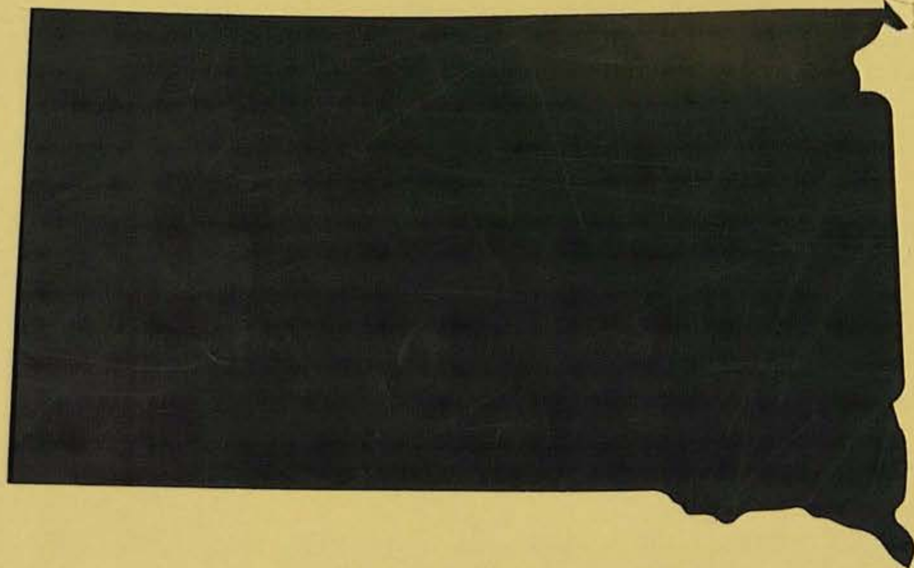



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COMBINING CAUSALITY TESTS AND PATH ANALYSIS
TO MODEL AGRICULTURAL MARKETS*

by

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Economics Staff Paper No. 85-5***
April 1985

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Combining Causality Tests and Path Analysis to Model Agricultural Markets


## ABSTRACT

Causality tests and path analysis are combined to create a new procedure for use in evaluating agricultural markets. The two complementary techniques combine to form a strong process for measuring the direction and strength of causal relationships within a structural equation model. An empirical example which evaluates midwestern corn market price relationships is presented.

Combining Causality Tests and Path Analysis
to Model Agricultural Markets

Causality tests and path analysis are two different statistical techniques that have been used separately by agricultural economists. In this paper, the two techniques are combined to create a new procedure for use in agricultural market analysis.

The two techniques each have weaknesses, but when combined their strengths compensate for those shortcomings to form a strong process for measuring the direction and strength of causal relationships within a model. The procedures prove to be complementary in that each tool provides additional measurement capabilities and eliminates some assumptions limiting the analytical power of the other technique.

This paper concentrates on introducing the proposed new procedure. First, both causality tests and path analysis are discussed briefly. The proposed joint application method is then illustrated using an empirical assessment of a model of midwestern corn market price relationships.

Weaknesses and Strengths of the Techniques

Causality tests are a relatively new and popular tool for agricultural price analysis. Although statistical definitions of causality have been available since the 1960's (Granger), they were not applied by agricultural economists until the late 1970's (Miller). During the first half of the 1980's, however, the technique was applied in numerous studies of agricultural markets (such as those by Bessler and Brandt, Heien, Weaver, Grant et al.).

One weakness of so-called "causality tests" developed by Granger and by Sims is that they do not measure the relative strength of relationships, they indicate only the direction of influence in time series data. However, they are a useful tool in that "knowledge of $Y_t$ increases ones ability to forecast $X_{t+1}$

in a least squares sense" (Conway et. al., p. 15). The tests indicate simply whether or not there is significant relative predictive efficiencies between variables. Therefore, the tests are a classification process designed to describe the relationship between only two variables. As such, they could be considered an "ordinal measure".

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). However, the technique is drawing some attention currently from economists in Europe (Breen) and continues to be applied by other social scientists (Fox).

