

Futures-Based Forecasts of U.S. Crop Prices

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Abstract

Over the last decade, U.S. crop prices have become significantly more volatile. Volatile markets pose increased risks for the agricultural market participants and create a need for reliable price forecasts. Research discussed in this paper aims to develop different approaches to forecast crop cash prices based on the prices of related futures contracts.

Corn, soybeans, soft red winter wheat, and cotton are the focus of this research. Since price data for these commodities are non-stationary, this paper used two approaches to solve it. The first approach is to forecast the difference in prices between current and future period and the second is to use the market condition regimes. This paper considers the five-year moving average approach as the benchmark when comparing these approaches.

This research evaluated model performance using R-squared, mean errors, root mean squared errors, the modified Diebold-Mariano test, and the encompassing test. The results show that both the difference model and the regime model render better performance than the benchmark in most cases, but without a significant difference between each other. Based on these findings, the regime model was used to make forecasts of the cash prices of corn and soybeans, the difference model was used to make predictions for cotton, and the benchmark was used to forecast the SRW cash price.

Futures-Based Forecasts of U.S. Crop Prices

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General Audience Abstract

This research attempts to develop models to forecast cash prices of corn, soybeans, wheat and cotton using the underlying futures prices. Two alternative approaches are proposed. The difference model focuses on forecasting the differences between current and future time prices. The regime model uses external data to determine potential structural breaks in price relationships. The out-of-sample performance of these models is compared to the benchmark of a five-year average using various performance criteria. The results show that the regime model performs better for corn and soybeans, while the difference model is the best one for cotton. For wheat, the results are mixed, but the benchmark seems to show better performance than the proposed models.

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Acronyms

USDA	United States Department of Agriculture
MDM	Modified Diebold-Mariano
SRW	Soft Red Winter Wheat
NASS	National Agricultural Statistics Service
CME	Chicago Mercantile Exchange
ICE	Intercontinental Exchange
ADF	Augmented Dickey–Fuller
Pperron	Phillips–Perron
ME	Mean Errors
RMSE	Root Mean Squared Errors
B	Benchmark
DM	Difference Model
RM	Regime Model

Chapter 1: Introduction

1.1 Problem statement

In volatile agricultural markets, price forecasts help form expectations that support investment, production and marketing decisions. United States crop prices have become significantly more volatile during the last decade. Figures 1 to 4 show changes in the national average cash prices of corn, soybean, wheat, and cotton over the period of 2000 to 2016.

Monthly corn prices ranged from 1.52 \$/bu to 7.63 \$/bu; soybean prices ranged from 4.09 \$/bu to 16.2 \$/bu; SRW 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 poses additional risks for agricultural market participants and creates a need for reliable price forecasts.

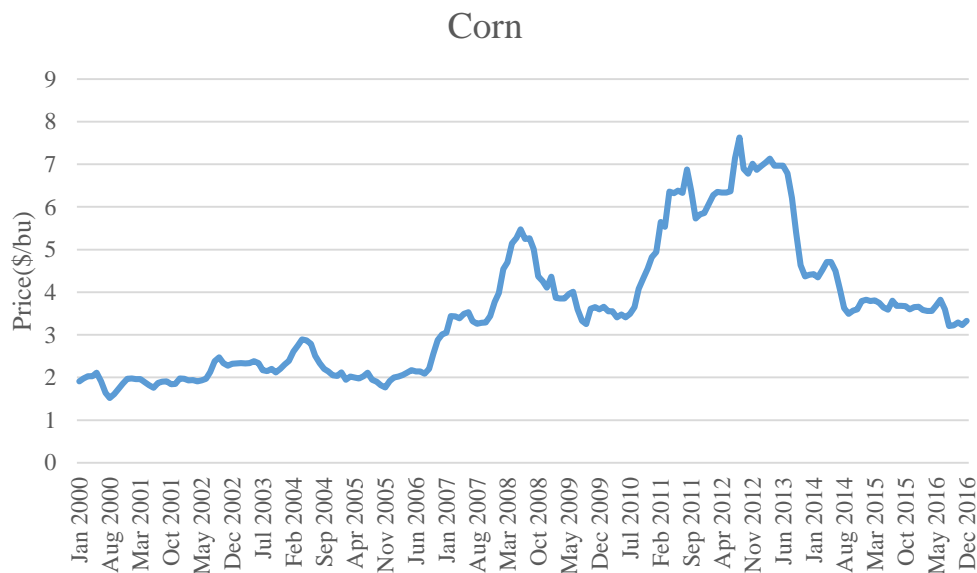


Figure 1. Commodity Cash Prices, 2000-2016 (corn)

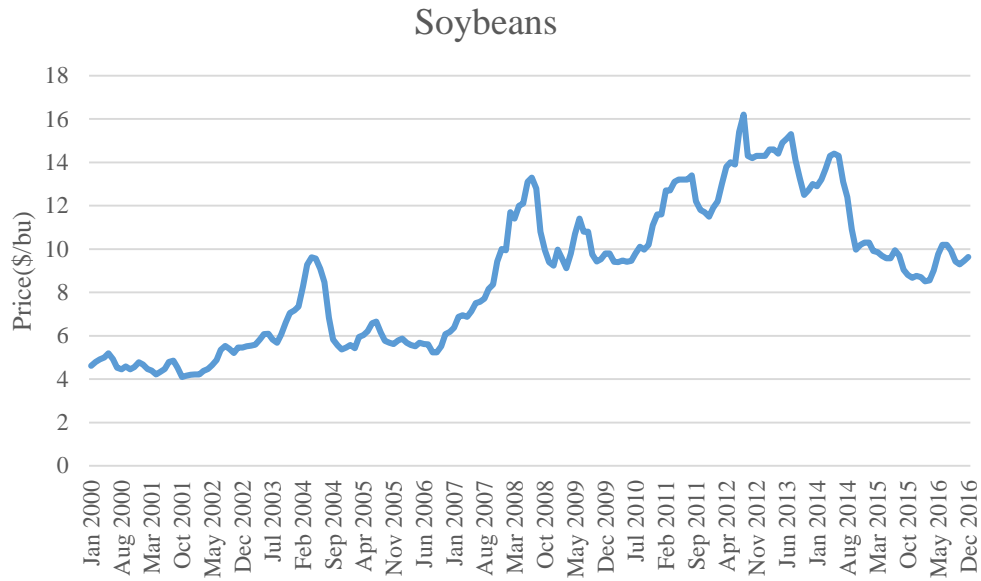


Figure 2. Commodity Cash Prices, 2000-2016 (soybeans)

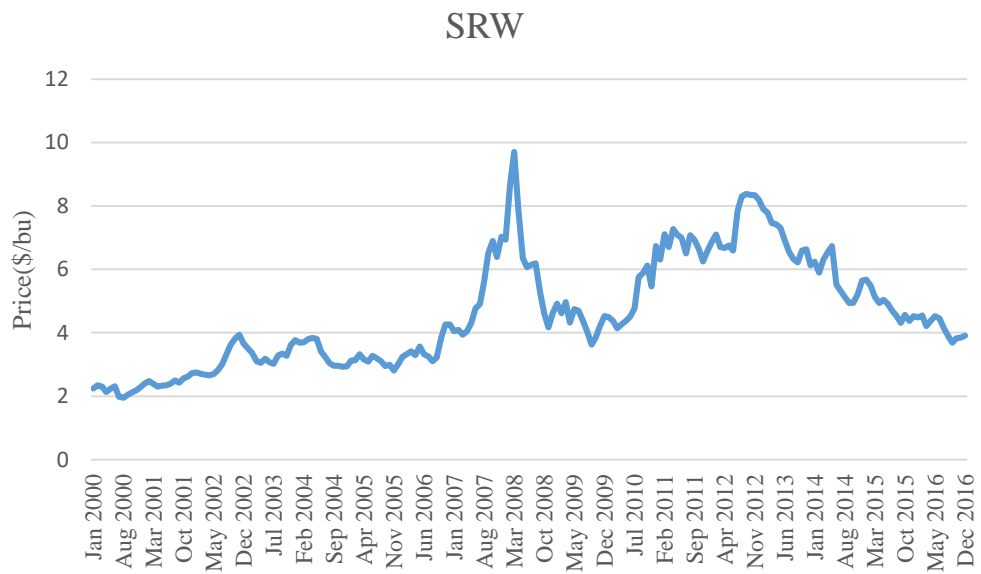


Figure 3. Commodity Cash Prices, 2000-2016 (SRW)

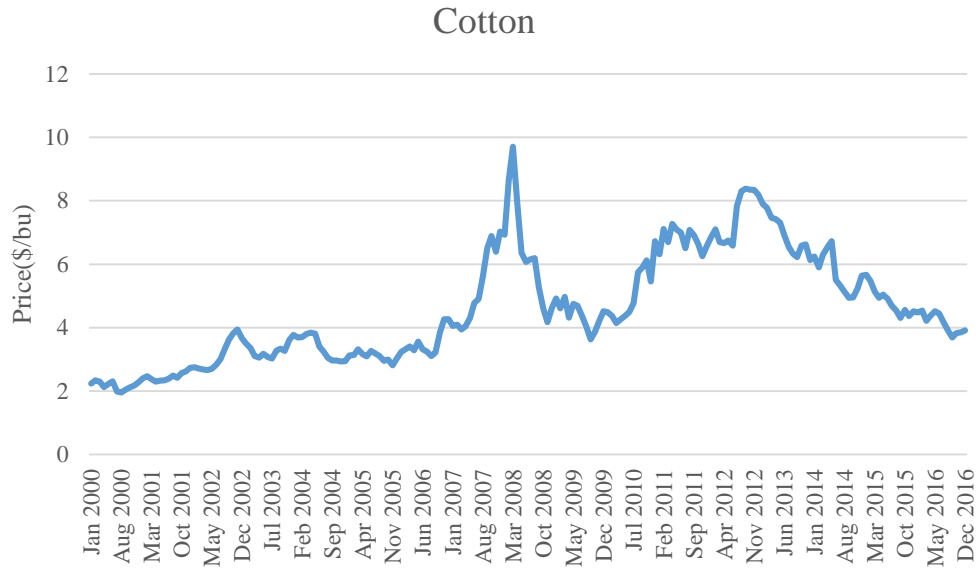


Figure 4. Commodity Cash Prices, 2000-2016 (cotton)

The US 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. At the same time, several studies (Chinn & Coibion, 2014; Husain & Bowman, 2004; Manfredo & Sanders, 2004; Reeve & Vigfusson, 2011; Tomek, 1997) 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. Another benefit of futures-based forecasts is that they can 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.

