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A Performance Comparison of a Technical Trading System with ARIMA and VAR Models for Soybean Complex Prices

by

Mary E. Gerlow, Scott H. Irwin, Carl R. Zulauf, and Jonathan N. Tinker *

December 1990

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ARIMA and VAR models are developed over the time period January 1974-December 1983 and then are used to forecast out-of-sample from January 1984 through June 1988. The CHL trading signals and out-of-sample two month ahead forecasts from the ARIMA and VAR models are used to take positions in the futures markets. The resulting trading returns are evaluated to determine the relative economic performance of the models within the soybean complex.

Of these models, the CHL technical trading system exhibits consistent trading returns across the soybean complex. Furthermore, the CHL technical trading system is robust across the two subperiods of the out-of-sample period, one of which is characterized by rising commodity prices and the other by declining commodity prices.

These results suggest that in the short run, regularities within a single price series can be used to forecast prices within the soybean complex. Further, technical trading system prove more useful in utilizing such regularities for forecasting than the autoregressive or moving average processes found in either ARIMA or VAR modeling techniques.

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Introduction

Technical trading systems are widely used in the futures industry. For example, Irwin and Brorsen report that over 80% of public futures funds managers rely on technical trading systems. Technical trading systems apply pre-specified trading rules to historical data series, usually prices, in an attempt to forecast future price trends and, thus, profitable trades. As such, they are built under the assumption that current market price changes are not independent of past market behavior. This same assumption underlies standard economic time series models, such as an Autoregressive Integrated Moving Average (ARIMA) model and a Vector Autoregressive (VAR) model. These models utilize autocorrelations and moving averages of past prices to forecast price levels. The similarity in underlying assumption raises the issue of the relative performance of a technical trading system with ARIMA and VAR models. This study presents such a comparison between technical trading systems, which evidence suggests are dominant in the futures industry, and standard time series forecasting techniques.

The comparative analysis will be conducted for soybean, soybean meal, and soybean oil prices over the period January 1974 through June 1988. The soybean complex commodities has been selected for analysis because there have been several studies of price forecasting within this complex. These analyses have used time-series models, as well as more traditional econometric models (Just and Rausser; Rausser and Carter; Wendland). Just and Rausser compare the accuracy of large scale econometric forecasts with futures market prices over the period 1976-1978, finding neither outperforms the other. Rausser and Carter investigate the forecast accuracy of multivariate and univariate time-series models over the period 1966-1976. They suggest that "excess returns" may be generated by using univariate model forecasts to take positions in the futures market (buy when the price forecast is higher than current futures prices; sell if the price forecast is less than the futures price). In contrast, Wendland finds univariate time-series analysis deficient in detecting market turning points over the 1976-1986 decade.

The technical trading system and time series models used in this study are presented in the next section. The models are then evaluated to determine their relative performance. Conclusions and implications for future research are drawn in the last section.

Construction of the Models

Channel Trading System

Comprehensive tests of various technical trading systems by Lukac, et al. and Lukac and Brorsen indicate that technical trading systems consistently earn above normal risk-adjusted rates of return. One explanation of this result is that futures markets are in short-run disequilibrium due to such factors as transactions costs, taxes, costs of obtaining and evaluating information, and information lags. Thus, price trends occur as the market

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Of these models, the CHL technical trading system exhibits consistent trading returns across the soybean complex. Furthermore, the CHL technical trading system is robust across the two subperiods of the out-of-sample period, one of which is characterized by rising commodity prices and the other by declining commodity prices.

These results suggest that in the short run, regularities within a single price series can be used to forecast prices within the soybean complex. Further, technical trading system prove more useful in utilizing such regularities for forecasting than the autoregressive or moving average processes found in either ARIMA or VAR modeling techniques.

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The comparative analysis will be conducted for soybean, soybean meal, and soybean oil prices over the period January 1974 through June 1988. The soybean complex commodities has been selected for analysis because there have been several studies of price forecasting within this complex. These analyses have used time-series models, as well as more traditional econometric models (Just and Rausser; Rausser and Carter; Wendland). Just and Rausser compare the accuracy of large scale econometric moves toward equilibrium. Trading rules that identify and follow these trends can earn substantial profits (Beja and Goldman; Lukac et al.; Lukac and Brorsen).

The technical system to be investigated in this study is the Close Channel System (CHL). Previous research indicates that the CHL system is one of the most successful trading systems and is used widely by traders (Irwin and Uhrig; Lukac et al.; and Lukac and Brorsen). Lukac, et al. find that the CHL's net mean monthly returns are the highest of 12 systems investigated using a portfolio of commodities. Further, the CHL system generates positive returns using soybeans as an individual investment.

