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FUTURES MARKET EFFICIENCY IN THE SOYBEAN COMPLEX

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I. Introduction

There is a growing awareness that much of the empirical work that has been conducted on futures market efficiency is without a sound foundation.[1] This empirical work has concentrated on a search or random walk or more general "Martingale" properties of futures prices. Both Danthine (1977) and Lucas (1978) have shown that the periodic failure of the Martingale property to hold is not evidence of market inefficiency. Danthine has criticized the Samuelson theoretical formulation noting a number of reasons why the link between a Martingale process and efficiency in futures markets may be broken.[2] Stein (1980) has convincingly argued that there is no direct relation between a Martingale property and economic welfare. In an insightful analysis of foreign exchange markets, Stein has stated:

> "The standard 'efficient' market tests used in connection with the stock market are not applicable to the foreign exchange (or any other) market where there is feedback from the price, which equates the stock demand to the stock in existence. . ., to the rate of change in the stock."

The feedbacks found in futures markets means that the search for Martingales in commodity futures markets has no direct implications for market efficiency; the Martingale property is neither a necessary nor a sufficient condition for efficiency. As shown by Stein, regardless of whether futures prices are a Martingale, avoidable welfare losses can occur. This welfare orientation places emphasis on the forecasting ability of futures markets.

The purpose of this paper is to examine the efficiency of futures markets by investigating their forecasting ability in terms of both bias and variability measures. In the terminology of Fama (1970), the issue of efficiency will be tested by a semistrong form measure.[3] This framework provides a more powerful test of commodity market efficiency than the various weak-form tests that have been advanced in the search for random walk or Martingale processes. However, it, too, is incomplete, since the efficient market hypothesis itself is defective. Grossman and Stiglitz (1980) have shown that, for the property of efficiency to hold, costless information is not only a sufficient condition but also a necessary condition.

The implication of the above results is that even if a particular model forecast is more accurate than the forecasts of futures markets, inefficiency does not necessarily follow. This condition is only necessary; inefficiency implies that a model does exist whose forecasts are more accurate than the futures market forecasts (relative accuracy condition). Sufficiency can be obtained by including the condition that the cost of constructing and utilizing the model does not exceed the incremental benefits appropriately adjusted by risk (relative cost/benefits condition). The two conditions--relative accuracy and cost/benefits--are necessary and sufficient for the inefficiency property of commodity futures markets.

We begin our examination with a review of the literature related to futures market efficiency. This review clearly demonstrates that there are both important theoretical and empirical implications of the efficiency property. This is followed by an empirical investigation of commodity futures market efficiency for the U. S. soybean complex.[4] The "relative accuracy" condition for the soybean, soybean oil, and soybean meal futures markets is investigated via structurally based ARIMA models. Rather than specifying *ad hoc* univariate or multivariate processes, we propose a structural monthly model of the U. S. soybean system and subsequently derive and estimate the associated multivariate transfer functions and the univariate ARIMA processes implied by the structural specification.

For two of the three commodities examined, the constructed models significantly "outperform" the futures market for both long- and short-range forecasts. This result is based on the mean-square prediction error criterion. The empirical results on the necessary, relative accuracy condition are supplemented in the conclusion section by a qualitative examination of the relative cost/benefit condition. Only if both conditions are satisfied can we infer the property of inefficiency for the soybean complex of futures markets.

II. Literature Review

There is an increasing number of theoretical models which assume *a priori* that futures markets are efficient. Danthine (1978); Feder, Just, and Schmitz (1979); and Holthausen (1979) have all demonstrated that, if futures markets are efficient, the relevant price signal to be used by producers is simply the futures price. These authors show, under the special assumptions imposed, that all risk-averse firms in the market will key their production decisions to the futures prices; thus, there is a separation of real production decisions from hedging decisions. These conceptual frameworks implicitly assume that futures markets generate rational expectations for subsequent spot prices and that a basis risk (the variability in the difference between futures and spot prices) does not exist. Along similar lines, Turnovsky (1979) has shown that, if futures markets are efficient, they will have the effect of stabilizing spot markets. Peck (1976) has argued that futures prices for storable commodities dampen spot price fluctuations by facilitating storage decisions. The theoretical model advanced by McKinnon (1967) suggests that futures markets may be a more effective vehicle than buffer stocks for stabilization. In a general context, Cox (1976) has argued that spot market prices provide more accurate signals for resource allocation if a futures market for the commodity in question exists.

The above work demonstrates that futures markets have some important implications for domestic stabilization schemes, international commodity agreements, informationally efficient spot markets, and the general form and shape of governmental intervention. These implications depend critically upon whether or not the futures markets are efficient. There have been a number of empirical studies which have investigated the efficiency issue. Some studies have focused on the use of mechanical filters to determine whether profits can be obtained from speculative positions in futures markets [Houthakker (1961); Cox (1976); Leuthold (1972); and Stevenson and Bear (1970)].[5] Still other work has investigated the efficiency issue by attempting to determine whether futures prices are random walks or more general Martingales [Brinegar (1970); Cargill and Rausser (1972, 1975); Labys and Granger (1970); Larson (1960); Leuthold; Smidt (1965); and Stevenson and Bear]. Some of this work rejects the hypothesis that futures price changes are "fair games" or Martingales [Cargill and Rausser (1972)]; other studies accept the hypothesis (Larson; Labys and Granger; and Stevenson and Bear); while still others are inconclusive (Brinegar). All of this work assumes that the variance of futures price changes are finite which Mann and Heifner (1976) find unacceptable. On the basis of their empirical work and the earlier observations of Houthakker (1961), it can be inferred that the underlying distribution of futures market changes is leptokurtic. Following similar work on the stock market, Mann and Heiffer suggest that the explanation for leptokurtosis is that the observations are drawn from stable Paretian distributions with infinite variances. A more plausible explanation for futures markets, advanced by Houthakker, is that leptokurticity is due to changing variance.

