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# EVALUATING INTERNATIONAL PRICE RELATIONSHIPS USING CAUSAL MODELS

by

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Evaluating international price relationships
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## ABSTRACT

This study proposes and evaluates a new procedure for use in analysis of both international and domestic agricultural markets and prices. The method combines causality tests and path analysis. Causal models of international prices of dairy products are presented as empirical examples. Results have implications for both dairy market structure and competitiveness, and the robustness of Granger-type causality tests.

# EVALUATING INTERNATIONAL PRICE RELATIONSHIPS USING CAUSAL MODELS

## 1. Background and Objectives

In many product markets, domestic supplies and prices are influenced by international prices. Price forecasts, marketing strategies, and general economic planning are based on hypotheses about interrelationships between markets. Analysts monitor market relationships and test hypotheses using regression/econometric models hoping to reach causal conclusions. However, one potential problem in market price analysis is the conflict between assumptions required for statistical modeling and the economic theory on which those models are based. For example, ordinary least squares (OLS) regression models assume that all explanatory variables are independent (Kennedy 1979). Yet, spatial equilibrium theory, such as that embodied in the Law of One Price, asserts that all prices for a commodity are related over time, space, and product form (Bressler and King 1970). This implies that prices used as explanatory variables will be correlated.

Therefore, the objective of this study is to propose and evaluate a new procedure which addresses some of the conflicting assumptions in both international and domestic agricultural market analysis. As an integration of causality testing and path analysis, the technique is intended to provide additional insight into causal relationships which may allow market analysts to improve their models and/or hypothesis tests. Case studies are presented which involve constructing causal models for evaluating international prices of two major dairy products. Butter and cheese were chosen as examples because they are related products and have similar markets, yet one is more differentiated than the other, providing insights into the effects on price of product form.

## 2. Testing Causal Relationships

Two techniques which have been used in the past to test causal relationships are "causality tests" and path analysis. In this section, both methods are discussed briefly and compared, the strengths and weaknesses of each being noted.

Causality tests developed by Granger (1969) and by Sims (1972) are designed to determine whether an instantaneous and/or "one-way" causal relationship exists between two variables. They are intended for use in establishing the direction of influence in time series data.[1] In a spatial model, the tests show "movement of information": new information on market X is acted on by market Y, thus triggering a change in price y. However, Conway et al. (1984, p. 15) found them to be a useful tool only when "knowledge of $Y_t$ increases one's ability to forecast $X_{t+1}$ in a least squares sense". They argued that the tests attempt to indicate simply whether there is significant predictive efficiencies between variables, which is not sufficient to establish the existence nor direction of a causal relationship.

Several tests of causality between time series variables have been developed since Granger's original work in the 1960's.[2] The most commonly used procedures for testing Granger-type causality include distributed lag regressions between pairs of variables which allow calculation of the well-known $F^*$ statistic, (Geweke 1980), and calculation of Pierce's U-statistic based on cross-correlations using univariate residuals from ARMA (mixed autoregressive moving average) models (as illustrated by Lee and Cramer 1985).

One weakness of Granger causality tests is that they do not measure the relative strength of relationships. Therefore, the tests are only a classification process designed to describe the relationship between only two variables. As such, they could be considered an "ordinal measure".

A second weakness of causality tests is that the econometric processes simply record information movements (correlation), but cannot be said to establish causation. The tests cannot distinguish between relationships which are real and those which are spurious (Pierce 1977, Ziemer and Collins 1984). Also, the omission of other variables influencing the two being tested may render any test results spurious. A negative result in a Granger causality test may be used to argue that the relevant variables are not causally related, but a positive result is not sufficient evidence of a causal ordering.

Path analysis was developed more than 60 years ago by an agricultural economist (Wright 1921, 1923, 1925), but has not been used widely by economists (Breen 1983). However, the technique is drawing some attention currently from economists in Europe (Breen 1983) and continues to be applied by other social scientists (Fox 1980, Blalock 1985).

The procedure provides a method of decomposing and interpreting linear relationships among a set of variables by making two assumptions: (1) a (weak) causal order among the variables is known, and (2) the relationships among the variables are causally closed (all relevant variables are included) (Nie et al. 1975, p. 383). Therefore, path analysis is a method for measuring the relative strengths of relationships between any number of variables in a model which was developed from theory or some unique prior hypothesis to be tested. The technique is useful in distinguishing between the parts of relationships consisting of what is believed to be causal effects and the part which is spurious or irrelevant. It does this for a structural equation model, given the assumptions above. However, a weakness of path analysis is that it cannot determine the causal ordering among variables (direction of influence). This means that unique structural forms cannot, in general, be identified using path analysis.

The aim of path analysis is the decomposition of the zero-order correlation between two variables into components due to various effects. The "fundamental theorem" of path analysis is given by Duncan (1966) as:

$$r_{ij} = \sum_q p_{iq} r_{qj} \,. \tag{1}$$

The equation states that the correlation (r) between variables i and j is equal to the sum of each of the path coefficients (p) from variable i to each q variable (the partial regression coefficients of i) multiplied by the correlations between j and each of the q variables. The q variables are all those with a direct path linking them to i.

By definition, a path-analytic decomposition reduces the model-implied correlation between a pair of variables into four types of effect (Breen 1983). These are (1) direct causal effects, equal to the path coefficient linking the two variables; (2) indirect causal effects, equal to the product of two or more path coefficients; (3) spurious components; and (4) unanalyzed effects, including the correlation between exogenous variables. Types (1) and (2) are causal effects; their sum is the total causal effect of one variable on another. Types (3) and (4) are noncausal components of the correlation between the variables.