1.2 Objectives of the research

This paper develops several models for forecasting cash prices of U.S. crops based on observed prices of the underlying futures contracts. Two alternative approaches are proposed. The difference model focuses on forecasting the differences between current and future time prices. The regime model uses external data to determine potential structural breaks in price relationships. The out-of-sample performance of these models is compared to the benchmark of a five-year average using various performance criteria. The preferred forecast methods are used to develop 16-months ahead forecasts for each crop included in this study.

1.3 Structure of this paper

This paper states the problems and the objectives in Chapter 1. The literature review is given in Chapter 2. Chapter 3 talks about the data sources, normality test, and stationary test. Chapter 4 shows the conceptual framework of this research and Chapter 5 performs the forecast evaluation. The summary and conclusions are given in Chapter 6 and 7, and a forecast of the cash prices for the coming 16 months for each of the commodities is given in Chapter 8.

Chapter 2: Literature Review

2.1 Literature review in cash price forecast

The cash prices of commodities can be forecasted in many different ways. Current studies show a variety of commodities forecasted by the researchers. Just & Rauser (1981) have

forecasted the price of commodities such as corn, wheat, soybean, and cotton. Conejo, Plazas, Espinola, and Molina (2005) have forecasted the electricity price using the Autoregressive Integrated Moving Average model. Rodriguez and Anders (2004) forecasted the energy price in Ontario. All these studies show the researchers' enthusiasm in forecasting prices for different commodities using different models.

Basis is defined as the difference between cash price and futures prices. In 1990s, the structural models, which included structural affect variables such as demand and supply in the model, were thought to be a good approach in forecasting the commodity price. The storage, transportation costs, local supply, and other elements are included in the structural model (Martin, Groenewegen, & Pidgeon, 1980). Just and Rausser (1981) compared the accuracy of major commodity price forecast models and the price-forecasting information in the futures contract. They tested corn, soybean, and wheat, and found the futures price performs better than the other forecasters such as structural models.

It is important to make an accurate forecast of the basis because it can be used to forecast the cash price in the future (Tonsor, Dhuyvetter, & Mintert, 2004). Several studies have been conducted to forecast the basis accurately. Hauser, Garcia, and Tumblin (1990) have found the moving historical averages of cash price as the most typical approach to forecast the basis. Hoffman (2005) has used a simple five-year moving average of cash price to forecast the basis and found a good performance of his approach. Payne and Karali (2015) tried to combine different forecast models to improve the basis forecast models. All of these studies have tried to make a more accurate forecast of the basis, thus, to render a better prediction of the cash price in the future. Irwin (2009) indicates that it gets harder to forecast the basis over time. The economy shocks may make it difficult to forecast the basis in the future.

Anton Bekkerman (2016) has worked on forecasting the local wheat price and basis analysis. Protein, harvest-period futures price, and changes in demand are thought by him to be the most important elements that affect the spot price.

2.2 Literature review in futures-based forecast

The US Department of Agriculture (USDA) and various private agencies generate price forecasts for the 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 having many price forecasts is their backward looking nature, as most statistical price models are based on patterns in the historical price series. At the same time, several studies (Chinn & Coibion, 2014; Husain & Bowman, 2004; Manfredo & Sanders, 2004; Reeve & Vigfusson, 2011; Tomek, 1997) have demonstrated that the futures-based forecasts perform well relative to the time-series and judgmental forecasts, especially during periods when there is a sizeable difference between the spot and futures prices. Another benefit of the futures-based forecasts is that they can be constructed for longer lead times (i.e. 12 months and 16 months ahead of the forecasts), as most futures contracts begin trading several years before their expiration. Therefore, the goal of this study is to develop futures-based price forecasting models for corn, soybeans, SRW, and cotton. Evaluation of the performance of these models revealed how informative such models were at various forecasting horizons and how well they performed relative to the five-year moving average B.

Chapter 3: Data

3.1 Data sources

This research obtained the monthly national cash price data for corn, soybeans, SRW, and upland cotton from the USDA – NASS Quick Stats. Since futures prices are traded nationally, to make them comparable, this paper chooses national cash price.

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. For example, the nearby contract of corn of

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

Spot Month	Corn (C)	Soybeans (S)	Wheat (CBOT_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}

March 2010 is May 2010 instead of March 2010. The futures contracts always expire within the first one or two weeks of the contract month, which may not be reliable enough to represent the futures price in that month. This research obtained futures prices from the Quandl. This paper used the Chicago Mercantile Exchange (CME) contracts for corn, soybeans and wheat and the Intercontinental Exchange (ICE) contracts for cotton. The range of these monthly prices starts from January 2000 to December 2016, which is because these years' commodity prices are more volatile than those before.

3.2 Descriptive statistics and normality test

Table 2 shows the descriptive statistics of cash prices for each commodity. It demonstrates variability in the commodity cash prices during the period of study, 2000–2016. The price of corn averaged 3.57 \$/bu, but ranged from 1.52 \$/bu to 7.63 \$/bu. The price of soybeans averaged 8.84 \$/bu with a standard deviation of 3.30 \$/bu. This paper also observed similar in wheat with an average price of 4.59 \$/bu and standard deviation of 1.73 \$/bu, and cotton with the mean price of 0.59 \$/lb and a standard deviation of 0.16 \$/lb. The coefficients of variation of each commodity show that corn has largest volatility among all. Soybeans and SRW have similar volatility while cotton has the least volatility.

Table 2. Descriptive Statistics of Cash Data, Jan 2000 - Dec 2016.

Variable	Obs	Mean	Std.Dev.	Min	Max	CV
corn	204	3.573	1.574	1.52	7.63	44
soybeans	204	8.842	3.295	4.09	16.20	37
SRW	204	4.591	1.725	1.95	9.70	38
cotton	204	0.585	0.161	0.27	0.94	27

The normality test is commonly conducted on the dependent variables before running any regressions. The Shapiro–Wilk test, published in 1965, is another frequently used test for normality. The null hypothesis of it is that the data are normally distributed. Table 3 shows the Shapiro–Wilk W test for the data. The results show that none of these four commodities’ cash prices are normally distributed. In the regression analysis, it is going to use t-test in examining the significance. The normal assumption of t-test says the sample mean of the data is assumed to be normally distributed. Within a large sample size ($N > 50$), the Central Limit Theorem states that the sample mean is approaching a normal distribution. In this case, the analysis of this paper is still valid to make an inference, since the dataset has more than 200 observations.

Table 3. Shapiro-Wilk W Test for Normal Data

Variable	Obs	Shapiro-Wilk W	z	Prob>z
corn	204	0.90	6.38	0.00
soycash	204	0.94	5.26	0.00
SRWcash	204	0.95	4.78	0.00
cotcash	204	0.97	3.19	0.00

Notes: the null hypothesis of W test is data normality.

3.3 Stationary test

This paper evaluated the stationarity of the price series using the augmented Dickey-Fuller unit root test (ADF) and the Phillips and Perron (1988) test (PP). The null hypothesis for both the tests is that there is a unit root in the data. In the presence of unit roots in the series, the standard ordinary least squares (OLS) models can no longer be applied, and there might be a

spurious regression. The results of the stationarity tests shown in Table 4 indicate fail to reject the null hypothesis in most cases, which means the price series are likely to be non-stationary. However, these standard unit root tests suffer from a well-known weakness when testing 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 fail to reject the null hypothesis. Therefore, two alternative approaches are used in this study to address non-stationarity or the structural break problems in the data: the DM and the RM, as described in the following section.

Table 4. 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)
Pperron	-1.55 (0.51)	-1.70 (0.43)	-1.91 (0.33)	-1.87 (0.35)
Pperron (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. Pperron stands for Phillips-Perron test. P-values are shown in parentheses. Asterisks show statistical significance: * p<0.10, ** p<0.05, *** p<0.01

Chapter 4: Conceptual framework

4.1 Original approach

The underlying premise of the futures-based forecasting of national monthly cash price for each commodity may be predicted using the futures price of its front contract. The model assumptions are that cash price and futures price of the same commodity have a linear relationship with each other. This linear model is defined by Equation 1:

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

where S is the cash or spot price, F is the price of the futures contract expiring closest but before the t , t represents the month of the forecasted cash price and k is the lead time for the futures prices used for forecasting. For example, to forecast the cash price of corn in June 2010 with k equal to 5, this paper is going to use the futures price of July 2010 contract in January 2010 (5 months earlier). This study have explored two versions of this basic relationship.

4.2 Benchmark

This paper used a five-year moving average cash price for each month as a benchmark for the performance evaluation, which was first used by Hoffman. Firstly, this approach calculated the basis, which is equal to cash minus the futures price, using the last 5 years. Then, it generated a five-year moving average by the months. For example, it would use the average basis of June 2011, June 2012, June 2013, June 2014 and June 2015 as the forecasted basis for June 2016. Finally, it calculated the predicted cash prices by adding the related futures prices to the basis.