Tomek and Gray (1970), Leuthold (1974), Gray (1977), Kofi (1973), and Stein (1981) investigated the forecasting ability of futures markets within the context of allocative efficiency. Tomek and Gray compared preplanting prices of the respective postharvest futures with their expiration prices. They found that the corn and soybean market prices (both storable commodities) are "good" forecasts and that the potato market prices (a nonstorable commodity) are "bad" forecasts. Both sets of forecasts for the period of analysis were found to be unbiased but the associated variance for the potato market was unacceptable.[6]

Kofi's results from 1953 to 1969 data show that, the longer the forecast horizon, the worse the futures markets perform as a predictor of spot prices. For corn and cattle, Leuthold also found that futures markets were efficient forecasters of spot prices for only near-maturity dates. Stein confirmed similar phenomena for corn, live cattle, and potatoes (1981).[7]

Stein carried the analysis a step further and placed emphasis not only on the biasedness of futures markets forecasts but, in addition, on the variance of the forecast error. The resulting variance of the forecast error and its implications for expected social loss, regardless of bias, led Stein to the conclusion that futures prices earlier than four months prior to delivery are useless forecasts of closing prices.

Much of the above empirical work stems from the earlier analysis by Working. In 1948, he wrote:

> "The idea that a futures market should quote different prices for difference future dates in accordance with developments anticipated between them cannot be valid when stocks must be carried from one date to another. It involves supposing that the market should act as a forecasting agency rather than as a medium for rational price formation when it cannot do both."

Along similar lines, in 1942, he stated that "It is not true that futures prices afford forecasts of price change in the sense in which one speaks of the price forecasts of a market analyst." He goes on to state, however, that "Neither is it true that futures prices provide no sort of forecast of price change."

Tomek and Gray (1970) attempted to clarify the conceptual views of Working but were largely unsuccessful for the reasons noted by Weymar (1966). Weymar argues correctly that Working's supply-of-storage theory is, in essence, a self-contained but static theory of intertemporal price relationships.[8] The conceptual inconsistency in Working's hypothesis was demonstrated by Weymar, who used the Muth (1961) rational expectation hypothesis to show that the spread between futures prices for two different dates of delivery should depend on expected stocks, not on stocks already in existence. The supply-of-storage theory by itself is a logically inconsistent view of intertemporal price relationships; stockholders' expectations about future stock levels must be determined to achieve internal consistency. Empirically, of course, Working's supply-of-storage theory may be closer to reality than a rational expectation formulation.

To be sure, there is a host of reasons why futures market prices may prove to be biased expectations of subsequent spot prices even in a completely dynamic rational-expectation formulation of both stock and futures markets for either storable or nonstorable commodities. Costs of information [Grossman and Stiglitz (1980)], risk aversion [Stein (1979), Sarris (1981)], irrational market participants, imperfect capital markets, and alternative transaction and information costs [Just and Rausser (1981)] can lead to discrepancies between current futures market quotes and (risk neutral) rational expectations of subsequent spot prices (conditioned on currently available probabilistic information). Even in a world which is perfect in all respects, under risk aversion, these discrepancies can be positive or negative--positive in the case of tight current supplies or negative in the case of large expected supplies.[9]

Clearly, the available literature emphasizes bias measures of future prices of subsequent spot prices and examines the volatility of such prices only as a by-product. For risk-averse decision makers, the volatility of futures prices assumes a central role when such observations are used as forecasts of subsequent spot prices [Just and Rausser (1981)]. In assessing the efficiency of futures markets and their allocative role in a world of uncertainty and costly information, the complete probability distribution of futures prices must be evaluated. By itself, a large variance of futures prices has no direct implications for efficiency; it may only be due to nonsystematic elements in the underlying spot market. However, if a forecasting scheme can be discovered which generates probability distributions--which in some sense stochastically dominate the futures-prices probability distributions--the necessary condition (relative accuracy) for inefficiency holds. For this reason, the following analysis will be a comparison of bias and volatility measures of the futures market with similar forecast measures generated from a time series, econometric-based model.

III. Soybean Complex

The market demand for soybeans is derived from soybean meal and soybean oil—its two major products. The value of soybeans is determined directly from the soy meal and the soy oil prices and also marginally by crushing and handling costs. The federal government's support price has not been a determinant of the price of soybeans for the past several years. However, it has been a determinant in corn which is a major complement in feed usage.

One 60 pound bushel of soybeans will yield approximately 11 pounds of soybean oil and 47 pounds of soybean meal. Most of the domestic consumption of soybean oil is in the form of food products, such as cooking and salad oils, and most of the soybean meal used domestically is in the high-protein portion of feed rations for poultry and livestock. Since there are numerous substitutes for soybean oil on the world market, its price is determined residually. The price of soybean meal, on the other hand, is more closely related to its own supply-demand situation which includes such factors as the price of corn.

For a monthly econometric model of the U. S. soybean complex, the following partially reduced form structure is proposed:

<u>Price of soybeans</u>

$$PS_t = \theta_{11} + \alpha_{12}\, PO_t + \alpha_{13}\, PM_t + \alpha_{14}(L)\, SS_t + \beta_{11}(L)\, ES_t + u_{1t} \qquad (1)$$

<u>Price of soybean oil</u>

$$PO_t = \theta_{21} + \alpha_{25}(L)\, SO_t + \alpha_{27}\, CS_t + \beta_{22}(L)\, OI_t + \beta_{23}(L)\, EO_t + u_{2t} \qquad (2)$$

Price of soybean meal

$$PM_t = \theta_{31} + \alpha_{36}(L)\ SM_t + \alpha_{37}\ CS_t + \beta_{34}(L)\ EM_t + \beta_{35}(L)\ PC_t + \beta_{36}(L)\ LI_t + u_{3t} \tag{3}$$

Stocks of soybeans

$$SS_t = \theta_{41} + \alpha_{41}\ PS_t + \alpha_{44}(L)\ SS_t + u_{4t} \tag{4}$$

Stocks of soybean oil

$$SO_t = \theta_{51} + \alpha_{52}\ PO_t + \alpha_{55}(L)\ SO_t + \alpha_{57}\ CS_t + u_{5t} \tag{5}$$

Stocks of soybean meal

$$SM_t = \theta_{61} + \alpha_{63}\ PM_t + \alpha_{66}(L)\ SM_t + \alpha_{67}\ CS_t + u_{6t} \tag{6}$$

