The Market Timing Value of Univariate and Multivariate Time Series Models Within the Soybean Complex

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The formation of commodity price expectations is important in the economic decision making process within agribusinesses. Nowhere is this more true than in the soybean processing industry. Soybean processors must formulate price expectations about soybean, soybean oil, and soybean meal markets as they make crucial decisions regarding long term profitability, such as plant capacity and operational efficiency. Importantly, processors use price forecasts in establishing profitable crush margins. To be useful, price forecasts should exhibit market timing ability. That is, forecasts should consistently place users on the correct side of the market. For market participants interested in evaluating forecasts, an important issue is whether the forecasts allow users to place themselves on the correct side of the market. The ability to be on the correct side of the market is especially important during major market upheavals when the opportunity for potential profits or losses may be greatest.

One analytical method frequently used by economists to generate price forecasts is time series analysis. Time series analysis is based upon the idea that changes in current prices are not independent of past market changes. Univariate time series analysis examines current market price changes as a product of historical behavior of price changes only. Advantages of univariate time series analysis in forecasting commodity prices are related to the ease of use and flexibility of the process. However, the use of only past prices to forecast future prices may mean that economic information is not incorporated into price forecasts. Multivariate time series analysis addresses this issue by including multiple economic variables which are theoretically important in the price forecasting process. A drawback to using multivariate analysis is the complexity of the data and estimation requirements.

In this study, we constructed both a univariate and a multivariate time series model of the soybean complex. We then used them to generate a set of one-three-, and six-month ahead forecasts which we evaluated using statistical tests of market timing ability. We used different forecast horizons to determine if market timing ability is sensitive to forecast length. We used Merton market timing tests to determine if either type of time series analysis aids the market participants in assuming positions on the correct side of the market within the soybean complex. This study also uses Cumby-Modest market timing tests to determine if there is any correlation between forecasting ability and the ability to predict actual large scale market moves.

Construction of the Model Specifications

ARIMA Model. An Autoregressive Integrated Moving Average (ARIMA) price forecasting model is based upon past behavior of a price series. It is composed of a p^{th} order autoregressive process [AR(p)] and/or a q^{th} order moving average process, [MA(q)]. This autoregressive process says that we can express the forecasted price as the weighted sum of previous prices and a random shock or white noise term. The moving average process expresses forecasted price as the weighted sum of current and past shocks to the system. The integration refers to the transformation of a non-stationary series (one with a perceived trend) to a stationary series by taking a d^{th} difference of the original values (Box and Jenkins).

The unrestricted ARIMA (p,d,q) model may be expressed as:

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

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 $B^d Z_t = Z_{t-d}$,
u_i = the weights attached to past prices in the AR process (i=1,...,p),
h_i = the weights attached to past innovative random shocks in the MA process (i= 1,..,q).

A necessary condition for applying time series models to a data series is a stationary series (devoid of trend). Soybean complex prices shifted upward in 1972-1973 because of 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 (Wendland). While distinct seasonal patterns are present after 1973, the average price level has not changed. 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 December 1989, to analyze the performance of the model. While monthly price data may tend to filter variation in the prices of the commodities within the soybean complex, fundamental information is only available on a monthly or longer basis. Therefore, to predict prices using both univariate and multivariate processes, the shortest feasible time horizon is one month.

To determine the autoregressive and moving average components of the ARIMA model for the prices of the three soybean complex commodities, we calculated the sample Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF). The sample ACF decays exponentially for each soycomplex price series indicating 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. This preferred specification indicates that we can forecast soybean, soybean oil, and soybean meal prices can be using prices from the last two months and a random shock term.

To determine if another model specification outperforms the AR(2) specification, we evaluated additional AR and MA terms. This process, referred to as model overfitting, is an accepted procedure for deriving the specification of an ARIMA model (Cryer). A superior specification results in improved statistical results.[1]

Testing for an improved model specification indicates that the AR(2) specification is best for forecasting soybean prices. However an ARMA(1,1) specification is better for both soybean meal and soybean oil prices. Thus, we can best forecast prices in these markets using a weighted combination of the last available monthly price and the random shock associated with that price, as well as an additional random shock term.