The CHL system forecasts an upward (downward) move in price when the closing futures price is higher (lower) than the highest (lowest) futures price during the previous L days (present day included). Positions are taken at the opening price on the day after the signal is generated. A trader is always in the market: a short (long) position is replaced with a long (short) position when a change in trading signal is triggered.

In this study, CHL trades are placed only in the nearby contract since the liquidity costs of placing and lifting positions deters traders from holding multiple or distant contract positions (Lukac, et al.). The channel length or time interval is 40 days. This is based on Lukac and Brorsen's finding that longer channel lengths (40 to 60 days) tend to outperform shorter lengths.

ARIMA Model

An Autoregressive Integrated Moving Average (ARIMA) model is based upon past behavior of a series as a p^{th} order autoregressive process [AR(p)] or a q^{th} order moving average process, [MA(q)], or a combination of both processes. The integration refers to the transformation of a non-stationary series to a stationary series by taking a d^{th} difference of the original values (Cryer). The unrestricted ARIMA (p,d,q) model may be expressed as:

$$(1 - u_1 B - u_2 B^2 - \ldots - u_p B^p)\, Z_t = (1 - h_1 B - h_2 B^2 - \ldots - h_q B^q)\, a_t \qquad (1)$$

where:

Z_t = the value of the series at time t

a_t = a white noise term or innovative random shock

B = the lag operator such that $B^d Z_t = Z_{t-d}$

A necessary condition for applying time series models to a data series is a stationary series (devoid of trend). An examination of Figures 1-3 indicates that soybean complex prices shift upward during 1972-1973. This shift reflects a surge in worldwide demand due to economic growth, a decision by the Soviet Union to import grain and oilseeds, and a reduction in the anchovy catch, an alternative supply of animal feed protein. After 1973, the price series are stationary. Therefore, by developing time series models using data after 1973, no transformations are necessary to create a stationary price series.

Data used to estimate the ARIMA model within the soybean complex are monthly average soybean prices at Chicago, Illinois and monthly average soybean meal and soybean oil prices at Decatur, Illinois from January 1974 through December 1983. Selection of this estimation period allows for a sufficient number of out-of-sample forecasts, from January 1984 through June 1988, to analyze the performance of the model.

To determine the autoregressive and moving average components of the ARIMA model, the sample Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF) of each of the series is calculated. The sample ACF decays exponentially for each soycomplex price series indicating that there is no moving average term. The associated PACF function for each series indicates that regularities in all three price series are best represented by an AR(2) process.

The residuals from the estimated AR(2) models are examined and found to be uncorrelated. Model overfitting, by sequentially adding or subtracting AR or MA components, does not improve upon the AR(2) specification of the soybean price series. However, model overfitting indicates that an ARMA(1,1) specification is an improved model (higher R^2, higher t statistics, and a lower Q statistic) for both the soybean meal and soybean oil price series.

As a new month is added in the out-of-sample forecast period, the sample ACF and PACF functions are recomputed and tested. The AR(2) model for soybeans and ARMA(1,1) model for soybean oil and soybean meal are consistent throughout the test period.

Although estimated over a different sample period, Wendland also specifies soybean prices as an AR(2) process and the soybean meal price series as an ARMA(1,1) process. However, the soybean oil price series is specified by Wendland as an ARMA(1,12) process, instead of the ARMA(1,1) process used here.

VAR Model

Ignoring deterministic components (trends, constants, etc.), the unrestricted form of a VAR process or model is given by:

$$Y_t = \phi(B)\ Y_t + a_t \tag{2}$$

where:

Y_t = m x 1 vector of observations on m series at time t

$\Phi(B)$ = m x m matrix of polynomials in the lag operator B (where $B^d Z_t = Z_{t-d}$)

a_t = m x 1 vector of error terms

The model is unrestricted in that the order of all of the polynomials in $\Phi(B)$ are the same and none of the coefficients of the polynomials are set to zero prior to estimation (Sims).

Carter and Rausser's monthly econometric model of the U.S. soybean complex was used as a guide for the VAR model constructed in this study. Variables in their model included:

Soybean Price	Soybean Crushings
Soybean Oil Price	Soybean Exports
Soybean Meal Price	Soybean Oil Exports
Soybean Stocks	Soybean Meal Exports
Soybean Oil Stocks	Corn Price
Soybean Meal Stocks	Crude Vegetable Oil Price Index

Monthly average soybean prices at Chicago, Illinois and monthly average soybean oil and soybean meal prices at Decatur, Illinois are the same as those used in the specification and estimation of the univariate models. Month end stocks of soybean oil and soybean meal at mills, total monthly U.S. soybean crushings, total monthly U.S.

soybean oil and meal exports, and the monthly average cash price of corn at Chicago, IL are taken from the Chicago Board of Trade Annuals and the USDA's Market News (various issues). The monthly average crude vegetable price index is obtained from the Bureau of Labor Statistics. Monthly stocks of soybeans are imputed from the preceding U.S. quarterly soybean stocks, monthly soybean crushings, and monthly soybean exports. During the harvest period, the amount of production harvested is estimated using the USDA harvest progress report. This estimation of production already harvested is added to the monthly stocks.