A weakness of path analysis is that it cannot determine the causal ordering among variables (direction of influence). It does provide 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 (Nie et. al., p. 383). Therefore, path analysis is a method for measuring the relative <u>strengths</u> of relationships between any number of variables in a model. The technique distinguishes 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.

Path analysis has at least three advantages over conventional regression (Breen, 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.

Complementary Techniques

Combining the two techniques helps illustrate that their strengths and weaknesses are complementary. In a network diagram of a model, causality tests can be used to determine whether or not a significant relationship exists between pairs of variables, and it can indicate the direction of influence (causal ordering). Path analysis can be applied to those orderings to estimate the relative strengths of relationships found using causality tests.

The combined Causality and Path (CAP) method begins with a structural equation model which is developed using economic theory. Theory is used to determine 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.

"Causality tests" may be said to show "movement of information": new information on X is acted on by Y, thus triggering a change in y. The econometric processes of causality tests outlined by Granger and by Sims simply record the information movements, but cannot be said to establish causation. The tests cannot distinguish between relationships which are real and those which are spurious (Ziemer and Collins). Therefore, the causal relationships expressed in the path diagram are assumed to exist, based on theoretical expectations. 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.

All expected relationships (paths) in the path diagram which have positive results for the Granger test are included in the path analysis. Relationships which show no sign of causality are dropped from further analysis.

One apparent conflict between the two procedures is that, in the past, cross sectional data has been used in path analysis (Nie, et. al.), while Granger causality tests are designed for use with time series data. There is, in fact, no conflict because path analysis can be applied to time series regression results with little adjustment necessary. The obvious effect on path analysis of using time series data is that it adds a temporal aspect to results. Therefore, to correctly reflect the causal relationship implied in the path model, it may be necessary to lag observations. If there is no instantaneous adjustment (causality) between variables, only 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 on the other.

In summary, the CAP method has three stages:

(1) specify a structural model which includes all interrelationships between variables expected according to economic theory,

(2) Granger test whether or not significant relationships exist and, if so, determine in which <u>direction</u> the information is moving, and

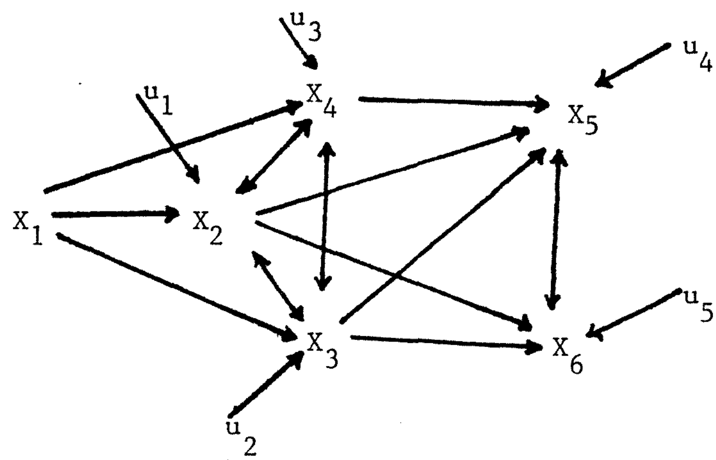
(3) use path analysis to decompose the statistical relationships between variables and establish the relative <u>strengths</u> of those relationships.

An example of the CAP method is presented in the following sections.

<u>Model of Corn Market Price Relationships</u>

The Law of One Price (Kohls and Uhl, p. 174-8) is used to derive hypothesized relationships between prices of corn at six markets. In general,

FIGURE 1. Path Diagram of Corn Market Model




$X_1$ = Memphis, $X_2$ = St. Louis, $X_3$ = Chicago, $X_4$ = Kansas City,

$X_5$ = Omaha, $X_6$ = Minneapolis

information and causality are expected to flow through the physical marketing channel in the opposite direction of product movements. Prices of all grain markets are linked through the physical arbitrage process, however.