Path analysis has at least three advantages over conventional regression (Breen 1983, p. 417-8). These include:

1. Using path analysis forces the analyst to specify a model of interrelationships between explanatory variables, enabling use of their intercorrelations to obtain better estimates of the effects of those variables on the dependent variables.
2. Path analysis allows determination of which variables in the model have the strongest causal relationship with the dependent variable.
3. The technique allows the analyst to model the specific ways in which this causal relationship is brought about and to assess the relative strength of each of these relationships.

Therefore, path analysis allows "ratio level" measurement of relationships between variables in a model.

## 3. The Causality and Path Method

In combining the two techniques, the procedures prove to be complementary in that each tool provides additional measurement capabilities and eliminates some of the assumptions limiting the analytical power of the other. Causality tests can be used to determine whether a significant relationship exists between pairs of variables, and can indicate the direction of influence (causal ordering). Path analysis can be applied to those orderings to estimate the relative strengths of relationships.

The combined Causality and Path (CP) method begins with a structural equation model which is developed using economic theory. Theory is used to hypothesize causality (as argued by Zellner 1971) and, therefore, to establish which relationships are to be tested. These relationships are presented as separate paths in the path diagram. All expected relationships (paths) in the diagram which have significant results for the Granger test are included in the path analysis. Relationships which show no sign of causality are dropped from further analysis. As such, Granger tests serve as a statistical filter in the "stepwise" CP procedure, but do not establish causality. Newbold (1979) suggested that models which ignore either theoretical or time series considerations are suboptimal. Therefore, the CP method attempts to balance the two.

The CP method offers some advantages over alternative procedures used to measure the relative strengths of variables in a model. For example, vector autoregression (VAR) has been proposed for use in analysis of multi-variate systems (Sims 1980, Bessler 1984). Two limitations of VAR, which are overcome by the CP approach, are that VAR cannot distinguish between spurious and real relationships between variables, and the VAR method cannot quantify indirect effects of variables upon one another. Relying on VAR to find statistically significant variables can lead to situations where spurious relationships are included in models (Ziemer and Collins 1984). Also, there are many cases in which it is expected that variables are only related indirectly, (especially in spatial equilibrium analysis) yet VAR cannot specifically account for such effects -- the results measure total effects only.

The CP method is applied to international dairy product markets in the following sections as an example of how the procedure can be used.

## 4. Model of International Dairy Price Relationships

The concept of a market involves "an area or setting within which producers and consumers are in communication with one another, where supply and demand conditions operate, and the title of goods is transferred" (Bressler and King 1970, p. 75). Therefore, McCalla (1981) notes that an international market is a set of points which are connected, directly or indirectly, by trade, irrespective of national boundaries. The most frequently encountered structural definition in international trade involves the description of markets in terms of major exporters and importers (McCalla 1981). These descriptions identify the quantitative importance of nations as a percentage of total trade.

The structure of the world dairy industry appears to be oligopolistic; a few nations control a majority of total trade (Blank 1983, Oskam 1985). This implies that such a market is imperfectly competitive. The nature of existing imperfections will determine how price is discovered in a market.

Establishing how international dairy prices are formulated is complicated by the fact that existing prices are correlated, which is consistent with both competition and with oligopolistic pricing methods such as price leadership. A market with such widespread interrelationships between variables (prices) is typical of those for which the CP method is intended.

For this study, two simple models were hypothesized, one each for butter and cheese. Both models are consistant with the hypothesis that major exporting nations in an international product market each have some influence on the price formation process, as described by oligopoly theory. In each model, six countries were hypothesized to have price interrelationships among them reflecting an imperfectly competitive market. The six countries were selected from those identified by the United States Department of Agriculture (1986) as being leading participants in the two markets. Combined they represent 61% and 65% of the world markets for butter and cheese. To allow evaluation of the impact of the EC, three member countries (Netherlands, France and Denmark) and three non-member countries (Switzerland, Australia and New Zealand) were chosen for study.

The form of the initial structural model (presented later) for each product specifies that every country's price is related to those of the other five countries. This specification is based on the hypothesis that there is only one (imperfectly) competitive "world" market for each product. This proposition is evaluated by comparing the actual causal relationships found to those expected to exist within various market structures, as explained by Blank (1985).

The data used were national average monthly F.O.B. prices of butter and cheddar cheese reported by European Communities for the ten years, 1975-84. Prices were quoted in U.S. dollars per ton to facilitate direct comparison of coefficients. Only price variables are used here because prices reflect the influence of all other economic variables in a competitive market. The objective of the CP analysis of these case studies is to assess market integration through pricing policies, such as price leadership, etc., not to consider production or political factors.

If the original price series is found not to be stationary, a first difference filter is frequently applied to remove the linear trend (Granger and Newbold). However, Sims (1980) and Litterman argued that stationarity may be unnecessary. Therefore, this study follows Granger's principle that series need only to be consistent (all either stationary or nonstationary) (Bessler and Kling).

5. Causality Tests for Dairy Product Models

In this study, Granger tests, as refined by Geweke (1980), were used to determine the nature of each bivariate relationship hypothesized. OLS regression on levels of time series data was used in the first test. To test for "one-way" causality running from one market, X, to another, Y, at time t, the following specification is used:

$$Y_t = a_1 + \sum_{j=1}^{p} a_{1j} Y_{t-j} + e_{1t}, \qquad (2)$$

$$Y_t = a_2 + \sum_{j=1}^{p} a_{2j} Y_{t-j} + \sum_{k=1}^{q} b_{2k} X_{t-k} + e_{2t} \qquad (3)$$

where p and q are the number of lags (j and k) used to eliminate autocorrelation, $e_{1t}$ and $e_{2t}$ are white noise residuals, $a_{1j}$ and $a_{2j}$ are parameters relating $Y_t$ and its lagged values, and $b_{2k}$ are parameters relating $Y_t$ and past values (from time t-k) of X. The sum of squared errors (SSE) from OLS regressions on (2) and (3) are used to calculate the $F^*$ statistic, which tests the (alternative) hypothesis that X causes Y (Pierce and Haugh 1977).