In order to develop a parsimonious VAR specification, this research uses the exclusion-of-variables approach, as outlined by Hsiao. Thus, each equation in the multiple equation system is examined in isolation. The independent variables are not ordered in importance prior to estimation so that the lags for each independent variable are established independent of the variables's order of entry into the equation. Lags of up to 24 months of each independent variable are regressed against the dependent variable in each equation. If the lagged independent variable reduces the final prediction error (FPE), then it is added to the equation (Akaike).

Using the procedure outlined, only nine of the variables specified by Carter and Rausser enter the VAR model: prices of soybeans, soybean oil, and soybean meal; stocks of soybeans, soybean meal, and soybean oil; exports of soybean meal and soybean oil; soybean crushings; and corn prices. The general structure of the mixed VAR used to forecast within the soycomplex can be found in the Appendix. Once each individual equation is specified, parameter estimates are computed by estimating the equations simultaneously as seemingly unrelated regressions.

Parameters for the VAR model are recomputed and tested each month in the out-of-sample forecast period. Throughout the test period, none of the previously excluded variables become significant in the later months.

Forecast Evaluation Results

A standard criteria of minimizing Root Mean Squared Error (RMSE) is used to measure the statistical accuracy of point forecasts from the ARIMA and VAR models. However, because the CHL system generates directional forecasts and not point forecasts, such a measure can not be applied to this system.[1]

An alternative approach to assessing the value of forecasting models is to begin with the basic assumption that forecasts only have positive value if they cause rational investors to alter their expectations about the future (Merton). This definition of value implies that the forecast not only differs from current expectations, but also becomes incorporated into expectations. Thus, positive trading returns should be generated by taking positions in the market which are consistent with a forecast which has value. Consequently, trading returns can be used to assess relative performance of alternative forecasting models.

To evaluate relative performance, the point forecasts generated by the ARIMA and VAR models are transformed into directional signals used to assume positions in the futures markets. A buy (sell) directional signal is consistent with an ARIMA or VAR forecast that exceeds (is less than) the current price for a futures contract traded for delivery at the end of the forecast horizon. Returns to positions generated by the ARIMA or VAR forecasts can be compared with returns to positions generated by the CHL technical trading system.

For the ARIMA and VAR models, a forecast horizon of two months is used because this is the closest approximation to the average trade length under the CHL system. Forecasts are generated on the last trading day of the month which is two months before the delivery month. The (buy) sell signals are implemented by taking a (long) short position on the next trading day. All positions are offset at the closing futures price on the tenth trading day of the delivery month.[2] For example, a buy signal is generated if, on the last trading day in January, the model forecasts a March soybean price that is higher than the closing futures price of the March soybean contract. Specifically, a signal variable, S_{ti}, is generated as follows:

$$\textit{Sell Signal}: \quad S_{ti} = -1 \qquad \text{if } MP_{ti} \leq FP_{t-2} \tag{3}$$

$$\textit{Buy Signal}: \quad S_{ti} = 1 \qquad \text{if } MP_{ti} > FP_{t-2} \tag{4}$$

where:

MP_{ti} = model forecasted price for month t and model i

FP_{t-2} = closing price of two-month ahead futures contract on the last trading day of month t-2.

Similar to Garcia, et al., buy and sell signals for the CHL, ARIMA, and VAR models are generated using forecasts only for delivery months of relevant futures contracts. This approach eliminates the need to adjust for the Chicago and Decatur non-delivery month basis in establishing positions in the futures markets. Since margin requirements can be satisfied by pledging U.S. Treasury Bills, the monthly percentage gross return from following the model generated signal is the monthly logarithmic change in futures prices over the holding period:

$$R_{ti} = \sum_j S_{tij} \, [\, \ln FP_{tj} - \ln FP_{t-1j}] \, * \, 100 \qquad (5)$$

where S_{tij} is defined as above for contract j, FP_{t-1j} is the futures price of contract j on the first day of the month, and FP_{tj} is the futures price of contract j on the last day of the month or holding period, whichever is appropriate, and ln indicates the natural logarithm. The percentage gross returns at the beginning and end of each month are calculated on all contracts held in a particular commodity market. This generates a series of monthly returns which can be compared across commodities and forecasting technologies.

Results for Entire Period

An examination of the percentage annualized mean returns in Table 1 indicates that only the CHL system results in positive returns across all three commodities. Moreover, CHL returns for soybeans, soybean meal, and soybean oil are significantly greater than zero at the 10% level of significance. In only one instance, the VAR model for soybeans, does another model generate nominal returns that exceed those generated by the CHL system.