4.3 Difference model

Based on previous studies (Algieri & Kalkuhl, 2014; Fernandez, 2017; Granger & Newbold, 1974; Hoffman et al., 2015; Pederzoli & Torricelli, 2013), this paper examined the

relationship between cash and futures in the difference form due to non-stationarity of the price series:

$$(2) \quad S_{t,k} - F_{t-k,1} = \beta_0 + \beta_1(F_{t,k} - F_{t-k,1}) + \varepsilon_{t,k}$$

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

Tomek (1997) suggested an alternative when commodity prices. “move from regimes with relatively little variability to regimes with great variability and possibly with large prices spikes,” these structural changes must be explicitly modeled. Verteramo and Tomek (2015) discussed that the regime shifts in the post 2005 price series are associated with the demand shifts, given a relatively fixed supply. Irwin and Good followed this approach in a series of studies (Good & Irwin, 2016a, 2016b, 2016c; S. Irwin & Good, 2016) focused on corn and soybean prices.

4.4 Regime model

To extend this approach to this study, this paper estimated the following regression for each crop, where the regime variables for each year, post 2005/06, were added to the traditional stocks-to-use equation:

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

Based on the magnitudes of the estimated λ coefficients, the analysis clustered the combinations of marketing years into the following four regimes for each commodity (except for soybeans, where three regimes were used): strong, moderately strong, moderately weak, and weak. This paper created a dummy variable for each regime and incorporated into the basic forecasting equation as shown:

$$(4) \quad S_{c,t,k} = \alpha_0 + \beta_1 F_{c,t-k} + \beta_2 \text{Strong}_c + \beta_3 \text{Moderately Strong}_c + \beta_4 \text{Moderately Weak}_c + \beta_5 \text{Weak}_c + \beta_6 \text{monthdummy}_c + \varepsilon_{c,t,k},$$

where c refers to a particular commodity, t represents the month for the forecasted cash price, k is the lead time of the futures price forecasts. The regime dummies take the value of 1 in the years indicated in Table 5, and 0 otherwise. This paper also considered seasonality in this model. This paper generated seasonality dummy variables for each commodity. For corn and soybean,

Table 5. Marketing Years of 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

there are two month dummy variables. This paper set the first dummy variable to be 1 in May, June, and July, and 0 otherwise. It set the second one to be 1 in September, October, and November, and 0 otherwise. It set dummy variable for SRW to be 1 in February, March, and

April, and 0 otherwise. There is no dummy variable for cotton since no significant seasonality appears.

4.5 In-sample evaluation

This paper estimated the DM (Equation 2) and RM (Equation 4) using the data from 2000 to 2016 with the lead time from 1 to 16 months. For example, to forecast the cash price of corn in June 2017, this paper used the monthly average prices of the futures contract expiring in July 2017, observed during February 2016 (16 months lead) through May 2017 (1 month lead), to generate the forecasts 1 through 16 months ahead.

One criteria which is frequently used in in-sample evaluation is the R-squared. It shows the ratio of the variation included in the regression, comparing with the total variation of the dependent variable. The regression with high R-squared is thought to have a good description of the dependent variable.

4.6 Out-of-sample evaluation

4.6.1 Out of sample forecast

This paper used the data from 2000 to 2012 to estimate the model for corn, soybeans, SRW, and cotton for the lead times from 1 to 16. These estimates were used to generate the forecasts for 2013. This paper re-estimated the model using the data from 2000 to 2013 to generate the forecasts for 2014. Thus, this paper generated 4 years of 16 out-of-sample forecasts for the out-of-sample evaluation of the model's predictive accuracy. This research calculated forecast errors as $e = \text{Actual} - \text{Forecasted}$. This paper also assessed the performance of the two alternative models for the out-of-sample period of January 2013–December 2016 focusing on the

bias as measured by mean errors (ME) and the size of errors as measured by root mean squared errors (RMSE).

Figures 5 to 8 compare the errors of three alternative forecast methods for the 6-months ahead forecasts for each commodity included in this study over the out-of-sample period. Figure 5 shows that with the exception of the January 2013 forecasts, most corn forecast errors were negative, suggesting a tendency to overestimate the observed prices, particularly in October and November of 2014. This pattern makes sense, as the prices were just coming off the highs observed in 2011–2013. The RM appeared to have the lowest bias in the 6 months–ahead corn forecasts. The soybean forecasts had mostly positive errors from mid-2013 to mid-2014, followed by negative errors from mid-2014 through mid-2016. Again, RM errors appeared slightly smaller than those of alternative forecasts. The pattern was very different for wheat forecasts, where DM had much larger errors associated with underestimation of wheat prices from June 2013 through May 2014, which was likely to be 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 biasness. These results for cotton were mixed, with an obvious tendency for positive errors throughout the out-of-sample period, suggesting underestimation, but no clear outperforming model.

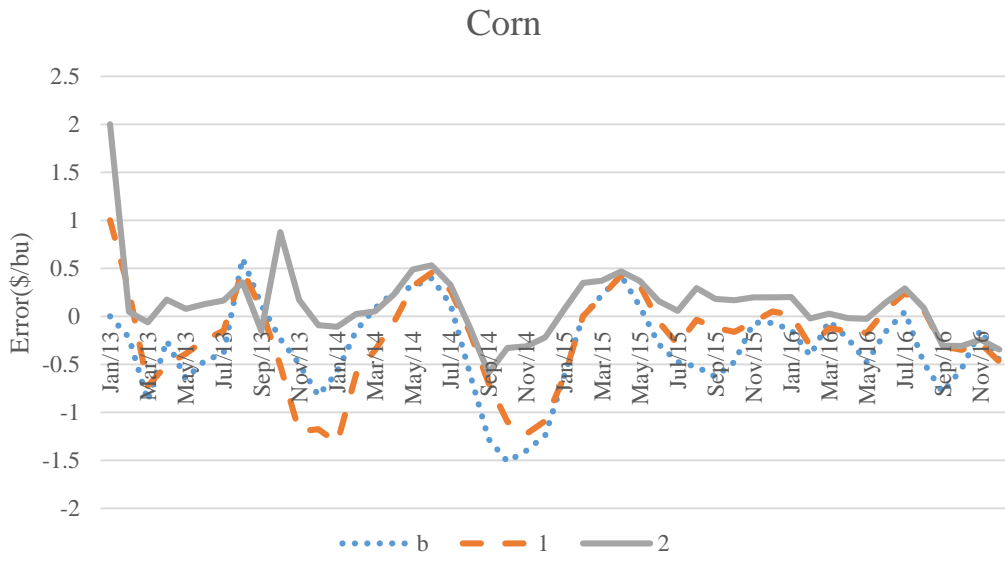


Figure 5. Out-of-sample Forecast Errors at k=6 (corn)

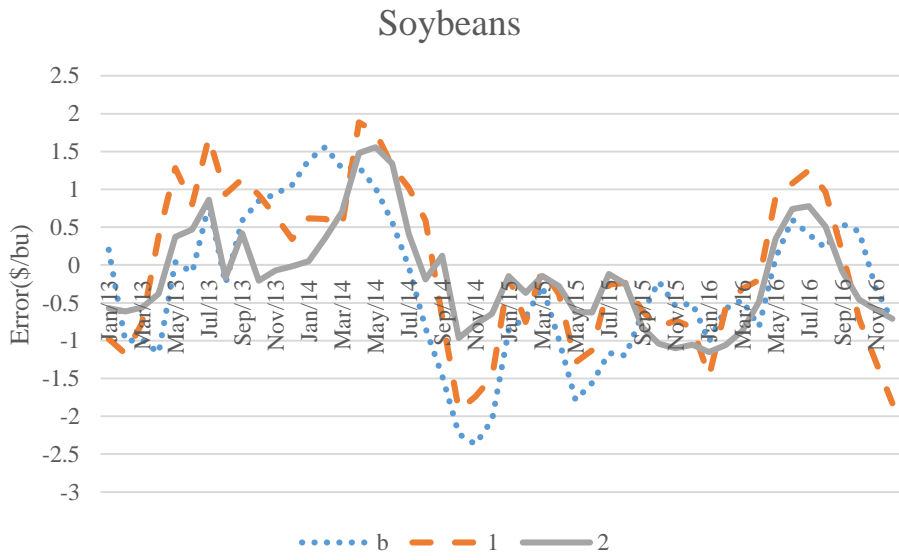


Figure 6. Out-of-sample Forecast Errors at k=6 (soybeans)

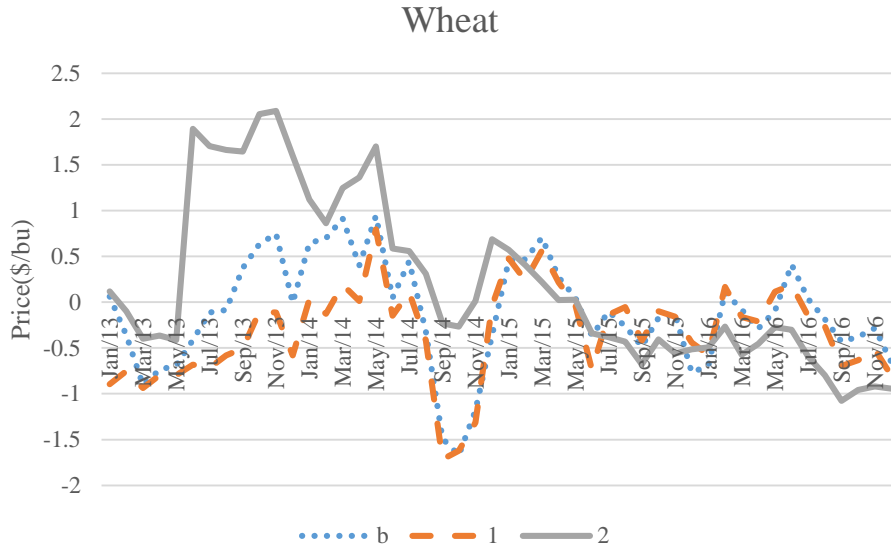


Figure 7. Out-of-sample Forecast Errors at k=6 (SRW)