Soybean crushings

$$CS_t = \theta_{71} + \alpha_{71}\ PS_t + \alpha_{72}\ PO_t + \alpha_{73}\ PM_t + \alpha_{74}(L)\ SS_t + \alpha_{76}(L)\ SM_t + \alpha_{77}(L)\ CS_t + \beta_{72}(L)\ OI_t + u_{7t} \tag{7}$$

where L is a lag operator defined as $L^n\ P_t = P_{t-n}$ and where

Endogenous Variables

PS_t = price of soybeans

PO_t = price of soybean oil

PM_t = price of soybean meal

SS_t = stocks of soybeans

SO_t = stocks of soybean oil

SM_t = stocks of soybean meal

CS_t = soybean crushings

Exogenous Variables

ES_t = soybean exports

OI_t = crude vegetable oil price index

EO_t = soybean oil exports

EM_t = soybean meal exports

PC_t = price of corn

LI_t = livestock price index

As shown by Zellner and Palm (1974), if a set of endogenous variables is generated by a dynamic simultaneous equation model, then it is often possible to solve for the transfer function of individual endogenous variables (such as soybean prices, PS_t) through algebraic manipulation. That is, each endogenous variable in a structural form model has associated with it an explicit and unique transfer function equation which expresses the endogenous variable as the linear combination of current and past values of the exogenous variables and an ARIMA error term. Similarly, given that each exogenous variable can be expressed in terms of an ARIMA process, it is possible to respecify the transfer function equation as an ARIMA process for each endogenous variable. The derivation of the alternative representations examined in the analysis to follow are presented in an Appendix.

For each transfer function equation [see Appendix (A.7)-(A.9)], from an estimation standpoint we are confronted with a multivariate model involving a multiple input-single output process. In contrast, the estimation of each final equation (see Appendix A.4) can be viewed as a univariate model involving a single output process. In the following empirical section, the transfer function form representation will be referred to as the multivariate model, and the final equation form representation will be referred to as the univariate ARIMA model. Note, also, that in both cases we report here only the unrestricted estimations of the soybean, soybean oil, and soybean meal prices.

IV. Empirical Analysis

An iterative procedure for identifying, estimating, and validating the transfer equation begins with investigating the stationarity assumption for each time series [Box and Jenkins (1970)]. Transforming the input data by the estimated univariate process removes all systematic components in the series and renders it purely exogenous. The stationary output series is also transformed by the parameters of the univariate input process in order to generate an output series that is predictable from the prewhitened (transformed) input series.

Data on monthly average soybean cash prices (PS_t), monthly average soybean oil prices (PO_t), monthly average soybean meal prices (PM_t), and monthly U. S. soybean exports (ES_t) were obtained from the Chicago Board of Trade (1960).[10] The monthly average crude vegetable oil price index (OI_t) was taken from the Bureau of Labor (various issues). This index is comprised of the price of cottonseed oil, corn oil, soybean oil, and peanut oil.

The iterative approach led to the following ARIMA processes for soybean exports and the vegetable oil price index:[11]

$$(1 - \underset{(6.0)}{.48}L)(1 - L^{12})\,ES_t = \underset{(5.05)}{13.04} + (1 - \underset{(18.6)}{.93}L^{12})\,\eta_{et}, \quad \chi^2\ (21\ \text{d.f.}) = 15.78 \tag{8}$$

$$(1 + \underset{(3.10)}{.28}L - \underset{(1.08)}{.10}L^2)(1 - L)\,OI_t = (1 + \underset{(2.07)}{.19}L^6 + \underset{(3.08)}{.29}L^{12})\,\eta_{vt}, \quad \chi^2\ (20\ \text{d.f.}) = 27.51 \tag{9}$$

and the following transfer function for soybean prices:

$$(1 - L)\,PS_t = \frac{\underset{(2.00)}{.0760} + \underset{(2.50)}{.0665}L \quad (1 - L^{12})}{1 + \underset{(7.19)}{.9319}L}\,ES_{t-1} + \underset{(8.83)}{.9182}\,(1 - L)\,OI_t$$

$$+ 1 + \underset{(3.86)}{.3221}L - \underset{(4.52)}{.3777}L^4 - \underset{(3.47)}{.2991}L^{12} \quad \eta_{st}, \quad \chi^2\ (21\ \text{d.f.}) = 22.04 \tag{10}$$

where values in parentheses are t ratios. In the case of (10), the chi-square value of 22.04 indicates that the structural representation of the model is adequate since, with 21 degrees of freedom, the critical value is 32.7. A check of the t ratios in (10) indicates that all of the parameters are statistically significant as are the noise parameters.

The estimated univariate ARIMA models for soybean, soybean oil, and soybean meal prices are reported in Table 1. The chi-square statistics suggest an adequate fit for all three models.

Forecasting Evaluation

The estimated equations presented in Table 1 and (8)-(10) are employed to serve as a norm against which we will test the forecasting ability and, hence, the efficiency of the soybean, soy oil, and soy meal futures markets. The planting-time forecasting ability of the soybean futures market is first evaluated; then the overall forecasting ability of each of the three futures markets is tested. The criteria employed are the mean-square prediction error and Theil's inequality coefficient. Specifically, for n pairs of predicted and actual price changes (P_i, A_i). The mean-square prediction error (MSE) for the set of all n observations is given by:

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (P_i - A_i)^2. \tag{11}$$

Theils's inequality coefficient (U) is the positive square root of:

$$U^2 = \frac{1/n \, \Sigma_{i=1}^{n} (P_i - A_i)^2}{1/n \, \Sigma_{i=1}^{n} A_i^2}. \tag{12}$$

TABLE 1.--Univariate ARIMA Models: Soybeans (PS_t), Soybean Oil (SO_t) and Soybean Meal (SM_t), 1966-1976

Model price	Estimated structure	χ^2	d.f.
Soybeans	$(1 + \underset{(7.08)}{.7028}L^2)(1 - L)\,PS_t = (1 + \underset{(1.06)}{.0392}L + \underset{(17.55)}{.9216}L^2)\,\varepsilon_{st}$	17.28	21
Soybean oil	$(1 + \underset{(6.09)}{.8108}L^3)(1 - L)\,SO_t = (1 + \underset{(3.53)}{.6293}L^3)\,\varepsilon_{st}$	27.01	24
Soybean meal	$(1 - L)\,SM_t = (1 + \underset{(3.14)}{.2634}L + \underset{(3.64)}{.3805}L^6)\,\varepsilon_{mt}$	13.74	24

As is well known, this coefficient ranges from zero to infinity and is equal to one for a random walk forecast. Forecasting accuracy increases with decreases in U.