When we added a new month in the out-of-sample forecast period, we recomputed and tested the sample ACF and PACF functions. Throughout the period studied, the AR(2) specification for soybeans and ARMA(1,1) specification for soybean oil and soybean meal remain the superior specifications.

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, Wendland specifies the soybean oil price series 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:

$$Y_t = \phi(B)\, Y_t + a_t \qquad (2)$$

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).

We used Rausser and Carter's monthly econometric model of the U.S. soybean complex 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. We got 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 from the Chicago Board of Trade Annuals and the USDA's Market News (various issues). We obtained the monthly average crude vegetable oil price index from the Bureau of Labor Statistics. We imputed monthly stocks of soybeans from the preceding U.S. quarterly soybean stocks, monthly soybean crushings, and monthly soybean exports. During the harvest period, we estimated the amount of production harvested using the USDA harvest progress report. We added this estimation of production already harvested to the monthly stocks estimate.

Using the exclusion-of-variables approached outlined by Hsiao, only nine of the variables specified by Rausser and Carter 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.[2] The general structure of the mixed VAR used to forecast within the soycomplex is in the Appendix. Once each equation is specified, we computed parameter estimates by estimating the equations simultaneously as seemingly unrelated regressions.

We recomputed parameters for the VAR model 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.

Tests of Market Timing Ability

Merton Test of Market Timing Ability. Merton's original derivation of forecast value begins with a basic assumption that forecasts only have positive value if they cause rational investors to alter their expectations about the future. If there is no such alteration, all of the information contained within the forecast has already been assimilated into the market. Consequently, the forecast has no positive value. Merton's methodology for obtaining the value of this forecast is independent of investor's preferences, endowments, or prior assessments of an asset's return stream.

To describe Merton's forecast model, define a forecast variable Z_{t+1} such that $Z_{t+1} = 1$ if the forecast, made at time t for period t+1 is that price will rise. If price is forecasted to stay constant or fall, $Z_{t+1} = 0$. Then, probabilities for Z_{t+1} conditional upon the realized change in price, M_{t+1}, are defined by:

$$p_1 = Prob\,(Z_{t+1} = 0 \mid M_{t+1} \leq 0) \tag{3}$$

$$1 - p_1 = Prob\,(Z_{t+1} = 1 \mid M_{t+1} \leq 0) \tag{4}$$

$$p_2 = Prob\,(Z_{t+1} = 1 \mid M_{t+1} > 0) \tag{5}$$

$$1 - p_2 = Prob\,(Z_{t+1} = 0 \mid M_{t+1} > 0) \tag{6}$$

Hence, p_1 is the conditional probability of a correct forecast given that $M_{t+1} \leq 0$, and p2 is the conditional probability of a correct forecast since $M_{t+1} > 0$. Merton assumes that p_1 and p_2 do not depend upon the magnitude of the realized change in price, M_{t+1}. So, the conditional probability of a correct forecast depends only on the realized direction of price change.

Under the previous assumptions, Merton proves that the sum of conditional probabilities p_1 and p_2 must exceed one for a model to exhibit forecasting value. In addition, it is not necessary that the conditional probabilities, p_1 and p_2, remain constant across time, only that their sum be stationary. It is also not necessary that $p_1 = p_2$, allowing for the possibility that a model is better equipped to forecast upward market moves than downward market moves, or vice versa (Henriksson and Merton).

Breen *et al.* show that Merton's test of market timing ability can be implemented in a regression framework. First, define a market direction variable $M_{t+i,j}$ such that:

$$M_{t+i,j,k} = 1 \text{ } if PF_{t+1,j,k} > PA_{t,j} \tag{7}$$

$$M_{t+i,j,k} = 0 \text{ } if PF_{t+1,j,k} \leq PA_{t,j} \tag{8}$$

where $PA_{t+i,j}$ is the actual price for period t+i (i = 1, 3, 6 months) and commodity j (j = soybeans, soybean oil, soybean meal). $PA_{t,j}$ is the actual cash price for period t and commodity j. Next, define a forecast direction variable $Z_{t+i,j,k}$ such that:

$$Z_{t+i,j,k} = 1 \ if PF_{t+1,j,k} > PA_{t,j} \tag{9}$$

$$Z_{t+i,j,k} = 0 \ if PF_{t+1,j,k} \leq PA_{t,j} \tag{10}$$

where $PF_{t+i,j,k}$ is the forecasted price for time period t+i and commodity j by forecast model k (k=univariate, multivariate). Then we can specify the following regression equation as:

$$Z_{t+i,j,k} = \alpha_{i,j,k} + \beta_{i,j,k} M_{t+i,j} + \varepsilon_{i,j,k}, \tag{11}$$

where $\varepsilon_{i,j,k}$ is a standard normal error term.

