Dynamic Relationships and Efficiency of Rice Byproduct Prices

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Abstract

This article analyzes the dynamic relationships among weekly prices of rice byproducts, long grain rice, and corn, using causality tests and dynamic multipliers The authors use forecasts to evaluate the time series model Rice byproducts prices may be influenced more by shifts in demand than in supply. Long grain rice prices are related to brewers and seconds prices, but not to bran or mill feed prices Mill feed and corn prices move together. Corn prices exhibited no consistent relationship with seconds, brewers, or long grain prices

Keywords

Prices, rice, byproducts, causality, multipliers

Byproducts are marketable items produced as "residues" in the process of making or transforming a particular commodity As such, the revenue from selling byproducts is usually quite small compared with the revenue obtained from the main commodity For this reason, the supply of byproducts is generally closely related to the supply of the commodity In other words, the price of the commodity may be a major shifter in the supply function for its byproducts. On the other end, byproducts may be used in some production processes in competition with other substitute products Then, the demand for byproducts could be heavily influenced by the price of these substitutes In a competitive market, the pricing of byproducts may depend on the price of the commodity simultaneously produced and on the price of products competing for their use If one is investigating price discovery for byproducts, empirical analysis of these price relationships is relevant In particular, knowledge of how short-term fluctuations in any of these prices influence the other prices, such as the direction, magnitude, and speed of price transmission from one market to another, would be useful

This article focuses on several major rice milling byproducts second heads, brewers rice, rice mill feed, and rice bran [1] Because these byproducts are used for feeding livestock or in breweries, they may be close substitutues for corn. Indeed, corn, second heads, brewers rice, and long grain rice are major inputs in the brewing industry, accounting for 99 percent of the grain used as the adjunct in the brewing process (*30*) [2] Brewers use about two times more corn than rice and rice byproducts. This article analyzes the dynamic relationships among weekly prices of rice byproducts, long grain milled rice, and corn The knowledge of such dynamic relationships can help rice millers formulate their marketing plans for rice byproducts More specifically, we investigate the strength of substitutability between rice byproducts and corn We also explore whether price adjustments have been caused by shifts in supply or shifts in demand Finally, by examining the speed of price adjustments among markets, we provide some evidence of the efficiency of the markets

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[1]Rice hulls, the major byproduct in terms of quantity, is of relatively little value It is sometimes ground and mixed with bran to form rice mill feed and has several other uses Because it is unimportant economically and no price series exist, rice hulls are not considered in this analysis

[2]Italicized numbers in parentheses refer to items in the references at this end of the article

A Theoretical Model

A theoretical discussion of competitive price determination is presented in this section Our discussion focuses on the hypothesized direction of price transmission effects We will discuss the price transmission between one byproduct, the main product (long grain rice), and the hypothesized substitute for the byproduct (corn) in the context of a static model, using the following notation upper case letters represent quantities whereas lower case letters represent the corresponding prices

Modeling Price Transmission

First, denote aggregate supply function for corn by

$$C^s = f_1(c, x) \tag{1}$$

where C^s is the quantity of corn supplied, c is the price of corn, and x represents other factors influencing supply (such as rainfall or Government farm programs) The demand for corn should not be greatly influenced by the price of rice or rice byproducts because only a small portion of corn is used where these are substitutes However, the aggregate derived demand function for corn is defined here in its more general form where

$$C^d = f_2(c, b, r, y) \tag{2}$$

where C^d is the quantity of corn demanded, b is the price of the rice byproduct, r is the price of long grain rice, and y is other factors Some of the rice byproducts compete with lower quality long grain rice Therefore, the aggregate derived demand for long grain rice (R^d) is specified as

$$R^d = f_3(c, b, r, v) \tag{3}$$

where v is a set of exogenous demand shifters The supply of milled long grain rice (R^s) would be affected by its own price as well as its byproducts

$$R^s = f_4(b, r, w) \tag{4}$$

where w is a set of exogenous supply shifters

The demand for the rice byproduct should be influenced by the prices of its two closest substitutes, corn and long grain rice Thus, the derived demand for the byproduct (B^d) is

$$B^d = f_5(c, b, r, z) \tag{5}$$

where z is a set of exogenous demand shifters The rice byproducts are basically produced in fixed proportions to the production of milled rice Thus, the supply of rice byproducts (B^s) is specified as