The typical decomposition of the numerator of U^2 will prove useful in the following analysis. It is:

$$1 = U^m + U^s + U^c. \tag{13}$$

The three ratios in (13) are often referred to as the bias proportion, the variance proportion, and the covariance proportion, respectively. U^m measures unequal central tendencies between the actual (A_i) and predicted (P_i) changes; U^s measures unequal variation between the actual and forecasted price changes; and U^c measures imperfect covariation between the pairs of predicted and actual price changes. In essence, U^m and U^s measure systematic forecast errors that should be small for appropriate forecasting models, and U^c measures a nonsystematic random error that is unavoidable.

Planting Time Forecasting Accuracy

The soybean crop year runs from September 1 through the end of August. However, the planting of soybeans in the United States generally takes place in May of every year, and most of the crop is harvested during the following September and October. The November futures contract, therefore, usually serves as the first new crop futures and the September contract as the last old crop futures, or as a transitional contract between the two crop years. The new and transitional crop futures are the most important contracts for soybean producers prior to the planting season.

In computing the quality statistics (MSE, U, U^m, U^s, and U^c), a number of operations were performed on the basic data. In particular, (1) the spot prices at time i were measured as the monthly average case prices in month i; (2) the futures market price forecasts are measured as the average of the last five closing prices of contract i + t settled in the month the forecast is made (month i); (3) the univariate model price forecasts are generated from the equations in Table 1, (they are ex ante forecasts made at the base of the forecast period, December 30, 1976, without the knowledge of 1977-1980 prices) and (4) the realized spot prices are taken to be the average cash prices, Chicago. It should be emphasized that the sample used in estimating the model is 1966 through 1976 whereas the model forecasts are made over the ex ante forecast period (nonsample), 1977-1980. Since the futures price quotes reflect current and any past information on structural shifts and are observed during the forecast period, the model is most certainly not given an unfair advantage over the futures market.

As is well known, futures prices do not always converge to the cash price in the month of its maturity. In order to check the robustness of the results presented below, an alternative procedure was substituted for (4); and the relevant statistics were reestimated. This alternative measured the realized spot prices by the average closing futures prices in the maturity month. The individual quality statistics were only changed marginally; thus, our results may be viewed as robust under (4). Note also that with respect to (2), the average of the last five closing prices in month i is the futures markets price forecast of the closing price in month i + t. The average of the last five prices in month i should reflect more up-to-date information than a monthly average of settlement prices. The forecasts of the ARIMA models are conditioned on monthly average prices; thus, futures market forecasts should also have some advantage on this score.

The accuracy of the price signal given by the soybean futures market is evaluated for the September and November contracts for the 1977-1980 forecast period. Table 2 displays the results. The quality of the price forecasts made during the preplanting period, which runs from the end of December through the end of April, is measured. The December-April period roughly corresponds to the period in which soybean producers would make planting decisions.

The forecast quality statistics in Table 2 indicate that the planting time multivariate soybean price forecasts are superior to the remaining forecasts. For both the September and November price forecasts, both the multivariate and univariate models "out performed" the futures market as their forecasts yielded a lower MSE and inequality coefficient (U). It is interesting to note that, except for the univariate model's November forecast, the futures market has the best bias proportion (U^m). For both contract months, however, the two models dominate the futures market in terms of the variance proportion (U^s).

In contrast to the ARIMA model, the multivariate model must forecast three variables (PS_t, ES_t, and OI_t) rather than one. The combined prediction errors of these three variables could very well render the multivariate model inferior to a univariate model.[12] The Theil statistics add further insight. The relatively large U^m values for the multivariate base forecasts indicate that a large proportion of the MSE for these forecasts is due to the model "missing" the means of the actual price changes. On the other hand, the multivariate model is superior to the univariate in predicting the variance (i.e., the U^s's are lower) of the price changes.

TABLE 2

Quality of Planting Time Soybean Price Forecasts
1977-1980

Forecast source and quality statistics	Contract forecasted	
	September	November
Futures market		
MSE	1.54	1.34
U^m	.02	.02
U^s	.82	.80
U^c	.16	.18
U	.73	.64
Univariate model		
MSE	1.01	1.21
U^m	.05	.00
U^s	.57	.64
U^c	.38	.36
U	.59	.60
Multivariate model		
MSE	.99	1.09
U^m	.43	.21
U^s	.41	.57
U^c	.16	.22
U	.34	.33
Random walk		
MSE	2.88	3.29
U^m	.01	.01
U^s	.99	.99
U^c	.00	.00
U	1.00	1.00
Sample size (n)	20	20

As the results in Table 2 suggest, soybean producers who conditioned their price expectations on the multivariate or ARIMA models would have come closer to making the optimal decision rules than would those who used the futures market prices for the 1977-1979 period. In this sense the soybean market does not provide an accurate signal for resource allocation. Future soybean prices do not fully reflect all available information. The multivariate and ARIMA models for both the September and November contracts more accurately reflect the same information available to the futures market.

General Forecasting Accuracy

Table 3 reports forecast quality statistics for the overall soybean, soybean oil, and soybean meal price forecasts. These forecasts were made from 3 to 10 months prior to the maturity of each futures contract for the 1977-1980 period. There are seven soybean, eight soybean oil, and eight soybean meal contracts traded on the Chicago Board of Trade each year; and forecasts were made of the price of each of these contracts. Due to space limitations, Table 3 reports results only for the futures market and the univariate ARIMA model forecasts. The forecasts and quality statistics were computed in the same manner as for Table 2. Similar computations were made for a multivariate transfer function model as well as a random walk model. In all cases, accuracy of the univariate ARIMA model forecasts were comparable to the multivariate model and significantly superior to forecasts generated by the random walk formulation. For soybeans, as well as soybean products, both conventional and updated ARIMA forecasts were obtained with basically similar results.[13]

As shown in Table 3, the univariate ARIMA soybean model has a consistently lower MSE and inequality coefficient (U) than the futures market for soybean

TABLE 3.--Accuracy of Soybean Complex Price Forecasts
Futures Market *vs.* Univariate ARIMA Models
1977-1980[a]

