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ON RISK, INFORMATION, AND CAUSALITY IN AGRICULTURAL MARKETS[1]

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INTRODUCTION

The presence of risk in agriculture is well known. Uncertain yields and relatively low price elasticities of demand provide the setting for rather large fluctuations in prices of agricultural products. Our professional efforts devoted to risk (its description and its management) are now quite abundant. For example, regional project W-149—"An Economic Evaluation of Managing Market Risk in Agriculture"—is currently active in fulfilling its purpose:

> to discuss the role of risk in agriculture, identify policies and institutions for reducing the adverse effects of risk, and evaluate the potential of these various policies and institutions for improving the well-being of agricultural producers and others affected by agricultural markets (agribusiness and consumers). (Just [14]).

And while our professional efforts in this area are abundant, our successes, in terms of recommendations, are not many. For we are still in the stage of studying and understanding existing markets and institutions. We have a long road to cover before we can recommend that this institution rather than that institution is better suited for risk reduction. If and when such recommendations can be made, we most surely will make them with the proviso that any changes we make or advocate are likely to advance the welfare of one group at the expense of some other group. Thus, our role in this area will likely be (is), the conditionally normative one taken in other areas of economics.

The purpose of this paper is to explore the relationships between risk and information and to focus on a fairly new analytical development in this area. To accomplish this, our first task is to argue that risk must be described by the distribution of probabilities over the set of possible outcomes of some unknown process. Then, we can view information as that upon which our probabilities are conditioned. Thus, institutions discussed and analyzed by W-149, such as government price supports, buffer stocks, contracting, crop insurance, improved forecasts, futures markets, and guaranteed credit, have the common aim of increasing the set of information upon which an economic agent makes his decisions. In other words, these institutions change the conditional probability distribution relevant for a particular decision.

Similarly, some of the consumer price reporting schemes discussed in this monograph (see Blake, *et al.* [2]) are involved with the influence of information on consumers' conditional probabilities. In these studies, we are interested in whether frequent reporting of prices for consumer goods (groceries) will change the probability distributions held by consumers. While more complex hypotheses are maintained (related to responses by retailers), they too rest on this notion of conditional probability. For example, the Purdue study (described in Blake, *et al.* [2]) is interested in the response of retailers to their perceptions of how consumers' probabilities change.

We conclude the first task by considering alternative sources of information and rational choice among them. We view this task as the more important and relevant. For today, we often hear potential users of information complain that they are deluged with information. Thus, an analysis of how one makes choices among potential information systems (structures) is particularly important.

We accomplish the second task, the role of information in conditional probability distribution, by focusing on an explicit information source and on a condition for its value in economic decisions. This condition—known in the literature as Granger-Wiener causality—suggests that variable X causes Y, with respect to a given universe or information set which includes at least both X and Y, if current Y can be better predicted by using past values of X than if these values were not used. In both cases—with or without X—all other information is used. The concept, which is rather new (Wiener wrote in the engineering literature in 1956 and Granger wrote in the economics literature in 1969), is quite useful for analysis of information that is commonly reported as time series. We suggest its use is more general, offering something for the prevision of all stochastically dependent events. Finally, we illustrate the time series applications of this concept to empirical series on Midwestern hog prices.

The paper is organized into three sections. First, we discuss information, risk and choice among alternative information sources (structures). Second, we discuss the concept of Granger-Wiener causality and briefly review how others have used it. Finally, we apply the concept to U.S. long prices.

RISK AND INFORMATION

The role of data and their conversion into information is to aid decision making which generally occurs in an uncertain environment. More specifically, the use of information about a particular market will not tell us with certainty what outcome will occur. Thus, our analysis of information will require something more than the rules and methods relevant to arguments made under certainty. An additional notion, probability (or degree of belief), is required to allow the ordering of possible outcomes. In this way, information can be viewed as an impulse, or a signal, that moves the decision maker from one set of beliefs to another. We then make decisions—choose an act from a number of available acts—based on expected benefits and costs (utility) derived from this new (final or posterior) set of beliefs.

We assume that all discussions about information must be cast in terms of probabilities, as does Fishburn [7]. He states, with little fanfare, and no proofs or lemmas, that probability is the "yardstick of uncertainty." Alternatively, one can take a more fundamental approach and actually derive the condition that probabilistic statements about uncertain events—and therefore, about the use and choices of information structures—are necessary and sufficient for behavior to be consistent with some fairly reasonable human characteristics. This is the approach taken by the contemporary mathematician and philosopher de Finetti [6]. Briefly, he shows that any alternative description of uncertain outcomes, such as point forecasts, confidence intervals, and the like, can have a "Dutch Book" made against them (a system of bets can be made such that one holding these non-probabilistic views will be sure to lose money). This will not be possible for beliefs stated in terms of coherent possibilities (they sum to one for mutually exclusive and exhaustive outcomes).

