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Futures-Based Forecasts of U.S. Crop Prices

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Abstract

This study proposed two futures-based models for forecasting cash prices of corn, soybeans, wheat and cotton over the period 2000-2016. The difference model predicts changes in cash prices as a function of changes in futures prices. The regime model specifies different market regimes and models cash price levels based on observed futures prices in various regimes. The out-of-sample performance of both models was compared to the benchmark of a 5-year moving average over the 2013-2016 sub-period. Our results suggest that the regime model performed best for corn and soybeans. While, neither model beat the benchmark for wheat at the longer forecasted horizons, the difference model performed well at short forecast horizons (up to 5-months ahead). Both models performed better than the benchmark for cotton price forecasts, but they were not significantly different from each other.

Key words: corn, soybeans, wheat, cotton, price forecasts, futures prices, forecast evaluation.

Introduction

In volatile agricultural markets, price forecasts help form expectations that inform investment, production and marketing decisions. U.S. crop prices have become significantly more volatile over the last decade. Figure 1 shows changes in national average cash prices for corn, soybean, wheat, and cotton over the past 17 years. Monthly corn prices ranged from 1.52$/bu to 7.63 $/bu, soybean prices from 4.09$/bu to 16.2$/bu, soft red winter wheat prices varied from 1.95$/bu to 9.7$/bu and cotton prices were as low as 0.27$/lb and as high as 0.94$/lb. This volatile market environment creates additional risks for agricultural market participants and provides a need for reliable price forecasts.

The U.S. Department of Agriculture (USDA) and various private agencies generate price forecasts for main agricultural commodities based on historical data, expert opinion, and current market information (Hoffman, Etienne, Irwin, Colino, & Toasa, 2015; Isengildina-Massa & MacDonald, 2013; Meyer, 1998; Westcott & Hoffman, 1999). One of the main drawbacks of many price forecasts is their backward looking nature as most statistical price models are based on patterns in historical price series. On the other hand, several studies (Chinn & Coibion, 2014; Husain & Bowman, 2004; Manfredo & Sanders, 2004; Reeve & Vigfusson, 2011; Tomek, 1997) have demonstrated that futures-based forecasts perform well relative to time-series and judgmental forecasts, especially during periods when there is a sizeable difference between spot and futures prices. Futures-based forecasts can also be constructed for longer lead times (i.e., 12 month and 16 months ahead forecasts) as most futures contracts begin trading several years before expiration. Therefore, the goal of this study was to develop futures-based price forecasting models for corn, soybeans, soft red winter (SRW) wheat, and cotton. Evaluation of these models' performance revealed how informative such models were at various forecasting horizons and how well they performed relative to a 5-year moving average benchmark.

Data

Monthly national cash price data for corn, soybeans, soft red winter (SRW) wheat, and cotton were obtained from USDA, NASS Quickstats. The prices of futures contracts expiring closest to, but not before, the cash market month represent a market consensus regarding the respective cash prices. The futures contract selection for each spot price month is shown in Table 1. Futures price data were obtained from Quandl. CME contracts were used for corn, soybeans, and wheat and ICE contracts were used for cotton.

Descriptive statistics shown in Table 2 demonstrate variability in commodity cash prices during the period of study, 2000-2016. The price of corn averaged \$3.57/bushel but ranged from \$1.52/bushel to \$7.63/bushel. The price of soybeans averaged \$8.84/bushel with a standard deviation of \$3.30\$/bu. Similar patterns were observed in wheat with an average price of \$4.59/bushel and a standard deviation of \$1.73/bushel, and cotton with mean price of \$0.59/lb and a standard deviation of \$0.16/lb. Figure 1 shows that this volatility was not uniform and increased substantially in the post 2005 sub-period. From the visual inspection of price series it is not clear whether they are stationary (have variances and covariances that are finite or independent of time).

The stationarity of the price series is evaluated using the augmented Dickey-Fuller unit root test (ADF) and the Phillips and Perron (1988) test (PP). The null hypothesis for both tests is that there is a unit root in the data. In the presence of unit roots in the series, standard ordinary least squares (OLS) models can no longer be applied and there may be a spurious regression.[2] Results of the stationarity tests shown in table 3 indicate that we failed to reject the null hypothesis in most cases, indicating that the price series are likely non-stationary. However, these standard unit root tests suffer from a well-known weakness when testing the stationarity of a series that exhibits a structural break. This is because they tend to mistakenly identify a structural break in the series as evidence of non-stationarity and therefore fail to reject the null hypothesis. Two alternative approaches are used in this study to address non-stationarity or structural break problems in the data: a difference model and a regime model, as described in the following section.

Conceptual framework

The underlying premise of futures-based forecasting models is that national monthly cash price for each commodity may be predicted using the futures price of its front contract:

$$S_{t,i} = \beta_0 + \beta_1 F_{t,i} + \varepsilon_{t,i}, \quad (1)$$

where *S* is cash or spot price, *F* is the price of the futures contract expiring closest to but not before *t*, *t* is the month of the forecasted cash price and *i* is the lead time for futures prices used for forecasting. For example, to forecast the cash price of corn in June 2010 with *i* equal to 5, the

[2] Specifically, spurious regressions are characterized by high R^2 and statistically significant t-statistics; however, their results have no economic meaning (Granger and Newbold, 1974).

futures price of a July 2010 contract in January 2010 (5 months earlier) will be used. Two versions of this basic relationship were explored in this study.

First, following previous studies (Algieri & Kalkuhl, 2014; Fernandez, 2017; Granger & Newbold, 1974; Hoffman et al., 2015; Pederzoli & Torricelli, 2013), the relationship between cash and futures prices was estimated in difference form due to potential non-stationarity of price series:

$$(2) \qquad S_{t,i} - F_{t-i,1} = \beta_0 + \beta_1\left(F_{t,i} - F_{t-i,1}\right) + \varepsilon_{t,i},$$

where $F_{t-i,1}$ is the price of the futures contract closest to expiring at the time the forecast is made, which may be viewed as an approximation for the current cash price and all other variables are as described in equation 1.

