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by

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Forecasting of Futures Prices: Using One Commodity to Help Forecast Another

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Forecasting of Futures Prices:
Using One Commodity to Help Forecast Another

Managers of businesses that involve agricultural commodities need price forecasts in order to manage the risk in either the sale or purchase of agricultural commodities. This paper examines whether commodity price forecasting model performance can be improved by the inclusion of price forecasts for other commodities within the model specification. We estimate 760 different models to forecast the prices of hog, cattle, corn, and soybean and find strong support for the inclusion of other commodity price forecasts in the best forecasting models. Unfortunately, the out-of-sample performance of these models is mixed at best. Still, the results suggest more work is called for to determine how best to use other commodity price forecasts to improve forecasting performance.

Keywords: price forecasting, model specification, Bayesian econometrics.

Introduction

Commodity price forecasting has a long history in both the agricultural economics literature and in the real-world application of farm and agribusiness management. People managing businesses that involve agricultural commodities need price forecasts in order to optimally plan their actions, including the use or non-use of hedging in order to manage their output or input price risk. Thus, the ability to generate quality forecasts of commodity prices is important.

The question this research seeks to answer is if commodity price forecasting models can be improved by the addition of forecasts of other, related commodity prices. While structural price forecasting models have commonly included variables that relate to other commodity markets (such as cattle slaughter data being included in a hog price forecasting model), the inclusion of the price forecast itself is new and untested as far as we know. Such a method is equivalent to a hybrid structural-reduced form model as the included commodity price forecasts are essentially a composite of information deemed useful to forecasting that commodity.

We test the ability of included commodity price forecasts to improve the forecasts of other commodities using data on the four most commonly forecast commodity prices: hog, cattle, corn, and soybean. For each of these four commodities, we forecast future prices both with and without other price forecasts included in the model to examine the relative forecast performance. We do all this within a Bayesian model uncertainty framework that is well-suited to the estimation and comparison of multiple models.

The paper proceeds with a literature review section, followed by an explanation of the methodology employed. Next we describe the data and present the results. The final section presents some conclusions.

Background and Literature Review

Price volatility is a fundamental feature of agricultural markets and one of the main sources of risk in commodity markets. Futures markets play a crucial role in the pricing and distribution of commodities. For farmers, processors, and other participants in commodity markets to properly manage their risks and attempt to maximize profits, commodity price forecasts are often useful.

Thus, these agents are continually looking for improved forecasts, as witnessed by the long history of research on this topic.

Cromarty and Myers (1975) noted that parsimony is desirable in forecasting model selection and good forecasting models are designed to incorporate new information as it becomes available, which makes the Bayesian framework ideal. Brandt and Bessler (1981) examined the empirical accuracy of several composite forecasting techniques for U.S hog prices based on the individual forecasts of econometric, ARIMA, and expert opinion methods and provided empirical evidence on the usefulness of composite forecasting. Brandt and Bessler (1983) found that combining forecasts from individual methods into a composite reduced the forecast error below that of any individual approach and that the use of price forecasts in developing a market strategy can improve the average price received for the product. Brandt (1985) later developed alternative forecasting approaches generating commodity price forecasts that can be combined with hedging to reduce price variability.

Gerlow et al. (1993) on the other hand shed light on forecasting performance evaluation, using several economic criteria, which are zero mean returns, zero risk-adjusted mean returns, the Merton test of market timing ability, and the Cumby-Modest test of market timing ability, to evaluate a set of well-known hog price forecasting models. Further, Dorfman (1998) created a new Bayesian method to form composite qualitative forecasts and showed that forming composite forecasts from a set of forecasts in the Bayesian framework improved performance in an application to the hog prices. Dorfman and Sanders (2006) also introduced a systematic Bayesian approach to handle model specification uncertainty in hedging models, which can be applied to data on the hedging of corn and soybeans and on cross-hedging of corn oil using soybean oil futures.

In this paper, we are interested in investigating whether the forecasts of one commodity can help improve the forecasts of a second commodity. Hog, cattle, corn, and soybean are chosen in this paper because they are the four most common commodities that have been looked at the agricultural economics literature on forecasting. Essentially, this is a new form of composite forecasting where model specification uncertainty is taken to include the possible inclusion of the forecasts from models of other, related commodities.