These initial comments suggest that information can be analyzed using the well-developed theories of choice under uncertainty. Such analyses have been undertaken in some rather abstract studies (see for example, Marschak and Radner [16]). We are aware of no empirical analysis reflecting these works. Nevertheless, we briefly review the basis of this abstract work, because it leads to some insights not readily available otherwise. We first give a brief summary of the expected utility hypothesis, a general theory of choice among abstract actions that can be directly applied to choice among sets of information (information structures). That is, the problem of choice among alternative information structures is a special case of choice among actions under uncertainty and thus, can be analyzed using the normative expected utility hypothesis. Some well-known results derived from this approach apply to the special case of choice among alternative information sets.

We will constrain our summary of the expected utility hypothesis to a single decision maker who must choose one action (A_i) from a known set of n actions: ($A_1, A_2, \ldots, A_n$). Each action is assumed to have a set of m uncertain consequences: ($C_{il}, C_{i2}, \ldots, C_{im}$), i = 1, 2, . . . , n. We assume that this idealized person has preferences defined over the set of consequences. More directly, it is usually assumed that he has a utility function (U) defined on C_{ij} such that $U(C_{ij}) > U(C_{ik})$, if he prefers consequence C_{ij} to C_{ik}. Since the decision must be made on the set of actions, and since preferences are defined on the set of consequences, a measure (or probability) is introduced which takes the uncertain utilities of each action into a certain expected utility. Expected utility is then a measure which can be used to order actions: The decision maker can rank each action based on the expected utility of its consequences.

This measure, or probability, represents the decision maker's degree of belief or strength of conviction that a particular consequence will result from a particular action. As such, it represents both data observed and analysis performed by the decision maker. We represent a particular structure (method or mode of inquiry) by Ω_ℓ, and assume there are $\ell = 1, 2, \ldots, p$ discrete structures available for the decision maker to use. As an example of alternative structures, Ω_1 might be a price forecasting model using an econometric model, and Ω_2 a price forecasting model using an autoregressive integrated moving average time series representation (see Leuthold, *et. al.* [15]). Each alternative structure yields a particular signal or unit of information, $\omega_{\ell k}$, where this signal is the particular conditioning element in the probability distribution. The decision problem typically specified in risk analysis is then given as:

$$\underset{\text{w.r.t. } a_i}{\text{Maximize}}\ E\,[U(a_i)] = \underset{a_i}{\text{Max.}} \sum_{j=1}^{m} U(C_{ij})\, P\,(C_{ij} \mid a_i, \omega_{\ell k})$$

$$i = 1, 2, \ldots, n;$$

where $P(C_{ij} \mid a_i, \omega_{\ell k})$ represents the probability of consequence C_{ij} occurring, given that action a_i is taken and information signal $\omega_{\ell k}$ is observed by the decision maker. The measure of information $\omega_{\ell k}$ is a specified signal observed from the information structure Ω_{ℓ}.[2]

Agricultural economists' studies of risk have generally focused on the elicitation of the utility function, $U(C_{ij})$. Not much work has been done in this frame work on the specification of the conditional probability distribution. Perhaps a reason for this is that the "objective" school of probability has been so dominant in much of our professional training. If probabilities are deemed objective in a frequency sense, no person-by-person assessment need be made. However, using the "subjective" approach, it is quite feasible that two decision makers, viewing the same data, might assign different probabilities to the same consequence, because each confronts the data with a different model or set of assumed conditions.

The treatment of the conditioning information as both data and analysis has its origins in earlier studies (see for example, Bonnen [3] or Morgenstern [18]). These studies correctly define data collection as the outcome of a planned process of analysis and measurement, where, before any data are collected, a prior model or "causative" view of the world is needed. Thus, we do not measure numbers haphazardly, but do so in a purposeful manner. Similarly, the measured data are not employed solus, but rather in the context of the model in which they are collected. For example, we collect data on such items as planted acreages of crops, broiler hatchings, and sow farrowings, because we have a well-defined cause-effect model underlying our analysis (e.g., increased plantings will, *ceteris paribus,* translate into lower prices at harvest time). In terms of a decision maker, the collected data and analysis represented by $\omega_{\ell k}$ will translate into higher or lower probabilities on specific consequences, and may result ultimately in the selection of different actions (a_i's).