A test of no "instantaneous" causality is used here also which is based on the residuals from equation (3) and those from

$$Y_t = a_3 + \sum_{j=1}^{p} a_{3j} Y_{t-j} + \sum_{k=0}^{q} b_{3k} X_{t-k} + e_{3t}. \qquad (4)$$

The value of tests for instantaneous causality is debated. In studies such as those by Price (1979) and by Layton (1984) it was argued that there is no logical conceptual framework from which to test for instantaneous causality. Conversely, Uri and Rifkin (1985) provided a definition of instantaneous causality to define the limits of a spatial market.

The appropriate number of lags (p and q) were hypothesized based on economic theory and their validity was examined with the use of Hannan's criterion (see Hannan 1980; Hannan and Rissanen

1982).[3] In theory, markets will be related by arbitrage through transportation of commodities from one market to another (Bressler and King 1970). Dairy products can be transported between any two of the markets being analyzed within one month (observation period). Therefore, ignoring the effects of trade barriers, lags of one month or less are expected in the price adjustment process. These theoretical expectations were supported by the statistical results. Hannan's tests were calculated for twelve month lags to assure that the true lag had been identified. All markets had lag structures of zero or one month. Therefore, all equations were estimated using one lagged variable (p=q=1).

## 5.1 Butter Causality Results

The causality test results presented in Table 1 lead to two general conclusions. First, they indicate that the butter market is imperfectly competitive, but has no clear market price leader. Second, the nature of the relationships within the market, illustrated in Figure 1, appears to support Blank's (1983) hypothesis that there are two supply regions and that nations compete more directly with other suppliers within their region than with suppliers from the other region.

The first conclusion is based on the implications of the combined results for the two different causality tests. In general, it is expected that each test evaluates a different aspect of market structure. The numerous significant results for the test of instantaneous causality is consistent with the hypothesis that there is little differentiation between the products of the relevant countries, and that those countries are in direct competition. These results support theoretical expectations concerning pricing behavior in competitive markets within a single spatial distribution system. Also, the relatively few cases of one-way causality implies that little, if any, market power is being exerted in the form of price leadership. By definition, a change in a leader's price would be followed by price changes for other market participants, which would create a temporal relationship detected by a one-way causality test between the leader and all followers.

The second conclusion is drawn from the difference in numbers of significant relationships involving countries in the "northern" and "southern" dairy supply regions. The northern supply region, consisting primarily of European countries, has many significant relationships between supplying nations included in Figure 1. Each of the four European countries included in this study are significantly related in some way to one another. On the other hand, the European suppliers feel very little causal influence from the two suppliers in the southern region, New Zealand and Australia.

## 5.2 Cheese Causality Results

General conclusions which can be drawn from the results presented in Table 2 are that cheese exporting nations trade in a single "world" market which is more oligopolistic than those for butter. Compared to the butter market results, two more significant relationships are found in the cheese model shown in

Figure 1, and more of those relationships reflect one-way causality.

The results imply the existence of a single world cheese market. Using the Law of Market Areas, specified by Bressler and King (1970) and others, it is expected that direct competition between firms producing an undifferentiated product will exist only along their common market area borders. In this study, market area borders constitute third countries in which the delivered prices from both suppliers are identical. The slightly lower number of significant relationships may result from the existence of a lower level of direct competition between geographically distant producers of butter than exists for cheese. This result is expected because butter is much less differentiated than cheese and, therefore, will have more distinct market areas for each supplier. Cheese, on the other hand, is a highly differentiated product, so that one supplier can successfully penetrate markets located closer to a competitor. In this way, cheese producers are all brought into direct contact with one another, while butter producers compete only indirectly with distant suppliers.

The fact that a majority of causal relationships found in the cheese model are of the one-way type supports the hypothesis that the market is oligopolistic (Blank 1985). As noted in the previous section, the frequency of instantaneous causal relationships in a market is expected to reflect the degree of product differentiation between suppliers. One-way causality reflects market power expressed as price leadership. Comparing butter and cheese results in this study, the cheese model has fewer instantaneous and more one-way relationships. This implies that the pricing system in the world cheese market is less perfectly competitive than that operating in the world butter market, and that cheese suppliers have relatively more influence on their prices.

6. Path Analysis of the Structural Equation Models

Nonrecursive, restricted models of the international markets for both butter and cheese are illustrated in Figure 1. The models were derived from the causality test results, reflecting all relationships found to be significant at the one percent level.

The models are considered to be "nonrecursive" because there are both "feedback" loops and reciprocal paths between variables. This means that the markets are expected to influence one another through both information flows and the potential of spatial arbitrage.

The models are "restricted" because additional *a priori* assumptions based on the causality results are made concerning the system of relationships. It is implied by the butter market path diagram, for example, that the path coefficient between Denmark (DN) and New Zealand (NZ) is zero; no direct path connects DN and NZ. In an unrestricted model all endogenous variables are affected directly by all variables of a higher causal order. Restricted models, such as these, have equations which are *overidentified* because there are two (or more) ways to estimate a parameter (Nie et al. 1975, p. 392).

The obvious effect on path analysis of using time series data is that it adds a temporal aspect. Rather than evaluating only the zero-order correlation between variables, higher orders of correlation may be included. The relevant order is determined by the lag structure identified using Hannan's Criterion in the causality test results. If there is not only instantaneous adjustment (causality) between variables, but also one-way causality with some lag structure, that lag structure must be used for the path model to more fully measure the effects of one variable upon another. In this study, lags of one period were used because that was the only significant lag based on Hannan's Criterion.