Methodology

The Basics

In this paper, we used the Bayesian approach to deal with model specification uncertainty for each commodity price forecasting model. For each commodity price to be forecast, we start with a set of possible forecasting models, estimate them all, and see which have the most posterior support from the data. This is done in two parts: the estimation of each model and the computation of each model's support.

For a given model j, for one commodity price, assume a linear regression model:

$$y = X_j\beta_j + \epsilon_j, j = 1, \ldots, M, \tag{1}$$

where y is the vector of observations on the dependent variable assumed identical in all models, X_j is the matrix of the independent variables for the j_{th} model considered, ϵ_j is the vector of random errors for the j_{th} model, and j denotes the model in the set of M models considered. The

differences between the models are restricted here to the matrix X of independent variables.

The prior distribution on the regression parameters β_j can be specified as

$$p(\beta_j) \sim N(b_{0j}, \sigma_j^2 V_{0j}), j = 1, \ldots, M, \tag{2}$$

where N represents the multivariate normal distribution, b_{0j} is the prior mean of the regression parameters for the j_{th} model and $\sigma_j^2 V_{0j}$ is the prior covariance matrix. The prior on σ_j^2 is specified as an inverse-gamma distribution, which is equivalent to a gamma distribution on σ_j^{-2},

$$p(\sigma_j^{-2}) \sim G(s_{0j}^{-2}, d_{0j}), j = 1, \ldots, M, \tag{3}$$

where G stands for the gamma distribution, s_{0j}^{-2} is the prior mean for the inverse error variance, and d_{0j} is the prior degrees of freedom. A higher value of d_{0j} indicates a more informative prior (Koop, 2003).

The likelihood function for each model can be specified as

$$L_j(y|\beta_j, \sigma_j^2, X_j) = (2\pi\sigma_j^2)^{-n/2} exp\{-0.5(y - X_j\beta_j)' \sigma_j^{-2}(y - X_j\beta_j)\}, j = 1, \ldots, M, \tag{4}$$

where the ϵ_j are assumed to follow a standard form of identically and independently distributed normal random variables.

Given these priors and the above likelihood function, the joint posterior distribution of β_j and σ_j^2 can be derived according to Bayes Theorem that the posterior distribution is proportional to the prior distribution times the likelihood function. The joint posterior can be written as

$$p(\beta_j, \sigma_j^2|y, X_j) \sim NG(b_{pj}, V_{pj}, s_{pj}^2, d_{pj}), j = 1, \ldots, M, \tag{5}$$

where

$$V_{pj} = (V_{0j}^{-1} + X_j' X_j)^{-1}, \tag{6}$$

$$b_{pj} = V_{pj}(V_{0j}^{-1} b_{0j} + (X_j' X_j)\hat{\beta}_j), \tag{7}$$

$$d_{pj} = d_{0j} + n_j, \tag{8}$$

and

$$s_{pj}^2 = d_{pj}^{-1}[d_{0j} s_{0j}^2 + (n_j - k_j)s_j^2 + (\hat{\beta}_j - b_{0j})'(V_{0j} + (X_j' X_j)^{-1})^{-1}(\hat{\beta}_j - b_{0j})], \tag{9}$$

where NG represents the joint normal-gamma distribution, $\hat{\beta}_j$ and s_j^2 are the standard OLS quantities and n_j and k_j are the rows and columns of X_j , respectively. Equations (6) to (9) together help define the parameters in the distribution. $s_{pj}^2 V_{pj}$ is the posterior mean of the variance, b_{pj} is the posterior mean of the coefficients, which are the weighted averages of the parameters of the prior distribution and the parameters that are derived from the maximum likelihood estimator based on the data, and d_{pj} is the posterior degrees of freedom.