The question of choice among alternative information structures and the related topic of information obsolescence, addressed by Bonnen [3], can be conveniently analyzed in the decision model described above. However, now the choice among actions is a choice among sets of information—between say, Ω_j and Ω_k. An individual quite often has a choice between more than one potential source of information; each offering a different distribution of benefits and costs. As an example, a farmer can base his marketing decisions on his own expertise and past observed prices. Alternatively, he can attend university outlook sessions for expert market analysis, or he can seek professional marketing advice from private forecasting groups. It is not hard to imagine that each structure can easily involve a different distribution of benefits and costs. A decision maker following the expected utility hypothesis, will choose structure k from a set of p structures, $\Omega_1, \Omega_2, \ldots, \Omega_p$ such that:

$$\sum_{j=1}^{m^*} U(C_{kj}) \;\; P\,(C_{kj} \mid \Omega_k) \geq \sum_{i=1}^{m} U(C_{\ell i}) \;\; P\,(C_{\ell i} \mid \Omega_\ell);$$

$$\ell = 1, 2, \ldots, p; \ell \neq k.$$

This last expression suggests that the decision maker chooses information structure k, if it yields a higher expected payoff than the remaining p - 1 structures.[3,4]

The rule given above shows that a decision maker will choose that information structure (or combination of structures) which leads to the highest expected payoff. This rule, then, naturally leads to a definition of information obsolescence, a topic given considerable discussion by Bonnen [3]. An information structure ℓ can be considered obsolete, with respect to structure k, if the expected utility from using structure k exceeds that from using structure ℓ. Using this definition of obsolescence, a number of points can be made. First, an information structure is obsolete only with respect to some alternative information structure. That is, obsolescence is a relative concept. Second, there is no "objective" measure of obsolescence. That is, as long as one recognizes that the only definition of probability which makes sense in decision making is the subjective one (and the list of those who take this view is vast and impressive: see de Finetti [6], Savage [22], Arrow [1]), then obsolescence exists only within the decision maker's mind. Of course, large numbers of decision makers may agree in their subjective assessments, and thus, large groups may agree that a particular structure is obsolete. Third, if the consequences are defined in terms of monetary gain (or wealth), then a necessary condition for information source ℓ to be deemed obsolete, with respect to information source k, for all risk averters is: The expected monetary gain from ℓ must fall below that from k.[5]

Generally, the use of a particular information structure (Ω_k) will involve a prior acquisition cost. This cost must be borne directly by the user (or group of users). In such a case, it is often not obvious that all possible information would be used. It may be rational to use a relatively less precise information source (structure) in order to forego the high cost of information collection, coding, transmittal, and decoding. In other words, the expected utility in the decision problem given above includes both benefits and costs present in the use of any particular structure. As an example of such a choice, consider the retail food store price reporting project currently going on at Purdue. The project is analyzing the effects of continuous price reporting of consumer food items. The study involves the use of the information by both the consumer and retail grocery stores. For the former group, this new or proposed structure must compete with existing structures that serve similar purposes. Prior shopping observations, active search, and newspaper advertising are alternative information structures, which may or may not involve lower acquisition costs.

In comparing the four alternative structures, our initial beliefs might suggest that prior shopping experience would result in the lowest expected cost in terms of inquiry, encoding, transmission, decoding, and deciding (if, for example, one is interested in choosing the lowest price supermarket). Likewise, we might expect it to offer the smallest benefits. On the other hand, active search by each consumer—each consumer doing comparison shopping at each retail outlet— will probably result in the highest inquiry costs.

In measuring the benefits among alternative structures, the usual benefits of making informed decisions, such as actually shopping at the lowest price store or combination of stores, will be most obvious. An interesting benefit investigated in the Purdue study is the dynamic relation between the results of the price reporting scheme and retail grocery store prices (see also Devine and Marion). That is, among the benefits which are possible, one is the feedback effect of the reporting schemes on consumer prices. In fact, we might hypothesize that these feedback or dynamic effects will be the interesting and most beneficial result of such schemes. Thus, among the benefits, which must be added up in a decision of whether to institute such a scheme, are the longer term expected benefits (if any) that can be demonstrated to follow from lower retail prices.

Causality and Information

So far, we have discussed information and choice among alternative sources in a rather abstract manner. Information is viewed as a signal upon which subjective probabilities concerning the outcomes of future events are conditioned.[6] We have argued that a standard economic choice problem exists when a decision maker is confronted with alternative sources—each providing a different distribution of benefits and costs. In short, the source selected gives the highest net expected payoff.