Breen *et al.* show that $\beta_{i,j,k} = P_{1\ i,j,k} + P_{2\ i,j,k} - 1$.[3] Thus, if $\beta_{i,j,k}$ is significantly greater than zero, then the forecasts have met the necessary and sufficient condition for market timing value (Breen, *et al.*.).

Cumby-Modest Market Timing Tests. Because the Merton market timing test assumes that conditional probabilities are independent of realized returns of investment alternatives, we did not include information which may be obtained by examining the magnitude of realized returns in this evaluation procedure. As a result, forecasters who occasionally predict market changes of large magnitude will not exhibit market timing ability under this framework (Cumby-Modest).

Cumby and Modest, adopting only Merton's original criteria of changing expectations due to forecast information, construct a general test of market timing ability. They hypothesize a linear relationship between a forecast and subsequent measures of relative economic returns. A generalized version of the model for testing market timing ability is:

$$P_{t+i,j} - P_{i,j} = \beta(FP^{t+i}_{i,j,k} - P_{i,j}) + \varepsilon_{t,j,k}, \tag{12}$$

where $P_{t,j}$ and $P_{t+i,j}$ are the actual prices at time period t and t+i, respectively for commodity j. $FP^{t+i}_{i,j,k}$ is the i[th] period ahead forecast of the price of commodity j made at time period t by model j and $\varepsilon_{t,j,k}$ is the standard normal error.

This framework examines the correlation between the size of actual price changes and the forecasted size of price changes. Thus, this test of market timing ability focuses upon the ability of a particular model to generate forecasts that accurately predict large price changes. The underlying notion is that a forecasting model which consistently predicts large market moves but is inconsistent in predicting small gyrations may still have forecasting value. If β is significantly greater than zero, then the forecasted price change is directly correlated with actual price changes. Thus, we can say the forecasts have market timing ability.

Results

Statistical Accuracy. We generated a series of price forecasts by the ARIMA and VAR forecasting models for each commodity within the soybean complex.

We present in Table 1 three common measures of accuracy to gain some insight into the statistical accuracy of the two forecasting models. Each is a form of measurement of the difference between the forecasted and actual prices of the soybean complex commodities. The simplest measure of accuracy is the mean or average error. However, mean error can be misleading because of the tendency for large positive and negative errors to offset each other. In order to correct for this problem, we frequently use root mean square error (RMSE). RMSE is useful because we can evaluate accuracy relative to the size of the average price. Furthermore, under a criteria of RMSE, large errors are given greater weight than under any mean weighting scheme. Finally, in order to facilitate comparison between the three commodities within the soybean complex, we also used root mean square percentage error (RMSPE). Comparisons of forecast accuracy across the commodities are not possible using mean error

Table 1.
Accuracy of ARIMA and VAR Forecasts of Soybean Complex Prices, January 1984–December 1989

Commodity	Forecast Horizon months	ARIMA model[ab]			VAR model[ab]		
		Mean Error	RMSE	RMSPE	Mean Error	RMSE	RMSPE
Soybeans	1	−0.0004	0.36	0.05	−0.06	0.36	0.05
Soybean oil	1	0.003	2.01	0.07	−0.13	1.83	0.07
Soybean meal	1	−0.06	13.20	0.06	−1.44	14.18	0.07
Soybeans	3	0.008	0.76	0.10	−0.22	0.80	0.13
Soybean oil	3	0.13	4.05	0.17	−0.53	4.03	0.17
Soybean meal	3	0.81	23.29	0.12	−3.48	25.41	0.14
Soybeans	6	0.01	1.04	0.15	−0.42	1.07	0.18
Soybean oil	6	−0.09	4.98	0.22	−1.34	4.95	0.26
Soybean meal	6	3.80	32.50	0.17	−4.33	32.42	0.19

[a] RMSE = Root Mean Square Error.
[b] RMSPE = Root Mean Square Percentage Error.

and RMSE since they are relative to average price. However, because we present RMSPE in percentage form across commodities, important comparisons can be made.