The ARIMA and VAR models offer a more mixed performance. Each model generates significantly positive returns at the 5% level of significance for soybean meal. The VAR also generates significant positive profits for soybeans. However, each model also generates significantly negative returns: ARIMA - soybeans; VAR - soybean oil.

Aggregating returns across the three soycomplex commodities reveals that the VAR model results in significantly negative returns across the complex while the ARIMA model and the CHL technical trading system generate positive returns. However, only the returns from the CHL technical trading system are significantly greater than zero.

Subperiod Analysis

To determine if these performance results are consistent across different market trends, the sample period is divided into two subperiods, January 1984 - March 1986 and April 1986 - June 1988. During the first subperiod, soybean prices decline over 30% from \$7.53/bushel to \$5.37/bushel. Soybean meal prices fall from \$201.90/ton to \$163.70/ton, a 20% decrease. Soybean oil prices decrease from \$28.26/cwt. to \$17.41/cwt., a decrease of 40%. Over the second subperiod, prices in the soybean market move from \$5.29/bu. to \$9.11/bu., a 70% increase. The soybean meal market experiences an 80% increase in price with movement from \$157.00/ton to \$287.80/ton. In the soybean oil market, prices increase by 55% from \$17.64/cwt. to \$27.49/cwt.

Results for the subperiod analysis are presented in Table 2. The CHL trading system produces significantly positive returns at the five percent level in both subperiods for soybean oil and soybean meal. Negative losses are generated in the first period for soybeans, but significant positive returns occur in the second period. In contrast, neither the ARIMA or VAR model generates significantly positive returns in both subperiods for any of the soycomplex commodities. Significantly positive returns are generated by the ARIMA model in the first period for soybean meal and soybean oil, by the VAR model in the first period for soybean meal, and by the VAR model in the second period for soybeans. Significantly negative returns occur during the first and second periods for the ARIMA model in soybeans and the VAR model in soybean oil.

Not surprisingly, the CHL system produces higher significant aggregate results for all three commodities over both subperiods (Table 2). Only the ARIMA model produces significant positive returns across the soybean complex and only over the first period. In total, the CHL system outperforms the VAR and ARIMA models by more during the second period of increasing prices than during the first period of decreasing prices.

Conclusions

Technical trading systems and standard economic time series are based upon a similar underlying assumption. Namely, current market prices are not independent of past market behavior. This study compares the performance of a technical trading system to an Autoregressive Integrated Moving Average (ARIMA) model and a Vector

Autoregressive (VAR) model in forecasting soybean, soybean meal, and soybean oil prices.

Trading signals, hence price trend forecasts, are generated from a popular technical trading system, the Channel system (CHL), over the period January 1984 - June 1988. Out-of-sample price forecasts are also generated over this period for ARIMA and VAR model fitted over the time period January 1974-December 1983. To evaluate relative performance across all three sets of forecasts, the point price forecasts from the ARIMA and VAR models are translated into price directional forecasts by assuming a price rise (decline) is forecasted if predicted price exceeds (is less than) current futures prices for the forecast horizon. Specifically, two month ahead forecasts from the ARIMA and VAR models and the trading signals from the CHL system are evaluated. An economic measure of forecast value, i.e. mean annual trading returns, are calculated over the entire out-of-sample period and two subperiods. One subperiod is characterized by rising soycomplex prices, while the other is characterized by declining commodity prices.

Of the three forecasting models, only the CHL technical trading system exhibits consistent economic value across the soybean complex over the time period examined. Furthermore, results for the CHL technical trading system are consistently significant and positive over both the subperiod of rising prices and decreasing prices.

These results suggest that in the short run, regularities within a single price series can be used to forecast future prices. Further, the CHL trading system is more useful in utilizing such regularities for forecasting than the autoregressive or moving average processes found in either ARIMA or VAR modeling techniques. This finding holds both in periods of decreasing and increasing commodity prices. However, advantages of the CHL trading system are most pronounced in rising markets.

The evidence presented in this study is far from conclusive, but it does suggest the desirability of future research on the relative forecasting ability of different techniques on various commodities across different market conditions. It also suggests that comparison of such models with the more ad hoc approaches used by traders might offer some insight into the usefulness of the forecasting techniques favored by economists and might be used to improve the forecasting performance of economic forecasting tools.

Endnotes

1. RMSE for ARIMA and VAR model forecasts are calculated over time horizons of 1, 2, 3, and 6 months. The ARIMA models have lower RMSE than the VAR forecasts with the exception of the two month forecast of soybean oil and the six month forecast of soybean meal; however, the differences in RMSE are relatively small. The ratio of the RMSE of the VAR model to the RMSE of the ARIMA model ranges from .95 to 1.13.