Model Specification Uncertainty

Now we describe the process for handling model specification uncertainty. First, a discrete prior weight is assigned to each model

$$p(M_j) = \mu_j, \sum_{j=1}^{M} \mu_j = 1. \tag{10}$$

Here we choose to use uninformative priors across the model specification, so all models are treated equally. In this case, $\mu_j = 1/\text{M}$, $\forall$j. Then, using the above results for the posterior distributions shown in (5), we derive the marginal likelihood functions by integrating out the parameter uncertainty to leave a marginal likelihood for each model,

$$p(y|M_j) = c_j[|V_{pj}|/|V_{0j}]^{1/2}(d_{pj}s_{pj}^2)^{-d_{pj}/2}, \tag{11}$$

where

$$c_j = \frac{\Gamma(d_{pj}/2)(d_{0j}s_{0j}^2)^{d_{0j}/2}}{\Gamma(d_{0j}/2)\pi^{n/2}}, \tag{12}$$

and Γ is the Gamma function. The marginal likelihood tells how well the model fits on average, where the averaging is over all possible parameter values. As shown in equation (11), the smaller the posterior mean of the variance is, the larger the marginal likelihood will be, which indicates that the better the model fits, the larger the marginal likelihood will be. Combining (11) and (12) by Bayes Theorem, the posterior probability of each model can be derived as follows

$$p(M_j|y) \propto \mu_j[|V_{pj}|/|V_{0j}]^{1/2}(d_{pj}s_{pj}^2)^{-d_{pj}/2} = \mu_j p(y|M_j), j = 1, \ldots, M. \tag{13}$$

Normalizing the values in (13) by dividing each value by the sum of the unnormalized posterior probabilities across all M models will make sure that these posterior model probabilities sum to unity. Denote these normalized posterior probabilities by

$$\omega_j = \frac{\mu_j p(y|M_j)}{\sum_{j=1}^{M} \mu_j p(y|M_j)}, j = 1, \ldots, M. \tag{14}$$

These posterior probabilities ω_j are the key to evaluating both general model specification uncertainty and the advantage of including forecasts of other commodity prices in the forecasting model. Models which receive higher posterior probabilities are better supported by the data, indicating that those models are preferred choices and can be expected to yield better forecasting performance.

Data

Data on the four commodity prices were collected from the CME Group, using monthly futures prices for lean hogs ($/lb), live cattle futures ($/lb), corn futures ($/bushel), and soybean futures ($/bushel).

Possible independent variables were selected based on ones commonly employed in previous studies in the literature. For the hog price forecasting models, these variables include the natural log of monthly disposable personal income (billion dollars), monthly commercial cattle slaughter (million heads), monthly broiler-type poultry eggs hatched (million eggs), the monthly number of sows farrowing (thousand heads), and monthly pork cold storage (million pounds). For the cattle price forecasting models, the independent variables considered are the same as the hog price forecasting model except pork storage is not included.

In the corn price forecasting model, the exogenous variables considered are monthly corn exports (million units), monthly corn inventory (million bushels), monthly lagged acres planted to corn (thousand acres), and monthly fuel ethanol production (million gallons). For the soybean price

forecasting model, the independent variables considered are the same things as in the corn model except the ethanol variable is not included.

Data come from Chicago Mercantile Exchange (CME), National Agricultural Statistics Services (NASS), and National Ocean Atmospheric Administration (NOAA).

All data are monthly extending from January 1981 to December 2012. We used the first twenty-six years for in-sample estimation, and then evaluated out-of-sample forecast performance over the last 72 observations, which are from 2007 to 2012.

Table 1 shows the set of variables considered in the model specification and the total number of forecasting models estimated for each of the four commodity prices.

Empirical Results

Beginning with the hog price forecasting models, Table 2 presents the posterior probabilities for the model specification. The probabilities shown in Table 2 are the probability that each of the variables listed belongs in the true model. These probabilities show that there is clear and overwhelming support for the inclusion of DSPI, HATCH, SF, PKST, and forecasts of cattle prices in the hog price forecasting model. Other variables have little to no posterior support for inclusion in the hog price forecasting model.

In terms of forecasting performance, Table 3 presents the mean squared error (MSE) over the 72 out-of-sample forecasts for the hog price for the five best and five worst performing forecasting models while Table 4 presents the MSEs of the five most probable and five least probable models; these are the models with the highest and lowest posterior model probabilities. The five most probable models are those that one would be most likely to choose ex ante before seeing out-of-sample forecasting performance. Unfortunately, what Table 4 shows is that the most probable models have forecasting performance, as measured by MSE, that is noticeably worse than the best hog price forecasting models in Table 3. The most probable model does have a smaller MSE than the average of the 240 hog price forecasting models, but it is not as good as hoped.