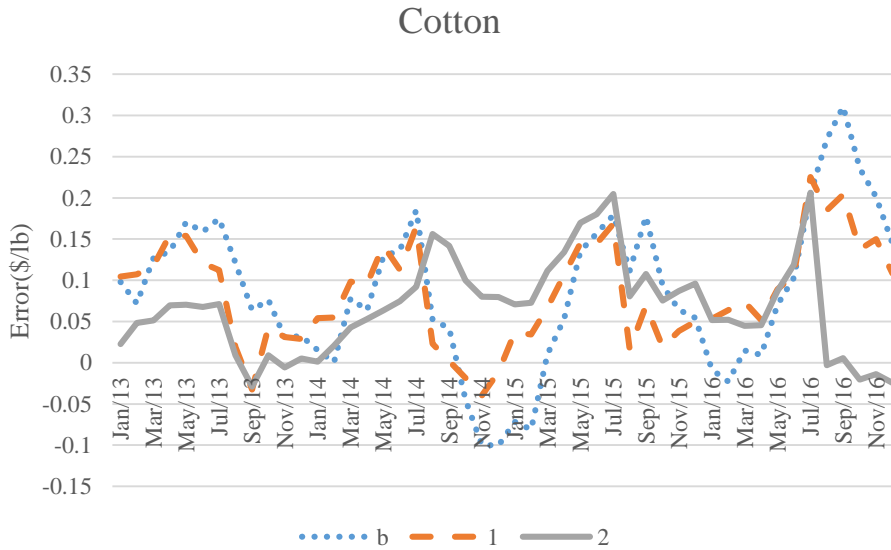


Figure 8. Out-of-sample Forecast Errors at k=6 (cotton)

4.6.2 Test of bias & size

In evaluation, bias and size are two features of errors that researchers want to check.

Mean error shows the mean value of errors, which can represent the biasness of each method.

RMSE shows the rooted mean squared errors, which can describe the size of errors of each method. MDM test gives a more straightforward way to compare two methods at one time.

Equation 5 is used to determine the mean error which is used to test for regression biased:

$$(5) \quad ME = \frac{1}{n} \sum_{i=0}^n e_i$$

The null hypothesis of the t-test was that the mean errors were not significantly different from 0.

A low p-value of this test meant the null hypothesis rejected that this estimate was biased.

The root mean squared error is a criterion for testing the error size with a larger RMSE indicating a larger error. The root mean squared errors were calculated by using Equation 6:

$$(6) \quad RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n e_i^2}$$

The difference between alternative forecasts was evaluated using the Modified Diebold-Mariano (MDM) test (Harvey, Leybourne, & Newbold, 1997). This test compares the difference between the two approaches with a formular using Equation 7:

$$(7) \quad MDM = \sqrt{\frac{T-1}{T \sum_{t=1}^n (d_t - \bar{d})^2}} \bar{d},$$

where $d = |e_1| - |e_2|$ (e_1 is error from model 1, and e_2 is error from model 2).

4.6.3 Encompassing test

Furthermore, this paper used the test of forecast encompassing (Manfredo & Sanders, 2004) to assess whether these alternative models add information to the B approach of using a five-year moving average as the forecast.

$$(8) \quad e_{1t} = \alpha + \lambda(e_{1t} - e_{2t}) + \varepsilon_t$$

where e_{1t} is the forecast error of an alternative model and e_{2t} is the error of the benchmark model. The null hypothesis is λ , which is equal to zero. Rejection of the null hypothesis means a combination of these two approaches will have less 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).

Chapter 5: Results

5.1 In-sample evaluation

The R-squared values for the DM and RM, estimated using the full data sample shown in Table 6, may be viewed as the in-sample measures of model fit. While the results of R-squared values of the RM appeared to much better than the DM, these findings should not be compared due to the differences in the dependent variables. The DM explained the change in cash price from the current to the forecasted month, while the RM predicted the level of cash price in the forecasted month. What could be compared were the changes in model performance across the forecasting horizons (k). For the DM, the R-squared decreased at shorter horizons and increased at longer horizons. For the RM, the R-squared of all the four commodities decreased gradually at longer horizons – a more anticipated pattern. Thus, the RM explained from 97% of the variation

Table 6. R-square of In-sample Test, 2000-2016.

k	DM				RM			
	corn	soybeans	SRW	cotton	corn	soybeans	SRW	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

Notes: In-sample test was done by running the regress models with the whole period from 2000 to 2016. R-squares were obtained from these models.

in one-month ahead corn prices to 91% of the variation in 16-month ahead corn prices. Similar patterns were observed in the other commodities with the cotton forecasts characterizing the lowest R-squared values, ranging from 69% for 16-month ahead forecasts to 81% for one-month ahead forecasts.

5.2 Out-of-sample evaluation

5.2.1 Test of bias & size

The average errors and the test of bias for alternative forecasting approaches are shown in Tables 7 to 10.

Table 7. Mean Errors and t-test for Alternative Forecasts, 2013-2016. (corn)

k	Corn					
	B		DM		RM	
1	0.21	***	0.18	***	0.15	***
2	0.12	*	0.10	**	0.11	**
3	0.01		0.01		0.10	**
4	-0.10		-0.08		0.10	**
5	-0.23	***	-0.18	**	0.08	*
6	-0.33	***	-0.26	***	0.08	*
7	-0.38	***	-0.30	***	0.09	**
8	-0.42	***	-0.36	***	0.11	**
9	-0.47	***	-0.41	***	0.11	**
10	-0.53	***	-0.47	***	0.12	***
11	-0.56	***	-0.51	***	0.13	***
12	-0.64	***	-0.54	***	0.12	***
13	-0.71	***	-0.60	***	0.12	***
14	-0.78	***	-0.68	***	0.11	**
15	-0.85	***	-0.73	***	0.10	**
16	-0.93	***	-0.81	***	0.09	*

Notes: 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. Asterisks show statistical significance: * p<0.10, ** p<0.05, *** p<0.01.

Results of ME, RMSE, and MDM test demonstrated that all the three forecasts of corn prices were biased in the out-of-sample period. The B and the DM had a tendency to overestimate the corn prices, resulting in negative errors, while the RM tended to underestimate the prices, leading to positive errors. The magnitude of bias, while significantly different from zero, appears much smaller for the RM, especially at the longer forecast horizons. The soybean price forecasts were biased as well in the out-of-sample period. All three approaches had a tendency to overestimate the soybean prices, resulting in negative errors. The magnitude of

Table 8. Mean Errors and t-test for Alternative Forecasts, 2013-2016. (soybeans)

Soybeans						
k	B		DM		RM	
1	0.28	***	0.26	***	0.37	***
2	0.21	*	0.21	**	0.31	***
3	0.11		0.13		0.16	**
4	-0.03		0.07		-0.03	
5	-0.17	*	0.00		-0.16	
6	-0.27	*	-0.03		-0.23	
7	-0.32	**	0.00		-0.25	
8	-0.39	**	-0.04		-0.27	*
9	-0.50	***	-0.17		-0.28	*
10	-0.61	***	-0.30	*	-0.29	*
11	-0.71	***	-0.33	*	-0.31	**
12	-0.80	***	-0.36	*	-0.32	**
13	-0.89	***	-0.43	**	-0.32	**
14	-1.00	***	-0.47	**	-0.33	**
15	-1.15	***	-0.56	**	-0.37	**
16	-1.34	***	-0.83	***	-0.42	**

Notes: 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. Asterisks show statistical significance: * p<0.10, ** p<0.05, *** p<0.01.

bias of the RM 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 RM also tended to be the smallest among all the approaches at longer horizons. The cotton price forecasts had a tendency to underestimate the prices, resulting in positive errors. The extent of bias of the DM and RM had similar ME patterns, and both of them were lower than the B.

Tables 11 to 14 compare the RMSEs of three forecast models for each crop. The RMSEs reflected the size of errors in the out-of-sample period. The smallest errors across the three forecasting alternatives for each forecast horizon were highlighted in bold. These results show that the errors of RM were the smallest for corn price forecasts. These RMSEs were consistent

Table 9. Mean Errors and t-test for Alternative Forecasts, 2013-2016. (SRW)

SRW Wheat							
k	B		DM		RM		
1	0.21	***	0.23	***	0.42	***	
2	0.15		0.14	**	0.33	***	
3	0.09		0.02		0.30	**	
4	0.03		-0.10		0.27	**	
5	-0.04		-0.22	***	0.24	*	
6	-0.11		-0.33	***	0.19		
7	-0.13		-0.41	***	0.09		
8	-0.16		-0.48	***	-0.04		
9	-0.19	*	-0.54	***	-0.13		
10	-0.22	*	-0.61	***	-0.19		
11	-0.25	**	-0.67	***	-0.20		
12	-0.29	**	-0.72	***	-0.18		
13	-0.33	***	-0.77	***	-0.16		
14	-0.41	***	-0.87	***	-0.14		
15	-0.55	***	-0.87	***	-0.15		
16	-0.54	***	-0.83	***	-0.22		

Notes: 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. Asterisks show statistical significance: * p<0.10, ** p<0.05, *** p<0.01.

across the forecast horizons while the B and DM errors increased substantially at longer horizons. These findings for soybeans were similar to those for corn. The only difference was that DM has least RMSE over the periods, which means it performed better in extremely short horizons (1-2 months ahead). On the other hand, the results for wheat were very different from the B, showing the best performance for 6- to 15-months ahead forecasts and the DM performing better at 1–5 months horizons. For cotton, the RM showed better performance at shorter horizons (2–9 months ahead) and the DM performed better at longer horizons (10–16 months ahead). The cotton price RMSEs of these two models were very similar and was smaller than the B. In summary, the RM was preferred for corn and soybeans; the DM and the B had better results in

Table 10. Mean Errors and t-test for Alternative Forecasts, 2013-2016. (cotton)

k	Cotton					
	Benchmark		Model 1		Model 2	
1	0.12	***	0.07	***	0.07	***
2	0.12	***	0.07	***	0.07	***
3	0.11	***	0.08	***	0.07	***
4	0.10	***	0.08	***	0.07	***
5	0.09	***	0.08	***	0.07	***
6	0.09	***	0.08	***	0.07	***
7	0.08	***	0.08	***	0.07	***
8	0.07	***	0.08	***	0.07	***
9	0.05	***	0.07	***	0.06	***
10	0.04	***	0.06	***	0.06	***
11	0.03	*	0.05	***	0.05	***
12	0.02		0.05	***	0.04	***
13	0.01		0.04	***	0.04	***
14	0.00		0.04	***	0.04	***
15	-0.01		0.03	***	0.04	***
16	-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. Asterisks show statistical significance: * p<0.10, ** p<0.05, *** p<0.01.

wheat; and the DM and RM showed better performance in cotton. The next set of results examines the statistical differences between the alternative models.