$$B^s = aR^s \tag{6}$$

where a is a constant of proportionality

If each market is in equilibrium, then one can complete the system of equations supply and demand in each market ($B^s = B^d$, $R^s = R^d$; $C^s = C^d$) Equations (1) to (6) can then be solved for the market equilibrium prices as reflected by the following reduced-form equations

$$c = g_1(\theta) \tag{7}$$

$$r = g_2(\theta) \tag{8}$$

$$b = g_3(\theta) \tag{9}$$

where $\theta = (x, y, v, w, z)$ These reduced-form equations simply state that prices are a function of the exogenous supply-demand shifters in equations (1) to (6), x, y, v, w, and z These equations are the general equilibrium relations which are relevant to analyze the effects of shifts in exogenous variables when a static model is appropriate However, the static model may not be appropriate if markets are slow to adjust Among several possible reasons for dynamic price movements is the possibility that market traders may make pricing decisions based on delayed information

The concept of market efficiency is related to the speed of price adjustments Fama defined an efficient market as one that fully reflects all available information If prices adjust instantaneously to exogenous shocks, then the market is efficient and, in the absence of transaction costs, price changes cannot be predicted ahead of time (5) When price adjustments are slow, the corresponding markets are then inefficient if price changes can be predicted ahead of time In this case, the dynamics of price transmission provide information on the degree of market inefficiency

The tests of efficiency used in this article are random walk type tests where the information set has been expanded to include several prices Danthine urged caution in interpreting zero autocorrelation in returns tests because they are simultaneous tests of market efficiency, perfect competition, risk neutrality, constant returns to scale, and the impossibility of corner optima, such as supply shortage or deficient demand (*4*) Frankel maintains the joint hypothesis even extends to include the absence of market "news" (*7*) Another criticism is, as Swamy, Barth, and Tinsley pointed out, that the rational expectations model, of which the efficient markets model is a special case, requires the equivalence of subjective and objective probabilities (*24*)

Prices in competitive markets are expected to fully adjust in the long run Arbitrage should become more effective over time as more information becomes available and as economic agents have time to adjust their decisions In this case, competitive prices would tend to converge to an equilbrium after a few periods, implying the dynamic price adjustment is stable The longrun adjustment is expected to be similar to the adjustment that would take place in a static framework Thus, the direction of lagged effects should be the same as the original shift in supply or demand

Motivation of the Time Series Approach

To examine price adjustments, we must introduce dynamics into the static model Our approach uses time series modeling The analysis is set in the context of the reduced-form equations (7), (8), and (9) made dynamic.

$$\begin{bmatrix} c_t \\ r_t \\ b_t \end{bmatrix} = h\,[\theta_t, \theta_{t-1} \quad] \tag{10}$$

where prices respond to the information provided by current and past supply/demand shifters, θ_r, θ_{r-1}, and so forth

The components of θ involve many factors (such as weather, rumors, sales, and expectations) which are difficult to measure, especially for short time periods such as a week An alternative approach used here is to assume that these many factors are generated by stochastic processes which can be identified and estimated In this time series modeling approach, we can alternatively express equation (10) as:

$$\begin{bmatrix} c_t \\ r_t \\ b_t \end{bmatrix} = d + s + e_t \tag{11}$$

As equation (11) shows, the price series decompose into three parts the deterministic part, d, the short memory portion, s (in this analysis s consists of lagged prices with the deterministic component subtracted), which is assumed to be covariance stationary, and the error term, e_t, which is a zero mean white noise process. The deterministic part, d, involves trend and seasonality factors which cause the mean of the price series to be a function of time These factors reveal nothing new about the market's response to information Because time series analysis methods assume that the mean is not a function of time and because we are interested in studying the market's use of information, the deterministic component, d, must be removed (filtered) The stochastic process, $s + e_t$, reflects how new information is processed by the markets If s is zero, then price adjustments are instantaneous, suggesting the markets are efficient, at least in a "weak form" sense (*5*)[3] The process $s + e_t$, is modeled by use of autoregressive models (*1*). The white noise process, e_t, reflects the price variations which are not predictable ahead of time