We now discuss the problem of how to empirically establish the usefulness of one information structure in changing beliefs about the outcome of future events.[7] Recall from above, an information structure (Ω_j) is deemed obsolete with respect to another structure (Ω_k), if the expected utility of k exceeds that of j. This definition is abstract and probably not directly applicable in most situations. In this section we explore one special approach to determining information obsolence by examining the usefulness of a particular time series X in predicting the future values of another time series Y. More specifically, the question of interest is whether conditioning predictions of future Y on past X and Y is any better than conditioning these predictions on only past Y.

The topic, generally known as Granger (of Granger-Wiener) causality, was first introduced in the literature by Granger [9]. Granger causality involves the identification and comparison of causal (or at least predictive) relations between variables.[8] Recall the definition: Variable X causes Y, with respect to a given information set, if current Y can be better predicted by using past values of X than if the values were not used. In both cases—with or without X—all other information is used.

This topic is related to the topic of market information and choice among alternative structures. If a particular structure does not meet this definition of causality (if past information on X does not help in predicting Y), then knowledge of X is superfluous for decision making, and can be ignored. This definition requires that only past values of X can be used to predict Y, and that these past values of X must do a better job of prediction that we do without X. Thus, for example, empirical studies showing that current X does well in explaining current Y do not necessarily meet this definition of causality. The literature contains many examples of such models, and we need not list them here. And, while these models aid in understanding various markets, they do not necessarily provide assistance in terms of prediction. More precisely, unless an information structure meets this new criterion of causality, the conditional probability distribution of future values of Y, which the decision maker holds at the time of a decision, will not be changed by knowledge of X. This assumes, of course, that some reasonable method of forming probabilities is employed.[9]

The strict application of this notion of causality to two sets of data differs somewhat from traditional econometric methods. Traditional methods do not fully utilize Y in their own predication; that is, the time series properties present in Y are not utilized in predicting Y. Thus, when Y is related to another time series X, which itself is not purged of its time series properties, unreal or spurious relations among the two sets of data may be obtained. This point has been made most convincingly by Granger and Newbold (1974). They show that relatively large measures of degree of fit, R^2, can be obtained between two unrelated series, each of which is generated independently by commonly observed time series processes.

Applications of Granger causality with the widest audiences are probably the work of Sims [23] on the causal relations between money and income, and Pierce's [19] study on the relations between money and interest rates. We know of no applications to agricultural markets.[10]

In applying Granger's definition of causality, alternative procedures have been followed. Sims [23] transforms both data sets, X and Y, using a common filter, which he argues is sufficient to remove all autoregressive patterns in most economic series. He then estimates regressions of the transformed Y variable on past and future values of the transformed X variable. Sims finds that the direction of causality between money and income runs from money to income, and not vice versa.

Because of the arbitrary nature of the Sims' filter, Pierce [19], Pierce and Haugh [20], and others suggest that these results may not be proper. Pierce and Haugh [20] and Haugh and Box [12] suggest the use of a two-step procedure to establish the existence of causality between two variables. First, properties are removed from each series X and Y, using the filtering procedures of say Box and Jenkins [4]. Second, the residuals from these transformed data are cross-correlated. Pierce and Haugh [20] demonstrate that variable X causes Y if the cross-correlations between the residuals from each transformed series are non-zero at positive lags. That is, current Y can be predicted by past X.

Numerous types of other causal relations involving instantaneous causality, feedback, and independence can be analyzed by these same cross-correlations. For example, if the above cross-correlation is non-zero at a log of zero, instantaneous causality exists. Or, if non-zero cross-correlations exist at both positive and negative lags, then a two-way, or feedback, relation exists between X and Y.

In the following section, we apply Pierce and Haugh's two-step procedure to test a causal relation in the U.S. hog market.

A CAUSAL RELATION IN THE HOG MARKET

In the previous section we argued that traditional econometric methods for establishing causal relations among information variables can be inadequate. We then reviewed a procedure that can establish causal (at least predictive) relations among variables.[11] The procedure requires that each series is filtered with an optimal filter, and then the resulting residuals are cross-correlated. A causal relation exists, running from X to Y, if these cross-correlations are non-zero at positive lags.