Alternatively, Tomek (1997) suggested that when commodity prices "move from regimes with relatively little variability to regimes with great variability and possibly with large price spikes," these structural changes must be explicitly modeled. Verteramo and Tomek (2015) discussed that regime shifts in post 2005 price series are associated with demand shifts given a relatively fixed supply. Irwin and Good followed this approach in a series of studies (2016a, 2016b, 2016c, 2016d, and 2016e) focusing on corn and soybean prices. To extend this approach to our study, the following regression was estimated for each crop where regime variables for each year post 2005 were added to the traditional stocks-to-use equation:

$$(3) \qquad S = \alpha + \beta\ (1/\ Stocks\text{-}to\text{-}Use\ Ratio) + \lambda_1\ 2007 + \ldots + \lambda_{10}\ 2016.$$

Based on the magnitudes of the estimated λ coefficients, we clustered the combinations of marketing years into the following four regimes for each commodity: strong, moderately strong, moderately weak, and weak as shown in table 4. Marketing years for soybeans were clustered into just three regimes: strong, moderately strong, and weak. According to USDA definitions, the marketing year for corn and soybeans lasts from September through August, wheat from June to May, and cotton August to July. A dummy variable for each regime was created and incorporated into the basic forecasting equation as following:

$$(4) \qquad S_{c,t} = \alpha_0 + \beta_1 F_{c,t-i} + \beta_2 Strong_c + \beta_3 Moderately\ Strong_c + \beta_4 Moderately\ Weak_c + \beta_5 Weak_c + \varepsilon_{c,t,i},$$

where *c* refers to a particular commodity, *t* represents the month of the forecasted cash price, and *i* the lead time of the futures price forecasts. Regime dummies take the value of one in the years indicated in table 4, and 0 otherwise.

Both difference model (equation 2) and regime model (equation 4) were estimated using data from 2000 to 2016 with lead times from one to 16 months. For example, to forecast the cash price of corn in June 2017, the average monthly prices of the futures contract expiring in July 2017 observed during February 2016 (16 months lead) through May 2017 (1 month lead) were used to generate 1 through 16 months ahead forecasts.

Forecast errors were calculated as *e = Actual - Forecasted*. Performance of the two alternative models was assessed for the out-of-sample period January 2013-December 2016 and focused on bias as measured by mean errors (ME) and size of errors as measured by root mean squared errors (RMSE). A 5-year moving average cash price for each month was used as a benchmark for performance evaluation. For example, the average of cash prices in June 2011, June 2012, June 2013, June 2014 and June 2015 was used as a forecasted cash price for June 2016. The difference between alternative forecasts was evaluated using a modified Diebold Mariano (MDM) test (Harvey, Leybourne, & Newbold, 1997):

$$(5) \qquad MDM = \sqrt{\frac{T-1}{\frac{1}{T}\sum_{i=1}^{n}(d_t-\bar{d})^2}}\,\bar{d},$$

where $\mathrm{d} = |e_1| - |e_2|$ (e_1 *is error* from model 1, and e_2 *is error* from model 2). Furthermore, the test of forecast encompassing (Manfredo & Sanders, 2004) was used to assess whether these alternative models add information to the benchmark approach of using a 5-year moving average as a forecast.

$$(6) \quad e_{1t} = \alpha + \lambda(e_{1t} - e_{2t}) + \varepsilon_t,$$

where e_{1t} is the forecast error of an alternative model and e_{2t} is the error of a benchmark model. The null hypothesis of encompassing test is λ equal to zero. Rejection of null hypothesis means that a combination of these two approaches will have smaller forecast errors than either of them. This also means that the alternative model contains all the information included in the benchmark model (Sanders & Manfredo, 2004; Colino & Irwin, 2008).

Performance Evaluation

R-squared values for difference and regime models estimated using the full data sample shown in Table 5 may be viewed as in-sample measures of model fit. While the results for the regime model appear much better than the difference model, these findings should not be compared because of differences in the dependent variables. The difference model explains the change in cash price from current to forecasted months, while the regime model predicts the level of cash price in the forecasted month. Changes in model performance across forecasting horizons (k) can, however, be compared. For the difference model, R-squared decreased at shorter horizons and increased at longer horizons. For the regime model, R-squared for all the four commodities decreased gradually at longer horizons, a more anticipated pattern. Thus, regime model explained from about 97% of variation in one-month ahead corn prices to 91% of variation in 16 month ahead corn prices. Similar patterns were observed in other commodities with cotton forecasts characterized by the lowest R-squared values ranging from 69% for 16-month ahead forecasts to 81% for one-month ahead forecasts.

The remainder of this section describes the results of out-of-sample tests that were used for performance evaluations. To perform these tests, the models were estimated for corn, soybeans, wheat, and cotton using data from 2000 to 2012 for lead times ranging from one to 16 months. These estimates were used to generate forecasts for 2013. The models were re-estimated using data from 2000 to 2013 to generate forecasts for 2014. Thus, four years of 16 out-of-sample forecasts were generated for out-of-sample evaluation of the model's predictive accuracy.