Data and Modeling Approach

This section presents the modeling approach used to investigate the dynamics of prices of four major rice byproducts: second heads, brewers rice, bran, and mill feed We investigated corn prices because corn is a major substitute for the byproducts We also investigated the relationships between the price of long grain rice and the prices of its byproducts Our analysis relies on both univariate and multivariate time series modeling

The data are weekly prices for October 1976 to September 1981 obtained from USDA publications: *Rice Market News*, *Rice Outlook and Situation Report*, and *Grain Market News* (*27*, *28*, *29*) The data include prices for rice byproducts in Texas, No 2 yellow corn in Kansas City, and No 2 long grain milled rice in Texas

[3]Fama distinguishes among different information sets in his definition of efficiency The information set for this weak form test of efficiency consists of past prices only

Trend and seasonality are deterministic components that reveal nothing new about the market's response to new information. Therefore, they must be filtered before applying time series analysis and testing the efficiency of information for shortrun analysis because they avoid the need to specify the longrun behavior of the process (*6*). Since this study attempts to model shortrun market fluctuations, trend components are removed by first differencing. Regressions against a linear time trend indicated no significant linear trend remained in the first differenced data. Seasonality components are removed by use of a spline function (*16*).[4] Spline functions were chosen in the absence of prior knowledge of the precise functional form because they provide a flexible method of approximating an unknown function with a minimum number of parameters. Examination of the periodogram of the filtered data indicated that the procedure removed seasonality.

The filtering process is designed to remove effects of transaction costs. The first-difference filter should negate the effect of time trends and transaction costs between locations and between levels of the marketing channel. The seasonal adjustment should remove the effects of storage costs.

Causality Tests

Time series models can give insight as to whether or not a market is efficient by examining causality and feedback relationships. Granger defined causality in terms of predictability: a variable X does not cause another variable Y, with respect to a given set of information that includes both X and Y, if Y cannot be predicted more accurately by use of past values of X than if the information about X is not used (*9*). If X does not cause Y, but Y causes X, the causality is unidirectional. If the causality is bidirectional (X causes Y and Y causes X), it is called a feedback relationship. The causality tests suffer from a number of theoretical problems (*3*). We follow Mishkin's caveat that "... the issue here is the predictive content of the information—which is what Granger causality is really meant to analyze—and does not involve the tricky concept of economic causality which has led to so much confusion in the literature" (*19*). Thus, "causality" tests are employed in this article as tests of relative predictive efficiencies.[5]

Fama's market efficiency tests, developed for security markets, can be used for commodity markets if the data transformations remove the effects of storage, transportation, and other transaction costs (*5*). Assuming these transformations are sufficient, if a model cannot be found that helps predict the future using only filtered data, the market is efficient in the weak form sense. For a univariate time series, the sufficient condition for an efficient market would be that the price series is an AR(O). This means that, except for seasonal adjustments, prices of the corresponding markets follow a random walk with drift.

Significance tests for the cross correlations and regression of Y on past X alone are biased if the series are highly correlated (*10*). To overcome the problems associated with analyzing two highly correlated series, a proposed method consists of fitting univariate time series models to the data and analyzing the cross correlations of the residuals (*11, 14*). One drawback of this approach, as Schwert demonstrated, is that this filtering procedure may not preserve causal relationships (*21*). Also, no inference on instantaneous causality can be made from examination of the cross correlations of the residuals (*18, 20*).

Following this approach, we selected the orders of the univariate models using Akaike's Information Criterion (AIC) (*1*).[6] The AIC is a weighting function between parsimony and accuracy. We estimated the parameters of the univariate models by the least square method. These estimates and their standard errors are consistent and asymptotically efficient if the residuals are uncorrelated and the true order is selected. However, Shibata demonstrated the AIC may overestimate the true order (*22*). Thus, our estimates will be consistent, in general, only if selection of the order of the model is not considered part of

[4]The spline function involves estimating different polynomials in time over different sections of the data and then placing restrictions on the functions to make them continuous and differentiable. In this case, we estimated four cubic polynomials in time, one for each calendar quarter. The switching points approximately coincide with quarterly stock reports.

[5]As Conway and his colleagues point out, this predictive efficiency is valid only in the linear least squares sense; nothing can be said about nonlinear prediction from these tests (*3*).