In this section this procedure is applied to quarterly (1958-1976) time series on Midwestern hog prices and sow farrowings.[12] Given the introductory nature of this paper, an analysis using these variables is important, because of the known biological lag between sow farrowings and hog marketings. We expect to find a strong causal relation between sow farrowings and hog prices. In fact, we expect to find a feedback type of relationship. That is, sow farrowings cause price and price causes sow farrowings. This, of course, is what our theory would suggest.

To carry out the first step of Pierce and Haugh's procedure for empirically identifying causal relations, the usual three-step univariate filtering procedures of Box and Jenkins are applied to each series. This will remove all the time series regularities in the variables. The estimated autocorrelation and partial autocorrelation functions for the price series are presented in Table 2.

Table 2: Estimated Autocorrelation and Partial Autocorrelation Functions on Levels and First Differences of Quarterly Prices of Midwest Hogs (1958-76)*

		(lags) 1	2	3	4	5	6	7	8	9	10	11	12	13	14
Prices	(1)	.93	.84	.74	.66	.55	.49	.46	.44	.39	.37	.34	.30	.25	.20
	(2)	.93	-.10	-.16	.08	-.27	.39	.06	-.04	-.15	.02	.03	-.03	-.03	-.16
VPrices	(1)	-.01	.07	-.14	.17	-.50	.03	-.10	.23	-.15	.15	-.08	.14	-.14	.14
	(2)	-.01	.07	-.14	.17	-.51	-.01	-.04	.12	-.02	-.12	-.08	.02	.06	.08

* The estimated autocorrelations are given in the row labeled (1) and partial autocorrelations in the row labeled (2). Estimated standard errors at low lags for both series are approximarely .11.

The autocorrelations of actual prices suggest the price series is non-stationary—the autocorrelations tail off slowly. Not much significance should be attributed to the average of this series, since it has been increasing over time. The autocorrelations of the differenced series exhibit no evidence of being non-stationary—the autocorrelations are small at all lags. Consequently, the following is based on an analysis of the differenced series, $(1\text{-}B)P_t$.

The pattern exhibited by the estimated autocorrelations and partial autocorrelations of the differenced price series reveals an irregularity (from a random series) at lag 5. For the most part, all other values are quite small. Thus, the estimated representation of quarterly hog prices is given by[13]

$$(1 - B)P_t = A_t - .49\,A_{t-5}.$$

This model gives fairly good fit, $R^2 = .90$, and the application of usual diagnostic checks to the residuals of this representation do not suggest an inadequacy. Note the first ten autocorrelations applied to the residuals observed from this model presented in Table 3.

Table 3: Estimated Autocorrelations Applied to the Residuals of the Representation, $(1 - B)P_t = A_t - .49\,A_{t-5}$ for Quarterly Midwest Hog Prices (1958-76)*

(lags) 1	2	3	4	5	6	7	8	9	10	11	12
.03	.01	-.09	.15	-.13	-.04	-.07	.15	-.07	.16	-.06	.09

* The standard errors at low lags are approximately .13.

Generally, these autocorrelations are quite small, compared to their standard errors. This suggests that the price series has been reduced to white noise—at least the residuals cannot be distinguished from white noise. The X^2 statistic applied to these autocorrelations is 20.5, well below the critical value for 35 degrees of freedom.

The same procedures were applied to the series on quarterly sow farrowings. Estimated autocorrelation and partial autocorrelation functions for sow farrowings are presented in Table 4.

Table 4: Estimated Autocorrelation and Partial Autocorrelation Functions on Quarterly Midwest Sow Farrowings (1958-76).*

	(lags) 1	2	3	4	5	6	7	8	9	10	11	12	13	14
(1)	-.21	-.13	-.26	.85	-.25	-.17	-.32	.76	-.26	-.19	-.33	.70	-.26	-.18
(2)	-.21	-.18	-.36	.81	-.32	-.15	-.06	.12	-.11	-.05	.01	-.02	-.07	-.01

* Same as Table 2

The estimated autocorrelations do not indicate non-stationary behavior, since they remain small at low lags. However, seasonal non-stationary behavior is indicated by the tailing off of the estimated autocorrelation at seasonal lags of 4, 8, 12, ... Consequently, a seasonal difference model, or a seasonal autoregressive model, was applied to the data. The latter gives a better fit. The model fit was:

$$(1 - .70B)\ (1 - .92B^4)\ SF_t = A_t$$

Again, this model gives us a good fit $R^2 = .89$, and the diagnostic checks applied to the residuals reveal nothing inappropriate about the results. The estimated autocorrelations applied to the residuals are given in Table 5.