In a nonrecursive model, different disturbance terms are not necessarily assumed to be uncorrelated, as they are in recursive models. To test the assumption of independent errors, a correlation analysis was performed on the residuals from OLS estimates of the six equations in each model. Each equation was found to be significantly correlated with some of the other five equations. This is to be expected in a model with a predominantly instantaneous (simultaneous) causal structure. Therefore, in this study Zellner's (1962) Seemingly Unrelated Regressions (SUR) technique was used to estimate path (regression) coefficients for both models. The simultaneous nature of the model implies that three stage least squares (3SLS) may ordinarily be a better estimating procedure. However, 3SLS could not be used because the models are of insufficient rank, which is not a problem for SUR.

Further discussion of the tradeoffs in choosing an estimation procedure is presented in the appendix.

## 6.1 Butter Results

The final SUR estimates of the butter equation model at time t are:

$$AL_t = \underset{(8.39)}{1.555NZ_t} \tag{5}$$

$$DN_t = \underset{(10.03)}{.839SZ_t} \tag{6}$$

$$FR_t = \underset{(2.11)}{1.132DN_t} + \underset{(3.64)}{1.672NL_t} - \underset{(-2.18)}{1.346SZ_t} \tag{7}$$

$$NL_t = \underset{(-2.27)}{-.417DN_t} + \underset{(3.60)}{.271FR_t} + \underset{(6.20)}{.887SZ_t} \tag{8}$$

$$NZ_t = \underset{(11.70)}{.417AL_t} + \underset{(3.80)}{.235SZ_t} \tag{9}$$

$$SZ_t = \underset{(9.01)}{.726DN_t} - \underset{(-3.41)}{.124FR_t} + \underset{(11.99)}{.458NL_t} + \underset{(3.81)}{.220NZ_t} \tag{10}$$

where AL is Australia, DN is Denmark, FR is France, NL is The Netherlands, NZ is New Zealand, and SZ is Switzerland. The figures in parentheses are t-statistics. The final equations contain only the independent variables which had a significant influence on the dependent variable; explanatory variables with insignificant t-statistics were dropped,[4] as suggested by Mason and Halter (1968). Also, unstandardized coefficients are estimated because the data are measured in identical units, which facilitates comparing parameters (Nie et al. 1975, p. 397).

The final butter market path diagram, derived from equations 5-10, is presented in Figure 2. Results of the path analysis are presented in Table 3. Each of the bivariate relationships represented as a path in the diagram were decomposed using techniques suggested by Nie et al. (1975); Fox (1980); and Breen (1983). The direct effects are the regression coefficients from equations 5-10, the indirect effects are calculated using equation 1, and the noncausal effects are the difference between total causal effects and the correlation between the two relevant markets.

The results in Table 3 illustrate the additional interpretive power of path analysis compared to either simple correlation analysis or multiple regression techniques. Had only correlation scores (r values shown in the last column of Table 3) been calculated for each bivariate relationship, the implied strength of those relationships would have been overestimated greatly in most cases (by an amount equal to the positive noncausal effects). On the other hand, if only regression had been used, the relationships would have been miscalculated in nine of fourteen cases because only direct effects are measured in regression analysis. Since path analysis does not assume (as does OLS regression) that all explanatory variables in an equation are exogenous, it estimates indirect causal effects as well as direct effects. In some cases (such as when measuring Switzerland's effect on France) this is very significant because the indirect effects are larger and of opposite signs than are the direct effects. In other cases (not shown in Tables 3-4) there are no direct effects at all, while there are significant indirect effects.

## 6.2 Cheese Results

The final SUR estimates of the cheese model at time t are:

$$AL_t = \underset{(2.54)}{.210NL_{t-1}} + \underset{(4.88)}{.218SZ_t} \tag{11}$$

$$DN_t = \underset{(8.47)}{.967NL_t} \tag{12}$$

$$FR_t = \underset{(2.75)}{.446NZ_t} + \underset{(10.19)}{.606SZ_t} \tag{13}$$

$$NL_t = \underset{(9.13)}{.928DN_t} \tag{14}$$

$$NZ_t = \underset{(2.65)}{.409AL_{t-1}} - \underset{(-1.64)}{.209DN_{t-1}} - \underset{(-3.09)}{.294FR_t} + \underset{(7.69)}{.778NL_t} - \underset{(-3.12)}{.172SZ_t} + \underset{(4.33)}{.197SZ_{t-1}} \tag{15}$$

$$SZ_t = \underset{(3.99)}{.807AL_t} + \underset{(9.97)}{1.218FR_t} - \underset{(-3.58)}{.746NZ_t} \tag{16}$$

The figures in parentheses are t-statistics. Once again, the final equations contain only significant independent variables. It is noted that several lagged variables remain in the equations for cheese, while all lagged explanatory variables proved to be insignificant in the butter model. The implications of these results and the path analysis are presented in the next section.

The final cheese market path diagram, derived from equations 11-16, is presented in Figure 2. Results of the path analysis are given in Table 4. Interpretation of Table 4 follows that of Table 3.

## 7. Implications of the Path Results

The path analysis results support the conclusions drawn earlier that there appears to be two international butter supply regions and a single world cheese supply region and that both markets are imperfectly competitive. The butter market diagram in Figure 2 shows that Australia and New Zealand (the southern suppliers) have little connection with European suppliers. Conversely, the cheese market diagram includes several interrelationships between European and southern suppliers.

The nature of paths remaining in the diagrams further supports the observations made earlier about the degrees of product differentiation in the two markets. The few one-way paths in the butter model in Figure 1 were found to be insignificant in the path analysis and were dropped from Figure 2, while several one-way (lagged) paths remain in the cheese model. Having only instantaneous (no lag) price relationships in the final butter model implies less product differentiation in that market than exists in the cheese market. Also, the fact that all the one-way arrows in Figure 2 point to either New Zealand or Australia indicates that Europe is the market leader (as expected). The southern suppliers likely follow, or respond to, European prices because northern suppliers have some degree of market power based on their established reputations and perceived product differentiation.