[6]Theoretical work has pointed out some potential problems with the AIC. Under certain conditions, the AIC can be undefined or may not have well defined maximum solutions (*22*).

the estimation procedure[7] We performed tests for causal direction and contemporaneous correlation The test statistics have chi-square distributions under the null hypotheses of no relationship

Multivariate time series methods allow for more than a comparison of pairs Sims argued causality tests using multivariate methods may be the most natural way of performing causality tests, but he rejected them because of lack of uniqueness of the joint autoregressive moving average (ARMA) process (*23*) One can avoid this difficulty by adhering strictly to a pure autoregressive (AR) model (*15*)

To further investigate multimarket price series relationships, we also modeled the price series by multivariate time series analysis, again in the context of an AR model We selected the order of the multivariate AR model using an AIC and estimated the multivariate model by seemingly unrelated regression. The test of causality in the context of a multivariate AR model involves testing the restriction that all lagged values of a particular variable are zero (*26*). For example, if the null hypothesis is that Z does not cause Y directly, we would test the restriction that the coefficients Z through Z_{t-2} are zero in the Y equation where p is the order of the AR model To check the adequacy of the AR model, we performed tests for white noise of the residuals using both Fisher's Kappa statistic and Bartlett's Kolmogorov-Smirnov statistic (*8*).

Multipliers

The causality tests previously mentioned provide no information about the dynamic properties of the model—that is, how the impact of price changes are transmitted through the markets They do not show the net impact of one market on another In a multimarket framework, a price change in one market has both a direct impact and an indirect impact on other markets Causality tests do not provide much information about efficiency in the presence of a feedback relationship Dynamic multipliers are useful for discussing efficiency because they incorporate both the direct and indirect impacts Thus, we further examined the dynamic properties of the underlying series by calculating dynamic multipliers for the multivariate autoregressive model

We did not use the traditional interpretation of dynamic multipliers in this analysis Typically, dynamic multipliers measure the change in the endogenous variable associated with a one-unit change in the exogenous variable (*2*) Because all predetermined variables are lagged endogenous variables, we calculated dynamic multipliers in this analysis assuming a one-time shock occurs through the error term Thus, this shock is not specified as to its origin, but rather it represents past shocks. The dynamic multiplier analysis involves the calculation of three different multipliers The mth delayed-run multiplier (DRM(m)) shows the impact of a one-time shock in time period t − m on price changes in time period t The mth intermediate-run multiplier (IRM(m)) measures the total impact of a one-time shock to the system on the expected price level m periods ahead The intermediate-run multiplier is the cumulative of the price changes which is the sum of the delayed-run multipliers The longrun multiplier (LRM) is the impact on the expected price when a new equilibrium is reached The longrun multiplier is the same as the intermediate-run multiplier as m approaches infinity (*2*)

In this analysis, the one-time shock occurs through the error terms in the autoregressive model for the deseasonalized price change. This shock results in both an immediate change in current price (P_t) and in a change in the expected value of future price changes. The DRM measures the change in the expected value of future price changes because it measures changes in the future values of the dependent variable, deseasonalized price changes Thus

$$\mathrm{DRM}(m)_{ij} = \frac{dE[\Delta P_i(t+m)]}{dP_j(t)} \tag{12}$$

The total change in E(P(t + m)), the expected value of price, m time periods in the future, resulting from a shock in time t is the change in expected future price changes which is the intermediate-run multiplier The intermediate- and longrun multipliers measure the change in the expected value of

[7] If the selection of the order of the model is considered part of the estimation process, an inconsistent estimate of the order of the model would affect the sampling estimates and these estimates would also be inconsistent Hannon's procedure would yield consistent and asymptotically efficient estimates However, Hannon's procedure is more likely to underestimate the order in small samples, thus producing more biased estimates in small samples (*12 13*)

$P_i(t+m)$ associated with a one-unit change in $P_j(t)$ which can be written as

$$\mathrm{IRM}(m)_{ij} = \frac{dE[P_i(t+m)]}{dP_j(t)} \tag{13}$$

$$= \sum_{k=1}^{m} \frac{dE[\Delta P_i(t+k)]}{dP_j(t)}$$

$$= \sum_{k=1}^{m} \mathrm{DRM}(k)_{ij}$$

where E is the expectation operator and $\mathrm{IRM}(m)_{ij}$ is the mth intermediate-run multiplier measuring the impact of P_j on P_i. The longrun multiplier is the limit of IRM as m approaches infinity