Table 5: Estimated Autocorrelations Applied to the Residuals of the Representation $(1-.70B)\ (1-.92B^4)\ SF_t=A_t$ for Quarterly Midwest U.S. Sow Farrowings (1958-76) *

(lags) 1	2	3	4	5	6	7	8	9	10	11	12
.22	-.01	-.12	-.28	-.20	-.00	.00	.01	.05	.06	-.09	.04

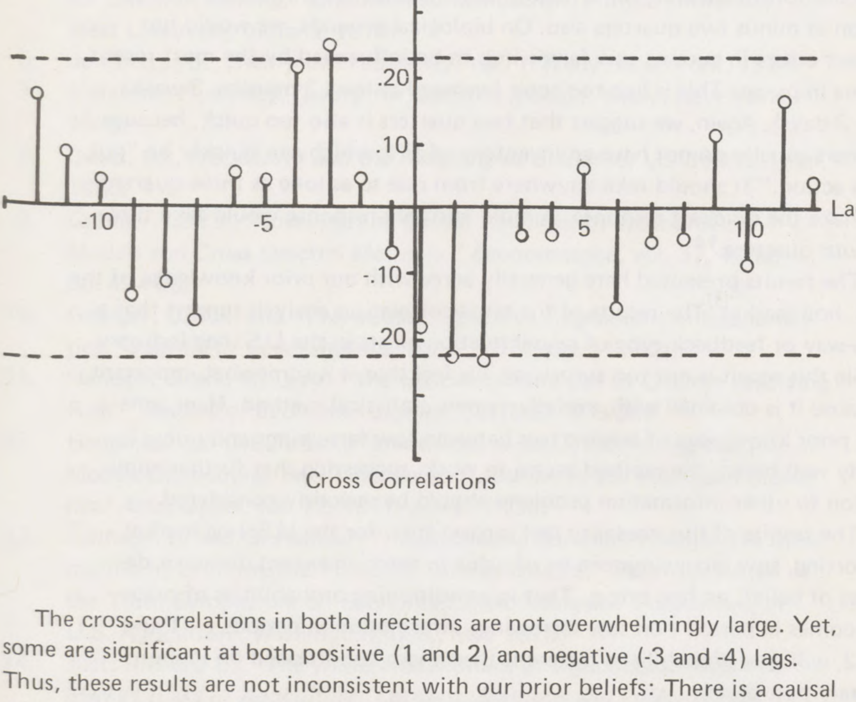
1 The standard errors at low lags are approximately .13.

Some may want to investigate the rather high estimated autocorrelation at lag 4. Other than this specific value, this model performs well; the X^2 statistic is again below the critical value (35.6 for 35 degrees of freedom). Thus, the hypothesis that the residuals are white noise is not rejected.

To complete Pierce and Haugh's two-stage procedure for identifying causal relations, we cross-correlated the residuals from the univariate models fit to both series (at long lags in either direction).

In Figure 2, we plot the cross-correlations for positive lags, which indicate the influence of sow farrowings in period t on price in future periods t + j. The negative lags suggest any influence of price in periods t – k on sow farrowings in period t. The dotted horizontal lines are drawn in at the approximate two standard error levels of ± .24.

Figure 2. Estimated Univariate Residual Cross-Correlation Function for Hog Prices and Sow Farrowings ($\frac{1}{\sqrt{N}}$ = .12.)



The cross-correlations in both directions are not overwhelmingly large. Yet, some are significant at both positive (1 and 2) and negative (-3 and -4) lags. Thus, these results are not inconsistent with our prior beliefs: There is a causal relation between sow farrowings and hog prices. We tested the causality hypothesis by calculating the U statistic, given by Pierce and Haugh, from the sum of squared cross-correlations. For causality running from sow farrowings to prices we calculated U_1 = 8.428. With three degrees of freedom, this number is significant at the 5 percent level. Going the other way, from prices to sow farrowings, we calculate U_2 = 12.12. With six degrees of freedom, this number is significant at the 10 percent level. Testing the overall relation, we have U_3 = 16.18, which, for seven degrees of freedom, is significantly different from zero at a significance level of 5 percent.

Further study of the cross-correlation function suggests that the cross-correlations are picking up the biological lag between farrowings and marketings. It takes about two quarters to bring pigs to market weight. Thus errors in sow farrowings in t should show up in errors in price in t + 2. It is quite interesting that we also find a relatively high negative cross-correlation at lag one, since one quarter is too soon for errors in sow farrowings to show up in actual marketings (of hogs). However, this intermediate influence may reflect inventory adjustments, which take place in anticipation of higher or lower marketings in the next quarter due to the knowledge of higher or lower sow farrowings.