A set of corn markets with an established pattern of physical movement was selected as an empirical example for the CAP method. Therefore, the model in the path diagram (Figure 1) represents the movement of information from consumers to producers of corn. However, major midwestern markets only are used in this analysis. Including markets at the Gulf of Mexico and in importing countries would be desirable to create a more complete model in which the assumption of causal closure is more realistic. This was not done because data available from those markets was not consistent in form with midwestern data series. Nevertheless, the model does provide a useful example of how the CAP method can be applied.

The data used was daily prices of No. 2 Yellow Corn for the crop year from October 1, 1982 to September 30, 1983. A single source (USDA) was used for all six data series to assure uniformity in price collection and reporting procedures. However, the original price series were found not to be stationary, therefore, a first difference filter was applied.

Causality Tests for Corn Model

Granger tests, refined by Geweke, are used to determine the nature of each bivariate relationship hypothesized. The first test, as outlined by Bessler and Brandt, directly utilizes ordinary least squares (OLS) regression on levels of time series data. To test causality running from one market, X, to another, Y, at time t, the following specification is used:

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

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

where p and q are the number of lags (j and k) used to eliminate autocorrelation, $e_{1t}$ and $e2t$ are white noise residuals, $a1j$ and $a2j$ are parameters relating $Y_t$ and its lagged values, and $b2k$ are parameters relating $Yt$ and past values (from time t-k) of X. The sum of squared errors (SSE) from OLS regressions on (1) and (2) are used to calculate the well-know statistic, F*, which tests the (alternative) hypothesis that X causes Y (Pierce and Haugh).

Bessler and Brandt also present a test of no instantaneous causality which is based on the residuals from equation (2) and those from

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

The appropriate number of lags (p and q) were specified by economic theory and their validity were examined with the use of the Final Prediction Error (FPE) test (Akaike). In theory, spatial markets will be related by physical arbitrage through transportation of commodities from one market to another (Bressler and King). Corn can be transported between any two of the markets being analyzed in one week or less. Therefore, lags of five days or less are expected in the price adjustment process.

The theoretical expectations were supported by the statistical results. FPE tests were calculated for ten day lags to assure that the minimum FPE had been identified. Memphis and St. Louis had one day lag structures, Omaha, Kansas City and Minneapolis had lags of five days, and Chicago had a zero day lag, according to the FPE test. Causality tests using both the minimum FPE and symmetric five day lags ($p = q = 5$) were estimated with virtually no difference resulting[1]. Therefore, only the symmetric equations are presented in this paper, following the precedent of previous studies (Bessler and Brandt).

The causality test results presented in Table 1 indicate that the markets studied are efficient in that they respond instantaneously to one another. The

TABLE 1. Causality Test Results for Midwestern Corn Market Daily Prices (Oct 1, 1982 to Sept 30, 1983)

| Bivariate Relationship[a] | One-way Causality | | Instantaneous Causality | |
|---|---|---|---|---|
| | F-Test | Q-Statistic | F-Test | Q-Statistic |
| $X_1 \rightarrow X_2$ | 2.25 | 13.61 | 71.91 | 17.12 |
| $X_2 \rightarrow X_1$ | 4.19 | 27.11 | | |
| $X_1 \rightarrow X_3$ | 2.51 | 16.44 | 60.07 | 18.43 |
| $X_3 \rightarrow X_1$ | 4.22 | 20.82 | | |
| $X_1 \rightarrow X_4$ | 0.62 | 17.49 | 60.95 | 20.18 |
| $X_4 \rightarrow X_1$ | 2.96 | 26.95 | | |
| $X_2 \rightarrow X_3$ | 0.36 | 19.83 | 69.39 | 24.39 |
| $X_3 \rightarrow X_2$ | 0.56 | 14.13 | | |
| $X_2 \rightarrow X_4$ | 0.92 | 15.83 | 79.13 | 11.27 |
| $X_4 \rightarrow X_2$ | 0.40 | 13.64 | | |
| $X_2 \rightarrow X_5$ | 0.31 | 18.75 | 104.41 | 19.48 |
| $X_5 \rightarrow X_2$ | 0.36 | 11.59 | | |
| $X_2 \rightarrow X_6$ | 0.39 | 12.95 | 108.06 | 34.08 |
| $X_6 \rightarrow X_2$ | 1.15 | 13.79 | | |
| $X_3 \rightarrow X_4$ | 1.51 | 18.38 | 77.63 | 11.56 |
| $X_4 \rightarrow X_3$ | 1.04 | 16.78 | | |
| $X_3 \rightarrow X_5$ | 1.05 | 19.43 | 108.56 | 11.33 |
| $X_5 \rightarrow X_3$ | 1.18 | 19.20 | | |
| $X_3 \rightarrow X_6$ | 0.42 | 18.94 | 91.27 | 27.40 |
| $X_6 \rightarrow X_3$ | 1.23 | 19.76 | | |
| $X_4 \rightarrow X_5$ | 0.75 | 19.88 | 130.52 | 33.49 |
| $X_5 \rightarrow X_4$ | 0.91 | 17.29 | | |
| $X_5 \rightarrow X_6$ | 0.55 | 13.15 | 88.39 | 18.06 |
| $X_6 \rightarrow X_5$ | 0.75 | 19.88 | | |