Because the IRM is simply the sum of the DRM, a measurement of the amount of time it takes the market to adjust to shocks is the highest value of m for which the delayed-run multiplier is significant Calculating this measurement of the adjustment period proves useful to discussing the speed of price adjustments

Prediction

One way to validate a model is to evaluate how well it predicts the aspects of the real world that it was designed to model We made and evaluated out-of-sample forecasts for the multivariate AR models as a means of validation The predictive ability of the model also gives some insight into the degree of inefficiency The real test of efficiency is whether or not the model can be used to predict the future with some degree of reliability and thus to develop profitable trading rules Out-of-sample forecasts will provide additional evidence to show if the model could have been used by a trader to make profits in the forecast period

We calculated forecasts for 13 weeks (October 1981 to December 1981) This relatively small sample implies that the forecast accuracy results should be interpreted with caution The forecasts can be computed as

$$P(t+h|t) = P(t+h-1|t) + \tilde{C}(t+h|t) + \Delta P(t+h|t) \tag{14}$$

where $P(t+h|t)$ is the predicted price in time, $t+h$, given the information available in t, $P(t)$ is the actual price in time, t, $\tilde{C}_{t+h}$ is the predicted seasonal price change in $t+h$ (predicted value of the spline function), $\Delta P(t+h|t)$ is the predicted deseasonalized price change (predicted value of the autoregressive model using deseasonalized price changes), and h is the number of steps ahead that the forecast is made This is dynamic simulation A static simulation is a series of one step-ahead forecasts We used both static and dynamic forecasts A static model should perform better because it uses more information (*17*)

We evaluated the forecasts using Theil's U2 statistic (*25*) The statistic compares the root mean squared errors from the time series forecasts with those obtained from a no-change model, that is, a random walk model In the absence of transaction cost, a market that follows a random walk is efficient Therefore, if the time series model cannot predict better than a random walk model, the market is considered efficient The U2 statistic is

$$U2 = \frac{\sqrt{\sum_{t=1}^{T} (\mathrm{Predicted}_t - \mathrm{Actual}_t)^2}}{\sqrt{\sum_{t=1}^{T} (\mathrm{Actual}_t)^2}} \tag{15}$$

where $\mathrm{Predicted}_t$ and Actual_t are a pair of predicted and observed changes from the previous actual level The U2 inequality coefficient ranges from zero to infinity If the predictions are perfect, then the predicted value equals the actual and U2 equals zero A no-change forecast model where the predicted value equals last period's price gives a U2 value of 1 Any value of U2 greater than 1 means the model is worse than a no-change forecast model

In addition to the 13 static and dynamic forecasts, a series of eight 6-week-ahead forecasts are made These forecasts are equivalent to the last predicted value of a six period dynamic simulation In calculating U2 statistics for these forecasts, we compared the 6-week-ahead forecasts with the actual values at the beginning of the dynamic simulations

Results

We used first differencing and spline functions to remove deterministic components and performed the analysis using the filtered data Using cross correlations of residuals from univariate models, we initially performed causality tests among alternative price series We then analyzed the dynamics of price relationships using multivariate modeling Dynamic multipliers provide useful information to investigate the economic implications of the models Next, we used forecasts of the prices to evaluate the ability of the time series model to describe and predict the actual behavior of the market

Univariate Results

We selected univariate AR models using the AIC and estimated the models by ordinary least squares procedures None of the models selected is an AR(0) (table 1) Given Fama's definition of market efficiency (in the weak form sense), all markets are inefficient in processing the information reflected in their own prices Long grain rice and corn prices have the shortest AR models with an AR(1) Second heads and mill feed both have an AR(5) which is the longest order Thus, the primary products are the quickest to adjust whereas the prices of the less important byproducts adjust more slowly

Comparing cross correlations of the univariate AR residuals reveals that bran and mill feed prices, by far, have the strongest relationship to the current period with a chi-square statistic three times that of any other byproduct price (table 2) Other prices with a contemporaneous relationship significant at the 5-percent level are seconds and bran, seconds and long grain, brewers and long grain, and mill feed and corn