Going back the other way, we find a three and four quarter lag between price errors and errors in sow farrowings. This is reasonably consistent with expectations. However, some might have expected a significant cross-correlation at minus two quarters also. On biological grounds, we would not expect errors in current sow farrowings to be influenced by the most recent errors in prices. This is just too soon (we need at least 3 months, 3 weeks, and 3 days). Again, we suggest that two quarters is also too quick, because farmers usually do not have an inventory of gilts which can quickly be "put into action." It should take anywhere from one to as long as three quarters to make the quickest response. A more leisurely response would take three or four quarters.[14]

The results presented here generally agree with our prior knowledge of the U.S. hog market. The results of the cross-correlation analysis suggest that a two-way or feedback type of causal relation exists in the U.S. hog industry. While this result is not too surprising, we feel that it is somewhat important because it is obtained with a relatively new statistical method. Here, where our prior knowledge of leading lags between sow farrowings and prices is fairly well based, the method seems to work, suggesting that further application to other information problems should be seriously considered.

The results of this causality test suggest that, for the U.S. hog market reporting, sow farrowings can be of value in forming expectations, or degrees of belief, on hog prices. That is, conditioning probabilities of price outcomes in period t on sow farrowings information in periods t - 1 and t - 2, will give probabilities different than those conditioned on immediately past prices.

This point (it would seem) is a necessary condition for the series on sow farrowings be of value to an economic agent forecasting prices. Additional analysis, as discussed above, would involve the weighing of expected benefits and costs of this information for a particular user. Thus, the fact that a series passes the causality test is not a sufficient condition for its being reported. However, because of the extreme complexity of measuring benefits to various agents, passing the causality test may be, in practical terms, all that we can realistically require.

REFERENCES

1. Arrow, K., "Alternative Approaches to the Theory of Choice in Risk-Taking Situations," *Econometrica,* 19(1951) 404-437.
2. Blake, B., R. Boynton, V. McCracken and J. Uhl, "Food Retail Price Reporting: Implications for Consumers, Market Behavior and Price Levels," Unpublished Manuscript, Purdue University, Department of Agricultural Economics, 1979.
3. Bonnen, J., "Improving Information on Agriculture and Rural Life," *American Journal of Agricultural Economics,* vol. 57, 1975, pp. 753-763.
4. Box, G.E.P. and G. Jenkins, *Time Series Analysis: Forecasting and Control,* Holden-Day, San Francisco, 1970.
5. Brandt, J. and D. Bessler, "Commodity Price Forecasting: Information for Decision Making," Unpublished Manuscript, Purdue University, West Lafayette, Indiana, 1979.
6. de Finetti, B., *Theory of Probability,* vol. 1, Wiley, New York, 1974.
7. Fishburn, P., *Utility Theory for Decision Making,* Wiley, New York, 1970.
8. Good, I.J., *Probability and the Weighing of Evidence,* London: Griffen, 1950.
9. Granger, C.W.J., "Investigating Causal Relations by Econometric Models and Cross Spectral Methods," *Econometrica,* vol. 37, 1969, pp. 424-38.
10. Granger, C.W.J., and P. Newbold, "Spurious Regressions in Econometrics," *Journal of Econometrics,* vol. 2, 1974, pp. 111-120.
11. Hanoch, G. and H. Levy, "The Efficiency Analysis of Choices Involving Risk," *Review of Economic Studies,* 36(1969) 335-346.
12. Haugh, L. and G.E.P. Box, "Identification of Dynamic Regression Models Connecting Two Time Series," *Journal of the American Statistical Association,* vol. 72, 1977, pp. 121-130.
13. Johnson, S. and G. Rausser, "Incorporating Specialists Subjective Information in Econometric Forecasts for Agriculture," Paper presented at the Third Symposium on Econometric Modeling and Forecasting in U.S. Agriculture, Washington, D.C., May 1978.
14. Just, Richard E., "The Welfare Economics of Agricultural Risk," in *Market Risks in Agriculture: Concept, Methods and Policy Issues,* Proceedings of Seminar on Regional Project W-149, Feb. 1978.
15. Leuthold, R., A. MacCormick, A. Schmitz, D. Watts, "Forecasting Daily Hog Prices and Quantities: A Study of Alternative Forecasting Techniques," *Journal of the American Statistical Association,* 65 (1970) 90-107.
16. Marschak, J. and R. Radner, *Economic Theory of Teams,* New Haven: Yale University Press, 1972.
17. Miller, S. and D. Kenyon, "Causal Relationships Between Live Hog Cash and Futures Prices," Clemson University Working Paper 3978, March 1978.