Moving to the cattle price forecasting models, Table 5 presents the posterior probabilities in favor of variable inclusion in the forecasting model. These results show that DSPI, CTSL, SF, and hog price forecasts have enormous support for inclusion in the cattle price forecasting model. No other variables have posterior support that reaches 0.10, so the model specification is quite clear. Tables 6 and 7 hold the MSEs of the best/worst performing models and the most/least probable models, respectively. These results show that the most probable cattle price forecasting models perform significantly worse than the best forecasting models, and even worse than the average MSE over all the cattle price forecasting models.

The corn price forecasting models provide mixed results in terms of the forecasting performance of the most probable models. Table 8 presents the posterior probabilities in favor of variable inclusion in the corn price forecasting model. These probabilities are not as clear on the correct model specification as for the hog and cattle price forecasting models. Hog forecasts have an 88 percent posterior probability of inclusion, ethanol production has a 58 percent probability and corn exports have a 40 percent probability. Every other variable has even lower posterior support for inclusion in the model than these three.

Tables 9 presents the MSEs of the five best and five worst performing corn price forecasting models. Table 10 displays the MSEs of the five most and least probable corn price forecasting models. While the most probable corn price forecasting model has terrible forecasting performance (nearly making it into the list of the five worst performing models), the second and third most probable corn price forecasting models have excellent forecasting performance with their MSEs being just outside the five best corn price forecasting models. This provides the best indication yet that this method has some promise.

Finally, the soybean price forecasting model specification results are in Table 11. The posterior probabilities show strong support for including soybean exports and hog price forecasts in the soybean price forecasting model and little posterior support for any other variables. Table 12 presents the MSEs for the five best and five worst performing forecasting models, while Table 13 displays the MSEs for the five most and five least probable models. While three of the five most probable soybean price forecasting models have smaller MSEs than the average, none is particular good.

Overall, the most probable models for our four commodities display only average forecasting performance among the entire set of models estimated. Yet, while the forecasting performance of these most probable models is not what we might have hoped for, we do find that within the lists of the five best forecasting models for each of the four commodity prices, models that include commodity price forecasts are heavily represented. Of those twenty top-performing models, thirteen include a forecast of a different commodity price. This suggests that it is worth pursuing how commodity price forecasts can be improved by the inclusion of other commodity price forecasts in the forecasting models.

Conclusions

The Bayesian model specification procedure applied here to the forecasting of four important commodity prices provided clear signals for three of the four commodity prices on model specification. Unfortunately, the models with the highest model probabilities based on the in-sample data did not deliver above average out-of-sample forecasting performance. Still, the fact that thirteen of the twenty best performing forecasting model specifications, as measured by out-of-sample mean squared error, contained price forecasts for a different commodity suggest that the idea of improving commodity price forecasting by including other forecasts in the model is correct. We need to do some more work on choosing the correct model for forecasting, but we are headed in the correct direction.

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Table 1. Variables Used to Predict Commodity Prices

Dependent Variable	Lags	Exogenous Variables
PH (cents per pound) (240 models)	AR(3) $\sim$ AR(12)	DSPI; CTSL; HATCH; SF ;PKST
PCA (cents per pound) (200 models)	AR(3) $\sim$ AR(12)	DSPI; CTSL; HATCH; SF
PC (cents per bushel) (176 models)	AR(3) $\sim$ AR(6)	EXPORT^c; INVT^c; ACRES^c; ETHANOL
PS (cents per bushel) (144 models)	AR(3) $\sim$ AR(6)	EXPORT^s; INVT^s; ACRES^s

