technical change. The latter is rejected in the U.S. and not rejected in Canada.

In Section 3, we described several special forms of the dynamic model that we will test. Beginning with the general dynamic model, the parameter restrictions are shown in equation (11) for each of these special cases. The

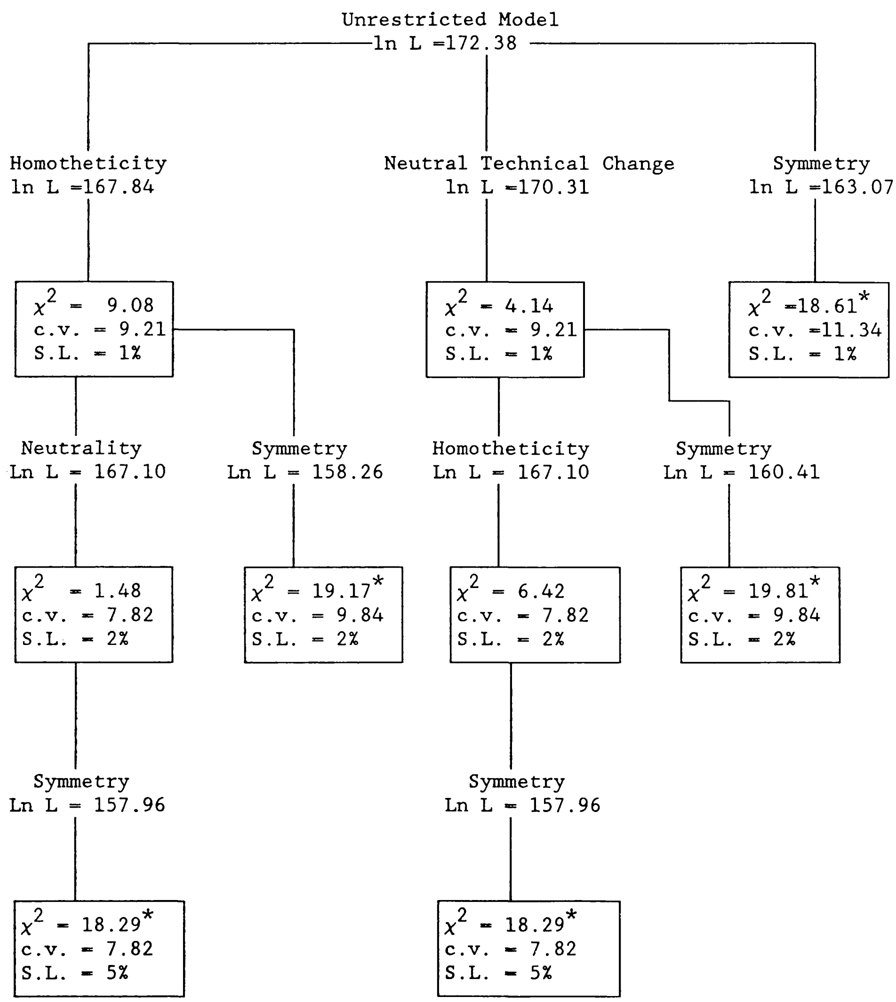

Fig. 2. Tests for theoretical restrictions, dynamic long-run Model: Canada.

autoregressive and partial adjustment models are more succinct representations that our general first-order dynamics.

The two simpler cases of the dynamic model are tested with two alternative maintained hypotheses in each country. In each country, the

[13] Our agriculture data set for the United States is considerably longer than the Canadian data. The tests reported in the text are for the full U.S. data set. We repeated these tests for a restricted U.S. data set that matched the years in the Canadian data. The tests results for the U.S. did not change. Differences between the Canadian and American estimates are not due to differences in the length of the data.