Table 11. Root Mean Squared Errors for Alternative Forecasts, 2013-2016. (corn)

Corn			
k	Benchmark	Model 1	Model 2
1	0.49	0.34	0.33
2	0.47	0.34	0.31
3	0.52	0.37	0.31
4	0.53	0.43	0.31
5	0.55	0.49	0.31
6	0.57	0.53	0.28
7	0.66	0.58	0.28
8	0.78	0.69	0.30
9	0.88	0.77	0.31
10	0.96	0.86	0.33
11	1.03	0.93	0.34
12	1.12	1.01	0.33
13	1.20	1.10	0.33
14	1.25	1.18	0.32
15	1.28	1.22	0.32
16	1.30	1.29	0.32

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. The bolded number is the smallest one among each three for one commodity at a certain level of k.

Table 12. Root Mean Squared Errors for Alternative Forecasts, 2013-2016. (soybean)

Soybeans			
k	B	DM	RM
1	0.73	0.54	0.75
2	0.80	0.65	0.77
3	0.85	0.79	0.62
4	0.93	0.94	0.58
5	0.97	1.01	0.63
6	1.01	1.03	0.67
7	1.16	1.05	0.70
8	1.31	1.10	0.73
9	1.42	1.14	0.76
10	1.53	1.21	0.78
11	1.64	1.29	0.79
12	1.74	1.37	0.79
13	1.83	1.48	0.81
14	1.89	1.54	0.81
15	1.97	1.61	0.84
16	2.08	1.69	0.86

Notes: 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. The bolded number is the smallest one among each three for one commodity at a certain level of k.

Table 13. Root Mean Squared Errors for Alternative Forecasts, 2013-2016. (SRW)

SRW			
k	B	DM	RM
1	0.53	0.41	0.66
2	0.65	0.47	0.76
3	0.72	0.53	0.88
4	0.71	0.55	0.95
5	0.64	0.56	0.95
6	0.59	0.61	0.93
7	0.65	0.66	0.88
8	0.74	0.77	0.86
9	0.78	0.85	0.86
10	0.81	0.92	0.90
11	0.84	0.99	0.94
12	0.87	1.04	0.96
13	0.90	1.10	1.00
14	0.93	1.18	0.99
15	1.00	1.17	1.01
16	1.04	1.14	1.01

Notes: 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. The bolded number is the smallest one among each three for one commodity at a certain level of k.

Table 14. Root Mean Squared Errors for Alternative Forecasts, 2013-2016. (cotton)

Cotton			
k	B	DM	RM
1	0.15	0.08	0.09
2	0.15	0.09	0.09
3	0.15	0.09	0.08
4	0.14	0.10	0.08
5	0.13	0.10	0.09
6	0.13	0.10	0.09
7	0.12	0.10	0.09
8	0.12	0.10	0.10
9	0.11	0.10	0.10
10	0.10	0.10	0.10
11	0.10	0.09	0.09
12	0.10	0.09	0.09
13	0.10	0.09	0.09
14	0.11	0.08	0.09
15	0.11	0.08	0.09
16	0.11	0.09	0.09

Notes: 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. The bolded number is the smallest one among each three for one commodity at a certain level of k.

Tables 15 and 18 show the results of the Modified Diebold-Mariano (MDM) tests for corn and soybeans and for wheat and cotton, respectively. The MAEs for each approach have been shown to facilitate interpretation of the MDM test results. The MDM test examines whether the difference between errors from two alternative models is significantly different from zero. A positive difference means that the first model has greater errors than the second one, indicating that the second model performs better based on smaller errors.

Table 15. MDM test for Alternative Forecasts, 2013-2016. (corn)

Corn									
Models	B	DM	RM	B&DM		B&RM		DM&RM	
k	MAE			MDM statistic					
1	0.36	0.35	0.34	4.53	***	6.22	***	1.32	
2	0.35	0.35	0.35	3.11	***	4.20	***	0.77	
3	0.38	0.38	0.37	4.03	***	4.18	***	1.84	*
4	0.40	0.42	0.39	2.36	**	4.06	***	2.54	**
5	0.43	0.51	0.43	1.93	*	4.24	***	3.05	***
6	0.45	0.59	0.46	1.26		4.31	***	3.51	***
7	0.52	0.64	0.48	2.35	**	5.18	***	3.82	***
8	0.62	0.71	0.51	2.49	**	6.08	***	4.50	***
9	0.73	0.79	0.53	3.27	***	7.72	***	5.83	***
10	0.82	0.87	0.56	2.90	***	8.53	***	7.13	***
11	0.89	0.93	0.57	3.40	***	8.58	***	7.63	***
12	1.00	1.02	0.57	3.89	***	10.13	***	8.98	***
13	1.08	1.10	0.57	3.69	***	10.64	***	9.15	***
14	1.12	1.19	0.56	2.22	**	10.18	***	9.32	***
15	1.13	1.28	0.55	1.00		9.26	***	9.58	***
16	1.14	1.36	0.55	-0.25		9.20	***	10.15	***

Notes: K is the forecast lead time. N= 48 For each value. MDM test follows t distribution. Asterisks show statistical significance: * p<0.10, ** p<0.05, *** p<0.01.

The MAEs helps to explain the size of errors associated with each approach. Since the null hypothesis is the difference is zero, rejection of the null implies that one model is significantly more accurate than the other. For example, the results for 1- and 2- step ahead forecasts of corn prices indicated both DM and RM were better than the B, but they were not better than each other. At all other forecast horizons, the RM was significantly more accurate than the DM and the B. A similar set of results with strong evidence of superior performance of the RM was shown for soybeans. The results for wheat and cotton, shown in Table 8b, were very different. The DM was better than the B for horizons 2–5. The signs of all other significant test

Table 16. MDM test for Alternative Forecasts, 2013-2016. (soybeans)

Soybeans									
Models	B	DM	RM	B&DM		B&RM		DM&RM	
k	MAE			MDM statistic					
1	0.55	0.51	0.63	2.88	***	0.37		-2.81	***
2	0.62	0.66	0.72	2.04	**	0.67		-1.44	
3	0.71	0.79	0.75	1.03		3.13	***	2.04	**
4	0.81	0.91	0.74	0.75		5.32	***	3.81	***
5	0.80	1.02	0.77	-0.47		3.58	***	4.42	***
6	0.85	1.09	0.82	-0.54		3.12	***	4.32	***
7	0.95	1.14	0.85	0.17		3.53	***	4.11	***
8	1.11	1.17	0.90	1.95	*	4.62	***	3.39	***
9	1.20	1.22	0.95	3.18	***	4.99	***	3.54	***
10	1.28	1.26	0.98	4.16	***	5.53	***	3.87	***
11	1.33	1.29	0.99	2.97	***	5.86	***	4.79	***
12	1.41	1.32	1.01	2.99	***	6.24	***	5.46	***
13	1.51	1.34	1.04	2.71	***	6.42	***	5.53	***
14	1.54	1.36	1.05	2.09	**	6.45	***	6.01	***
15	1.61	1.38	1.09	1.84	*	6.69	***	7.16	***
16	1.72	1.43	1.11	2.78	***	6.98	***	6.21	***

Notes: K is the forecast lead time. N= 48 For each value. MDM test follows t distribution. Asterisks show statistical significance: * p<0.10, ** p<0.05, *** p<0.01.

statistics for wheat were negative, suggesting the first model used for comparison was better; the B was better than RM at horizons 5–8; the B was better than DM at horizons 9–15; the DM was better than RM at horizons 1–7. Based on these findings, only DM offered advantages for wheat price forecasting at short horizons (1–5), but haven’t been able to beat the B in all the other cases. Our results for cotton were slightly better: Both the DM and RM were significantly better than the B at horizons 1–8 and 13–16; but the errors from each model were not significantly different from each other. In summary, the RM was preferred for corn and soybeans, the B was

Table 17. MDM test for Alternative Forecasts, 2013-2016. (SRW)

SRW						
Models	B	DM	RM	B&DM	B&RM	DM&RM
k	MAE			MDM statistic		
1	0.40	0.44	0.59	1.54	-0.97	-1.75 *
2	0.47	0.46	0.72	2.63 **	-0.52	-1.91 *
3	0.54	0.53	0.85	3.44 ***	-1.01	-2.47 **
4	0.55	0.56	0.95	3.57 ***	-1.61	-2.89 ***
5	0.50	0.62	1.06	2.27 **	-2.29 **	-2.92 ***
6	0.46	0.67	1.11	0.04	-2.73 ***	-2.59 **
7	0.50	0.75	1.06	-0.63	-2.38 **	-1.87 *
8	0.56	0.84	1.01	-1.55	-1.77 *	-0.75
9	0.60	0.92	0.96	-2.52 **	-1.46	-0.03
10	0.64	0.98	0.95	-2.94 ***	-1.46	0.25
11	0.67	1.02	0.95	-3.17 ***	-1.33	0.77
12	0.73	1.03	0.97	-2.88 ***	-0.95	1.03
13	0.77	1.05	1.00	-3.03 ***	-0.64	1.20
14	0.78	1.06	1.03	-3.57 ***	-0.36	1.76 *
15	0.85	1.00	1.11	-2.01 *	0.08	1.34
16	0.86	0.97	1.19	-1.41	-0.02	0.91

Notes: K is the forecast lead time. N= 48 For each value. MDM test follows t distribution. Asterisks show statistical significance: * p<0.10, ** p<0.05, *** p<0.01.

the best for wheat (except short horizons of less than 5 months, where DM performed better), and both DM and RM worked well for cotton.