The results in Table 1 show that regardless of the measure used, the accuracy of the models tends to deteriorate as the time horizon lengthens. The only exception is the mean error associated with the six-month ahead forecast of soybean oil prices generated by the ARIMA model. In terms of the size of the average error associated with the model forecasts, the ARIMA model is statistically more accurate in generating point forecasts than the VAR model across all commodities and time horizons.

In terms of RMSE the results are not as consistent. In eight of the nine cases, there are small differences in the magnitude of the RMSE. In four of these eight cases (forecasts of soybean oil prices across all horizons and the six-month ahead forecast of soybean meal) the VAR model generates the more accurate forecasts (smaller RMSE terms). In the remaining cases, the ARIMA model generates the more accurate price forecasts.

In terms of RMSPE, there is no magnitude difference between the ARIMA and VAR models with respect to the one-month ahead forecasts of soybeans and soybean oil prices or the three-month ahead forecast of soybean oil prices. In all other cases, the ARIMA model forecasts are more accurate. The RMSPE results also show that in terms of statistical accuracy, each model appears to be more proficient in generating forecasts of soybean prices than in generating soybean product prices.

Merton Test Results. A problem involved in estimating equations (11) and (12) via ordinary least squares (OLS) is that serial correlation is introduced into the error term for equations corresponding to three- and six-month ahead forecasts. This is due to the overlapping nature of the forecasting horizons. Box and Jenkins (1976) demonstrate that such overlapping introduces a moving average process into the error term of the order i-1, where i is the forecast horizon. Newey and West (1987) have developed a covariance estimator that is consistent with respect to this type of serial correlation. We use this covariance estimator in the case of three- and six-month ahead forecasts.

We present Merton market timing results for one-, three-, and six-month ahead forecasts in Table 2. At a ten percent significance level, the ARIMA model successfully predicted the direction of price movements in both the soybean and soybean oil market at one-month ahead forecast horizon and for soybean oil at a six-month ahead forecast horizon. The VAR model generated forecasts that accurately predicted directional moves of prices in both the soybean and soybean oil markets at forecast horizons of one and six months. The six month ahead forecasts of soybean oil prices by both the ARIMA and

VAR models had market timing ability, with slope coefficients significant at the five percent level.

Neither model generates directionally accurate forecasts of the soybean meal price. Moreover, neither of the models is successful in forecasting directional movement at the three month horizon for any commodity.

Cumby-Modest Test Results. We also present the Cumby-Modest results for one-, three-, and six-month ahead forecasts in Table 2. The t-statistics for the β coefficients show that neither model generates forecasts that predict large market changes beyond a one month horizon. This indicates that the ability of these models to predict directional change at a six month horizon, is not consistently correlated with large scale market moves.

At the ten percent significance level, the VAR model generates a set of forecasts which have market timing ability at the one month horizon in both the soybean and soybean oil markets. This corresponds with the earlier finding of Merton market timing ability by VAR forecasts within these markets. Thus, at very short horizons, the VAR model can consistently forecast directional

Table 2.
Merton Market Timing Tests and Cumby-Modest Market Timing Tests of Time Series Forecasts within the Soybean Complex, January 1984–December 1989