As listed in Table 1, in the hog forecasting model, the hog price (PH) to be forecast is the monthly lean hog futures price ($/lb) as given by CME group. Among the exogenous variables considered for the hog forecasting model, DSPI denotes the monthly disposable personal income (billion dollars) which has been taken natural logarithm; CTSL denotes monthly commercial cattle slaughter (million heads); HATCH denotes monthly broiler-type poultry eggs hatched (million eggs); SF denotes monthly number of sows farrowing (thousand heads); PKST denotes monthly pork cold storage (million pounds). In the cattle forecasting model, the cattle price (PCA) to be forecast is the monthly live cattle futures price ($/lb) as given by CME group. The independent variables considered are basically the same things as in the hog model except the PKST variable. In the corn forecasting model, the corn price (PC) to be forecast is the monthly corn futures price ($/bushel) as given by CME group. Among the exogenous variables considered for the corn forecasting model, EXPORT^c denotes monthly corn export (million units); INVT^c denotes monthly corn inventory (million bushels); ACRES^c denotes monthly lagged acreages planted for corn (thousand acres); ETHANOL denotes monthly fuel ethanol production (million gallons). In the soybean forecasting model, the soybean price (PS) to be forecast is the monthly soybean futures price ($/bushel) as given by CME group. The independent variables considered are the same things as in the corn model except the ETHANOL variable.

Table 2. Hog Price Forecasting Model Specification (240 Models)

Model Traits	Post Probability
Include AR(3)	0.991
Include DSPI	1.000
Include CTSL	0.019
Include HATCH	0.983
Include SF	1.000
Include PKST	0.999
Include Cattle Forecasts	0.929
Include Corn Forecasts	0.034
Include Soybean Forecasts	0.038
No Forecasts	<0.001

Table 3. Top 5 and Bottom 5 Hog Price Forecasting Models by MSE

Top 5 Models by MSE	**MSE**	**Post Probability**
1) AR(11)+DSPI$_t$+CTSL$_{t-1,t-2}$+HATCH$_{t-1,t-2}$+SF$_{t-1}$+PKST$_{t-1}$	34.093	<0.001
2) AR(11)+DSPI$_t$+CTSL$_{t-1,t-2}$+HATCH$_{t-1,t-2}$+SF$_{t-1}$+PKST$_{t-1}$ +Cattle Forecasts$_t$	34.369	<0.001
3) AR(10)+DSPI$_t$+CTSL$_{t-1,t-2}$+HATCH$_{t-1,t-2}$+SF$_{t-1}$+PKST$_{t-1}$	34.463	< 0.001
4) AR(6)+DSPI$_t$+CTSL$_{t-1,t-2}$+HATCH$_{t-1,t-2}$+SF$_{t-1}$+PKST$_{t-1}$	34.674	< 0.001
5) AR(7)+DSPI$_t$+CTSL$_{t-1,t-2}$+HATCH$_{t-1,t-2}$+SF$_{t-1}$+PKST$_{t-1}$	34.722	< 0.001
Bottom 5 Models by MSE		
1) AR(6)+DSPI$_t$+CTSL$_{t-1,t-2}$+HATCH$_{t-1,t-2}$+PKST$_{t-1}$ +Corn Forecasts$_t$	51.708	<0.001
2) AR(7)+DSPI$_t$+CTSL$_{t-1,t-2}$+HATCH$_{t-1,t-2}$+PKST$_{t-1}$ +Corn Forecasts$_t$	51.555	<0.001
3) AR(10)+DSPI$_t$+CTSL$_{t-1,t-2}$+HATCH$_{t-1,t-2}$+PKST$_{t-1}$ +Corn Forecasts$_t$	51.343	<0.001
4) AR(9)+DSPI$_t$+CTSL$_{t-1,t-2}$+HATCH$_{t-1,t-2}$+PKST$_{t-1}$ +Corn Forecasts$_t$	51.203	<0.001
5) AR(3)+DSPI$_t$+CTSL$_{t-1,t-2}$+HATCH$_{t-1,t-2}$+PKST$_{t-1}$ +Corn Forecasts$_t$	50.899	<0.001
Mean MSE	38.998	
Median MSE	37.391	

Table 4. Top 5 and Bottom 5 Hog Price Forecasting Models by Posterior Probability

