Lead-Lag Price Relationships Between Thinly and Heavily Traded Commodity Markets

by

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Introduction

In the literature, price behavior on thin or illiquid futures markets has been distinguished from that on more liquid markets. Thin futures markets have been generally viewed as deviations from the competitive norm for several reasons; including sluggish price behavior (Brinegar), biased prices (Gray, Martin and Storey), and greater volatility in prices (Friedman). These markets have been characterized as lacking sufficient speculative activity and as being inferior to liquid markets in terms of their ability to discover prices.

A characteristic of past research on illiquid futures markets is that it has concentrated on the study of price behavior within the individual markets themselves. Noncompetitive price behavior found in thin markets has resulted in their being classified as inefficient compared with liquid markets.

Unlike earlier research on thin markets, our paper focuses on the causal link between commodity futures prices in markets for which few transactions occur with large price variability and the more heavily traded markets for substitutable commodities. It identifies and estimates the structural link between two classes of commodity markets: those which have a heavily speculative interest and those which do not. We are determining the direction of causation between prices and because causality is a statement of forecasting ability, we investigate the out-of-sample forecasting performance of models relating to the futures price series. Thus, we address the question of the relative quality of information reflected in thin as compared with liquid futures markets.

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The working hypothesis in this paper is that thinly traded markets lead more heavily traded markets. The basis for this hypothesis is that commercial interests generally base their trading on accurate fundamental information and these participants often have a larger impact on price behavior in less liquid markets. An acceptance of the null hypothesis suggests that, in a forecasting sense, thinly traded markets may be more efficient (Stein) than the more liquid markets. The alternative hypothesis that liquid markets lead thin markets is also tested.

The markets chosen for empirical analysis in this paper are Chicago soybeans, a heavily traded market, and Winnipeg rapeseed, a thinly traded market. Soybeans and rapeseed are highly substitutable oilseeds and the demand for these products is derived from their oil and meal content. Soybeans are comprised of approximately 18 percent oil and 80 percent meal, whereas rapeseed contains about 41 percent oil and 57 percent meal. The development in the 1960's of rapeseed varieties, which are both low in euric acid and glucosinolate, has made the oilseed highly competitive with soybeans. This results from the fact that rapeseed oil and soybean oil are competitive substitutes as vegetable oils and in addition, rapeseed meal is used as a substitute for soybean meal in livestock rations.

Rapeseed and soybeans are, of course, only a part of the entire oilseed complex. One could alternatively consider other price linkages in this complex, such as the lead-lag relationship between soybean oil and rapeseed futures. The results presented here are preliminary in the sense that they are for a single, but important, link in the oilseed complex. This analysis could also be extended to other commodity group intra-relationships, such as the Kansas City-Chicago or the Minneapolis-Chicago wheat futures markets.

Methodology

This paper is a study of the causality relationship between rapeseed, R_t, and soybean, S_t, futures prices. Granger's definition of causality among time series is employed to determine which price series is causing the other.

Accepting Granger's definition of causality, suppose that a strong correlation is observed between two random variables, R_t and S_t, measured at time period $t = 1, 2, \ldots, T$. Let all the information available at time n be denoted by Ω_n and denote by $\Omega_n - R_n$ this information, except the values taken by R_t up to time n. Let MSE $(S_{n+1} \mid \Omega_n - R_n)$ denote the mean-square of the one step forecast error of S_{n+1} based on the information set $\Omega_n - R_n$. Granger's definition then implies R_t causes S_t if,

$$(1) \qquad \text{MSE}\ (S_{n+1} \mid \Omega_n) < \text{MSE}\ (S_{n+1} \mid \Omega_n - R_n)$$

In other words, R_t is said to cause S_t if an optimal forecasting model for S_{t+1} using past values of S_t and R_t performs better than one using only past values of S_t.

To make this definition of causation operational some simplifications are required. Linear forecasts will only be considered and the universal information set Ω_n will be replaced by the past and present values of the set of time series, $I_n : \left\{ R_{n-j}, S_{n-j}, j \geq 0 \right\}$.

An excellent survey of empirical applications of Granger's definition of causality that have appeared in the literature is found in Pierce and Haugh. A regression procedure, which tests for causality after transforming the time series by a common filter, was developed by Sims (1972) and has been used in numerous subsequent studies. However, the application of this procedure may prove misleading (Pierce and Haugh) in those instances where the filtered variables still contain serial correlation and causality is thus detected when it may not exist.

To treat autocorrelation more adequately, Haugh then developed an approach to detect causality by the use of cross-correlation analysis rather than regression analysis on the filtered data. This methodology has also been extensively applied. However, Sims (1977) has argued that there may be a tendency for the elements of the sample cross-correlogram of the prewhitened series to be biased towards zero due to specification error.

To avoid this problem, Ashley, Granger and Schmalensee have recently developed a more detailed approach to the question of causality, by analyzing the out-of-sample forecasting performance of models of the original series of interest. This does not preclude the use of the cross-spectrum between the prewhitened variables as a step in identifying the models relating to the original series. The out-of-sample forecasting performance of these models is then used to test hypotheses about causation.