Commodity	Forecast Horizon	ARIMA model βm	ARIMA model βcm	VAR model βm	VAR model βcm
	months				
Soybeans	1	0.14	3.66	0.21	2.91
		(1.54)*	(2.26)**	(1.90)**	(2.24)**
Soybean oil	1	0.32	4.72	0.18	3.02
		(2.79)**	(2.87)**	(1.58)*	(1.66)***
Soybean meal	1	0.07	1.99	0.02	1.68
		(0.57)	(1.30)*	(0.15)	(1.09)
Soybeans	3[a]	–0.29	-15.49	0.04	-7.13
		(–2.76)	(–5.68)	(0.56)	(–1.59)
Soybean oil	3[a]	–0.05	–19.70	–0.03	–15.58
		(–0.57)	(–5.47)	(–0.20)	(–3.47)
Soybean meal	3[a]	–0.13	–17.65	0.08	–4.79
		(–1.01)	(–6.00)	(0.75)	(–1.00)
Soybeans	6[a]	-0.05	-22.43	0.13	-14.10
		(-0.33)	(-4.08)	(1.50)	(-1.49)
Soybean oil	6[a]	0.17	–28.67	0.08	–21.75
		(1.75)**	(–4.22)	(1.72)**	(–2.71)
Soybean meal	6[a]	–0.20	–28.23	0.08	–4.28
		(–2.15)	(–6.59)	(0.85)	(–0.42)

Note: The figures in parentheses are t-statistics. Two (one) stars indicates significance at the 5% (10%) level.
[a] Newey-West heteroskedastic, autocorrelation consistent covariance matrix is used to derive standard error estimates.

changes in these markets with some degree of precision and there is marked correlation between accurate predictions and large scale market moves.

The forecasts generated by the ARIMA model have Cumby-Modest market timing ability across all three commodities at the one month horizon. Again, in the soybean and soybean oil market this corresponds with the Merton market timing test results. However, the ARIMA model does not generate a set of one-month ahead forecasts which have Merton market timing ability in the soybean meal market. Thus, while the ARIMA model does not yield a high percentage of directionally accurate forecasts of soybean meal prices, the accurate forecasts tend to be those that show large-scale changes in market price.

Summary and Conclusions

For agribusinesses within the soybean complex, developing and evaluating forecasts of soybean, soybean oil, and soybean meal prices is an important component in economic decision making. A crucial aspect of this evaluation procedure is determining the market timing ability of the price forecasts. We presented two tests of market timing ability. In the first, we examined the ability of the forecasts to place a user consistently on the correct side of the market. In the second, we tested the ability of the forecasts to place users on the correct side of the market during periods of major price changes.

We constructed a univariate and multivariate time series model of the soybean complex over the time period January 1974 to December 1983. We generated one-, three-, and six-month ahead out-of-sample forecasts by each model over the period January 1984 to December 1989. We evaluated these forecasts in each market across different forecast horizons to determine if either methodology could produce price forecasts with market timing ability.

Neither model generates a set of forecasts which have market timing ability at a three-month ahead forecast horizon. At a longer six-month ahead horizon, the VAR model generates forecasts that consistently predict the direction of price movements in two of three markets (soybeans and soybean oil). In contrast, the ARIMA model only has six-month ahead directional market timing ability in the soybean oil market. Neither set of forecasts can consistently forecast large price changes at this longer horizon when the potential market opportunities for profits or losses may be greatest.

Both the ARIMA and the VAR models can consistently forecast both the direction and scale of price changes in the soybean and soybean oil markets at a one-month ahead horizon. However, the ARIMA model also exhibits a high correlation between actual price change and forecasted price change in the soybean meal market at the one-month ahead horizon.

This study of the soybean complex finds that univariate models are slightly more proficient at generating useful forecasts over short time horizons. It also suggests that while the VAR models may be more useful at longer forecast horizons, they may not offer substantial improvement over the simpler univariate models. Thus, these results suggest that simple univariate price forecasting methodologies may have value to agribusiness decision makers within the soybean complex. Soybean processors can make use of this type of information in building and assessing potential marketing strategies. For example, suppose that forecasts from simple univariate models show that soybean prices and soybean product prices are going to rise within the next month. Soybean processors could use this information to test soybean complex hedging strategies. In addition, this information may be a crucial input into decisions regarding the sale versus storage of soybean products.

The evidence presented in this paper is not conclusive, but it does suggest the desirability of future research on the market timing ability of different techniques on various commodities across different forecasting horizons.

