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

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Abstract

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. Sometimes the most important forecasting component is simply whether the price will move up or down. Such binary forecasts are commonly referred to as qualitative forecasts. This paper examines whether qualitative forecasting of commodity prices can be improved by the inclusion within the model specification of price forecasts for other commodities. We use hog prices as a test case 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 qualitative forecasts can be improved through the inclusion of other commodity price forecasts in our models.
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1 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.

Because in many situations, the key part of a price forecast is whether the price will move up or down in the future, we focus here on qualitative forecasts of the direction of price changes. We test the ability of included commodity price forecasts to improve the qualitative forecasts of hog prices using data on three other commonly forecast commodity prices: cattle, corn, and soybeans. We forecast hog 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.

2 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. 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 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. Feather and Kaylen (1989) suggested a procedure for the formation of a conditional "composite" qualitative forecast, the theoretical development of which was followed by an empirical application using quarterly hog prices. The results showed the composite allows the possibility of avoiding reliance on an inferior forecasting method.

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. 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 they then 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, we propose 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. We demonstrate this by constructing qualitative hog price forecasts with a set of models some of which include price forecasts for cattle, corn, or soybean prices.

3 Methodology

The Basics

In this paper, we used the Bayesian approach to deal with model specification uncertainty. To forecast hog price movements, 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, 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 hog prices 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

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

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 is derived according to Bayes Theorem that the posterior distribution is proportional to the prior distribution times the likelihood function. The joint posterior distribution is

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

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.

For each model, after generating point forecasts using the posterior means of the parameters found above and the actual values of the independent variables, we convert the point forecasts into directional forecasts using the simple rule:

$$f_t = \begin{cases} 1 & \text{if } \hat{P}_t \text{ - } P_{t-1} > 0 \\ 0 & \text{if } \hat{P}_t \text{ - } P_{t-1} \leq 0 \end{cases}, \tag{10}$$

where f_t is a dichotomous variable denoting a price forecast of either up (1) or down (0) and P_t denotes the commodity price at t time period. The set of f_t are our qualitative forecasts.

Model Specification Uncertainty

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

$$p(M_j) = \mu_j, \sum_{i=1}^{M} \mu_j = 1. \tag{11}$$

Here we choose to use uninformative priors across the model specification, so all models are treated equally. In this case, $\mu_j = 1/M$, $\forall j$. 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,

$$p(y|M_j) = c_j[|V_{pj}|/|V_{0j}]^{1/2}(d_{pj}s_{pj}^2)^{-d_{pj}/2}, \tag{12}$$

where

$$c_j = \frac{\Gamma(d_{pj}/2)(d_{0j}s_{0j}^2)^{d_{0j}/2}}{\Gamma(d_{0j}/2)\pi^{n/2}}, \tag{13}$$

and Γ is the Gamma function. The marginal likelihood measures how well the model fits on average, where the averaging is over parameter values with posterior support. As shown in equation (12), 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 is given by

$$p(M_j|y) \propto \mu_j[|V_{pj}|/|V_{0j}]^{1/2}(d_{pj}s_{pj}^2)^{-d_{pj}/2} = \mu_j p(y|M_j), j = 1, \ldots, M. \tag{14}$$

Dividing each value in (14) by the sum of the unnormalized posterior probabilities across all M models produces normalized posterior model probabilities that sum to one. Denote these normalized posterior probabilities by

$$\omega_j = \frac{\mu_j p(y|M_j)}{\sum_{i=1}^{M} \mu_j p(y|M_j)}, j = 1, \ldots, M. \tag{15}$$

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.

4 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 for 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 29 years for in-sample estimation, and then evaluated out-of-sample forecast performance over the last 36 observations, which are from 2010 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.

5 Empirical Results

Table 2 presents the posterior probabilities for the hog price forecasting 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 helping to uncover a model specification, the Bayesian approach provides excellent guidance.

Table 3 presents the out-of-sample forecasting performance of the 36 qualitative forecasts for the four best and worst forecasting models among the 240 specifications estimated. These best models perform quite well, with the top model accurately forecasting the direction of price movement in 30 out of 36 cases (83.33 percent). The next three models correctly forecast 29 out of 36, only one forecast worse. Interestingly, these best forecasting models all have longer autoregressive processes (with 9 or 10 lags) than the posterior model probabilities suggested would be best and also include corn price forecasts, not the cattle price forecasts favored by the posterior model probabilities.

Table 4 presents the forecasting performance of the five most probable and five least probable models; these are the models with the highest and lowest posterior model probabilities. The 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 performances, as measured by percent of correct predictions, that are noticeably worse than the best hog price forecasting models in Table 3. The most probable model correctly forecasts 23 out of the 36 price change signs (63.89 percent) with the other models in Table 4 predicting from 18 to 24 correctly. These most probable models do forecast more than 50 percent of the directions of movement correctly, which is some consolation, but their performance is not as good as hoped.