Figure 2 compares the errors of three alternative forecast methods (benchmark, model 1=difference model, model 2=regime model) for 6-months ahead forecasts for each commodity included in this study over the out-of-sample period. This figure shows that with the exception of January 2013 forecasts, most corn forecast errors were negative, suggesting a tendency to overestimate observed prices, particularly in October and November 2014. This pattern makes sense as prices were just coming off the highs observed in 2011-2013. The regime model appears to have the lowest bias in these 6-months ahead corn forecasts. Soybean forecasts had mostly positive errors from mid-2013 to mid-2014, followed by negative errors from mid-2014 through mid-2016. Again, model 2 (regime model) errors appear slightly smaller than those of alternative forecasts. The pattern is very different for wheat forecasts where model 2 has much larger errors associated with underestimation of wheat prices from June 2013 through May 2014, which was likely caused by an incorrect assumption regarding the market regime used for this marketing year. Looking back at the selection of market regimes described in table 4, there was only a single year, 2008/09 that had conditions similar to 2013/14, which is what likely caused this mistake. Results for cotton are mixed, with an obvious tendency for positive errors throughout the out-of-sample period. This suggests underestimation, but no clear outperforming model. Statistical differences across forecasting methods for all forecasting horizons will be examined in the remainder of this section.

Average errors and the test of bias for alternative forecasting approaches are shown in table 6. Results demonstrate that all three corn price forecasts were biased in the out-of-sample period. The benchmark and the difference models had a tendency to overestimate corn prices (resulting in negative errors), while the regime model tended to underestimate prices leading to positive errors. The magnitude of bias, while significantly different from zero, appears much smaller for the regime model, especially at longer forecast horizons. Soybean price forecasts were also biased in the out-of-sample period. All three approaches had a tendency to overestimate soybean prices (resulting in negative errors). The magnitude of bias of the regime model tended to be the smallest across the three methods at longer horizons. A similar pattern was observed for wheat price forecasts. The size of bias of the regime model also tended to be the smallest among all approaches at longer horizons. Cotton price forecasts had a tendency to underestimate prices (resulting in positive errors). The extent of bias of the difference model and regime model were close to each other and both of them were lower than the benchmark.

Table 7 compares RMSEs for three forecast alternatives for each crop. RMSEs reflect the size of errors in the out-of-sample period. The smallest errors across three forecasting alternatives for each forecast horizon are highlighted in bold. Results show that the errors of model 2 (regime model) were the smallest for corn price forecasts. These RMSEs of model 2 were consistent across forecast horizons while benchmark and model 1 (difference model) errors increased substantially at longer horizons. Findings for soybeans were similar to those for corn. The only difference was that model 1 performed better in extremely short horizons (1-2 months ahead) while model 2 had smaller errors for the remainder of the forecasting cycle. On the other hand, results for wheat were very different with the benchmark showing the best performance for 6- to 15-months-ahead forecasts and model 1 performing better at 1-5 months horizons. For cotton, model 2 had better performance at shorter horizons (2-9 months ahead) and model 1 performed better at longer horizons (10-16 months ahead). The cotton price RMSEs of these two models were very similar, and smaller than the benchmark. In summary, model 2 was preferred for corn and soybeans, model 1 and the benchmark for wheat, and both models 1 and 2 for cotton. The next set of results examines the statistical differences between the alternative models.

Tables 8a and 8b show the results of the Modified Diebold-Mariano (MDM) tests for corn and soybeans and for wheat and cotton, respectively. MAEs for each approach are shown to facilitate interpretation of the MDM test results. MDM tests examine whether the difference between errors from two alternative models are significantly different from zero. A positive difference means that the first model has more errors than the second one, indicating that the second model performs better based on smaller errors. MAEs help uncover the size of errors associated with each approach. Since the null hypothesis is that the difference is zero, rejection of the null implies that one model is significantly more accurate than the other. For example, results from the 1- and 2- step ahead forecasts of corn prices indicate that both model 1 and model 2 are better than the benchmark, but not better than each other. At all other forecast horizons, model 2 is significantly more accurate than model 1 and the benchmark. A similar set of results with strong evidence of superior performance of model 2 is shown for soybeans. Results for wheat and cotton shown in table 8b are very different. Model 1 is better than the benchmark for horizons 2-5. The signs of all other significant test statistics for wheat are negative, suggesting that the first model used for comparison is better: benchmark is better than model 2 at horizons 5-8; benchmark is better than model 1 at horizons 9-15; model 1 is better than model 2 at horizons 1-7. Based on these findings, only model 1 offers advantages for wheat price forecasting at short horizons (1-5), but to the model has not beat the benchmark in all other cases. Results for cotton are slightly better: both model 1 and 2 are significantly better than the benchmark at horizons 1-8 and 13-16; but the errors from each model are not significantly different from each other. In summary, model 2 was preferred for corn and soybeans, the benchmark was best for wheat (except short horizons of less than 5 months where model 1 performed better), and both model 1 and model 2 worked well for cotton.

Table 9 shows the results of forecast encompassing tests. The first set of results compares the benchmark and model 1 (difference model) and the results demonstrate that model 1 added information to the benchmark for corn at forecast horizons 1-13 and for other commodities at all forecast horizons. This means that a combination of these two approaches would have a smaller forecast error than the benchmark. Comparison of the benchmark and model 2 in the second set of results reveals that model two added value to the benchmark forecasts for corn, soybeans and cotton at all forecast horizons, and for wheat at horizons 1,2, and 7-16. Thus, even though the proposed models did not beat the benchmark in terms of accuracy for wheat, they are still adding useful information that may help reduce forecast errors.

Summary and Conclusions

This study proposed two futures-based models for forecasting cash prices of corn, soybeans, wheat and cotton over the period 2000-2016. The difference model predicts changes in cash prices as a function of changes in futures prices. The regime model specifies different market regimes and models cash price levels based on observed futures prices in various regimes. The out-of-sample performance of both models was compared to the benchmark of a 5-year moving average over the 2013-2016 sub-period. Our results suggest that the regime model performed best for corn and soybeans. While neither model beat the benchmark for wheat at the longer forecast horizons, the difference model performed well at short forecast horizons (up to 5-months ahead). Both models performed better than the benchmark for cotton price forecasts, but they were not significantly different from each other. Encompassing tests demonstrated that the proposed models provide useful information even for wheat price forecasts that were not able to outperform the benchmark. Overall, this study demonstrates that futures prices provide useful information for anticipating future cash prices. Since the benefits of combination forecasts have been demonstrated in previous literature (e.g., Colino, Irwin and Garcia, 2008), it would be interesting to investigate whether combining the difference and the regime model approaches proposed in this study would result in better forecasts.