Table 18. MDM test for Alternative Forecasts, 2013-2016. (cotton)

Cotton								
Models	B	DM	RM	B&DM		B&RM		DM&RM
k	MAE			MDM statistic				
1	0.13	0.14	0.12	5.25	***	3.96	***	-0.92
2	0.12	0.14	0.12	4.58	***	3.92	***	-0.17
3	0.12	0.13	0.11	3.62	***	3.64	***	0.97
4	0.11	0.12	0.10	2.81	***	3.16	***	1.62
5	0.10	0.12	0.09	2.51	**	2.90	***	1.69 *
6	0.10	0.11	0.08	2.44	**	2.61	**	1.56
7	0.10	0.10	0.08	2.28	**	2.21	**	1.28
8	0.10	0.09	0.08	1.99	*	1.72	*	1.04
9	0.09	0.09	0.08	0.90		1.00		0.70
10	0.09	0.10	0.09	0.66		0.66		0.38
11	0.08	0.11	0.09	0.72		0.64		0.25
12	0.08	0.12	0.10	1.42		1.11		0.25
13	0.09	0.12	0.10	2.42	**	1.72	*	0.08
14	0.09	0.11	0.11	3.10	***	2.44	**	0.14
15	0.10	0.11	0.11	3.67	***	3.02	***	0.25
16	0.10	0.11	0.11	4.07	***	3.30	***	0.46

Notes: K is the forecast lead time. N= 48 For each value. MDM test follows t distribution. Asterisks show statistical significance: * p<0.10, ** p<0.05, *** p<0.01.

Figure 9 to 11 shows more significantly about the model performance between each pair of models. The two straight lines are the upper bound and lower bound of confidence intervals at

95% level. The bars which exceed the bounds indicate that they are significant at 5% level, that is, these two models have significantly different performance. The bars which exceed the upper bound have large positive test statistics, which means the first approach in MDM test has larger errors than the second approach. The bars which exceed the lower bound means that the first approach has less errors than the second one. These figures also give the same conclusion as in the tables.

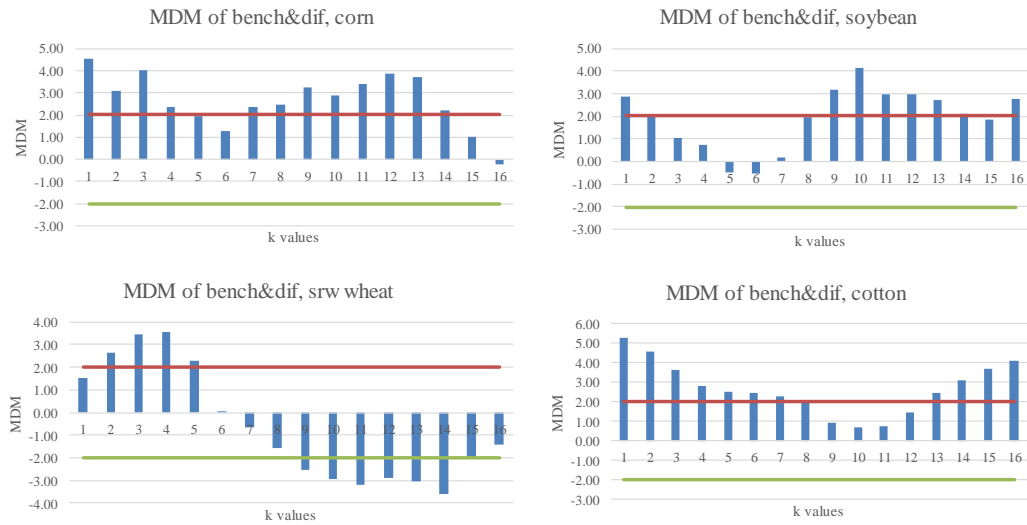


Figure 9. MDM test between B & DM

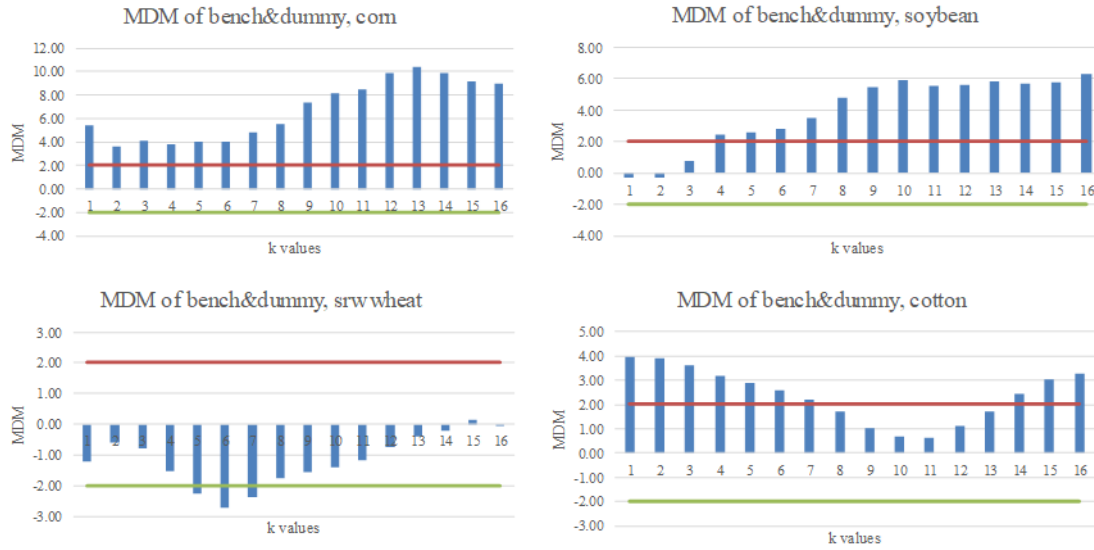


Figure 10. MDM test between B & RM

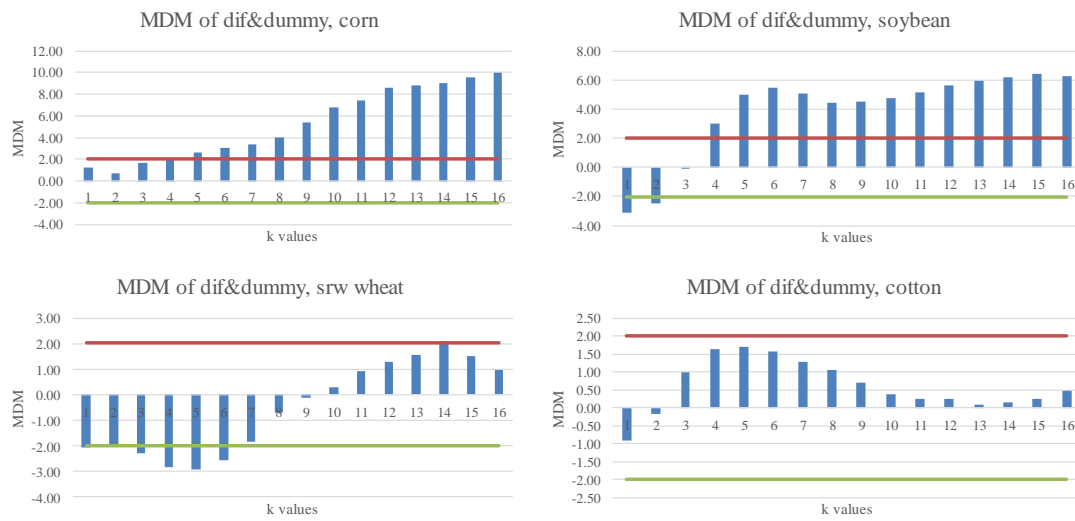


Figure 11. MDM test between DM & RM

5.2.2 Encompassing test

Tables 19 and 20 show the results of forecast encompassing tests. The first set of results compared the B and DM, and the results demonstrate the DM added information to the B for corn at forecast horizons 1–13 and for other commodities at all forecast horizons. This means a combination of these two approaches would have a smaller forecast error than the B.