TABLE 2

Tests of alternative dynamic structures: Canada and United States

Case	D.F.	Unrestricted	Autoregressive (ln L)	(χ^2)	Partial adjustment (ln L)	χ^2	C.V.
United States							
A	10	262.21	249.23	25.96 *	223.17	78.07 *	23.21
B	8	258.88	246.92	23.91 *	223.14	71.47 *	20.09
Canada							
C	10	172.38	158.19	28.38 *	150.74	43.29 *	23.21
D	6	167.10	152.96	28.28 *	145.65	42.90 *	16.81

Notes:
(1) An asterisk (*) denotes rejection at the 1% significance level.
(2) Case A and C impose adding up only. Case B imposes homotheticity and the case A constraints. Case D imposes homotheticity and neutral technical change and the case D constraints.

first maintained hypothesis is the unrestricted dynamic model. The results of these tests are shown as case A for United States and case C for Canada in Table 2. In each country, the autoregressive model and the partial adjustment model are rejected conditional on the unrestricted dynamic model.

In the next set of tests of the dynamic structure, we incorporate the results from Figs. 1 and 2, which test theoretical restrictions on the equilibrium model, into the maintained hypothesis.

For the United States, the results from Fig. 1 show that a model with homotheticity can not be rejected. Consequently, we impose this constraint on the maintained hypothesis and re-test the simpler dynamic models. These results are shown as case B in Table 2. Once again, both of the simpler dynamic models are rejected. However, the rejection of the autoregressive model is quite weak.

The tests for Canadian agriculture shown in Fig. 2 do not reject the hypothesis that the long-run cost function is homothetic with neutral technical change. These characteristics are imposed on the maintained hypothesis and the tests for the dynamic structure were redone. The results are shown as case D in Table 2. For Canada, the results are almost identical to case C and indicate rejection of both simpler dynamic models.

Although it would have been appealing to have simplified our dynamic model, the results for both countries under a variety of assumptions do not support the simpler models.

Our results are similar in a number of aspects to those in Vasavada and Chambers (1986) and more particularly, Tsigas and Hertel (1989). Vasavada and Chambers estimate a cost of adjustment model in which they test [14] for the adjustment of all factors. They find that all factors are not variable except for materials in one of their two models. Since their disequilibrium model is different from ours, there is a need for further work to test alternative models of short-run disequilibrium. Fundamentally, this will test the usefulness of cost of adjustment models. Some evidence on this issue is provided in Tsigas and Hertel (1989). Use farm level data, they estimate both a cost of adjustment model and a disequilibrium model which is related to Nadiri and Rosen's (1969) model. In our terminology, their data-based model was found to be more acceptable. However, they do not explicitly compare the two models and so there results are interesting but not conclusive.

6. CONCLUSIONS

This research has a number of broader implications for future research and perhaps policy that are somewhat more positive than our relatively negative test results.

First, what we have called data based models have a useful role in future applied research. They place less a priori structure on the dynamic problem but they permit the testing of a variety of alternatives. For example, our results indirectly cast doubt on the cost of adjustment models as do the results of Tsigas and Hertle. These models almost always assume that some factors are variable, that is, in short-run equilibrium. As Tsigas and Hertle note, they also require a fairly restrictive form of short-run equilibrium. Our results suggest that no factors may be variable in which case the cost of adjustment models are misspecified. In our current research work, we are more explicitly testing the cost of adjustment models in the context of data-based models.

Second, the pursuit of more appropriate dynamic models with a stronger theoretical basis should continue. The choice of a dynamic model is not resolved by our research and we do not think that data based models are the long run objective. Dynamic economic theory does not currently provide enough structure for empirical research to adopt a particular dynamic structure. There is a need for more extensive theoretical developments accompanied by the testing of the dynamic theory. The data-based models will be required in this testing.

[14] In many cost of adjustment studies, some factors are assumed to be variable without any testing.

Third, what might one do in practical empirical production studies while waiting for more rigorous models? Models that assume long run equilibrium in the demand for some or all inputs should be used cautiously. It would be better to use a data-based model that avoids these assumptions. This may not be possible if the data are very limited but at least some testing for non-equilibrium should be done.

For policy purposes, empirical production models are useful as sources of estimates of the size and time path of responses in the production sector to policy changes. Misspecified models will lead to errors in the size or time path of the producer sector's response to a policy change. One can not say in advance, whether the error is of practical significance. However, to avoid the possibility of serious errors, the practice recommended in point three above should be followed in policy models.

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