It is expected that international trade in agricultural products is imperfectly competitive for a number of reasons (McCalla 1981). Several aspects of the path results illustrate that these dairy products do not have efficient spatial markets. For example, the total causal effect of one variable on another would never exceed the correlation between the two in an efficient market. The presence of negative causal effects and correlations also indicates that non-market factors are influencing the interrelationships. Finally, the large noncausal effects observed indicate the relative importance of their components, which could include currency exchange shifts, trade barriers, noncompetitive marketing practices such as long term contracting between exporters and importers, and other factors.

Differences in the path diagrams shown in Figures 1 and 2 have implications for the robustness of bivariate causality tests. The fact that variables had to be dropped from the multivariate path equations indicates a weakness of Granger tests - the real impact of one variable on another may be overstated in bivariate tests. It is likely that some variables had a significant causality test result due to indirect causal or noncausal effects being included in the bivariate analysis. Path analysis, on the other hand, allows comparison between the relative effects of all explanatory variables in a system. This illustrates the additional power of the "ratio measurement" possible with path analysis, compared to the limited "ordinal" measurements provided by causality tests, and demonstrates the advantages of using a composite technique such as CP.

8. Summary

This paper presents a new procedure for evaluating price relationships between agricultural markets. The CP method combines causality and path analysis to measure the direction and strength of "causal" relationships between prices in different markets. These two techniques are complementary in their relative strengths and weaknesses.

International markets for butter and cheese were analyzed as simple case studies. In general, the price relationships found in both markets are indicative of imperfect competition. Pricing in the cheese market, however, appears to exhibit the influence of more market power than does the butter market. Using the CP method, the movement and effects of that price information can be modeled.

In a general evaluation of the CP procedure, the method appears to have potential for improving agricultural economists' ability to analyze complex causal relationships. This is especially true when theoretical expectations include indirect, as well as direct, effects between variables in a model. CP analysis also can aid in detecting appropriate uses of related techniques, such as causality tests of the form used here. The empirical results presented here, for example, have raised some methodological issues concerning the robustness of commonly used bivariate causality tests. Therefore, CP analysis may be a useful addition to many market/price assessments.

## APPENDIX: Choosing An Estimation Method

The main concern of the CP method is causal model development. After a path model is specified using CP, it is expected that whatever econometric procedure is appropriate for that specification would be used in estimation of the path coefficients. However, in international spatial pricing CP models, it is unlikely that many exogenous variables will be found; theory says that all markets are related spatially through transportation. This creates conflict between the aims of CP and the requirements for usual econometric estimation procedures. The CP method will frequently lead to models which are of insufficient rank to allow estimation using systems methods such as 3SLS.

Although simple, the dairy models in this paper illustrate the tradeoffs faced in dealing with this conflict. As specified in Figure 1, the models are each a nonrecursive system, implying that 3SLS is the best estimation procedure. Yet the models have no exogenous variable, so they are of insufficient rank and 3SLS cannot be performed.

Respecifying models is a common approach to this problem. Describing the dairy models as sets of single equations enables use of OLS. However, OLS is clearly inappropriate in this case because it assumes independent error terms and that all explanatory variables are exogenous. A frequently used alternative is to specify a model as a block-recursive system. 3SLS can be used along with OLS as part of this estimation procedure. In the case of these dairy markets, a block-recursive design introduces misspecification error into the estimated coefficients because some of the expected interactions between endogenous variables are lost; variables must be dropped to meet rank conditions.

The tradeoff recommended here is to use SUR on the models specified by theory and the causality test filter. SUR can be estimated as a nonrecursive system with correlated error terms and not be limited by the rank conditions; no variables need be dropped from any equations to allow estimation. The only difference between SUR and 3SLS is that SUR assumes all right-side variables to be exogenous, and 3SLS does not. This means that SUR uses actual observations for all explanatory variables, whereas 3SLS uses predicted values for observations of endogenous variables. Therefore, using SUR in this model introduces bias if the predicted and actual values differ sufficiently to alter estimated coefficients of endogenous variables. It is argued here that this small amount of bias is a good trade to avoid the specification error of dropping variables expected to be highly significant. Dropping variables eliminates the ability to evaluate interactions. The point of the entire CP exercise would be defeated if an accurate estimate of all interactions between relevant variables could not be derived.

# FOOTNOTES

1. For applications by agricultural economists, see Bessler and Brandt (1982); Blank (1985); Grant, et al. (1983); Heien (1980); Lee and Cramer (1985); Miller (1979); Uri and Rifkin (1985); Weaver (1980); and Ziemer and Collins (1984).
2. Representative survey papers include Pierce and Haugh (1977); Geweke, Meese and Dent (1983); and Conway, et al. (1984).
3. Previous studies involving Granger causality tests, such as that by Bessler and Brandt (1982), have used Akaike's Final Prediction Error (FPE) test to determine lag structures. Unfortunately, Akaike's method for fitting autoregressions produces inconsistent estimates of the orders of autoregressive (AR), moving average (MA), or mixed autoregressive moving average (ARMA) processes (Shibata 1976). Hannan's criterion uses recursive techniques to ensure consistent estimates.
4. All variables in price models such as these are expected to be related somewhat to one another, implying possible multicollinearity. This problem is handled here by formalizing relationships among regressors in a simultaneous equation system (Kennedy 1979, P. 132) which is estimated in a stepwise manner using the "full information" method of SUR. In this way, chances of induced specification error are minimized.

# REFERENCES

Akaike, H. (1969). "Fitting Autoregressive Models for Prediction," American Institute of Statistical Mathematics 21, 243-7.

Bessler, D. (1984). "An Analysis of Dynamic Economic Relationships: An Application to the U.S. Hog Market," Canadian Journal of Agricultural Economics 32, 109-124.