Comparison of the B and RM in the second set of results reveals the RM added value to the B forecasts for corn, soybeans and cotton at all forecast horizons, and for wheat at horizons 1, 2,

Table 19. Encompassing Test for Alternative Forecasts, 2013-2016. (B&DM)

k	B & DM							
	Corn		Soybeans		SRW		Cotton	
1	9.29	***	7.00	***	7.51	***	12.27	***
2	6.80	***	5.29	***	7.54	***	12.18	***
3	6.80	***	3.49	***	6.93	***	11.60	***
4	4.92	***	2.28	**	6.15	***	9.95	***
5	3.58	***	1.78	*	4.91	***	8.65	***
6	2.30	**	2.12	**	3.69	***	7.63	***
7	3.04	***	3.10	***	4.68	***	6.91	***
8	3.32	***	3.81	***	4.59	***	6.63	***
9	3.87	***	4.25	***	4.05	***	5.74	***
10	3.57	***	4.58	***	3.66	***	5.37	***
11	3.90	***	4.49	***	3.22	***	5.28	***
12	2.97	***	4.20	***	3.16	***	6.54	***
13	2.23	**	3.59	***	2.47	**	9.72	***
14	1.15		3.06	***	2.33	**	10.71	***
15	-0.08		2.61	**	3.03	***	11.73	***
16	-1.40		2.79	***	3.94	***	9.30	***

Notes: K is the forecast lead time. N= 48 For each value. The null hypothesis is slope equal to 0. Asterisks show statistical significance: * p<0.10, ** p<0.05, *** p<0.01.

and 7–16. Thus, even though the proposed models did not beat the B in terms of accuracy for wheat, they still added useful information that may help reduce the forecast errors.

Figure 12 and 13 show the same conclusion and more clearly than above. The two straight lines are the boundaries of confidence interval. The fitted lines which are above the upper bound or below the lower bound are significant. That is, one of the compared two models is significantly encompassing the other one. The fitted lines above the upper bound indicate that the alternative model contains more information than the benchmark model. Here, it means both DM and RM contains more information than B.

Table 20. Encompassing Test for Alternative Forecasts, 2013-2016. (B&RM)

B & RM								
k	Corn		Soybeans		SRW		Cotton	
1	9.52	***	2.68	***	3.18	***	9.21	***
2	9.52	***	3.46	***	2.53	**	10.77	***
3	11.20	***	6.68	***	1.56		11.99	***
4	10.78	***	8.75	***	0.86		11.26	***
5	10.18	***	8.35	***	0.47		10.88	***
6	9.50	***	8.00	***	0.85		11.03	***
7	12.05	***	9.43	***	2.81	***	11.32	***
8	13.92	***	10.35	***	4.11	***	10.52	***
9	15.16	***	10.82	***	4.96	***	10.09	***
10	15.55	***	11.30	***	5.45	***	10.16	***
11	16.60	***	12.10	***	5.66	***	10.75	***
12	17.34	***	13.01	***	5.50	***	11.20	***
13	18.28	***	13.13	***	5.27	***	11.67	***
14	19.05	***	13.25	***	4.70	***	11.82	***
15	18.99	***	12.91	***	3.52	***	12.05	***
16	17.58	***	12.65	***	3.31	***	12.30	***

Notes: K is the forecast lead time. N= 48 For each value. The null hypothesis is slope equal to 0. Asterisks show statistical significance: * p<0.10, ** p<0.05, *** p<0.01.

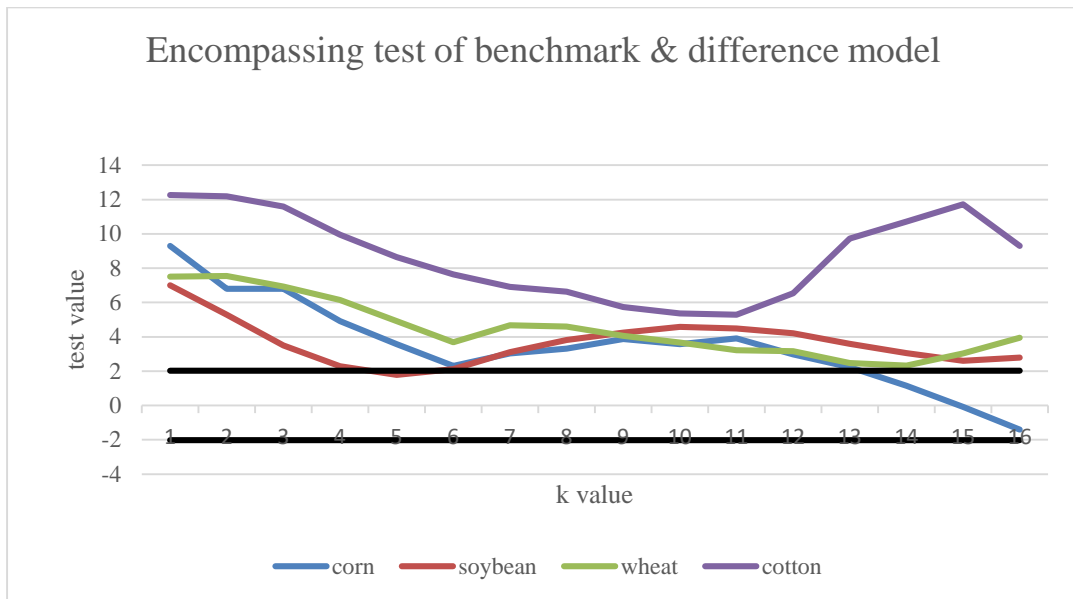


Figure 12. Encompassing test between B & DM

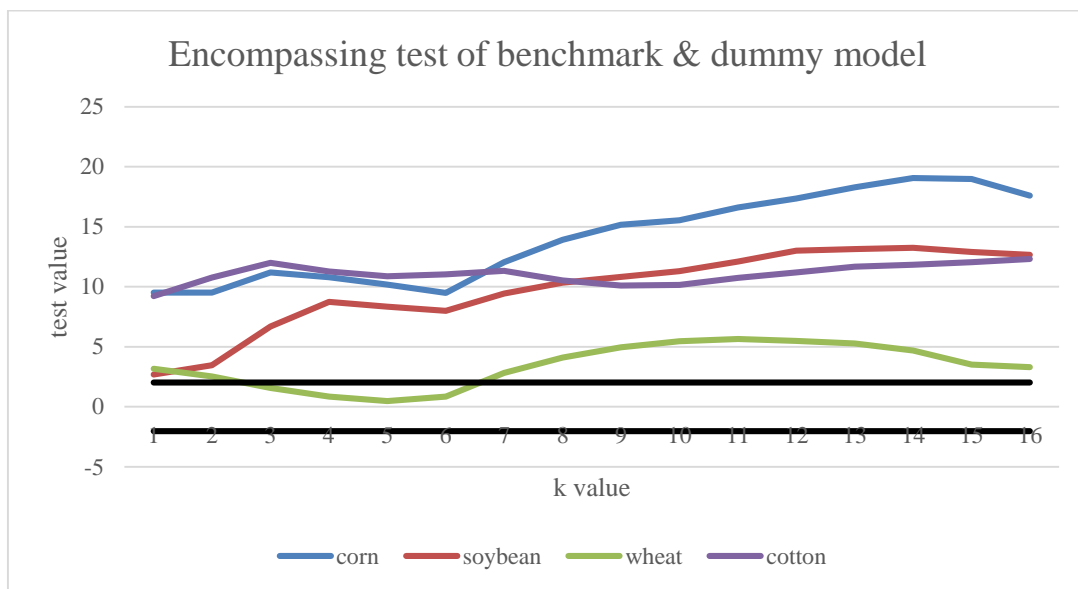


Figure 13. Encompassing test between B & RM

Chapter 6: Summary

The R-squares of the DM decreased in shorter horizons and increased in longer horizons. The R-squares of the RM decreased over all the horizons. The performance evaluation section examined how these three approaches performed under each criteria of the out-of-sample test. The mean errors showed that all the three forecasts were biased. The DM and RM had less root mean squared errors than the B for corn, soybean, and cotton, while the B had less root mean squared errors for SRW. The RM had the lowest errors in most of the horizons. The MDM test showed that both the DM and RM were better compared to the B, especially in corn, soybeans, and cotton. For SRW, there was no big difference between the DM and RM, and it seemed the B showed better performance than both of them, especially in MDM test results. The DM tended to be better than the RM for cotton, while the RM was better for corn and soybeans. Comparing with the B, the encompassing test results showed that the DM and RM were both adding information to the B, which meant they encompassed the B. Both of them had information not included in the B. It also meant that combining B with either the DM or RM would reduce the forecast errors.

Overall, from the results of all these tests indicate, this paper considered the RM to have the best forecast performance for corn and soybean. The best choice in forecasting SRW prices was the B. Both the DM and RM were better than the B for cotton, but with no great difference between each other.

Chapter 7: Conclusion

This paper has aimed to find a model to forecast the commodity cash prices accurately. This paper examined three approaches to determine the best one. The three approaches used in

this analysis are the five-year moving average, the DM, and the RM. The following approaches were used to determine accuracy: mean errors, root mean squared errors, the MDM test, and the encompassing test.

Based on the analysis described above, the RM has been chosen to make forecasts of corn and soybeans, the DM will be used to make predictions for cotton, and the B will be used to forecast for SRW.

The future studies can focus on combining the DM and RM together to consider a mixed model in forecasting commodity cash prices.

Chapter 8: Forecast for Commodity Cash Prices.

On the basis of the above discussions, the DM has been chosen to make price forecasts for cotton, the RM to make predictions for corn and soybeans, and the B to foresee SRW cash prices. Upon these choices, this paper has attempted predictions for each commodity for the coming 16 months. Also, confidence intervals have been shown in the figures of corn, soybean, and cotton. Soft red winter wheat doesn't have a confidence interval since it is a moving average approach. This paper calculated the confidence intervals are with a confidence level at 80%.