2. The tenth trading day of the delivery month is chosen as the date to offset the position because it allow returns to be accrued over the majority of the delivery month's trading days yet avoids some of the potential market fluctuations which may occur as the delivery date approaches.

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Table 1. Futures Trading Returns Based on ARIMA, VAR, and Channel System Forecasts, January 1984 - June 1988.

Commodity/Statistic	Model		
	ARIMA	VAR	Channel
Soybeans			
Mean Return (annual percentage)	-13.51**	6.33**	5.06*
Standard Deviation (annual percentage)	20.02	20.32	20.65
t-value	-4.91	2.27	1.78
Soybean Meal			
Mean Return (annual percentage)	16.48**	15.57**	26.60**
Standard Deviation (annual percentage)	28.27	28.56	24.85
t-value	4.24	3.97	7.79
Soybean Oil			
Mean Return (annual percentage)	5.03	-35.58**	23.06**
Standard Deviation (annual percentage)	32.86	30.95	28.10
t-value	1.11	-8.37	5.98
Complex Return			
Mean Return (annual percentage)	2.66	-4.56**	18.24**
Standard Deviation (annual percentage)	18.46	17.72	18.47
t-value	1.05	-1.87	7.19

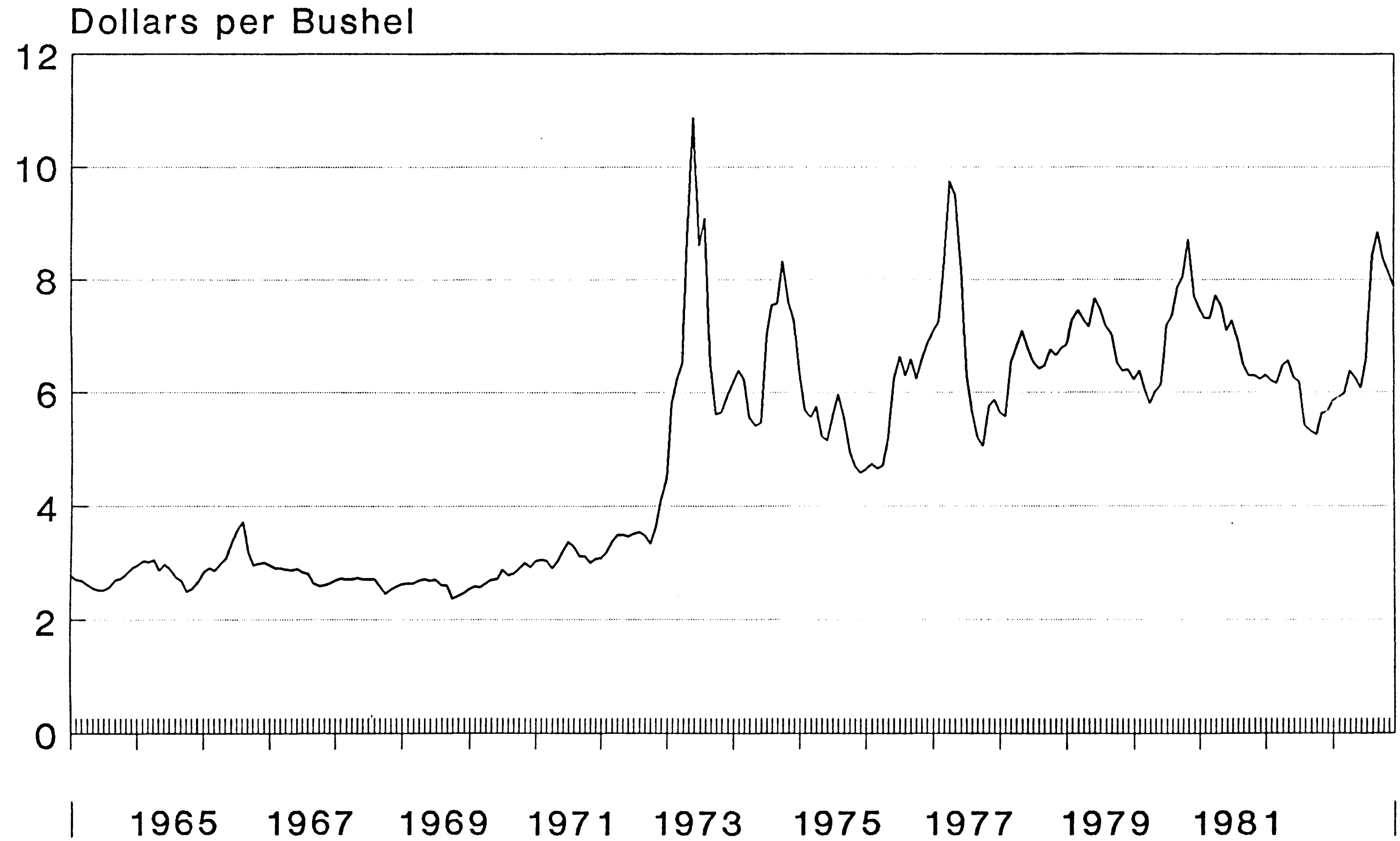
Note: Two stars (one star) indicate(s) the mean of returns is significantly different from zero at the 5% level (10% level).