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Table 1. Front Futures Contract Selection for Various Spot Months.

Spot Month	**Corn (C)**	**Soybeans (S)**	**Wheat (W)**	**Cotton (CT)**
January_t	March(CH)_t	March(SH)_t	March(WH)_t	March(CTH)_t
February_t	March(CH)_t	March(SH)_t	March(WH)_t	March(CTH)_t
March_t	May(CK)_t	May(SK)_t	May(WK)_t	May(CTK)_t
April_t	May(CK)_t	May(SK)_t	May(WK)_t	May(CTK)_t
May_t	July(CN)_t	July(SN)_t	July(WN)_t	July(CTN)_t
June_t	July(CN)_t	July(SN)_t	July(WN)_t	July(CTN)_t
July_t	September(CU)_t	August(SQ)_t	September(WU)_t	October(CTV)_t
August_t	September(CU)_t	September(SU)_t	September(WU)_t	October(CTV)_t
September_t	December(CZ)_t	November(SX)_t	December(WZ)_t	October(CTV)_t
October_t	December(CZ)_t	November(SX)_t	December(WZ)_t	December(CTZ)_t
November_t	December(CZ)_t	January(SF)_{t+1}	December(WZ)_t	December(CTZ)_t
December_t	March(CH)_{t+1}	January(SF)_{t+1}	March(WH)_{t+1}	March(CTH)_{t+1}

Note: Corn, soybeans and wheat are CBOT contracts; cotton is an ICE contract.

Table 2. Descriptive Statistics for Cash Prices, Jan 2000 - Dec 2016.

Variable	Mean	Std.Dev.	Min	Max
Corn	3.573	1.574	1.52	7.63
Soybeans	8.842	3.295	4.09	16.20
Wheat	4.591	1.725	1.95	9.70
Cotton	0.585	0.161	0.27	0.94

Note: N=204

Table 3. Stationarity Analysis of Cash Prices, 2000-2016.

	Corn	Soybeans	Wheat	Cotton
ADF	-1.28 (0.64)	-1.45 (0.56)	-1.86 (0.35)	-1.68 (0.44)
ADF (trend)	-0.78 (0.97)	-1.27 (0.89)	-1.62 (0.78)	-2.14 (0.52)
ADF (drift)	-1.28 (0.10)	-1.45* (0.07)	-1.86** (0.03)	-1.68** (0.05)
PP	-1.55 (0.51)	-1.70 (0.43)	-1.91 (0.33)	-1.87 (0.35)
PP (trend)	-1.39 (0.86)	-1.95 (0.63)	-1.76 (0.73)	-2.46 (0.35)

Notes: ADF stands for Augmented Dickey Fuller test. PP stands for Phillips-Perron test. P-values are shown in parentheses. Asteriscs show statistical significance: * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 4. Marketing Years Corresponding to Alternative Market Regimes.

Commodity Marketing Year Market Price Regime	**Corn** Sep.-Aug.	**Soybean** Sep.-Aug.	**Wheat** Jun.-May	**Cotton** Aug.-Jul.
Strong	2011/12; 2012/13	2012/13	2011/12; 2012/13	2011/12; 2007/08
Moderately Strong	2010/11	200/11; 2011/12; 2013/14	2008/09; 2013/14; 2014/15	2010/11; 2012/13; 2013/14
Moderately Weak	2007/08; 2008/09; 2013/14	-----	2009/10; 2010/11; 2015/16	2014/15; 2008/09; 2015/16
Weak	2009/10; 2014/15; 2015/16;	2007/08; 2008/09; 2009/10; 2014/15; 2015/16	2007/08	2009/10

Table 5. R-squared Values of Full-Sample Models, 2000-2016.

	Difference model				Regime model			
k	Corn	Soybeans	Wheat	Cotton	Corn	Soybeans	Wheat	Cotton
1	0.24	0.40	0.32	0.04	0.97	0.98	0.94	0.81
2	0.20	0.37	0.26	0.11	0.96	0.96	0.90	0.81
3	0.19	0.35	0.18	0.24	0.95	0.95	0.87	0.82
4	0.22	0.37	0.16	0.43	0.94	0.93	0.85	0.83
5	0.22	0.38	0.18	0.56	0.93	0.92	0.84	0.84
6	0.22	0.38	0.20	0.61	0.93	0.91	0.82	0.84
7	0.24	0.38	0.18	0.62	0.92	0.90	0.80	0.82
8	0.22	0.35	0.16	0.64	0.91	0.90	0.80	0.80
9	0.22	0.34	0.16	0.62	0.91	0.90	0.79	0.78
10	0.22	0.34	0.15	0.60	0.91	0.89	0.79	0.75
11	0.24	0.37	0.15	0.59	0.91	0.89	0.79	0.73
12	0.25	0.40	0.18	0.59	0.91	0.89	0.78	0.71
13	0.26	0.42	0.19	0.59	0.91	0.89	0.76	0.70
14	0.27	0.46	0.17	0.60	0.91	0.90	0.75	0.69
15	0.29	0.48	0.24	0.61	0.91	0.91	0.76	0.69
16	0.32	0.51	0.30	0.62	0.91	0.90	0.76	0.69

Note: k is forecast lead time in months.

Table 6. Out-of-Sample Mean Errors and t-test for Alternative Forecasts, 2013-2016.