Figures 14 to 17 show the predicted commodity cash prices (blue), lower bound (grey), and upper bound (orange). The corn cash price is thought to decrease to the lowest between October 2017 to November 2017. The lowest price is predicted to be around 3.35 \$/bu. Afterwards, the price will reach its peak in May 2018 at 3.7 \$/bu. Soybeans has a similar pattern as corn, ranging from 8.8 to 10.5 \$/bu. The only difference is the soybean price decreases slowly in the beginning and then increases quickly afterward. These results follow the farm cycle that corn and soybeans' cash prices reduce during their harvest period. The SRW cash price will

remain stable at around 4.5 \$/bu until May 2018. After that, this paper predicted the wheat price to drop to 3 \$/bu. It also predicted cotton to start at 0.67 \$/lb in July 2017 and then fall to the bottom in November 2017 to 0.57 \$/lb. The price of cotton will be stable around 0.58 \$/lb after that.

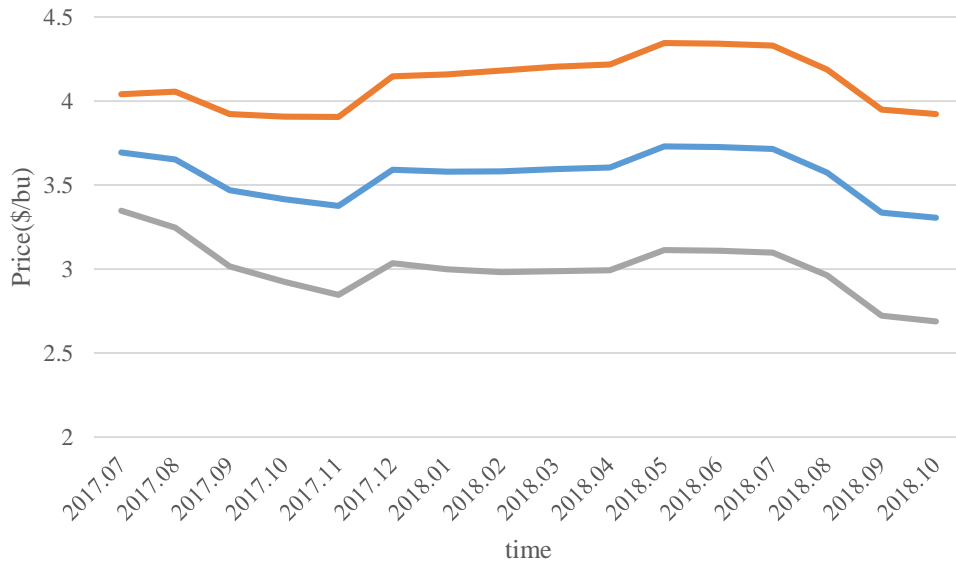


Figure 14. Corn price forecast (2017.07-2018.10)

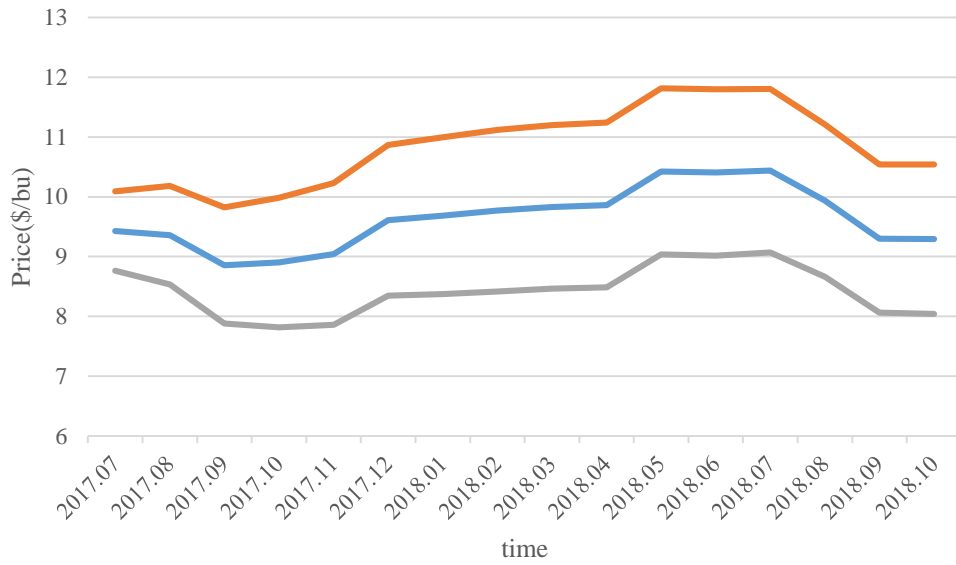


Figure 15. Soybeans price forecast(2017.07-2018.10)

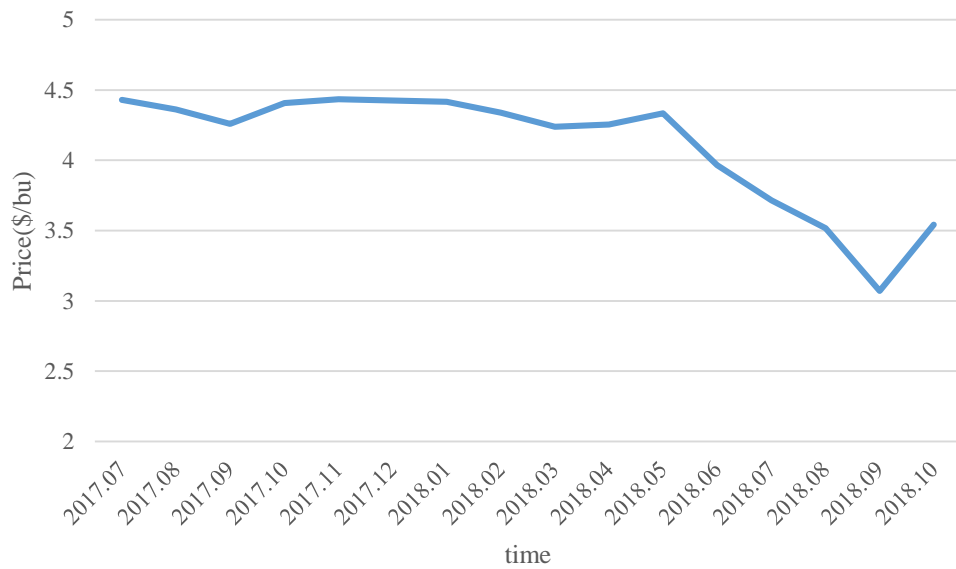


Figure 16. SRW price forecast (2017.07-2018.10)

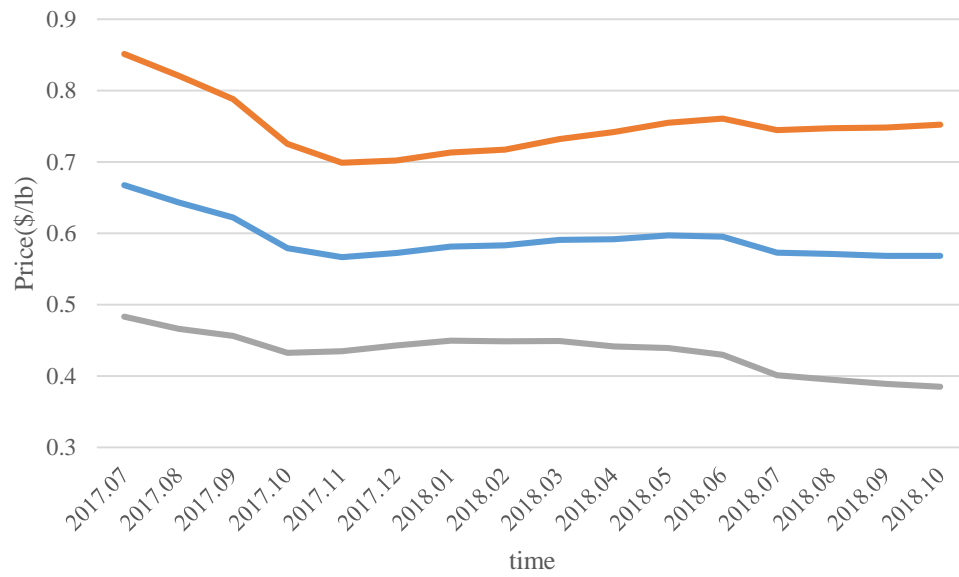


Figure 17. Cotton price forecast (2017.07-2018.10)

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Appendix

Appendix A Contract Information

The corn futures contract is measured in 5000 bushels per unit. The price of corn futures contract is in cents per bushel. There are five futures contracts of corn, which are named as CH (March), CK (May), CN (July), CU (September), and CZ (December). These five contracts are different from each other depending on the months they are terminated to trade. The termination of trading is on the business day prior to the 15th calendar day of the contract month. The quality of corn used in these contracts is the No.2 Yellow Corn.

The soybean futures contract is measured in 5000 bushels per unit. The price of soybean futures contract is in cents per bushel. There are seven futures contracts of soybean, which are named as SF (January), SH (March), SK (May), SN (July), SQ (August), SU (September), and SX (November). These seven contracts are different from each other depending on the months they are terminated to trade. The termination of trading is on the business day prior to the 15th calendar day of the contract month. The quality of soybean used in these contracts is the No.2 Yellow Soybean.

The wheat futures contract is also measured in 5000 bushels per unit. The price of wheat futures contract is also in cents per bushel. There are five futures contracts of wheat, which are named as WH (March), WK (May), WN (July), WU (September), and WZ (December). These five contracts are different from each other depending on the months they are terminated to trade. The termination of trading is on the business day prior to the 15th calendar day of the contract month. The quality of wheat used in these contracts is the No.2 Soft Red Winter Wheat.

The cotton futures contract is measured in 50000 pounds net weight. The price of cotton futures contract is in cents and hundredths of a cent per pound. There are five futures contracts of

cotton, which are named as CTH (March), CTK (May), CTN (July), CTV (October), and CTZ (December). These five contracts are different from each other depending on the months they are terminated to trade. The termination of trading is on the 17th business day from the end of the spot month. The quality of cotton used in these contracts is the No.2 Cotton.