The approach to the analysis of causality between S_t and R_t in this paper follows that in Ashley, Granger and Schmalensee. It can be summarized by the following steps.

The first step is to identify and estimate a univariate forecasting model for each time series. The univariate models can be represented as equation (2) and (3) for R_t and S_t, respectively.

$$A(B)\,R_t = \alpha_1 + C(B)\,u_t \tag{2}$$

$$D(B)\,S_t = \alpha_2 + E(B)\,v_t \tag{3}$$

where A, C, D and E are polynomials in the lag operator B.

The univariate models are also referred to as prewhitening filters because they remove autocorrelation between R_t and S_t, which could lead to overestimating the degree of correlation between the two series. That is, the two series u_t and v_t are, by construction, white noise series. Box and

Jenkins provide a useful approach for identifying and estimating univariate models as in (2) and (3).

Next, a bivariate model relating the residuals u_t and v_t is identified, estimated, and diagnostically checked. This procedure is outlined by Granger and Newbold. The bivariate models chosen in this paper can be represented as:

$$(4) \qquad S_t = \alpha_3 + F\,(B)\,S_t + G\,(B)\,R_t + H\,(B)\,\eta_t$$

The model for the original series, S_t, is then specified by combining the univariate models with the bivariate model for the residuals.

Finally, the bivariate model is used to generate a set of one-step forecasts for a post-sample period. These forecast errors are then compared to those provided by the univariate model for S_t.

Because the two forecast error series produced are most likely to be cross-correlated and autocorrelated and have non-zero means, no direct test for the significance of improvements in mean-square forecasting error is available. However, Ashley, et al., have developed the following indirect procedure to test whether or not the bivariate model is a significant improvement over the univariate model.

The difference between the univariate and bivariate mean-squared errors can be expressed as:

$$(5) \qquad MSE_u - MSE_b = [S_u^2 - S_b^2] + [(M_u)^2 - (M_b)^2]$$

where $MSE_{u,\,b}$ are the mean-squared errors, $S^2_{u,\,b}$ the sample variances and $M_{u,\,b}$ the sample means of the forecast errors from the univariate (u) and bivariate models (b), respectively.

Alternatively, expression (5) can be written as:

$$(6) \qquad MSE_u - MSE_b = \hat{cov}\,(\delta,\,\gamma) + [(M_u)^2 - (M_b)^2]$$

where $\hat{cov}$ is the sample covariance, and where:

$$\delta_t = e_t^u - e_t^b$$

and

$$\gamma_t = e_t^u + e_t^b$$

denoting the one-step ahead post-sample forecast errors made by the univariate model by e_t^u, and those by the bivariate model as e_t^b.

Then, consider the regression equation

(7) $$\delta_t = \alpha + \beta\,(\gamma_t - \bar{\gamma}) + z_t$$

where $\bar{\gamma}$ is the sample mean of γ_t and z_t is an error term. Ashley, et al., have shown that α is the difference in mean forecast error and β is proportional to the difference in forecast error variance between the univariate and bivariate models. Testing the significance of the decrease of the mean-square forecast error in going from the univariate to the bivariate model is equivalent to testing the null hypothesis

(8) $$H_o : \alpha = 0 \text{ and } \beta = 0$$

against the alternative that both are nonnegative and at least one is positive. Brandt and Bessler have shown this test to be valid as long as M_u, $M_b > 0$. If these error series have negative means then a simple transformation must be applied to them so that the hypothesis test is conditionally valid. This transformation involves multiplying the forecast errors by minus one.

Empirical Results

The data used in this study were daily futures prices of the November 1979 rapeseed and soybean contracts. Daily closing prices were obtained from the statistical annuals of the Winnipeg Commodity Exchange for rapeseed and the Chicago Board of Trade for soybeans. These daily prices were then expressed as percentage changes $(P_t - P_{t-1})/P_{t-1}$ or returns in order to render the observed series stationary.

The first 187 observations from the sample were used for identification and estimation of the univariate and bivariate models. The remaining 53 observations were reserved for post-sample forecasting.

Employing the Box-Jenkins iterative methodology led to the following ARIMA processes for soybean and rapeseed daily futures price returns:

$$(9) \qquad \underset{(1.63)}{(1 + .13\,B} - \underset{(1.08)}{.08\,B^2)}\,(1 - B)\,S_t = (1 - \underset{(40.31)}{.95)}\,v_t$$

$$\chi^2\ (21\ \text{d.f.}) = 37.65$$

$$(10) \qquad (1 - B)\,R_t = (1 - \underset{(37.95)}{.94)}\,u_t$$

$$\chi^2\ (23\ \text{d.f.}) = 28.12$$

where values in parentheses are t ratios. With 21 degrees of freedom, the critical chi-square value is 35.5 at a .025 level of significance. For 23 d.f. the critical value is 38.1. Thus, the univariate representations in (9) and (10) seem adequate. In other words, they produce essentially white noise residuals.