Table 2. Futures Trading Returns Based on ARIMA, VAR, and Channel System Forecasts, January 1984 - March 1986 and April 1986 - June 1988.

Commodity/Statistic	Model					
	ARIMA		VAR		Channel	
	1984:1-1986:3	1986:4-1988:6	1984:1-1986:3	1986:4-1988:6	1984:1-1986:3	1986:4-1988:6
Soybeans						
Mean Return (annual percentage)	-12.86**	-14.13**	-3.58	15.89**	-4.51	14.27**
Standard Deviation (annual percentage)	20.94	19.08	21.25	18.99	18.80	21.98
t-value	-3.13	-3.85	-0.86	4.35	-1.22	3.37
Soybean Meal						
Mean Return (annual percentage)	23.56**	9.66	26.71**	4.84	18.99**	33.93**
Standard Deviation (annual percentage)	24.67	31.22	24.41	31.75	25.54	23.98
t-value	4.87	1.61	5.58	0.79	3.79	7.35
Soybean Oil						
Mean Return (annual percentage)	12.50*	-2.16	-38.49**	-32.78**	18.36**	27.60**
Standard Deviation (annual percentage)	34.51	32.86	32.28	29.58	31.40	24.42
t-value	1.85	1.11	-6.08	-5.76	2.98	5.87
Total Complex						
Mean Return (annual percentage)	7.73**	-2.21	-5.12	-4.02	10.94**	25.27**
Standard Deviation (annual percentage)	15.38	20.91	18.66	16.77	17.38	19.24
t-value	2.56	-0.55	-1.40	-1.25	3.21	6.82

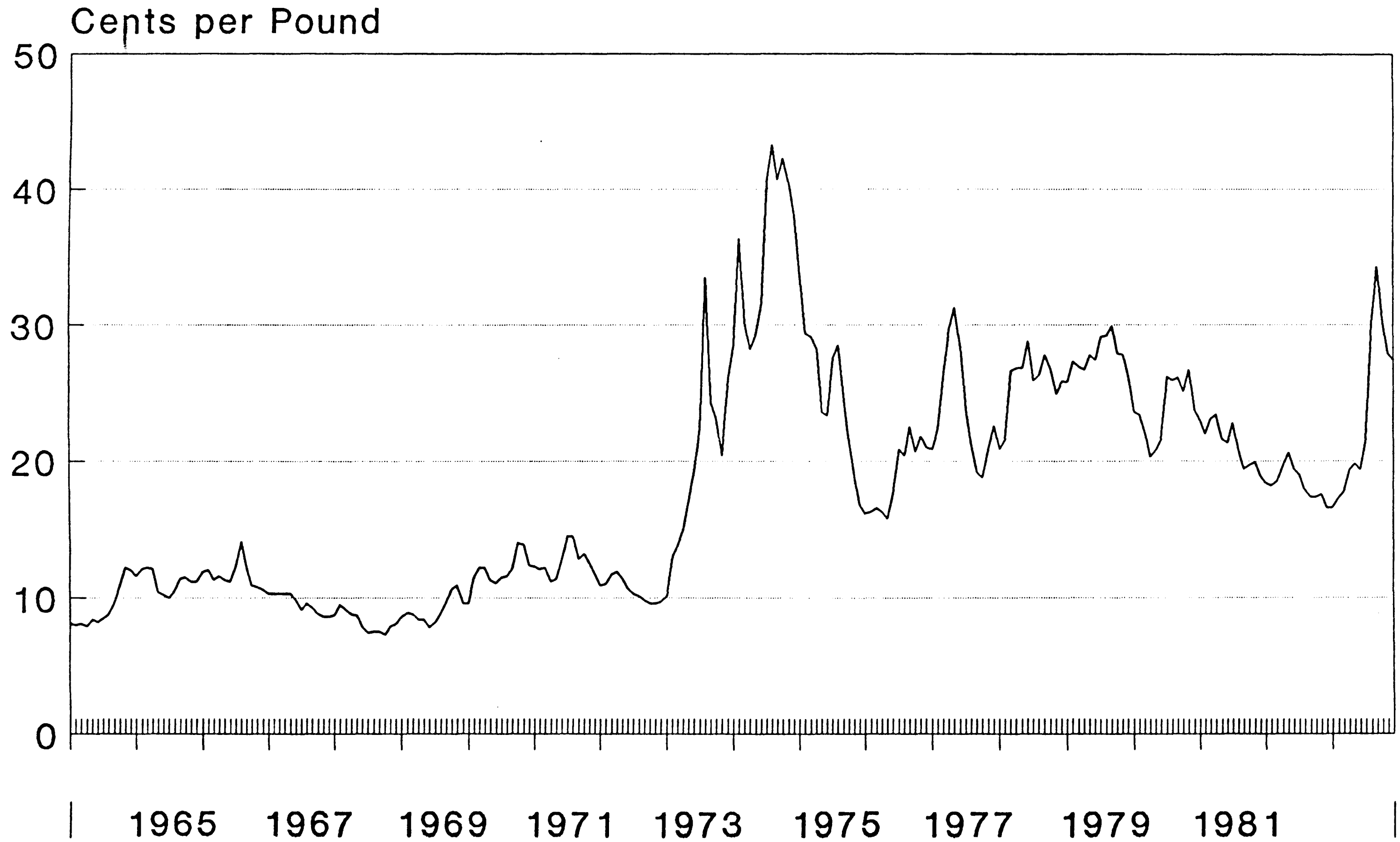
Note: Two stars (one star) indicate(s) the mean of returns is significantly different from zero at the 5% level (10% level).