Comparing cross correlations involving 10 lags contains only two "causality" results significant at the 5-percent level (table 2) Long grain prices lead brewers prices, and corn prices lead long grain prices Only bran and mill feed have a strong relationship

The causality results using either 5 or 20 lags are different (table 3) Together these have five "causality" results that are significant at the 5-percent level Both results also show long grain prices cause brewers prices However, none of the other causality results is consistent, suggesting that these results may be spurious Seconds prices and bran prices are not caused by any of the other prices regardless of the choice of length of lag

Table 1—Univariate autoregressive models[1]

Series	Intercept	Lag						AIC order	R-squared
		1	2	3	4	5	6		
Long grain	- 0 5430 (- 13)[1]	- 0 1524 (- 2 45)[2]						1	0 023
Seconds	- 0819 (- 03)	- 0440 (- 70)	- 0 0112 (- 18)	- 0 0995 (- 1 61)	- 0 0859 (1 38)	- 0 1726 (- 2 73)[2]		5	055
Brewers	3396 (25)	- 0077 (- 12)	- 0454 (- 73)	- 0659 (- 1 05)	1569 (250)[2]			4	032
Bran	- 1662 (- 16)	2860 (4 62)[2]	0469 (73)	- 1984 (- 3 21)[2]				3	117
Mill feed	- 0734 (- 11)	2612 (414)[2]	0220 (34)	2077 (3 25)[2]	- 2100 (- 3 23)[2]	- 0981 (- 1 53)		5	149
Corn	- 1595 (- 24)	2561 (4 24)[2]						1	066

Blanks indicate not applicable
[1]t-values are in parentheses
[2]Significant at the 5-percent level

Table 2—Bivariate causality results for rice byproduct prices, using 10 lags[1]

Commodity		Null hypothesis		
Y1	Y2	Y1 ≠> Y2	Y2 ≠> Y1	No contemporaneous correlation
Seconds	Brewers	2 2	6 4	0 01
Seconds	Bran	12 2	5 2	4 10[2]
Seconds	Long grain	8 3	11 6	12 10[2]
Seconds	Mill feed	5 1	11 9	20
Seconds	Corn	18 2	9 1	2 40
Brewers	Long grain	16 2	24 2[2]	4 20[2]
Brewers	Mill feed	4 9	11 6	03
Brewers	Corn	4 8	13 3	92
Bran	Mill feed	16 2	19 5	36 60[2]
Bran	Corn	10 5	14 1	1 2
Long grain	Mill feed	5 3	10 6	003
Long grain	Corn	5 2	20 2[2]	40
Mill feed	Corn	6 9	15 6	4 50[2]

[1]The test statistic is calculated including 10 lags and is distributed chi-square with 10, 10, and 1 degrees of freedom for each respective test Thus the critical values at the 5-percent level are 18 3 18 3, and 3 84, respectively

[2]Significant at the 5-percent level

Table 3—Bivariate causality relationships for rice byproduct prices, using 5 and 20 lags[1]

Commodity		Null hypothesis			
		5 lags		20 lags	
Y1	Y2	Y1 ≠> Y2	Y2 ≠> Y1	Y1 ≠> Y2	Y2 ≠> Y1
Seconds	Brewers	1 7	4 4	28 8	9 2
Seconds	Bran	4 4	2 3	19 5	10 2
Seconds	Long grain	6 9	9 8	26 1	22 8
Seconds	Mill feed	2 6	93	24 7	20 1
Seconds	Corn	5 4	5 4	33 3[2]	22 7
Brewers	Bran	7 4	2 6	25 9	17 2
Brewers	Long grain	12 1[2]	20 7[2]	22 7	44 9[2]
Brewers	Mill feed	3 4	3 8	14 2	22 8
Brewers	Corn	1 4	3 1	9 3	33 1
Bran	Long grain	7 7	3 0	26 6	14 9
Bran	Mill feed	12 6[2]	9 6	26 8	24 5
Bran	Corn	4 5	10 3	20 6	18 5
Long grain	Mill feed	8	7 8	11 4	18 2
Long grain	Corn	3 4	7 0	16 3	29 5
Mill feed	Corn	6 0	8 3	16 9	20 2