NOTE: The significant value at the one percent confidence level for the F-test for one-way causality is 3.02 and the chi square value for the Q-statistic is 21.67. For instantaneous causality the F-test value is 2.80 and the chi square value is 20.09.

[a] $X_1$ = Memphis, $X_2$ = St. Louis, $X_3$ = Chicago, $X_4$ = Kansas City, $X_5$ = Omaha, $X_6$ = Minneapolis.

consistently positive instantaneous causality results support theoretical expectations concerning competitive markets within a single spatial distribution system. Apparently, price information is disseminated and acted upon within a single day (observation period) throughout the entire market.

The limited one-way causality between the individual market locations is probably due to arbitrage within spatial and time dimensions of markets, and contract delivery specifications. "To arrive" contracts that specify delivery as much as 15 to 30 days after the price was set are an example of this arbitrage. If all contracts had called for immediate delivery, more one-way causality would be expected in the data.

In summary, each causality test evaluates a different aspect of market efficiency. The test for instantaneous causality indicates whether or not market information flows are efficient. Results for the one-way causality test help identify the physical arbitrage process and its lag structure (if allowed by the data specifications). Yet, regardless of whether one or both causality tests give positive results, more detailed information is available from path analysis of the data.

<u>Path Analysis of the Structural Equation Model</u>

A nonrecursive restricted model of the midwestern corn market is illustrated in Figure 1. It was derived from the causality test results and theoretical expectations of an inverse relationship between product and information flows.

The model is considered "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 model is "restricted" because additional assumptions are made concerning the system of relationships. It is implied by the path diagram, for example, that the path coefficient between Memphis and Omaha ($P_{15}$) is zero; no direct path connects $X_1$ and $X_5$. In an unrestricted model all endogenous variables are affected directly by all variables of a higher causal order. Restricted models, such as this, are overidentified because there are two (or more) ways to estimate a parameter (Nie et al., p. 392).

The structural equations specifying the model are

$$(4) \quad X_2 = \gamma_{21}X_1 + \beta_{23}X_3 + \beta_{24}X_4 + u_1$$

$$(5) \quad X_3 = \gamma_{31}X_1 + \beta_{32}X_2 + \beta_{34}X_4 + u_2$$

$$(6) \quad X_4 = \gamma_{41}X_1 + \beta_{42}X_2 + \beta_{43}X_3 + u_3$$

$$(7) \quad X_5 = \beta_{52}X_2 + \beta_{53}X_3 + \beta_{54}X_4 + \beta_{56}X_6 + u_4$$

$$(8) \quad X_6 = \beta_{62}X_2 + \beta_{63}X_3 + \beta_{65}X_5 + u_5$$

where the Xs are price variables for the following markets:

$X_1$ is Memphis,
$X_2$ is St. Louis,
$X_3$ is Chicago,
$X_4$ is Kansas City,
$X_5$ is Omaha, and
$X_6$ is Minneapolis.

The $\gamma_{ij}$ and $\beta_{ij}$ terms are the path (regression) coefficients of, respectively, exogenous and endogenous variables reflecting the strength of the influence of the $X_j$ market on the $X_i$ market. The error terms in the path model are $u_1$ to $u_5$.