Model price	Forecast horizon (number of months away) 3	4	5	6	7	8	9	10
SOYBEAN								
Futures market								
MSE	1.67	1.80	1.60	1.29	1.20	1.15	1.01	.88
U^m	.02	.02	.01	.02	.01	.00	.00	.00
U^s	.77	.67	.60	.57	.48	.58	.46	.54
U^c	.21	.31	.39	.41	.51	.42	.54	.46
U	.89	.87	.81	.80	.74	.74	.70	.70
Univariate model								
MSE	.91	.86	.86	.63	.63	.64	.60	.50
U^m	.00	.01	.01	.05	.05	.05	.03	.01
U^s	.18	.28	.41	.43	.46	.51	.39	.30
U^c	.82	.71	.58	.52	.49	.44	.58	.69
U	.66	.60	.59	.56	.54	.55	.54	.53
Sample size (n)	27	26	26	25	25	24	23	22
SOYBEAN OIL								
Futures market								
MSE	17.38	20.94	22.06	17.38	19.17	19.69	20.71	19.87
U^m	.02	.01	.04	.06	.06	.10	.14	.18
U^s	.52	.55	.50	.43	.42	.37	.20	.30
U^c	.46	.44	.46	.51	.52	.53	.66	.52
U	.96	.94	.96	.90	.97	.96	1.11	1.09
Univariate model								
MSE	24.11	24.24	24.24	21.69	21.75	22.38	23.20	23.81
U^m	.61	.60	.60	.60	.60	.60	.63	.69
U^s	.05	.12	.13	.11	.08	.07	.05	.03
U^c	.34	.28	.27	.29	.32	.33	.32	.28
U	1.13	1.01	1.00	1.01	1.03	1.02	1.18	1.19
Sample size (n)	31	30	30	29	29	28	27	26
SOYBEAN MEAL								
Futures market								
MSE	1,559	1,958	1,704	1,512	1,377	1,262	1,046	1,015
U^m	.01	.00	.02	.01	.01	.04	.08	.17
U^s	.62	.70	.61	.62	.63	.53	.53	.39
U^c	.37	.30	.37	.37	.36	.43	.39	.45
U	.94	.92	.85	.82	.82	.76	.74	.83
Univariate model								
MSE	1,064	1,070	1,069	966	928	958	876	802
U^m	.01	.01	.01	.03	.02	.02	.00	.00
U^s	.11	.30	.31	.41	.36	.32	.24	.14
U^c	.89	.69	.68	.56	.62	.66	.76	.86
U	.78	.68	.67	.65	.68	.67	.68	.74
Sample size (n)	31	30	30	29	29	28	27	26

[a]Soybean--bushels, soybean oil--pounds, and soybean meal--tons.

price forecasts ranging from 3 to 10 months away. This ability of the univariate model to outpredict the futures market is attributable to the relatively equal variation (U^S) between the actual and the univariate forecasted price changes.[14]

Note that the predictability of the soybeans futures market deteriorates as the distance to maturity decreases. This same phenomena is also observed for soybean meal futures prices but not for soybean oil price forecasts. The forecasting accuracy of the soybean oil futures prices improves as we draw closer to the contract expiration date. The deterioration of forecasting accuracy for soybeans and soybean meal is due in part to the peculiar features of the forecast horizon. The years, 1978 and 1979, experienced soybean crop failures in Brazil, a country for which little prior sample information existed.[15] As expected, the deterioration of forecasting accuracy is more pronounced when the data for 1980 is deleted from the forecast horizon. In addition to the consecutive years of crop failure in Brazil, the deterioration of forecasting accuracy may be due to the relatively volatile nature of the soybean market. Similar results were obtained by Just and Rausser (1981); they noted that the soybean futures market is one of the more active and fluctuating markets which makes it relatively attractive to speculators. "For this reason, phenomena unrelated to the cash market play a greater role in short-run trading and price fluctuations, so that the more predictable market movements only tend to occur over a longer time horizon." (Just and Rausser, 1981, p. 201).

The results for soybean oil prices show that the univariate ARIMA forecasts are inferior to the futures market forecasts. The soybean oil univariate model tends to "miss" the mean price changes by a larger degree than the futures market. Of the three futures markets studied, the soybean oil market appears to be the most efficient. Note, however, that for longer range forecasts (9–10 months), the random walk model ($U = 1$) is superior to the futures market forecasts.

In the case of soybean meal futures, the forecasting superiority of the univariate ARIMA model indicates market inefficiency in Fama's semistrong form. The relatively poor performance of the futures market is attributed to the fact that it overestimates the variance of the price changes.

An important issue is whether or not the MSE's of the overall futures market forecasts are significantly different from the MSE's of the ARIMA model forecasts in Table 3. To perform such a test (paired t test), let the MSE statistics for the futures market be represented by x_1 and those for the ARIMA model by x_2. We have eight observations on both x_1 and x_2. Supposing that x_1 and x_2 are jointly distributed with means and variances (μ_1, σ_1) (μ_2, σ_2), respectively, and correlation parameter, ρ, then the null hypothesis may be tested:

$$H_0: \ \Delta + \mu_1 - \mu_2 = 0.$$

The variable, $z = x_1 - x_2$, is distributed with mean Δ and variance $\sigma^2 = \sigma_1^2 + \sigma_2^2 + 2\rho\, \sigma_1\, \sigma_2$. If Δ is not significantly different from zero, then the MSE's of the futures market forecasts are not significantly different from the MSE's of the competing ARIMA forecasts. The 95 percent confidence intervals for the mean of z for soybeans, soybean oil, and soybean meal were found to be $.621 \pm .159$, -3.52 ± 1.247, and 462.5 ± 197.9, respectively. As expected, for soybeans and soybean meal, the relevant intervals do not include zero. Hence, on the basis of this test, the MSE's of the futures forecasts are statistically different than those of the ARIMA forecasts for soybeans and soybean meal and, thus, are inferior. The opposite result holds for the soybean oil market.

V. Conclusion

We have constructed a simple model to describe the price formulation process in the soybean complex and estimated the implied ARIMA models of soybeans, soybean oil, and soybean meal prices. Employing the mean-square prediction error criterion, the forecasting accuracy of the multivariate and ARIMA models were compared with those of the futures markets as well as the random walk representations. It was found that the multivariate and ARIMA models "outperform" the futures markets for soybeans and soybean meal but not soybean oil for both long- and short-run horizons.