Notes

1. Improved statistical results in the model overfitting procedure includes higher R^2, higher t-statistics, and a lower Q-statistic.
2. In order to develop a parsimonious VAR specification, this research uses a form of 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).
3. Note that:

$$E(Z_{t+i,j,k} \mid M_{t+i,j}=0) = \alpha_{i,j,k} = \text{Prob}(Z_{t+i,j,k} = 1 \mid M_{t+i,j}=0) = 1 - P_{1\,i,j,k} \qquad (13)$$

and

$$E(Z_{t+i,j,k} \mid M_{t+i,j}=1) = \alpha_{i,j,k} + \beta_{i,j,k} = \text{Prob}(Z_{t+i,j,k} = 0 \mid M_{t+i,j}=1) = P_{2\,i,j,k} \qquad (14)$$

Subtracting equation (13) from (14) produces the result.

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Appendix

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

$$SBP = \alpha + \beta_1 SBP_{t-1} + \beta_2 SBP_{t-2} + \varepsilon_1 \tag{15}$$

$$SOP = \alpha + \beta_1 SOP_{t-1} + \beta_2 SOP_{t-2} + \varepsilon_2 \tag{16}$$

$$\begin{aligned} SMP = {} & \alpha + \beta_1 SMP_{t-1} + \beta_2 SMP_{t-2} + \beta_3 SMP_{t-10} + \gamma_1 SMS_{t-1} + \gamma_2 SMS_{t-2} + \\ & \gamma_3 SMS_{t-3} + \gamma_4 SMS_{t-11} + \gamma_5 SMS_{t-12} + \psi_1 SBP_{t-1} + \psi_2 SBP_{t-2} + \varepsilon_3 \end{aligned} \tag{17}$$

$$\begin{aligned} SMS = {} & \alpha + \beta_1 SMS_{t-1} + \gamma_1 SOS_{t-1} + \gamma_2 SOS_{t-2} + \gamma_3 SOS_{t-3} + \psi_1 SOE_{t-1} \\ & + \lambda_1 SBP_{t-1} + \lambda_2 SBP_{t-2} + \varepsilon_4 \end{aligned} \tag{18}$$

$$\begin{aligned} SOS = {} & \alpha + \beta_1 SOS_{t-1} + \gamma_1 SBS_{t-1} + \gamma_2 SBS_{t-2} + \gamma_3 SBS_{t-3} + \gamma_4 SBS_{t-11} + \gamma_5 SBS_{t-12} \\ & + \psi_1 SMS_{t-1} + \psi_2 SMS_{t-2} + \psi_3 SMS_{t-3} + \lambda CP_{t-1} + \theta_1 SBP_{t-1} + \theta_2 SBP_{t-2} \\ & + \theta_3 SBP_{t-3} + \phi_1 SOP_{t-1} + \varepsilon_5 \end{aligned} \tag{19}$$

$$SOE = \alpha + \beta_1 SMS_{t-1} + \beta_2 SMS_{t-2} + \beta_3 SMS_{t-3} + \gamma_1 SMP_{t-1} + \psi_1 SBP_{t-1} + \psi_2 SBP_{t-2} + \psi_3 SBP_{t-3} + \gamma_1 CP_{t-1} + \varepsilon_6 \quad (20)$$

$$SBS = \alpha + \beta_1 SBS_{t-1} + \beta_2 SBS_{t-2} + \beta_3 SBS_{t-3} + \beta_4 SBS_{t-2} + \beta_5 SBS_{t-10} + \beta_6 SBS_{t-11} + \beta_7 SBS_{t-12} + \beta_8 SBS_{t-13} + \beta_9 SBS_{t-14} + \gamma_1 CSH_{t-1} + \gamma_2 CSH_{t-2} + \psi_1 SBP_{t-1} + \gamma_1 SOS_{t-1} + \theta_1 SOE_{t-1} + \phi_1 SMP_{t-1} + \varepsilon_7 \quad (21)$$

$$CSH = \alpha + \beta_1 CSH_{t-3} + \beta_2 CSH_{t-7} + \beta_3 CSH_{t-8} + \beta_4 CSH_{t-9} + \beta_5 CSH_{t-13} + \beta_6 CSH_{t-16} + \varepsilon_8 \quad (22)$$

$$CP = \alpha + \beta_1 CP_{t-1} + \beta_2 CP_{t-2} + \gamma_1 CSH_{t-1} + \lambda_1 SMP_{t-1} + \varepsilon_9 \quad (23)$$

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