To eliminate the alpha terms, the first differenced data was scaled to zero means, but not fully standardized to unit variance. In this case, the data are measured in identical units and the objectives are to describe causal processes and compare parameters, therefore unstandardized coefficients are estimated (Nie et al., p. 397).

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 five equations. Each equation was found to be significantly correlated ($r > .08$ at the five percent confidence level -- Kachigan, p. 290) with at least two of the other four equations. Therefore, in this study Zellner's (1962) Seemingly Unrelated Regressions (SUR) technique was used to estimate path (regression) coefficients. The standard errors of the SUR estimates were smaller than those of the OLS estimates, indicating that the SUR estimates are more efficient.

Normally, the adequacy of a restricted (cross sectional) model is tested using the large sample chi square log likelihood method (Nie, et. al., p. 394). However, the statistic could not be calculated here because the SUR technique does not estimate a separate SSE for each equation in the model. Yet, the F-statistic for each of the two restricted equations in the OLS model was higher than that for the unrestricted model specification. Therefore, since the restricted OLS model improved on the unrestricted model and the SUR estimates were more efficient than the OLS estimates, the time series model was judged to perform satisfactorily.

The SUR estimates of the structural equation model are presented below.

$$X_2 = \underset{(2.75)}{.151X_1} + \underset{(7.14)}{.445X_3} + \underset{(9.31)}{.500X_4} \tag{9}$$

$$X_3 = \underset{(1.62)}{.084X_1} + \underset{(7.14)}{.374X_2} + \underset{(7.69)}{.392X_4} \tag{10}$$

(11) $X_4 = -.017X_1 + .530X_2 + .493X_3$
$(-0.29) \quad (9.44) \quad (7.79)$

(12) $X_5 = .131X_2 + .228X_3 + .159X_4 + .418X_6$
$(2.97) \quad (4.69) \quad (3.79) \quad (8.92)$

(13) $X_6 = .277X_2 + .196X_3 + .614X_5$
$(5.21) \quad (3.11) \quad (9.01)$

The figures in parentheses are t-statistics.

Results of the path analysis are presented in Table 2. Each of the bivariate relationships represented as a path in the diagram were decomposed using techniques suggested by Nie, et. al., Fox, and Breen, as described below.

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 as

(14) $r_{iq} = \sum_{p} p_{iq} r_{jq}$

The equation states that the correlation between variables i and j is equal to the sum of each of the path coefficients 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. 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. (1) and (2) are causal effects; their sum is the total causal effect of one variable on another. (3) and (4) are non-causal components of the correlation between the variables.

The results in Table 2 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 2) been calculated for each bivariate relationship, the implied strength of those relationships would have been overestimated greatly. On the other hand, if multiple regression had been used the relationships would have been underestimated in 14 of 16 cases because only direct causal effects are measured. Since path analysis does not assume (as does regression) that all explanatory variables in an equation are exogenous, it estimates the indirect causal effects as well as the direct effects. In some cases (such as between St. Louis and Omaha) this is very significant because the indirect effects are much larger than are the direct effects.

Summary of Corn Market Results

Evidence of instantaneous causality in the model supports assertions concerning the efficiency of pricing in the corn market. However, acceptance of the hypothesis does not provide much guidance in analysis of price relationships between markets. In contrast, the path analysis results do provide insights into the pricing relationships. The direct effects are generally greatest when dealing with interfacing spatial markets. This implies that information does not simply flow through marketing channels in the opposite direction of commodity movements. Rather, the price determination process involves a set of spatial markets. Price changes in distant markets will be reflected directly and through intervening spatial markets. Using the CAP method, the movement and effects of that price information can be modeled.