Our results support the necessary, relative accuracy condition for futures market inefficiency. The sufficient, relative costs/benefits condition for inefficiency, however, has not been formally examined. To be sure, the cost of utilizing the soybean-complex futures market prices for forecasting purposes is certainly less costly than the use of the estimated ARIMA models. Nevertheless, the empirically constructed forecasting models advanced in this paper have been kept deliberately simple. The marginal costs of additional information associated with utilizing these models are quite low. In fact, it can be argued that their marginal costs may be lower than that faced by most traders in futures markets who take some account of the causal influences represented in the structural model (1) through (7). The ARIMA models are nothing more than simplified versions of this structural representation.

Of course, the level of additional cost must be compared to the marginal benefits appropriately adjusted for risk. Among the potential benefits, speculative profits is perhaps the most important. Using the ARIMA models to indicate the direction of futures market price changes along with the naive trading strategy of buying-and-hold if the predicted price exceeds the futures price and vice versa, rather substantial training profits can be generated. To document this result, simulations are currently being conducted. In these simulations, expected returns and alternative risk measures are computed and summarized. On the basis of the preliminary simulation results, it appears that opportunities exist in the soybean complex for "excess returns", i.e., returns which exceed normal returns adjusted for risk. The reporting of these results wil await another occasion.

Appendix

If a set of endogenous variables is generated by a dynamic simultaneous equation model and certain conditions are met, a number of alternative representations of (1)-(7) are possible. In addition to the familiar reduced-form and final-form representations, the system (1)-(7) can be stated in final equation form or transfer function equation form.[16] To illustrate the derivation of the latter two forms, (1)-(7) can be written in structural form as:

$$H_y(L)\ Y_t = \theta + H_x(L)\ X_t + F_y(L)\ \xi_{yt}. \tag{A.1}$$

Given the stochastic nature of the elements appearing in X_t, each exogenous variable can be expressed in terms of an ARIMA process or, in general, as

$$J(L)\ X_t = F_x(L)\ \xi_{xt}. \tag{A.2}$$

Combining (A.1) and (A.2), we have

$$\begin{bmatrix} H_y(L) & -H_x(L) \\ 0 & J(L) \end{bmatrix} \begin{bmatrix} Y_t \\ X_t \end{bmatrix} = \begin{bmatrix} F_y(L) & 0 \\ 0 & F_x(L) \end{bmatrix} \begin{bmatrix} \epsilon_{yt} \\ \xi_{xt} \end{bmatrix} \tag{A.3}$$

$$G(L)\ Z_t = F(L)\ \xi_t.$$

Note that, if G(L) is a matrix of degree 0 and L, (A.3) is a moving average process; while, if F(L) is a matrix of degree 0 and (L), (A.3) is an autoregressive process. Assuming G(L) is a full rank and the process is stable, then (A.3) can be solved for Z_t as either an infinite moving process or a finite order autoregressive moving average process. The latter process has been defined as the final equation form (Zellner and Palm) and may be represented as:

$$\left|G(L)\right| Z_t = G^*(L)\, F(L)\, \xi_t \tag{A.4}$$

where $G^*(L)$ is the adjoint matrix, and $\left|G(L)\right|$ is the determinant of the matrix $G(L)$.

Each of the equations appearing in (A.4) is in ARIMA form. The empirical versions of these equations can be derived directly from the estimated structural model (A.1) and the ARIMA process for X_t or estimated directly. Obviously, these two methods of obtaining the final-form equations can lead to drastically different results. If (A.1) is badly misspecified and the sample data contains much information, one would not expect the equations derived from the structural form to perform as well as the direct estimation of these equations. The former equations can be referred to as the restricted final equations, while the latter may be defined as the unrestricted final equations.

To derive the transfer function equation representation, we may operate directly with (A.1) rather that (A.3). Specifically, the system of "transfer equations" is given by:

$$\left|H_y(L)\right| Y_t = \theta' + H_y(L)^* H_x(L)\, X_t + H_y(L)^* F_y(L)\, \xi_{yt} \tag{A.5}$$

where $\left|H_y(L)\right|$ and $H_{11}(L)^*$ are, respectively, the determinant and adjoint matrix associated with $H_y(L)$. Given (1)-(7), the transfer function explaining soybean prices may be extracted from (A.5) as:

$$\left|H_y(L)\right| PS_t = \theta_s' + \left|h_{11}\right| \beta_{11}(L)\, ES_t + \left|h_{71}\right| \beta_{72}(L)\, OI_t + \left[\frac{\phi_s(L)}{\theta_s(L)}\right] \xi_{yt} \tag{A.6}$$

where $\left|h_{ij}\right|$ is the cofactor of the i,jth element of $H_y(L)$; $\beta_{ij}(L)$ denotes elements of $H_x(L)$; and $\phi_s(L)/\theta_s(L)$ is the first row of $H_y(L)^* F_y(L)$. This transfer function indicates that the price of soybeans depends on its own lagged values, current and lagged values of soybean exports, and the vegetable oil price index. This equation describes a two input-single output transfer process as an autoregressive moving average process. Note that this mixed process can be alternatively described by an infinite moving average process in exogenous variables plus an error term. If we difference the variables, the intercept term vanishes, and moving average equivalent of (A.6) is:

$$\Delta PS_t = \frac{\left|h_{11}\right| \beta_{11}(L)}{\left|H_y(L)\right|} \Delta ES_t + \frac{\left|h_{71}\right| \beta_{72}(L)}{\left|H_y(L)\right|} \Delta OI_t + \eta_{st} \tag{A.7}$$

where Δ is the first difference operator, and η_{st} is an error term which has its own ARIMA process.