[1]The test statistic is a distributed chi-square with m degrees of freedom Thus, the critical values at the 5-percent level are 11 1 and 31 4, respectively

[2]Significant at the 5 percent level

Multivariate Results

We selected an AR(1) from the AIC criterion for the multivariate model (table 4) The multivariate R-squared values are lower than the univariate R-squared values for seconds, brewers rice, and mill feed These three price series have univariate AR orders of 4 or 5, and we did not include these lags in the multivariate model Multivariate causality results can be determined if one examines the significance of individual coefficients (table 4) The multivariate causality results show that long grain prices cause second prices, corn prices cause bran prices, and bran and mill feed prices have a feedback relationship Thus, long grain prices, corn prices, and brewers prices are not led by any other prices and appear to be efficient in processing information from the other markets The null hypothesis of white noise residuals is not rejected for any of the price series when both Fisher's Kappa statistic and Bartlett's Kolmogorov-Smirnov statistic are used (*8*).

The measurement of the adjustment period shows all prices adjust very quickly, with the longest impact taking 2 weeks (table 5). The own-price longrun multiplier of the long grain prices is significantly less than 1, indicating that any price changes are later modified This change could result if the Texas long grain price overreacted to new information The own-price multiplier for bran, mill feed, and corn prices are significantly greater than 1, indicating these markets respond gradually (1-2 weeks) to new information

Corn has a large impact on the other markets, ranging from 0.22 for mill feed to 0 42 for bran, however, only the impact on bran is significant at the 5-percent level The impact of corn is large because the means and standard deviations of the other prices are larger than those for corn.

All prices are measured in cents per hundredweight, but 100 pounds of corn is worth less than 100 pounds of the other commodities Long grain prices have a small, but significant, impact on prices of second heads (0.08). Mill feed and bran both affect each other, with mill feed having the larger impact (0 39 vs 0 18)

Table 4—Multivariate autoregressive model for rice byproducts[1]

Independent variable	Dependent variable[1]					
	Long grain$_t$	Seconds$_t$	Brewers$_t$	Bran$_t$	Mill feed$_t$	Corn$_t$
Intercept	0 09405 (02)	0 4500 (17)	0 4374 (33)	- 0 0028 (- 00)	- 0 0316 (- 05)	0 0148 (02)
Long grain$_{t-1}$	- 1598 (- 2 52)[2]	1007 (2 43)[2]	- 0222 (- 1 05)	0185 (1 17)	0024 (22)	0050 (- 49)
Seconds$_{t-1}$	0735 (76)	- 0908 (- 1 43)	0563 (1 74)	- 0444 (- 1 84)	0048 (29)	- 0020 (- 13)
Brewers$_{t-1}$	- 0765 (- 40)	- 0391 (- 32)	- 0208 (- 33)	0153 (32)	- 0202 (- 62)	- 0161 (- 53)
Bran$_{t-1}$	- 4324 (- 1 62)	- 1511 (- 87)	- 1144 (- 1 29)	2045 (3 09)[2]	1113 (2 44)[2]	0006 (01)
Mill feed$_{t-1}$	- 0298 (- 08)	2497 (97)	0763 (58)	2776 (2 83)[2]	1738 (2 57)[2]	- 0711 (1 12)
Corn$_{t-1}$	4242 (1 11)	2493 (1 00)	2276 (1 79)	2017 (2 12)[2]	1042 (1 59)	2824 (4 59)[2]
R-squared	040	037	028	150	104	080