	Corn			Soybeans			Wheat			Cotton		
k	Benchmark	Model 1	Model 2	Benchmark	Model 1	Model 2	Benchmark	Model 1	Model 2	Benchmark	Model 1	Model 2
1	0.21 ***	0.18 ***	0.15 ***	0.28 ***	0.26 ***	0.37 ***	0.21 ***	0.23 ***	0.42 ***	0.12 ***	0.07 ***	0.07 ***
2	0.12 *	0.10 **	0.11 **	0.21 *	0.21 **	0.31 ***	0.15	0.14 **	0.33 ***	0.12 ***	0.07 ***	0.07 ***
3	0.01	0.01	0.10 **	0.11	0.13	0.16 **	0.09	0.02	0.30 **	0.11 ***	0.08 ***	0.07 ***
4	-0.10	-0.08	0.10 **	-0.03	0.07	-0.03	0.03	-0.10	0.27 **	0.10 ***	0.08 ***	0.07 ***
5	-0.23 ***	-0.18 **	0.08 *	-0.17 *	0.00	-0.16	-0.04	-0.22 ***	0.24 *	0.09 ***	0.08 ***	0.07 ***
6	-0.33 ***	-0.26 ***	0.08 *	-0.27 *	-0.03	-0.23	-0.11	-0.33 ***	0.19	0.09 ***	0.08 ***	0.07 ***
7	-0.38 ***	-0.30 ***	0.09 **	-0.32 **	0.00	-0.25	-0.13	-0.41 ***	0.09	0.08 ***	0.08 ***	0.07 ***
8	-0.42 ***	-0.36 ***	0.11 **	-0.39 **	-0.04	-0.27 *	-0.16	-0.48 ***	-0.04	0.07 ***	0.08 ***	0.07 ***
9	-0.47 ***	-0.41 ***	0.11 **	-0.50 ***	-0.17	-0.28 *	-0.19 *	-0.54 ***	-0.13	0.05 ***	0.07 ***	0.06 ***
10	-0.53 ***	-0.47 ***	0.12 ***	-0.61 ***	-0.30 *	-0.29 *	-0.22 *	-0.61 ***	-0.19	0.04 ***	0.06 ***	0.06 ***
11	-0.56 ***	-0.51 ***	0.13 ***	-0.71 ***	-0.33 *	-0.31 **	-0.25 **	-0.67 ***	-0.20	0.03 *	0.05 ***	0.05 ***
12	-0.64 ***	-0.54 ***	0.12 ***	-0.80 ***	-0.36 *	-0.32 **	-0.29 **	-0.72 ***	-0.18	0.02	0.05 ***	0.04 ***
13	-0.71 ***	-0.60 ***	0.12 ***	-0.89 ***	-0.43 **	-0.32 **	-0.33 ***	-0.77 ***	-0.16	0.01	0.04 ***	0.04 ***
14	-0.78 ***	-0.68 ***	0.11 **	-1.00 ***	-0.47 **	-0.33 **	-0.41 ***	-0.87 ***	-0.14	0.00	0.04 ***	0.04 ***
15	-0.85 ***	-0.73 ***	0.10 **	-1.15 ***	-0.56 **	-0.37 **	-0.55 ***	-0.87 ***	-0.15	-0.01	0.03 ***	0.04 ***
16	-0.93 ***	-0.81 ***	0.09 *	-1.34 ***	-0.83 ***	-0.42 **	-0.54 ***	-0.83 ***	-0.22	-0.02	0.02 **	0.04 ***

Notes: Model 1 refers to difference model and Model 2 refers to regime model. K is the forecast lead time. N= 48 For each value. Mean error is in $/bu for corn, soybeans, and wheat and in $/lb for cotton. The null hypothesis for t-test is mean=0. Asteriscs show statistical significance: * p<0.10, ** p<0.05, *** p<0.01.

Table 7. Out-of-Sample Root Mean Squared Errors for Alternative Forecasts, 2013-2016.

	Corn			Soybeans			SRW Wheat			Cotton		
k	Benchmark	Model 1	Model 2	Benchmark	Model 1	Model 2	Benchmark	Model 1	Model 2	Benchmark	Model 1	Model 2
1	0.49	0.34	**0.33**	0.73	**0.54**	0.75	0.53	**0.41**	0.66	0.15	**0.08**	0.09
2	0.47	0.34	**0.31**	0.80	**0.65**	0.77	0.65	**0.47**	0.76	0.15	0.09	**0.09**
3	0.52	0.37	**0.31**	0.85	0.79	**0.62**	0.72	**0.53**	0.88	0.15	0.09	**0.08**
4	0.53	0.43	**0.31**	0.93	0.94	**0.58**	0.71	**0.55**	0.95	0.14	0.10	**0.08**
5	0.55	0.49	**0.31**	0.97	1.01	**0.63**	0.64	**0.56**	0.95	0.13	0.10	**0.09**
6	0.57	0.53	**0.28**	1.01	1.03	**0.67**	**0.59**	0.61	0.93	0.13	0.10	**0.09**
7	0.66	0.58	**0.28**	1.16	1.05	**0.70**	**0.65**	0.66	0.88	0.12	0.10	**0.09**
8	0.78	0.69	**0.30**	1.31	1.10	**0.73**	**0.74**	0.77	0.86	0.12	0.10	**0.10**
9	0.88	0.77	**0.31**	1.42	1.14	**0.76**	**0.78**	0.85	0.86	0.11	0.10	**0.10**
10	0.96	0.86	**0.33**	1.53	1.21	**0.78**	**0.81**	0.92	0.90	0.10	**0.10**	0.10
11	1.03	0.93	**0.34**	1.64	1.29	**0.79**	**0.84**	0.99	0.94	0.10	**0.09**	0.09
12	1.12	1.01	**0.33**	1.74	1.37	**0.79**	**0.87**	1.04	0.96	0.10	**0.09**	0.09
13	1.20	1.10	**0.33**	1.83	1.48	**0.81**	**0.90**	1.10	1.00	0.10	**0.09**	0.09
14	1.25	1.18	**0.32**	1.89	1.54	**0.81**	**0.93**	1.18	0.99	0.11	**0.08**	0.09
15	1.28	1.22	**0.32**	1.97	1.61	**0.84**	**1.00**	1.17	1.01	0.11	**0.08**	0.09
16	1.30	1.29	**0.32**	2.08	1.69	**0.86**	1.04	1.14	**1.01**	0.11	**0.09**	0.09

Notes: Model 1 refers to difference model and Model 2 refers to regime model. K is the forecast lead time. N= 48 For each value. Root mean squared error is in $/bu for corn, soybeans, and wheat and in $/lb for cotton. Smallest errors across alternative forecasts for each k are highlighted in bold.