18. Morgenstern, O., *On the Accuracy of Economic Observations,* (second edition), Princeton: Princeton University Press, 1963.
19. Pierce, D.A., "Relationships—and Lack Thereof—Between Economic Time Series, with Special Reference to Money and Interest Rates," *Journal of the American Statistical Association,* vol. 72, 1977, pp. 11-21.
20. Pierce, D.A., and L.D. Haugh, "Causality in Temporal Systems," *Journal of Econometrics,* vol. 5, 1977, pp. 265-292.
21. Rutledge, D. "Trading Volume and Price Variability: New Evidence on the Price Effects of Speculation," Chicago Board of Trade Seminar, May 1978.
22. Savage, L., *The Foundation of Statistics,* New York: John Wiley, 1954.
23. Sims, C., "Money, Income and Causality," *American Economic Review,* vol. 62, 1972, pp. 540-52.
24. Wiener, Norbert, "The Theory of Prediction," in E.F. Bechenbach, editor, *Modern Mathematics for Engineers,* series 1, McGraw-Hill, New York, 1956.

FOOTNOTES

[1] Professor Aaron C. Johnson, Jr. made many helpful suggestions on an earlier draft of this paper. All errors remain the responsibility of the author.

[2] Good gives a general treatment of probability. In doing so, he treats $\omega\chi_k$ as the state of the mind of the decision maker. Here, our focus is stronger, in that we want to explicitly define that state of mind by the information—outcome from data and analysis—possessed by the decision maker. This point has recently been made more emphatically by de Finetti's paradoxical statement "that probability does not exist." His point (as he states) is that no "objective" probability exists, i.e., that any probability will differ from person to person, depending on the state of ignorance of the decision maker.

[3] In an abstract sense, one can treat composite forecasts—forecasts or structures based on a combination of two separate forecasts—as separate structures. For more discussion of composite forecasts see Johnson and Rausser on conceptual matters and Brandt and Bessler for an empirical application.

[4] The conditional probabilities given above should, strictly speaking be written as $P(C_j \mid \Omega_k; \Gamma_j)$. Here, the new symbol Γ_j represents the information we have on information set Ω_k.

[5] The general stochastic dominance theorems of Hanoch and Levy can be applied to the analysis of choice among alternative information structures. We will not pursue these in this paper.

[6] The events do not have to be future events. Indeed, one can also hold a degree of belief or probability on events which have already occurred.

[7] Recall from section 2, we defined obsolescence in terms of the subjective probability distribution of a particular individual. Thus, we cannot say one source is obsolete with respect to another, unless we directly assess the subjective probabilities of an individual decision maker. One approach here essentially follows the work of de Finetti in providing a somewhat mechanical or standardized procedure to aid such an assessment. In his own words:

> As far as the evaluation of probabilities is concerned, one would be unable to avoid the dilemma of either imposing an unequivocal criterion, or in the absence of such a criterion, of admitting that nothing really makes sense because everything is completely arbitrary. Our approach, in what follows is entirely different. We shall present certain of the kinds of considerations which do often assist people in the evaluation of their probabilities, and might be of use to you as well. On occasion, these lead to evaluations which are generally accepted. . .

[8] The word causality is a somewhat unfortunate use of the word. Perhaps the word predictability or prevision should be substituted.

[9] For a general treatment of the relationship between data and subjective probabilities we again refer the reader to de Finetti. His concepts of exchangeability and partial exchangeability can, it would seem, be extended to multiple time series.

[10] Since our initial work on this topic a number of applications have been brought to our attention. Professor William G. Tomek has pointed out two studies which predate our work. These are: Rutledge, and Miller and Kenyon.

[11] We do not wish to imply that the causal analysis discussed under the heading of Granger causality is necessarily different from econometric methods. Indeed it is not. However, when dealing with time series data, we must proceed in a manner similar to that suggested by the Granger causality work—i.e. we must take into account the time series properties of our data.

[12] We would like to thank Professor Jon Brandt, Department of Agricultural Economics at Purdue for these data.

[13] We follow the usual notation and write the error or disturbance in period t–j as A_{t-j}. The operator B refers to the lag operator, $(1 - B^n)P_t = P_t - P_{t-n}$.

[14] The author's knowledge of the biological processes behind hog production is based solely on conversations with Professors Tim Baker and Jon Brandt. Any errors are probably a result of the author's misinterpretations.