Corresponding transfer function equations can be derived for soybean oil and soybean meal prices; they are:

$$\begin{aligned} \Delta PO_t = & \frac{-\left|h_{12}\right|\beta_{11}(L)}{\left|H_y(L)\right|} \Delta ES_t + \left[\frac{\left|h_{22}\right|\beta_{22}(L) - \left|h_{72}\right|\beta_{72}(L)}{H_y(L)}\right]\Delta OI_t \\ & + \frac{\left|h_{22}\right|\beta_{23}(L)}{H_y(L)} \Delta EO_t + \eta_{ot} \end{aligned} \tag{A.8}$$

$$\begin{aligned} \Delta PM_t = & \frac{\left|h_{13}\right|\beta_{11}(L)}{\left|H_y(L)\right|} \Delta ES_t + \frac{\left|h_{73}\right|\beta_{72}(L)}{\left|H_y(L)\right|} \Delta OI_t + \frac{\left|h_{33}\right|\beta_{34}(L)}{\left|H_y(L)\right|} \Delta EM_t \\ & + \frac{\left|h_{33}\right|\beta_{35}(L)}{\left|H_y(L)\right|} \Delta PC_t + \frac{\left|h_{33}\right| \beta_{36}(L)}{\left|H_y(L)\right|} \Delta LI_t + \eta_{mt}. \end{aligned} \tag{A.9}$$

As is the case of soybean prices, each transfer function form equation (A.8) and (A.9) expresses an endogenous variable as a function of only its lagged values and current and lag values of the appropriate exogenous variables along with the error-term process. Note also that, as with the final form equations (A.4), both restricted and unrestricted transfer functions may be empirically estimated.

Footnotes

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[1]An efficient market, as defined by Fama (1970, page 383) generates prices which, at any point in time, ". . . fully reflect all available information."

[2]Both Danthine and Lucas note that the numerous zero autocorrelation return tests reported in the literature are, in effect, simultaneous tests of market efficiency, perfect competition, risk neutrality, constant returns to scale, and the impossibility of corner optima.

[3]In Fama's classification scheme, three groups of efficient market tests are distinguished--weak, semistrong, and strong forms. The information set for weak form tests is confined to historical market prices. Semistrong-form tests measure the market's adjustment to historical prices plus all other relevant public information, and strong-form tests measure its adjustment to "inside" information not available to the public. The only published work to date employing the semistrong form for futures markets is Leuthold and Hartmann (1979). These authors have tested the efficiency of the hog futures market by comparing it to forecasts generated from a simple two-equation, econometric model of the U. S. hog market. Their results indicate that the simple econometric model forecasts are sometimes a more accurate indicator of subsequent spot prices than those forecasts generated by the hog futures market.

[4]The United States is by far the world's most important producer of soybeans; over the period 1976–1978, its average annual production was 1.6 million bushels which comprises over 60 percent of the total world soybean production.

[5]This work has been criticized by Cargill and Rausser for its lack of a statistical basis for drawing inferences. Such filters are not a substitute for formal statistical analysis.

[6]Tomek and Gray argue that the superior forecasting performance for the storable commodities results from the "self-fulfilling" character imparted to forward prices that is due to adjustable inventories. By contrast, forward prices for nonstorable commodities would be "self-defeating" if they reflected anything other than the long-run equilibrium price prior to actual planting decisions. These interpretations fail to take into account the possible rational-expectations role of futures markets. Such a formulation would explain that the results obtained by Tomek and Gray for potatoes result from a "diffuse information base" while the results obtained for corn and soybeans result from a "tighter information base."

[7]Stein misinterpreted his empirical results. This misinterpretation resulted from the use of a statistical test that is not necessary for the property of biasedness. Although the estimated β coefficients differ significantly from zero and from unity and the intercept α is significantly different from zero, in the equation

$$p_t = \alpha + \beta\, p^f_{t,t-1}$$

where p_t denotes the spot price at time t and $p^f_{t,t-i}$ denotes the futures quote at time t − i for a contract that matures at time t, the futures price can still be an unbiased forecast. In particular, if $p^f_{t,t-i}$ is an unbiased forecast of p^s_t, then

$$\bar{p}^f_{t,t-i} - \bar{p}^s_t = 0,$$

and

$$\alpha - (1 - \beta)\, \bar{p}^f_{t,t-i} = 0$$

where $\bar{p}^s_t$ and $\bar{p}_{t,t-i}$ are the means of the cash and futures price series. For further details, see Martin and Garcia (1981).

[8]Working (1949) argued forcefully that ". . . it is only supplies already in existence which have any significant bearing on . . . current inter-temporal price relation(s) . . . ." (p. 27, emphasis in original). This view argues that the spread between futures prices for two different dates of delivery and the spread between spot and futures prices depend solely on current stocks.

[9]Of course, the rational expectation of a future spot price conditioned on available information is unobservable. A theoretical model can be advanced for estimating such a conditional rational expected price along the lines of Muth (1961). The readily observable magnitude that is often referred to as the price of storage in the presence of futures markets (namely, the difference between the current spot price and the future price quoted for some subsequent data) may be, and empirically is, both negative and positive depending upon current and future expected market conditions. The fact that such observable magnitudes are negative or positive, however, does not mean that the

future price quote is biased as well. For a formal demonstrtion of this result, see Sarris (1981).

[10]The estimation of the parameters of the transfer function is based on 14 years of monthly data beginning in 1966. Identification and estimation of the function is done with the first 132 observations, and the last 36 are saved to test its forecasting accuracy.

[11]A computer program, written by David Pack, was used for the time series analysis.

[12]In fact, for a forecast horizon which does not include 1980, the univariate model proved superior to the multivariate model.

[13]The updated forecasts are simply the original univariate ARIMA forecasts corrected each time period for the error made in the previous one-period-away forecast. [Details on this corrective error adjustment procedure may be found in Box and Jenkins (page 134)]. Only in the case of soybean oil prices did the updated univariate ARIMA forecasts prove superior to the conventional ARIMA forecasts. Hence, Table 3 reports the updated univariate ARIMA forecasts for soybean oil prices and the conventional univariate ARIMA forecasts for soybeans and soybean meal.

[14]The multivariate transfer function model for soybeans has an even lower associated U^S value, but it tends to overestimate average price changes.

[15]Only in the 1970s did Brazil become a major producer and exporter of soybeans. The per-acre yields of soybeans in Brazil for the years, 1978 and 1979, average only 70 percent of the more normal yields of 1976, 1977, 1980, and 1981.

[16]Zellner and Palm have shown that both these forms imply the maximum lag structure. In the case of model (1)-(7), their maximum structure turns out to be an uninteresting upper bound.

References

Box, G. E. P., and G. M. Jenkins, Time Series Analysis: Forecasting and Control (San Francisco: Holden-Day, 1970).

Brinegar, Claude S., "A Statistical Analysis of Speculative Price Behavior," Food Research Institute Studies IX (1970), Supplement.

Bureau of Labor, Monthly Labor Review (various issues).

Cargill, Thomas F., and Gordon C. Rausser, "Temporal Price Behavior in Commodity Futures Markets," Journal of Finance 30 (Sept. 1975), 1043-1053.