Bessler, D. and Brandt, J. (1982). "Causality Tests in Livestock Markets," American Journal of Agricultural Economics 64, 140-4.

Blalock, H. (1985). Causal Models in the Social Sciences, 2nd Ed., Aldine Publishing Company, New York.

Blank, S. (1985). "Using Causality and Supply Response Models in Interpreting Foreign Agricultural Policies", Agribusiness: An International Journal 1, 177-183.

_____ (1983). World Markets and Prices for Dairy Products, Bureau of Agricultural Economics Occasional Paper No. 83, Australian Government Publishing Service, Canberra.

Breen, R. (1983). "Path Analysis: An Example", Journal of Agricultural Economics 34, 417-425.

Bressler, R. and King, R. (1970). Markets, Prices, and Interregional Trade, John Wiley & Sons, New York.

Conway, R., Swamy, P., Yanagida, J. and von zur Muehlen, P. (1984). "The Impossibility of Causality Testing", Agricultural Economics Research 36, 1-19.

Duncan, O. (1966). "Path Analysis: Sociological Examples", American Journal of Sociology 72, 1-16.

European Communities, Eurostat, Statistical Office, Brussells, Belgium, various issues.

Fox, J. (1980). "Effect Analysis in Structural Equation Models: Extensions and Simplified Methods of Computation", Sociological Methods & Research 9, 3-28.

Geweke, J. (1980). "Inference and Causality in Economic Time-Series Models", in Handbook of Econometrics, Z. Griliches and M. Intrilligator (eds), North-Holland Publishing Company, Amsterdam, Chapter 17.

Geweke, J., Meese, R., and Dent, W. (1983). "Comparing Alternative Tests of Causality in Temporal Systems", Journal of Econometrics 21, 161-194.

Granger, C. (1969). "Investigating Causal Relationships by Econometric Models and Cross-Spectral Methods", Econometrica 37, 424-438.

Grant, W., Ngenge, A., Brorsen, B. and Chavas, J. (1983). "Grain Price Interrelationships", Agricultural Economics Research 35, 1-9.

Hannan, E. (1980), "The Estimation of the Order of an ARMA Process," The Annals of Statistics 8:1071-1081.

Hannan,E. and Rissanen, J. (1982), "Recursive Estimation of Mixed Autoregressive-Moving Average Order," Biometrika 69:81-94.

Heien, D. (1980). "Markup Pricing in a Dynamic Model of the Food Industry", American Journal of Agricultural Economics 62, 10-18.

Kennedy, P. (1979). A Guide to Econometrics, The MIT Press, Cambridge, Massachusetts.

Layton, A. (1984), "A Further Note on the Detection of Granger Instantaneous Causality", Journal of Time Series Analysis 5:15-7.

Lee, E. and Cramer, G. (1985). "Causal Relationships Among World Wheat Prices", Agribusiness: An International Journal 1, 89-97.

Mason, R. and Halter, A. (1968). "The Application of a System of Simultaneous Equations to an Innovation Diffusion Model", Social Forces 47, 182-195.

McCalla, A. (1981). "Structural and Market Power Considerations in Imperfect Agricultural Markets", in Imperfect Markets in Agricultural Trade, A. McCalla and T. Josling (eds), Allanheld and Osmun, Montclair, New Jersey.

Miller, S. (1979). "Univariate Residual Cross Correlation Analysis: An Application to Beef Prices", North Central Journal of Agricultural Economics 1, 141-6.

Newbold, P. (1979). "Time Series Model Building and Forecasting Methods in Economics," IHS Journal 3, 101-24.

Nie, N., Hull, C., Jenkins, J., Steinbrenner, K. and Bent, D. (1975). Statistical Package for the Social Sciences, 2nd Ed., McGraw-Hill Book Company, New York.

Oskam, A. (1985), "A Super-levy System for the Dairy Sector: Consequences and Alternatives", European Review of Agricultural Economics 12, 431-448.

Pierce, D. (1977). "Relationships - and the Lack Thereof - Between Economic Time Series, With Special Reference to Money and Interest Rates", Journal of the American Statistical Association 72, 11-22.

Pierce, D. and Haugh, L. (1977). "Causality in Temporal Systems: Characterizations and a Survey", Journal of Econometrics 5, 265-293.

Price, J. (1979), "The Characterization of Instantaneous Causality: A Correction", Journal of Econometrics 10:253-6.

Shibata, R. (1976), "Selection of the Order of an Autoregressive Model by Akaike's Information Criterion," Biometrika 63:117-126.

Sims, C. (1972). "Money, Income, and Causality", American Economic Review 62, 540-552.

_____ (1980). "Macroeconomics and Reality," Econometrica 48, 1-48.

United States Department of Agriculture (1986), Foreign Agriculture Circular, Dairy, Washington, D.C. (and previous issues).

Uri, N. and Rifkin, E. (1985). "Geographic Markets, Causality and Railroad Deregulation," Review of Economics and Statistics 67, 422-8.

Weaver, R. (1980). "The Causal Linkage of Control Policy and its Targets: The Case of Wheat", American Journal of Agricultural Economics 62, 512-6.

Wright, S. (1921). "Correlation and Causation", Journal of Agricultural Research 20, 557-585.

_____ (1923). "Theory of Path Coefficients: A Reply to Niles", <u>Genetics</u> 8, 239-255.

_____ (1925). <u>Corn and Hog Correlations</u>, U.S. Department of Agriculture, Bulletin 1300.

Zellner, A. (1962). "An Efficient Method of Estimating Seemingly Unrelated Regressions and Tests for Aggregation Bias", <u>Journal of the American Statistical Association</u> 57, 585-612.

_____ (1971). <u>An Introduction to Bayesian Inference in Econometrics</u>, John Wiley & Sons, New York.

Ziemer, R. and Collins, G. (1984). "Granger Causality and U.S. Crop and Livestock Prices", <u>Southern Journal of Agricultural Economics</u> 16, 115-120.