Figure 1. Soybean Prices
Monthly Average, 1/1964 - 12/1983



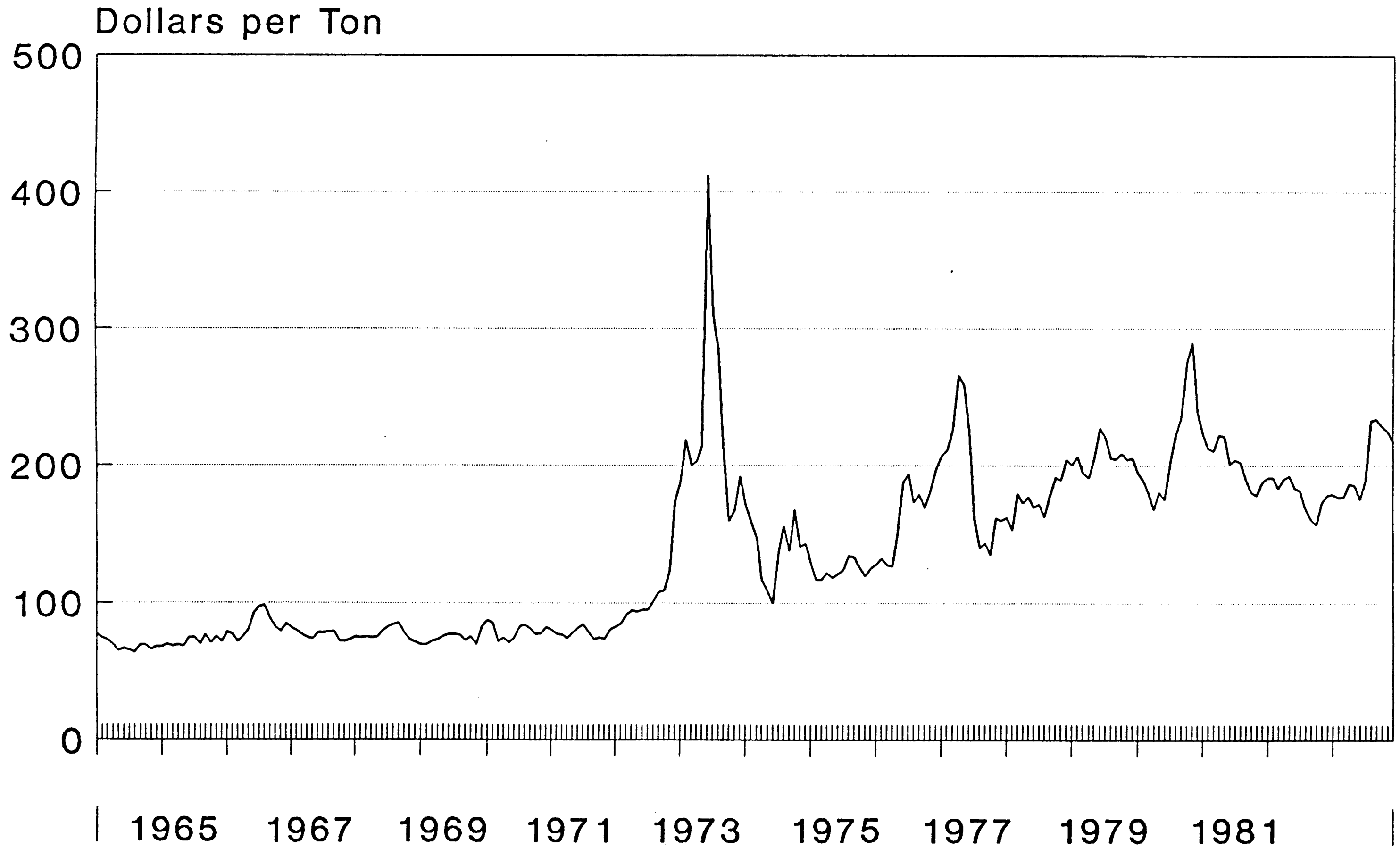
Cash: Chicago, Illinois

Figure 2. Soybean Oil Prices
Monthly Average, 1/1964 - 12/1983



Cash: Decatur, Illinois

Figure 3. Soybean Meal Prices
Monthly Average, 1/1964 - 12/1983



Cash: Decatur, Illinois

Appendix

The General Specification of the Mixed VAR Model of the Soybean Complex

$$SBP = \alpha + \beta_1 SBP_{t-1} + \beta_2 SBP_{t-2} + \epsilon_1 \tag{6}$$

$$SOP = \alpha + \beta_1 SOP_{t-1} + \beta_2 SOP_{t-2} + \epsilon_2 \tag{7}$$

$$\begin{aligned} SMP = {} & \alpha + \beta_1 SMP_{t-1} + \beta_2 SMP_{t-2} + \beta_3 SMP_{t-10} + \gamma_1 SMS_{t-1} + \gamma_2 SMS_{t-2} + \gamma_3 SMS_{t-3} \\ & + \gamma_4 SMS_{t-11} + \gamma_5 SMS_{t-12} + \psi_1 SBP_{t-1} + \psi_2 SBP_{t-2} + \epsilon_3 \end{aligned} \tag{8}$$

$$\begin{aligned} SMS = {} & \alpha + \beta_1 SMS_{t-1} + \gamma_1 SOS_{t-1} + \gamma_2 SOS_{t-2} + \gamma_3 SOS_{t-3} + \psi_1 SOE_{t-1} + \lambda_1 SBP_{t-1} \\ & + \lambda_2 SBP_{t-2} + \epsilon_4 \end{aligned} \tag{9}$$

$$\begin{aligned} SOS = {} & \alpha + \beta_1 SOS_{t-1} + \gamma_1 SBS_{t-1} + \gamma_2 SBS_{t-2} + \gamma_3 SBS_{t-3} + \gamma_4 SBS_{t-11} + \gamma_5 SBS_{t-12} \\ & + \psi_1 SMS_{t-1} + \psi_2 SMS_{t-2} + \psi_3 SMS_{t-3} + \lambda_1 CP_{t-1} + \theta_1 SBP_{t-1} + \theta_2 SBP_{t-2} \\ & + \theta_3 SBP_{t-3} + \phi_1 SOP_{t-1} + \epsilon_5 \end{aligned} \tag{10}$$