[1]t values are in parentheses
[2]Significant at the 5-percent level

Table 5—Longrun multipliers for rice byproduct prices

Impact[1]	Multipler	t-value	Prob > |t|	Adjustment period[2]
BW -> BW	0 972	-0 46	0 64235	0
TX -> BW	- 017	- 97	33466	0
SC -> BW	054	1 79	07521	0
BN -> BW	- 135	-1 26	20710	0
MF -> BW	037	34	80779	0
CN -> BW	284	1 68	09352	0
BW -> TX	- 076	- 47	63872	0
TX -> TX	860	-2 98	00320[3]	1
SC -> TX	083	91	36438	0
BN -> TX	- 500	-1 77	07839	0
MF -> TX	- 213	- 53	59437	0
CN -> TX	34	76	44943	0
BW -> SC	- 053	- 46	64582	0
TX -> SC	077	2 32	02135[3]	1
SC -> SC	927	-1 28	20109	0
BN -> SC	- 185	- 92	35915	0
MF -> SC	182	64	52197	0
CN -> SC	326	1 03	30605	0
BW -> BN	006	09	92842	0
TX -> BN	015	77	43906	0
SC -> BN	- 051	-1 51	13258	0
BN -> BN	1 312	2 61	00953[3]	2
MF -> BN	390	2 30	02196[3]	1
CN -> BN	419	2 22	02731[3]	2
BW -> MF	- 026	- 58	56200	0
TX -> MF	005	36	72074	0
SC -> MF	- 003	- 14	88880	0
BN -> MF	176	2 26	02457[3]	2
MF -> MF	1 247	2 24	02598[3]	1
CN -> MF	224	1 82	06972	0
BW -> CN	- 019	- 46	64296	0
TX -> CN	- 006	- 54	58816	0
SC -> CN	- 004	- 21	83768	0
BN -> CN	- 009	- 13	89395	0
MF -> CN	- 123	-1 24	21471	0
CN -> CN	1 362	3 28	00118[3]	1

[1]BW = brewers, TX = long grain, SC = seconds, BN = bran, MF = mill feed, CN = corn
[2]The adjustment period is the time the delayed-run multiplier takes to become insignificant at the 5 percent significance level
[3]Significantly different from 1 (0) for the own (cross) price multiplier at the 5 percent level

The only U2 value less than 1 for the static simulations of the multivariate model is for mill feed, whereas corn has the largest U2 value at 3 45 (table 6) The multivariate AR model does not predict as well as a random walk model which implies that the market is efficient as the model could not be used to make an "above-normal" profit The six-step-ahead U2 values are similar to those for the static forecasts As expected, the dynamic forecasts are poor, with U2 values ranging from 1 68 for mill feed to 7 47 for brewers These predictions are for a relatively small sample (13 observations), but they imply that inefficiency is low, if it exists

Conclusions

We used univariate and multivariate time series modeling to investigate rice byproduct pricing Most of the relationships between the price series investigated are weak Most prices are not even related in the current period, implying these commodities do not compete with each other Mill feed and corn prices move together, implying that there may be some substitution between these commodities Corn prices have no consistent relationship (current or lagged) with seconds, brewers rice, or long grain prices, implying corn and these commod-

Table 6—Predictive performance of the multivariate autoregressive model for rice byproduct prices using Theil s U2 statistic[1]

Price series	Static forecasts[2]	Dynamic forecasts[2]	Six-step-ahead forecasts[3]
Long grain	2 03	6 51	2 16
Seconds	1 42	6 12	1 50
Brewers	2 94	7 47	1 93
Bran	1 05	3 69	94
Mill feed	95	1 68	94
Corn	3 45	6 01	6 24

[1]A no change model has a U2 value of 1 0 (25)
[2]Calculated using 13 out of-sample forecasts
[3]Calculated using 8 out of sample forecasts

ities do not exhibit close substitutability There may be some substitution between long grain and either seconds or brewers rice. Long grain rice prices are related to brewers and seconds prices, but not to bran or mill feed prices Because the prices of long grain rice and the four byproducts are not all related, shifts in the supply of rough rice were probably less important in pricing rice byproducts during the observation period. In other words, the results suggest that rice byproduct prices may be more influenced by shifts in their demand than shifts in their supply Further research analyzing these should, therefore, try to focus on the determinants of the derived demand for rice byproducts.

All price series analyzed here are inefficient in processing information reflected in their own prices according to the univariate results. However, most of the prices are fairly efficient with respect to the information reflected by the other prices. The low R-squared values, short adjustment periods, and poor forecasts all indicate that the degree of inefficiency in these markets may be low

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In Earlier Issues

In view of current concerns over Government regulation and of the debates on new food and agricultural policy direction and legislation, dairy policy merits careful consideration Some important questions that need to be answered are How much instability can be expected as a result of program removal? Is this expected level of instability tolerable? Who might suffer as a result of this level of instability, and by how much? Who might benefit from removal of the dairy programs, and in what way?

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