Table 8a. Out-of-Sample Rooted MDM test for Alternative Forecasts, 2013-2016.

	Corn						Soybeans					
Models	B	1	2	B&1	B&2	1&2	B	1	2	B&1	B&2	1&2
k	MAE			MDM statistic			MAE			MDM statistic		
1	0.36	0.35	0.34	4.53 ***	6.22 ***	1.32	0.55	0.51	0.63	2.88 ***	0.37	-2.81 ***
2	0.35	0.35	0.35	3.11 ***	4.20 ***	0.77	0.62	0.66	0.72	2.04 **	0.67	-1.44
3	0.38	0.38	0.37	4.03 ***	4.18 ***	1.84 *	0.71	0.79	0.75	1.03	3.13 ***	2.04 **
4	0.40	0.42	0.39	2.36 **	4.06 ***	2.54 **	0.81	0.91	0.74	0.75	5.32 ***	3.81 ***
5	0.43	0.51	0.43	1.93 *	4.24 ***	3.05 ***	0.80	1.02	0.77	-0.47	3.58 ***	4.42 ***
6	0.45	0.59	0.46	1.26	4.31 ***	3.51 ***	0.85	1.09	0.82	-0.54	3.12 ***	4.32 ***
7	0.52	0.64	0.48	2.35 **	5.18 ***	3.82 ***	0.95	1.14	0.85	0.17	3.53 ***	4.11 ***
8	0.62	0.71	0.51	2.49 **	6.08 ***	4.50 ***	1.11	1.17	0.90	1.95 *	4.62 ***	3.39 ***
9	0.73	0.79	0.53	3.27 ***	7.72 ***	5.83 ***	1.20	1.22	0.95	3.18 ***	4.99 ***	3.54 ***
10	0.82	0.87	0.56	2.90 ***	8.53 ***	7.13 ***	1.28	1.26	0.98	4.16 ***	5.53 ***	3.87 ***
11	0.89	0.93	0.57	3.40 ***	8.58 ***	7.63 ***	1.33	1.29	0.99	2.97 ***	5.86 ***	4.79 ***
12	1.00	1.02	0.57	3.89 ***	10.13 ***	8.98 ***	1.41	1.32	1.01	2.99 ***	6.24 ***	5.46 ***
13	1.08	1.10	0.57	3.69 ***	10.64 ***	9.15 ***	1.51	1.34	1.04	2.71 ***	6.42 ***	5.53 ***
14	1.12	1.19	0.56	2.22 **	10.18 ***	9.32 ***	1.54	1.36	1.05	2.09 **	6.45 ***	6.01 ***
15	1.13	1.28	0.55	1.00	9.26 ***	9.58 ***	1.61	1.38	1.09	1.84 *	6.69 ***	7.16 ***
16	1.14	1.36	0.55	-0.25	9.20 ***	10.15 ***	1.72	1.43	1.11	2.78 ***	6.98 ***	6.21 ***

Notes: B is the benchmark model, 1 is the Difference model, and 2 is the Regime model.K is the forecast lead time. N= 48 for each value. MDM test follows t distribution. Asteriscs show statistical significance: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 8b. Out-of-Sample Rooted MDM test for Alternative Forecasts, 2013-2016.

	Wheat						Cotton					
Models	B	1	2	B&1	B&2	1&2	B	1	2	B&1	B&2	1&2
k	MAE			MDM statistic			MAE			MDM statistic		
1	0.40	0.44	0.59	1.54	-0.97	-1.75 *	0.13	0.14	0.12	5.25 ***	3.96 ***	-0.92
2	0.47	0.46	0.72	2.63 **	-0.52	-1.91 *	0.12	0.14	0.12	4.58 ***	3.92 ***	-0.17
3	0.54	0.53	0.85	3.44 ***	-1.01	-2.47 **	0.12	0.13	0.11	3.62 ***	3.64 ***	0.97
4	0.55	0.56	0.95	3.57 ***	-1.61	-2.89 ***	0.11	0.12	0.10	2.81 ***	3.16 ***	1.62
5	0.50	0.62	1.06	2.27 **	-2.29 **	-2.92 ***	0.10	0.12	0.09	2.51 **	2.90 ***	1.69 *
6	0.46	0.67	1.11	0.04	-2.73 ***	-2.59 **	0.10	0.11	0.08	2.44 **	2.61 **	1.56
7	0.50	0.75	1.06	-0.63	-2.38 **	-1.87 *	0.10	0.10	0.08	2.28 **	2.21 **	1.28
8	0.56	0.84	1.01	-1.55	-1.77 *	-0.75	0.10	0.09	0.08	1.99 *	1.72 *	1.04
9	0.60	0.92	0.96	-2.52 **	-1.46	-0.03	0.09	0.09	0.08	0.90	1.00	0.70
10	0.64	0.98	0.95	-2.94 ***	-1.46	0.25	0.09	0.10	0.09	0.66	0.66	0.38
11	0.67	1.02	0.95	-3.17 ***	-1.33	0.77	0.08	0.11	0.09	0.72	0.64	0.25
12	0.73	1.03	0.97	-2.88 ***	-0.95	1.03	0.08	0.12	0.10	1.42	1.11	0.25
13	0.77	1.05	1.00	-3.03 ***	-0.64	1.20	0.09	0.12	0.10	2.42 **	1.72 *	0.08
14	0.78	1.06	1.03	-3.57 ***	-0.36	1.76 *	0.09	0.11	0.11	3.10 ***	2.44 **	0.14
15	0.85	1.00	1.11	-2.01 *	0.08	1.34	0.10	0.11	0.11	3.67 ***	3.02 ***	0.25
16	0.86	0.97	1.19	-1.41	-0.02	0.91	0.10	0.11	0.11	4.07 ***	3.30 ***	0.46