TABLE 1. Causality Test Results for International Butter Market

| Variables[a] (X/Y) | One-way Causality X→Y (F-Test) | One-way Causality X←Y (F-Test) | Instantaneous Causality X—Y (F-Test) |
|---|---|---|---|
| AL/FR | 9.29** | 1.09 | 1.90 |
| DN/FR | 16.35** | 2.86 | 1.42 |
| NL/FR | 10.46** | 1.58 | 12.35** |
| NZ/FR | 6.91* | 0.04 | 8.15* |
| SZ/FR | 11.35** | 0.83 | 10.73** |
| AL/NL | 0.01 | 1.42 | 0.77 |
| DN/NL | 0.03 | 0.90 | 24.01** |
| NZ/NL | 1.09 | 1.46 | 7.13* |
| SZ/NL | 0.22 | 1.73 | 59.45** |
| AL/NZ | 0.74 | 3.26 | 28.82** |
| DN/NZ | 4.14 | 0.22 | 5.59* |
| SZ/NZ | 5.99* | 0.60 | 8.56** |
| AL/SZ | 0.00 | 4.27 | 1.10 |
| DN/SZ | 0.66 | 0.64 | 62.59** |
| AL/DN | 2.55 | 4.86* | 0.03 |

[a] AL = Australia, DN = Denmark, FR = France, NL = Netherlands, NZ = New Zealand, SZ = Switzerland.

** Significant F-test at the one percent level.
* Significant F-test at the five percent level.

TABLE 2. Causality Test Results for International Cheese Market

| Variables[a] (X/Y) | One-way Causality X→Y (F-Test) | One-way Causality X←Y (F-Test) | Instantaneous Causality X—Y (F-Test) |
|---|---|---|---|
| AL/FR | 0.16 | 10.70** | 10.22** |
| DN/FR | 6.41* | 3.16 | 4.88* |
| NL/FR | 2.92 | 3.95 | 5.98* |
| NZ/FR | 0.63 | 38.02** | 13.21** |
| SZ/FR | 0.05 | 2.25 | 49.52** |
| AL/NL | 0.26 | 20.52** | 1.22 |
| DN/NL | 8.29* | 1.90 | 9.75** |
| NZ/NL | 0.51 | 19.65** | 1.12 |
| SZ/NL | 1.76 | 3.16 | 2.70 |
| AL/NZ | 24.53** | 4.05 | 0.47 |
| DN/NZ | 16.28** | 8.09* | 1.55 |
| SZ/NZ | 36.67** | 1.33 | 15.60** |
| AL/SZ | 0.02 | 2.94 | 17.55* |
| DN/SZ | 5.18* | 1.64 | 1.40 |
| AL/DN | 4.70* | 29.87** | 0.15 |

[a] AL = Australia, DN = Denmark, FR = France, NL = Netherlands, NZ = New Zealand, SZ = Switzerland

** Significant F-test at the one percent level.
* Significant F-test at the five percent level.

TABLE 3. Path Analysis Results for Butter Market

| Bivariate Relationship[a] | Causal Effects Direct ($Path_{ij}$) | Indirect | Total | Noncausal | Total Correlation ($r_{ij}$) |
|---|---|---|---|---|---|
| AL ⟶ NZ | .4168 | 0 | .4168 | .3865 | .8033 |
| DN ⟶ FR | 1.1317 | -.3406 | .7911 | -.1190 | .6721 |
| DN ⟶ NL | -.4174 | .5622 | .1448 | .6287 | .7735 |
| DN ⟶ SZ | .7264 | -.1041 | .6223 | .2730 | .8953 |
| FR ⟶ NL | .2714 | -.0663 | .2051 | .4779 | .6830 |
| FR ⟶ SZ | -.1235 | .1244 | .0009 | .6128 | .6137 |
| NL ⟶ FR | 1.6723 | -.1814 | 1.4909 | -.8079 | .6830 |
| NL ⟶ SZ | .4582 | -.2065 | .2517 | .6040 | .8557 |
| NZ ⟶ AL | 1.5549 | 0 | 1.5549 | -.7516 | .8033 |
| NZ ⟶ SZ | .2199 | 0 | .2199 | .5139 | .7338 |
| SZ ⟶ DN | .8390 | 0 | .8390 | .0563 | .8953 |
| SZ ⟶ FR | -1.3455 | 1.8472 | .5017 | .1120 | .6137 |
| SZ ⟶ NL | .8870 | -.4577 | .4293 | .4264 | .8557 |
| SZ ⟶ NZ | .2349 | 0 | .2349 | .4989 | .7338 |

[a] AL = Australia, DN = Denmark, FR = France, NL = Netherlands, NZ = New Zealand, SZ = Switzerland.

Note: Only relationships in which there was a direct causal effect (path) are decomposed here. Other relationships, involving indirect effects only, can be decomposed if desired.