We also formed a composite forecast using the posterior model probabilities to construct a weighted average of all the 240 individual model forecasts. Because this is qualitative forecasting, if the sum of the posterior model probabilities on the set of models that predicted 1 is greater than 0.50, the composite forecast is a 1. The composite qualitative forecast correctly forecast 23 out of 36 out-of-sample price movements, the same as the most probable model.

Overall, the most probable models for hog prices displayed only slightly above average forecasting performance among the entire set of models estimated. Yet, while the forecasting performance of the most probable models is not what we might have hoped for, we do find that the best forecasting models include price forecasts of another commodity price (corn in our case). 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.

6 Conclusions

The Bayesian model specification procedure applied here to the qualitative forecasting of hog prices provided clear signals for the model specification of our hog price forecasting model. Unfortunately, the models with the highest model probabilities based on the in-sample data did not deliver above average out-of-sample qualitative forecasting performance. Still, the fact that the best performing model specifications, as measured by out-of-sample percent correct predictions, contained price forecasts for a different commodity (corn) 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)	AR(3)	DSPI; CTSL; HATCH; SF
PC (cents per bushel)	AR(3)	EXPORT^c; INVT^c; ACRES^c; ETHANOL
PS (cents per bushel)	AR(3)	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 4 and bottom 4 hog price forecasting models

by the percentage of correct out-of-sample forecasts

Top 4 models	% forecasts correct	Post Probability
1) AR(10)+DSPI$_t$+CTSL$_{t-1,t-2}$+SF$_{t-1}$+PKST$_{t-1}$ +Corn Forecasts$_t$	0.8333	<0.001
2) AR(8)+DSPI$_t$+CTSL$_{t-1,t-2}$+SF$_{t-1}$+PKST$_{t-1}$ +Corn Forecasts$_t$	0.8056	<0.001
3) AR(9)+DSPI$_t$+CTSL$_{t-1,t-2}$+SF$_{t-1}$+PKST$_{t-1}$ +Corn Forecasts$_t$	0.8056	<0.001
4) AR(9)+DSPI$_t$+CTSL$_{t-1,t-2}$+HATCH$_{t-1,t-2}$ +SF$_{t-1}$+PKST$_{t-1}$+Corn Forecasts$_t$	0.8056	<0.001
Bottom 4 models	**% forecasts correct**	**Post Probability**
1) AR(5)+CTSL$_{t-1,t-2}$+HATCH$_{t-1,t-2}$+SF$_{t-1}$+PKST$_{t-1}$	0.4444	<0.001
2) AR(5)+DSPI$_t$+CTSL$_{t-1,t-2}$+SF$_{t-1}$+PKST$_{t-1}$	0.4444	<0.001
3) AR(4)+DSPI$_t$+CTSL$_{t-1,t-2}$+HATCH$_{t-1,t-2}$+SF$_{t-1}$ +Cattle Forecasts$_t$	0.4444	<0.001
4) AR(4)+DSPI$_t$+CTSL$_{t-1,t-2}$+HATCH$_{t-1,t-2}$+PKST$_{t-1}$ +Cattle Forecasts$_t$	0.4444	<0.001

Table 4. Top 5 and bottom 5 hog price forecasting models by posterior probability

5 Most Probable Models	Post Probability	% forecasts correct
1) AR(3)+DSPI$_t$+HATCH$_{t-1,t-2}$+SF$_{t-1}$+PKST$_{t-1}$ +Cattle Forecasts$_t$	0.908	0.6389
2) AR(3)+DSPI$_t$+HATCH$_{t-1,t-2}$+SF$_{t-1}$+PKST$_{t-1}$ +Soybean Forecasts$_t$	0.035	0.5833
3) AR(3)+DSPI$_t$+HATCH$_{t-1,t-2}$+SF$_{t-1}$+PKST$_{t-1}$ +Corn Forecasts$_t$	0.030	0.6667
4) AR(3)+DSPI$_t$+CTSL$_{t-1,t-2}$+SF$_{t-1}$+PKST$_{t-1}$ +Cattle Forecasts$_t$	0.011	0.5000
5)AR(4)+DSPI$_t$+HATCH$_{t-1,t-2}$+SF$_{t-1}$+PKST$_{t-1}$ +Cattle Forecasts$_t$	0.007	0.5556
5 Least Probable Models	**Post Probability**	**% forecasts correct**
1) AR(12)+CTSL$_{t-1,t-2}$+HATCH$_{t-1,t-2}$+SF$_{t-1}$ +PKST$_{t-1}$+Soybean Forecasts$_t$	<0.001	0.6111
2) AR(12)+CTSL$_{t-1,t-2}$+HATCH$_{t-1,t-2}$+SF$_{t-1}$ +PKST$_{t-1}$+Corn Forecasts$_t$	<0.001	0.6667
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	0.6389
4) AR(12)+CTSL$_{t-1,t-2}$+HATCH$_{t-1,t-2}$ +SF$_{t-1}$+PKST$_{t-1}$+Cattle Forecasts$_t$	<0.001	0.6111
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	0.6667
Composite forecasts		0.6389