________, "Time and Frequency Domain Representations of Futures Prices as a Stochastic Process," Journal of the American Statistical Association, 67 (Mar. 1972), 64-67.

Chicago Board of Trade, Futures Trading Seminar History and Development I (Madison: Mimir Publishers, Inc., 1960).

Cox, Charles C., "Futures Trading and Market Information," Journal of Political Economy 84 (1976), 1215-1237.

Danthine, J. P., "Information, Futures Prices, and Stabilizing Speculation," Journal of Economic Theory 17 (1978), 79-98.

________, "Martingale, Market Efficiency and Commodity Prices," European Economic Review 10 (1977), 1-17.

Fama, Eugene F., "Efficient Capital Markets: A Review of Theory and Empirical Work," Journal of Finance 25 (1970), 383-417.

Feder, Gershon, Richard E. Just, and Andrew Schmitz, "Futures Markets and the Theory of the Firm Under Price Uncertainty," Quarterly Journal of Ecoomics 94 (Mar. 1979), 317-328.

Gray, R., "The Futures Market for Maine Potatoes," in Selected Writings on Futures Markets II, Anne E. Peck, ed. (Chicago Board of Trade, 1977).

Grossman, S. J., and J. E. Stiglitz, "The Impossibility of Informationally Efficient Markets," American Economic Review, 70 (1980), 393-408.

Holthausen, Duncan M.,"Hedging and the Competitive Firm Under Price Uncertainty," American Economic Review 69 (1979), 989-995.

Houthakker, Hendrik S., "Systematic and Random Elements in Short-Term Price Movements," American Economic Review 50 (1961), 164-172.

Just, Richard E., and Gordon C. Rausser, "Commodity Price Forecasting With Large-Scale Econometric Models and the Futures Market," American Journal of Agricultural Economics 63 (1981), 197-208.

Kofi, T. A., "A Framework for Comparing the Efficiency of Futures Markets," American Journal of Agricultural Economics 55 (Nov. 1973), 584-594.

Labys, Walter C., and C. W. J. Granger, Speculation, Hedging and Commodity Price Forecasts (Lexington, Massachusetts: D. C. Heath and Company, 1970).

Larson, A. B., "Measurement of a Random Process in Futures Prices," Food Research Institute Studies 1(3) (1960), 313-324.

Leuthold, Raymond M., "Random Walk and Price Trends: The Live Cattle Futures Market," Journal of Finance 27 (Sept. 1972), 879-889.

________, "The Price Performance on the Futures Market of a Nonstorable Commodity: Live Beef Cattle," American Journal of Agricultural Economics 56 (1974), 271-279; also in Selected Writings on Futures Markets II, Anne E. Peck, ed. (Chicago Board of Trade, 1977), 375-386.

Leuthold, R. M., and P. A. Hartmann, "A Semi-Strong Form Evaluation of the Efficiency of the Hog Futures Market," American Journal of Agricultural Economics 61 (Aug. 1979), 482-488.

Lucas, Robert E., Jr., "Asset Prices in an Exchange Economy," Econometrica 46 (Nov. 1978), 1429-1445.

Mann, Jitendar S. and Richard G. Heifner, The Distribution of Short-Run Commodity Price Movements, U. S. Economic Research Service, Technical Bulletin No. 1536 (Mar. 1976).

Martin, Larry, and Philip Garcia, "The Price-Forecasting Performance of Futures Markets for Live Cattle and Hogs: A Disaggregated Analysis," American Journal of Agricultural Economics 63 (1981), 209-215.

McKinnon, Ronald I. "Futures Markets, Buffer Stocks and Income Stability for Primary Products," Journal of Political Economy 75 (1967), 844-861.

Muth, John F., "Rational Expectations and the Theory of Price Movements," Econometrica 29 (1961), 315-335.

Peck, Anne E., "Futures Markets, Supply Response and Price Stability," Quarterly Journal of Economics 90 (1976), 407-423.

________, "Stochastic Speculative Prices," Proceedings of the National Academy of Science of the U.S.A. 68 (1971), 335-337.

Samuelson, Paul A., "Proof That Properly Anticipated Prices Fluctuate Randomly," Industrial Management Review 6 (Spring 1965), 41-49.

Sarris, Alexander H., "Speculative Storage, Futures Markets, and the Stability of Commodity Prices," Department of Agricultural and Resource Economics, Working Paper No. 160, University of California, Berkeley, February, 1981.

Smidt, S., "A Test of the Serial Independence of Price Changes in Soybean Futures," Food Research Institute Studies 5(2) (1965), 117-136.

Stein, Jerome L., "Spot Forward and Futures," in Research and Finance I, Haim Levy, ed. (Greenwich, Connecticut: J. A. I. Press, 1979).

_______, "The Dynamics of Spot and Forward Prices in an Efficient Foreign Exchange Market," American Economic Review 70 (Sept. 1980), 565-583.

_______, "Speculative Price: Economic Welfare and the Idiot of Chance" (unpublished paper), 1980a.

Stevenson, R. A., and R. M. Bear, "Commodity Futures, Trends or Random Walks " Journal of Finance 25 (Mar. 1970), 65-81.

Tomek, W. G., and R. W. Gray, "Temporal Relationships Among Prices on Commodity Futures Markets: Their Allocative and Stabilizing Roles," American Journal of Agricultural Economics 52 (Aug. 1970), 372-380.

Turnovsky, Stephen J., "Futures Markets, Private Storage, and Price Stabilization," Journal of Public Economics 12 (1979), 301-327.

Weymar, F. Helmut, "The Supply of Storage Revisited," American Economic Review 56 (1966), 1226-1234.

Working, Holbrook, Quotations on Commodity Futures as Price Forecasts," Econometrica 10 (Jan. 1942), 39-52.

_______. "Theory of the Inverse Carrying Charge in Futures Markets," Journal of Farm Economics 30 (1948), 1-28.

_______. "Theory of Price Storage," American Economic Review 39 (1949), 1254-1262 (reprinted in Anne E. Peck, ed., Selected Writings of Holbrook Working (Chicago: Chicago Board of Trade, 1977).

Zellner, A., and F. Palm, "Time Series Analysis and Simultaneous Equation Econometric Models," Journal of Econometrics 2 (April 1974), 17-54.