5 Most Probable Models	**Post Probability**	**MSE**
1) AR(3)+DSPI$_t$+HATCH$_{t-1,t-2}$+SF$_{t-1}$+PKST$_{t-1}$ +Cattle Forecasts$_t$	0.908	37.872
2) AR(3)+DSPI$_t$+HATCH$_{t-1,t-2}$+SF$_{t-1}$+PKST$_{t-1}$ +Soybean Forecasts$_t$	0.035	45.230
3) AR(3)+DSPI$_t$+HATCH$_{t-1,t-2}$+SF$_{t-1}$+PKST$_{t-1}$ +Corn Forecasts$_t$	0.030	47.612
4) AR(3)+DSPI$_t$+CTSL$_{t-1,t-2}$+SF$_{t-1}$+PKST$_{t-1}$ +Cattle Forecasts$_t$	0.011	38.179
5) AR(4)+DSPI$_t$+HATCH$_{t-1,t-2}$+SF$_{t-1}$+PKST$_{t-1}$ +Cattle Forecasts$_t$	0.007	37.347
5 Least Probable Models		
1) AR(12)+CTSL$_{t-1,t-2}$+HATCH$_{t-1,t-2}$+SF$_{t-1}$+PKST$_{t-1}$ +Soybean Forecasts$_t$	<0.001	36.099
2) AR(12)+CTSL$_{t-1,t-2}$+HATCH$_{t-1,t-2}$+SF$_{t-1}$+PKST$_{t-1}$ +Corn Forecasts$_t$	<0.001	36.628
3) AR(12)+DSPI$_t$+CTSL$_{t-1,t-2}$+HATCH$_{t-1,t-2}$+SF$_{t-1}$+PKST$_{t-1}$ +Soybean Forecasts$_t$	<0.001	38.287
4) AR(12)+CTSL$_{t-1,t-2}$+HATCH$_{t-1,t-2}$+SF$_{t-1}$+PKST$_{t-1}$ +Cattle Forecasts$_t$	<0.001	37.138
5) AR(12)+DSPI$_t$+CTSL$_{t-1,t-2}$+HATCH$_{t-1,t-2}$+SF$_{t-1}$+PKST$_{t-1}$ +Corn Forecasts$_t$	<0.001	42.396

Table 5. Cattle Price Forecasting Model Specification (200 Models)

Model Traits	Post Probability
Include DSPI	0.999
Include CTSL	0.957
Include HATCH	0.054
Include SF	0.991
Include Hog Forecasts	1.000
Include Corn Forecasts	<0.001
Include Soybean Forecasts	<0.001
No Forecasts	<0.001

Table 6. Top 5 and Bottom 5 Cattle Price Forecasting Models by MSE

Top 5 Models by MSE	**MSE**	**Post Probability**
1) AR(3)+DSPI$_t$+CTSL$_{t-1}$+HATCH$_{t-1}$+SF$_{t-1,t-2}$ +Soybean Forecasts$_t$	17.390	<0.001
2) AR(5)+DSPI$_t$+CTSL$_{t-1}$+HATCH$_{t-1}$+SF$_{t-1,t-2}$ +Corn Forecasts$_t$	17.418	<0.001
3) AR(5)+DSPI$_t$+CTSL$_{t-1}$+HATCH$_{t-1}$+SF$_{t-1,t-2}$	17.437	<0.001
4) AR(3)+DSPI$_t$+CTSL$_{t-1}$+HATCH$_{t-1}$+Soybean Forecasts$_t$	17.528	<0.001
5) AR(5)+DSPI$_t$+CTSL$_{t-1}$+HATCH$_{t-1}$+SF$_{t-1,t-2}$ +Soybean Forecasts$_t$	17.610	<0.001
Bottom 5 Models by MSE		
1) AR(3)+DSPI$_t$+HATCH$_{t-1}$+SF$_{t-1,t-2}$	25.129	<0.001
2) AR(3)+DSPI$_t$+HATCH$_{t-1}$+SF$_{t-1,t-2}$+Hog Forecasts$_t$	24.998	0.007
3) AR(4)+DSPI$_t$+HATCH$_{t-1}$+SF$_{t-1,t-2}$+Hog Forecasts$_t$	24.370	0.001
4) AR(4)+DSPI$_t$+HATCH$_{t-1}$+SF$_{t-1,t-2}$	23.341	<0.001
5) AR(3)+CTSL$_{t-1}$+HATCH$_{t-1}$+SF$_{t-1,t-2}$+Corn Forecasts$_t$	23.202	<0.001
Mean MSE	19.794	
Median MSE	19.741	