Notes: B is the benchmark model, 1 is the Difference model, and 2 is the Regime model.K is the forecast lead time. N= 48 for each value. MDM test follows t distribution. Asteriscs show statistical significance: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 9. Out-of-Sample Encompassing Test for Alternative Forecasts, 2013-2016.

	Benchmark & Model 1				Benchmark & Model 2			
k	Corn	Soybeans	SRW Wheat	Cotton	Corn	Soybeans	SRW Wheat	Cotton
1	9.29 ***	7.00 ***	7.51 ***	12.27 ***	9.52 ***	2.68 ***	3.18 ***	9.21 ***
2	6.80 ***	5.29 ***	7.54 ***	12.18 ***	9.52 ***	3.46 ***	2.53 **	10.77 ***
3	6.80 ***	3.49 ***	6.93 ***	11.60 ***	11.20 ***	6.68 ***	1.56	11.99 ***
4	4.92 ***	2.28 **	6.15 ***	9.95 ***	10.78 ***	8.75 ***	0.86	11.26 ***
5	3.58 ***	1.78 *	4.91 ***	8.65 ***	10.18 ***	8.35 ***	0.47	10.88 ***
6	2.30 **	2.12 **	3.69 ***	7.63 ***	9.50 ***	8.00 ***	0.85	11.03 ***
7	3.04 ***	3.10 ***	4.68 ***	6.91 ***	12.05 ***	9.43 ***	2.81 ***	11.32 ***
8	3.32 ***	3.81 ***	4.59 ***	6.63 ***	13.92 ***	10.35 ***	4.11 ***	10.52 ***
9	3.87 ***	4.25 ***	4.05 ***	5.74 ***	15.16 ***	10.82 ***	4.96 ***	10.09 ***
10	3.57 ***	4.58 ***	3.66 ***	5.37 ***	15.55 ***	11.30 ***	5.45 ***	10.16 ***
11	3.90 ***	4.49 ***	3.22 ***	5.28 ***	16.60 ***	12.10 ***	5.66 ***	10.75 ***
12	2.97 ***	4.20 ***	3.16 ***	6.54 ***	17.34 ***	13.01 ***	5.50 ***	11.20 ***
13	2.23 **	3.59 ***	2.47 **	9.72 ***	18.28 ***	13.13 ***	5.27 ***	11.67 ***
14	1.15	3.06 ***	2.33 **	10.71 ***	19.05 ***	13.25 ***	4.70 ***	11.82 ***
15	-0.08	2.61 **	3.03 ***	11.73 ***	18.99 ***	12.91 ***	3.52 ***	12.05 ***
16	-1.40	2.79 ***	3.94 ***	9.30 ***	17.58 ***	12.65 ***	3.31 ***	12.30 ***

Notes: Model 1 is difference model and Model 2 is regime model. K is the forecast lead time. N= 48 for each value. The null hypothesis is slope equal to 0. Asteriscs show statistical significance: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