TABLE 2. Path Analysis Results for Midwestern Corn Market Daily Prices (Oct 1, 1982 to Sept 30, 1983)

| Bivariate Relationship[a] | Causal Effects Direct $(Path_{ij})$ | Indirect | Total | Noncausal | Total Covariance $(r_{ij})$ |
|---|---|---|---|---|---|
| $X_1 \dashrightarrow X_2$ | .1514 | .0290 | .1804 | .5982 | .7786 |
| $X_1 \dashrightarrow X_3$ | .0842b | .0783 | .1625 | .5901 | .7527 |
| $X_1 \dashrightarrow X_4$ | -.0169b | .1694 | .1525 | .5886 | .7411 |
| $X_2 \dashrightarrow X_3$ | .3744 | .2076 | .5820 | .2153 | .7973 |
| $X_2 \dashrightarrow X_4$ | .5295 | .1844 | .7139 | .0938 | .8077 |
| $X_2 \dashrightarrow X_5$ | .1311 | .3809 | .5120 | .3429 | .8549 |
| $X_2 \dashrightarrow X_6$ | .2770 | .3455 | .6225 | .2334 | .8559 |
| $X_3 \dashrightarrow X_2$ | .4450 | .2464 | .6914 | .1059 | .7973 |
| $X_3 \dashrightarrow X_4$ | .4925 | .2356 | .7281 | .0696 | .7977 |
| $X_3 \dashrightarrow X_5$ | .2276 | .3687 | .5963 | .2629 | .8592 |
| $X_3 \dashrightarrow X_6$ | .1960 | .4579 | .6539 | .1833 | .8372 |
| $X_4 \dashrightarrow X_2$ | .5004 | .1745 | .6749 | .1328 | .8077 |
| $X_4 \dashrightarrow X_3$ | .3921 | .1873 | .5794 | .2183 | .7977 |
| $X_4 \dashrightarrow X_5$ | .1592 | .3461 | .5053 | .3539 | .8592 |
| $X_5 \dashrightarrow X_6$ | .6136 | c | .6136 | .2595 | .8731 |
| $X_6 \dashrightarrow X_5$ | .4184 | c | .4184 | .4547 | .8731 |

[a] $X_1$ is Memphis, $X_2$ is St. Louis, $X_3$ is Chicago, $X_4$ is Kansas City, $X_5$ is Omaha, $X_6$ is Minneapolis.

[b] Insignificant t-test at the five percent confidence level.

[c] There are no indirect effects in the relationships between Omaha and Minneapolis, as specified in this model.

## Concluding Comments

This paper presents a new procedure for evaluating price relationships between agricultural markets. The CAP procedure 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.

The direction and strength of pricing influences between six major midwestern corn markets were analyzed using the CAP technique. The hypothesis of instantaneous causality was accepted for the markets. These results are supportive of the perception of the corn market being an efficient market. The path analysis provided additional insights into the direct and indirect causal relationships between the markets.

The path analysis appears to indicate that price information is filtered through a set of spatial markets rather than simply flowing in the opposite direction of the product. Some advantages of path analysis are that it requires specification of theoretical expectations, and its ability to identify direct and indirect causal relationships.

The CAP procedure has potential for improving agricultural economists' ability to analyze complex causal relationships. The empirical results presented here raise some methodological issues, such as: are causality tests appropriate between markets where physical arbitrage is limited or where several spatial markets exist between the markets? The simple corn market CAP analysis appears to question such applications of causality tests. CAP analysis of additional markets will be required before this question can be answered appropriately. If causality tests are not to be abused as a "tool", approaches must be developed that will enable economists to properly specify and identify causal relationships.

## FOOTNOTES

1. In general, the results presented in Table 1 did not change when nonsymmetric lag structures were used. Although the values changed, significant F-tests remained significant and insignificant F-tests did not become significant. However, the Q statistics for nearly all equations increased when a nonsymmetric specification was used, as would be expected. Using nonsymmetric lag structures decreased the number of lags used in many equations which, in turn, decreased the amount of autocorrelation removed and, therefore, led to higher Q statistics. As a result, six of the 24 one-way causality estimates had Q statistics indicating significant autocorrelation when nonsymmetric lags were used, compared to one significant Q for the 24 estimates using symmetric lags. For instantaneous causality results, the number of significant Q's from the 12 equations estimated using symmetric and nonsymmetric lags, respectively, was zero and six. Therefore, the results from nonsymmetric specifications were judged to be unreliable in this case.

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