Table 7. Top 5 and Bottom 5 Cattle Price Forecasting Models by Posterior Probability

5 Most Probable Models	**Post Probability**	**MSE**
1) AR(6)+DSPI$_t$+CTSL$_{t-1}$+SF$_{t-1,t-2}$+Hog Forecasts$_t$	0.449	20.023
2) AR(3)+DSPI$_t$+CTSL$_{t-1}$+SF$_{t-1,t-2}$+Hog Forecasts$_t$	0.276	22.553
3) AR(5)+DSPI$_t$+CTSL$_{t-1}$+SF$_{t-1,t-2}$+Hog Forecasts$_t$	0.157	19.960
4) AR(4)+DSPI$_t$+CTSL$_{t-1}$+SF$_{t-1,t-2}$+Hog Forecasts$_t$	0.060	21.556
5) AR(6)+DSPI$_t$+HATCH$_{t-1}$+SF$_{t-1,t-2}$+Hog Forecasts$_t$	0.032	21.577
5 Least Probable Models		
1) AR(12)+DSPI$_t$+CTSL$_{t-1}$+HATCH$_{t-1}$+SF$_{t-1,t-2}$ +Soybean Forecasts$_t$	<0.001	20.042
2) AR(12)+DSPI$_t$+CTSL$_{t-1}$+HATCH$_{t-1}$+SF$_{t-1,t-2}$ +Corn Forecasts$_t$	<0.001	19.234
3) AR(12)+CTSL$_{t-1}$+HATCH$_{t-1}$+SF$_{t-1,t-2}$ +Soybean Forecasts$_t$	<0.001	19.488
4) AR(12)+CTSL$_{t-1}$+HATCH$_{t-1}$+SF$_{t-1,t-2}$ +Corn Forecasts$_t$	<0.001	21.044
5) AR(11)+DSPI$_t$+CTSL$_{t-1}$+HATCH$_{t-1}$+SF$_{t-1,t-2}$ +Soybean Forecasts$_t$	<0.001	20.121

Table 8. Corn Price Forecasting Model Specification (176 Models)

Model Traits	Post Probability
Include AR(3)	0.999
Include EXPORT^c	0.396
Include ETHANOL	0.585
Include INVT^c	0.018
Include ACRES^c	0.001
Include Hog Forecasts	0.879
Include Cattle Forecasts	0.121
Include Soybean Forecasts	<0.001
No Forecasts	<0.001

Table 9. Top 5 and Bottom 5 Corn Price Forecasting Models by MSE

Top 5 Models by MSE	**MSE**	**Post Probability**
1) AR(3)+INVT$_t^c$+ETHANOL$_t$+Hog Forecasts$_t$	3212.168	<0.001
2) AR(4)+INVT$_t^c$+ETHANOL$_t$+Hog Forecasts$_t$	3217.035	<0.001
3) AR(4)+INVT$_t^c$+ETHANOL$_t$	3230.131	<0.001
4) AR(3)+INVT$_t^c$+ETHANOL$_t$+Cattle Forecasts$_t$	3231.853	<0.001
5) AR(3)+INVT$_t^c$+ETHANOL$_t$	3232.035	<0.001
Bottom 5 Models by MSE		
1) AR(5)+EXPORT$_t^c$+ACRES$_t^c$+Hog Forecasts$_t$	4267.035	<0.001
2) AR(4)+EXPORT$_t^c$+ACRES$_t^c$+Hog Forecasts$_t$	4262.992	<0.001
3) AR(3)+EXPORT$_t^c$+ACRES$_t^c$+Hog Forecasts$_t$	4259.665	<0.001
4) AR(6)+EXPORT$_t^c$+ACRES$_t^c$+Hog Forecasts$_t$	4244.118	<0.001
5) AR(5)+EXPORT$_t^c$+Hog Forecasts$_t$	4240.135	<0.001
Mean MSE	3621.853	
Median MSE	3612.215	