$$\begin{aligned} SOE = {} & \alpha + \beta_1 SMS_{t-1} + \beta_2 SMS_{t-2} + \beta_3 SMS_{t-3} + \gamma_1 SMP_{t-1} + \psi_1 SBP_{t-1} + \psi_2 SBP_{t-2} \\ & + \psi_3 SBP_{t-3} + \lambda_1 CP_{t-1} + \epsilon_6 \end{aligned} \tag{11}$$

$$\begin{aligned} SBS = {} & \alpha + \beta_1 SBS_{t-1} + \beta_2 SBS_{t-2} + \beta_3 SBS_{t-3} + \beta_4 SBS_{t-4} + \beta_5 SBS_{t-10} + \beta_6 SBS_{t-11} \\ & + \beta_7 SBS_{t-12} + \beta_8 SBS_{t-13} + \beta_9 SBS_{t-14} + \gamma_1 CSH_{t-1} + \gamma_2 CSH_{t-2} + \psi_1 SBP_{t-1} \\ & + \lambda_1 SOS_{t-1} + \theta_1 SOE_{t-1} + \phi_1 SMP_{t-1} + \epsilon_7 \end{aligned} \tag{12}$$

$$\begin{aligned} CSH = {} & \alpha + \beta_1 CSH_{t-3} + \beta_2 CSH_{t-7} + \beta_3 CSH_{t-8} + \beta_4 CSH_{t-9} + \beta_5 CSH_{t-13} \\ & + \beta_6 CSH_{t-16} + \epsilon_8 \end{aligned} \tag{13}$$

$$CP = \alpha + \beta_1 CP_{t-1} + \beta_2 CP_{t-2} + \gamma_1 CSH_{t-1} + \lambda_1 SMP_{t-1} + \epsilon_9 \tag{14}$$

where:

SBP = Soybean Price
SOP = Soybean Oil Price
SMP = Soybean Meal Price
SMS = Soybean Meal Stocks
CP = Corn Price
SOS = Soybean Oil Stocks
SOE = Soybean Oil Exports
SBS = Soybean Stocks
CSH = Soybean Crushings