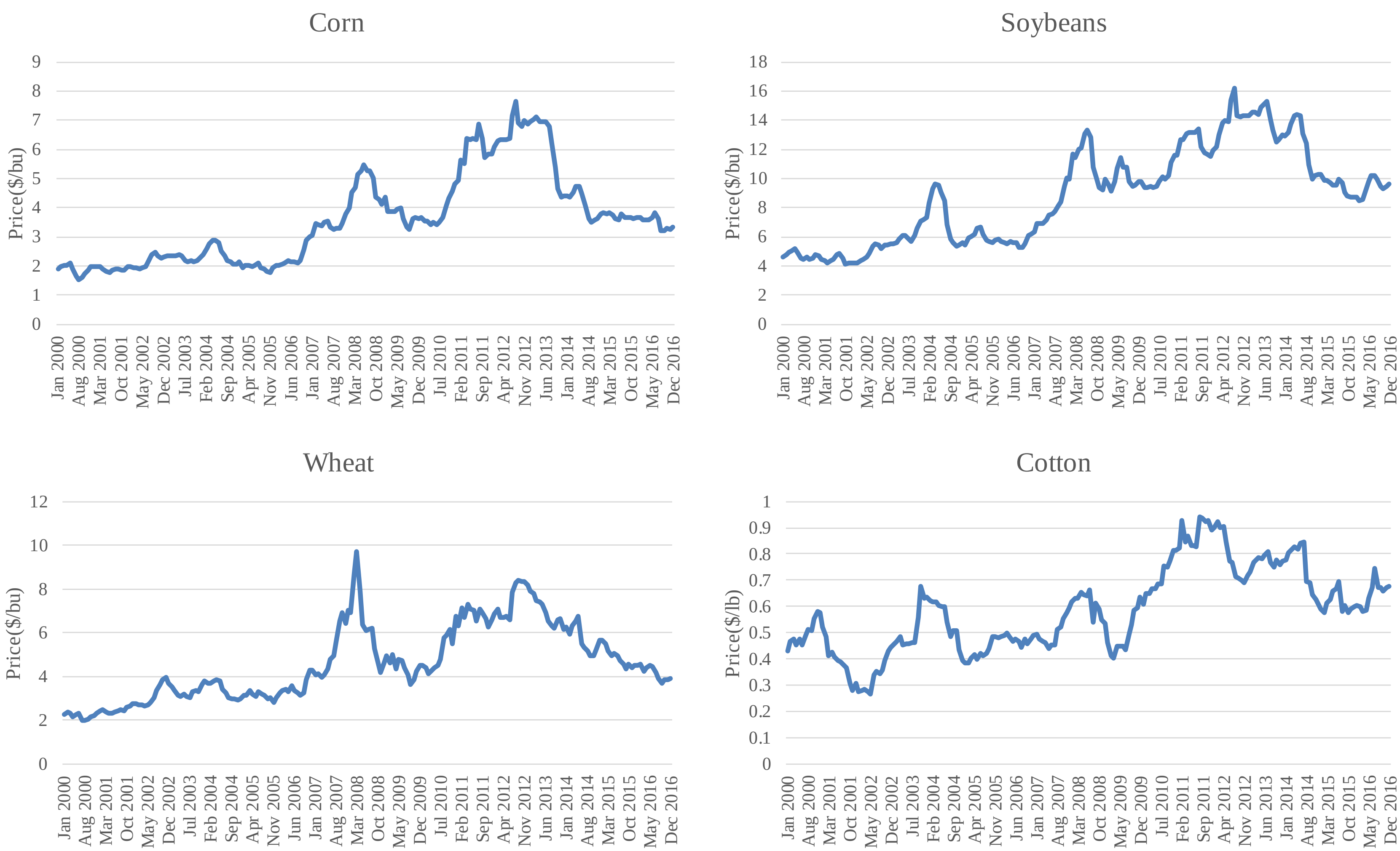

Figure 1. Commodity Cash Prices, 2000-2016.

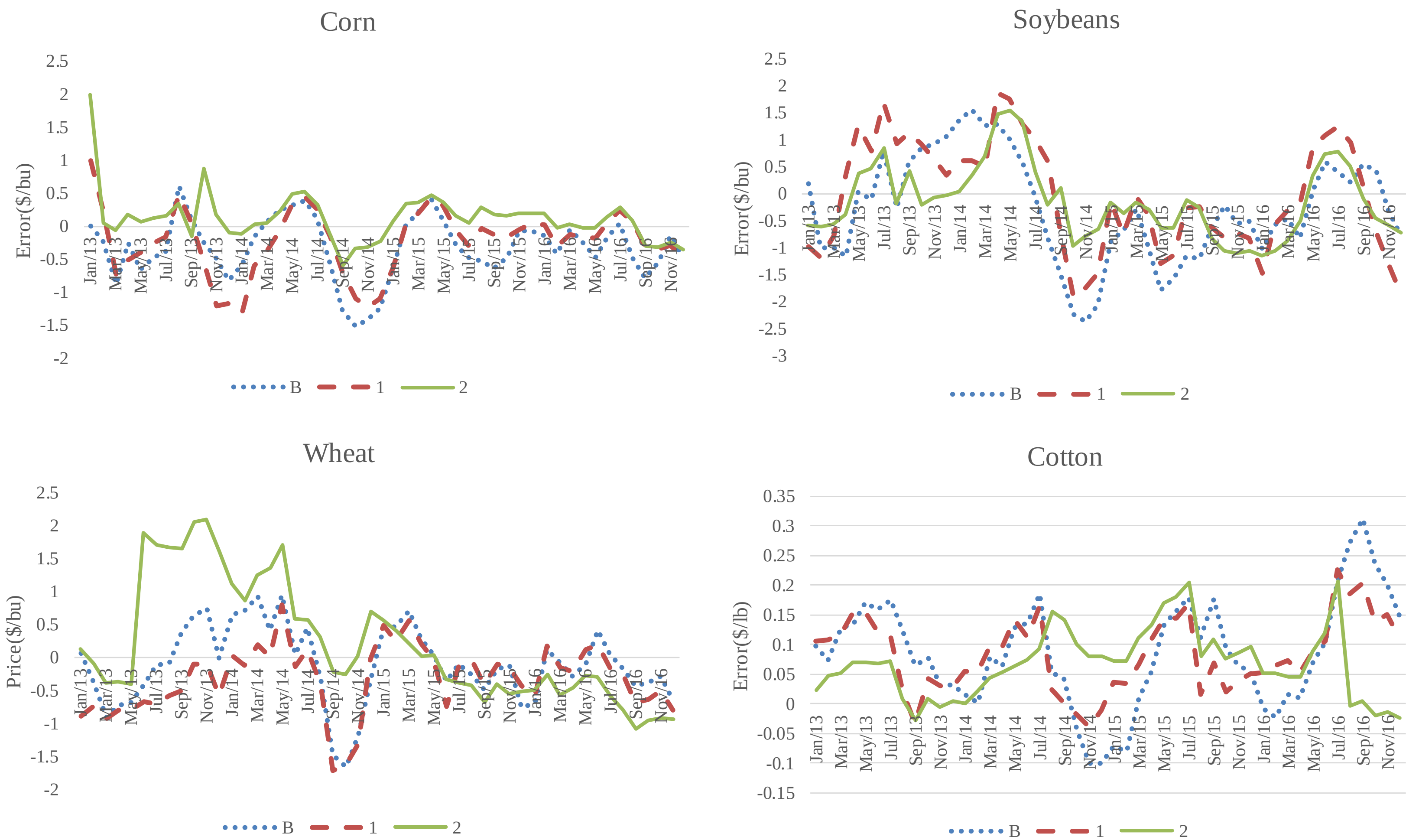

Figure 2. Out-of-Sample Errors for 6-months-ahead Forecasts.

Notes: B is benchmark, 1 is the difference model and 2 is the regime model.