Table 10. Top 5 and Bottom 5 Corn Price Forecasting Models by Posterior Probability

5 Most Probable Models	**Post Probability**	**MSE**
1) AR(3)+EXPORT^c_t+Hog Forecasts$_t$	0.341	4234.079
2) AR(3)+ETHANOL$_t$+Hog Forecasts$_t$	0.278	3290.471
3) AR(3)+ETHANOL$_{t-1}$+Hog Forecasts$_t$	0.245	3281.752
4) AR(3)+EXPORT^c_t+Cattle Forecasts$_t$	0.055	3795.655
5) AR(3)+ETHANOL$_t$+Cattle Forecasts$_t$	0.031	3425.002
5 Least Probable Models		
1) AR(6)+ACRES^c_t+INVT^c_t	<0.001	3626.306
2) AR(6)+ACRES^c_t+ETHANOL$_t$	<0.001	3425.822
3) AR(6)+ACRES^c_t+EXPORT^c_t	<0.001	3985.728
4) AR(5)+ACRES^c_t+INVT^c_t	<0.001	3663.519
5) AR(6)+EXPORT^c_t+INVT^c_t	<0.001	3678.861

Table 11. Soybean Price Forecasting Model Specification (144 Models)

Model Traits	Post Probability
Include AR(3)	0.995
Include EXPORT^s	0.971
Include INVT^s	0.027
Include ACRES^s	0.002
Include Hog Forecasts	0.787
Include Cattle Forecasts	0.208
Include Corn Forecasts	0.005
No Forecasts	<0.001

Table 12. Top 5 and Bottom 5 Soybean Price Forecasting Models by MSE

Top 5 Models by MSE	**MSE**	**Post Probability**
1) AR(6)+EXPORT^s_t+Corn Forecasts$_t$	128.819	<0.001
2) AR(6)+EXPORT^s_t+ACRES^s_t+Corn Forecasts$_t$	128.858	<0.001
3) AR(6)+EXPORT^s_t+INVT^s_t+Corn Forecasts$_t$	129.932	<0.001
4) AR(5)+EXPORT^s_t+Corn Forecasts$_t$	130.166	<0.001
5) AR(5)+EXPORT^s_t+ACRES^s_t+Corn Forecasts$_t$	130.202	<0.001
Bottom 5 Models by MSE		
1) AR(3)+ACRES$^s_{t-1}$+Hog Forecasts$_t$	163.636	<0.001
2) AR(3)+ACRES^s_t+Hog Forecasts$_t$	161.507	<0.001
3) AR(4)+ACRES$^s_{t-1}$+Hog Forecasts$_t$	159.932	<0.001
4) AR(5)+ACRES$^s_{t-1}$+Hog Forecasts$_t$	159.880	<0.001
5) AR(6)+ACRES$^s_{t-1}$+Hog Forecasts$_t$	159.647	<0.001
Mean MSE	142.796	
Median MSE	141.178	

Table 13. Top 5 and Bottom 5 Soybean Price Forecasting Models by Posterior Probability

5 Most Probable Models	**Post Probability**	**MSE**
1) AR(3)+EXPORT^s_t+Hog Forecasts$_t$	0.393	140.806
2) AR(3)+EXPORT$^s_{t-1}$+Hog Forecasts$_t$	0.367	144.052
3) AR(3)+EXPORT^s_t+Cattle Forecasts$_t$	0.116	138.946
4) AR(3)+EXPORT$^s_{t-1}$+Cattle Forecasts$_t$	0.084	141.242
5) AR(3)+INVT^s_t+Hog Forecasts$_t$	0.012	151.086
5 Least Probable Models		
1) AR(6)+ACRES^s_t+INVT^s_t	<0.001	142.848
2) AR(5)+ACRES^s_t+INVT^s_t	<0.001	144.382
3) AR(6)+ACRES^s_t+EXPORT^s_t	<0.001	133.947
4) AR(4)+ACRES^s_t+INVT^s_t	<0.001	145.016
5) AR(5)+ACRES^s_t+EXPORT^s_t	<0.001	135.064