Identification and estimation of the bivariate model yields in addition to equation (10) the following final model for soybeans:

$$(11) \qquad (1 - B)\,S_t = (\underset{(8.27)}{-.38\,B})\,(1 - B)\,R_t + \frac{\overset{(1.17)}{(1 - .10\,B)}}{\underset{(36.8)}{(1 - .94\,B)}}\,\eta_t$$

$$\chi^2\ (22\ \text{d.f.}) = 23.00$$

In addition to equation (9) the estimated final bivariate model for rapeseed is:

$$(12) \qquad (1 - B)\, R_t = \underset{(10.87)}{(-.39\, B)}\, (1 - B)\, S_t + \frac{\overset{(1.73)}{(1 + .56\, B)}}{\underset{(1.06) \qquad (2.32)}{(1 - .32\, B - .65\, B^2)}}\, \varepsilon_t$$

$$\chi^2 \text{ (21 d.f.)} = 29.89$$

For both bivariate models, the relatively low chi-square values indicate the residual series pass the standard statistical test for whiteness.

Forecasting Performance

The univariate and bivariate rapeseed and soybean models estimated above can now be compared for post-sample forecasting performance in order to test our causality hypotheses. The entire post-sample mean-squared error for the bivariate soybean model is 82.7 percent lower than for the univariate model, indicating the bivariate model forecasts relatively well. For rapeseed the bivariate model provides a smaller improvement in forecasting ability, as its post-sample mean-squared error is only 32.8 percent lower than for the univariate model.

To indirectly test the statistical significance of these differences, the regression equation in (7) is estimated for both the rapeseed and soybean post-sample forecasts after multiplying the univariate and bivariate forecast errors by minus one. For soybeans, the o.l.s. results are:

$$(13) \qquad \delta_t^s = \underset{(-.20)}{-.00016} + \underset{(3.73)}{.12868}\, (\gamma_t^s - \bar{\gamma}^s)$$

$$R^2 = .22 \qquad \text{d.w.} = 2.36$$

In (13) the intercept has a negative sign but the low t-value indicates the term is statistically insignificant. However, with a t statistic of 3.73, $\hat{\beta}_s$ is significant since $t_{.025} = 2.0$. This result indicates the mean-square forecast error for the bivariate soybean model is significantly smaller than it is for the univariate model. The estimated coefficients indicate the bivariate model has a much smaller forecast error variance than the univariate forecast and, therefore, the null hypothesis of the thin rapeseed market leading the liquid soybean market cannot be rejected.

To test the alternative hypothesis, the coefficients of (7) were estimated for the rapeseed bivariate and univariate models after multiplying the forecast errors of the univariate model by minus one. The o.l.s. results are:

(14) $$\delta_t^r = \underset{(0.18)}{.00049} + \underset{(0.58)}{.18746}\,(\gamma_t^r - \bar{\gamma}^r)$$

$$R^2 = .01 \qquad d.w. = 1.78$$

Both the intercept and slope coefficients in (14) have low associated t-values, indicating statistical insignificance. The alternative hypothesis of the liquid soybean market leading the thin rapeseed market must therefore be rejected.

Conclusions

The structural link between thin and liquid futures markets for substitute commodities has been the focus of this paper. Taken alone, thin futures markets have been viewed in the literature as biased and inefficient. Liquid futures markets, on the other hand, have been characterized as being efficient. In this paper we have studied the lead-lag price relationship between the Winnipeg rapeseed and the Chicago soybean futures market. The former is generally considered a thin market and the latter a liquid market.

Because, on average, commercial trading accounts for over 80 percent of the volume in the rapeseed market and approximately only 50 percent in the soybean market, our null hypothesis was that rapeseed futures prices lead soybean futures prices. Commercial interests generally trade on more accurate information (than do speculators) and they have a proportionately larger impact on price behavior in the rapeseed market, as compared with soybeans. The alternative hypothesis of soybean prices leading rapeseed prices was also tested.

In order to test our hypotheses, we empirically studied the causal link between the November 1979 futures contract prices in soybeans and rapeseed. A bivariate soybean time series model, with rapeseed prices as an explanatory variable, was found to outperform the post-sample forecasts of the univariate soybean model. This result implies rapeseed prices "cause" soybean prices using Granger's definition of causality. The reduction in mean-square prediction error in going from the univariate to the bivariate model is attributed to a reduced forecast error variance. On the other hand, the bivariate rapeseed model did not outperform the post-sample forecasts of the univariate model.

These conclusions are at this stage conditional on the limited data set employed in this paper. The further study of the causal link between soybeans and rapeseed, with additional data and the extension of this technique to other markets, will ascertain whether the findings here are unique to this case and period or are of more general validity.

Nevertheless, these results should invoke renewed interest in the behavior of prices on thin futures markets. Prices on these markets are driven primarily by commercial interests and they are, therefore, very useful informational sources.

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