TABLE 4. Path Analysis Results for Cheese Market

| Bivariate Relationship[a] | Causal Effects: Direct ($Path_{ij}$) | Causal Effects: Indirect | Causal Effects: Total | Noncausal | Total Correlation ($r_{ij}$) |
|---|---|---|---|---|---|
| AL → NZ | .4094[b] | -.1226 | .2868 | -.4089 | -.1221 |
| AL → SZ | .8070 | -.0830 | .7240 | -.0259 | .6981 |
| DN → NL | .9278 | 0 | .9278 | -.1704 | .7574 |
| DN → NZ | -.2089[b] | .7778 | .5689 | -.5094 | .0595 |
| FR → NZ | -.2935 | .1400 | -.1535 | .0312 | -.1223 |
| FR → SZ | 1.2183 | .2190 | 1.4373 | -.6163 | .8210 |
| NL → AL | .2100[b] | -.0254 | .1846 | .3647 | .5493 |
| NL → DN | .9673 | 0 | .9673 | .2099 | .7574 |
| NL → NZ | .7781 | -.1419 | .6362 | -.1383 | .4979 |
| NZ → FR | .4461 | -.4519 | -.0058 | .1165 | -.1223 |
| NZ → SZ | -.7461 | .5434 | -.2026 | -.1322 | -.3348 |
| SZ → AL | .2177 | 0 | .2177 | .4804 | .6981 |
| SZ → FR | .6057 | .0513 | .6570 | .1640 | .8210 |
| SZ → NZ | .0258[c] | -.0886 | -.0628 | -.2720 | -.3348 |

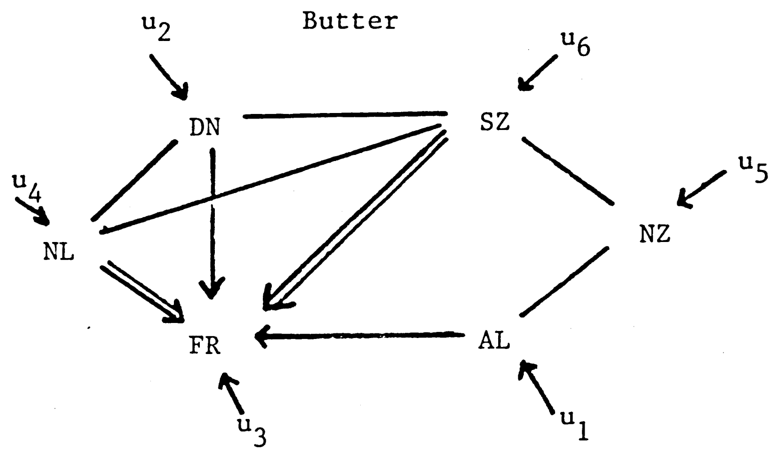
[a] AL = Australia, DN = Denmark, FR = France, NL = Netherlands, NZ = New Zealand, SZ = Switzerland.

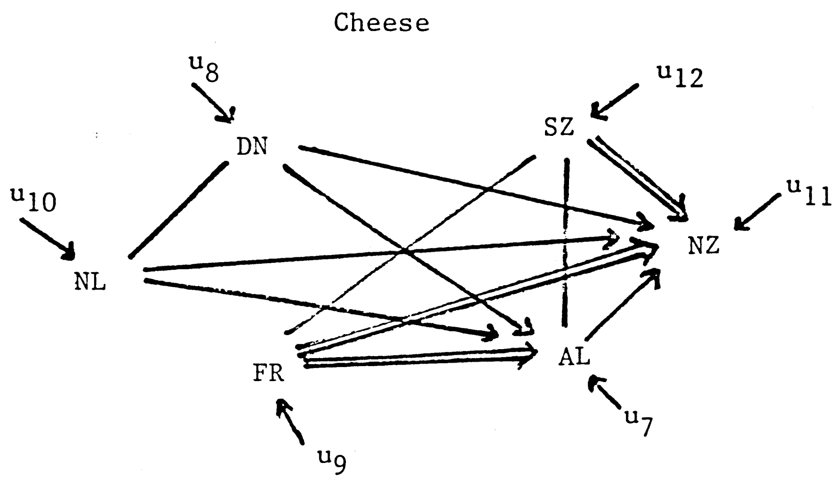
[b] Regression coefficient of the independent variable lagged one period.

[c] Sum of the regression coefficients of the original variable and of that variable lagged one period.

Note: Only relationships in which there was a direct causal effect (path) are decomposed here. Other relationships, involving indirect effects only, can be decomposed if desired.

Figure 1. Path Diagram Derived From Causality Test Results




Number and Type of Causal Relationships in Models:

| | | Butter | Cheese |
|---|---|---|---|
| Instantaneous | (X-Y) | 5 | 3 |
| One-way | (X→Y) | 2 | 5 |
| Both | (X⇒Y) | 2 | 3 |

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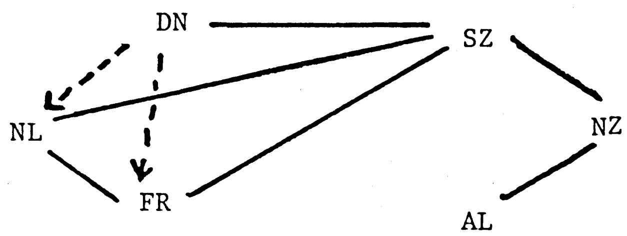
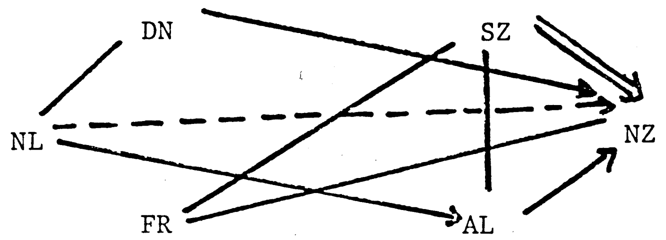
AL = Australia, DN = Denmark, FR = France, NL = Netherlands, NZ = New Zealand, SZ = Switzerland, u = error term.

Figure 2. Path Diagram Derived from Path Analysis

Butter




Cheese




Number and Type of Causal Relationships in Models:

| | | Butter | Cheese |
|---|---|---|---|
| Instantaneous in both directions | (X—Y) | 6 | 4 |
| Instantaneous in one direction | (X-->Y) | 2 | 1 |
| One-way | (X→Y) | 0 | 3 |
| Instantaneous in both directions and one-way | (X⇒Y) | 0 | 1 |

AL = Australia, DN = Denmark, FR = France, NL = Netherlands, NZ = New Zealand, SZ = Switzerland.