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Seon-Woong Kim and B. Wade Brorsen

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Seon-Woong Kim

and

B. Wade Brorsen[1]

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[1] Seon-Woong Kim is a Ph. D candidate (seonwoong.kim@okstate.edu) and B. Wade Brorsen is a regents professor and A.J. and Susan Jacques Chair (wade.brorsen@okstate.ed), Department of Agricultural Economics, Oklahoma State University, Stillwater, Oklahoma. Brorsen receives financial support from the Oklahoma Agricultural Experiment Station and USDA National Institute of Food and Agriculture, Hatch Project number OKL02939.

Forecasting Urea Prices

Over the past decade the price of urea has been quite volatile, especially after 2008. The high price volatility and the relatively slow transportation in the urea fertilizer industry make production planning and inventory management difficult. In this study, we construct a urea price forecasting model and compare its performance with Fertilizer Week, a commercial forecast. To construct forecast models, autoregressive (AR), seasonal autoregressive (SAR), and autoregressive-generalized autoregressive conditional heteroskedasticity (ARGARCH) models with/without exogenous variables such as Henry Hub natural gas, Brent oil, and U.S. corn prices are used with various rolling windows. Autoregressive model with exogenous variable (ARX) using the window size of 48 months outperforms our other models. There is no statistical difference between ARX with the window size of 48 month and Fertilizer Week even though Fertilizer Week is better based on forecasting accuracy measures. The combination model using the two models is statistically better than Fertilizer Week alone.

***Key words*:** Fertilizer, forecasting, ARX, GARCH, MDM test, encompassing test, forecasting accuracy, optimal forecasting conditions.

Introduction

Urea is one of the most important solid nitrogen fertilizers[1] in the United States, with yearly consumption increasing as much as 2.72% between 1992 and 2011(USDA 2013a). The price of urea has risen since 2002 and also fluctuated dramatically (Casavant et al. 2010) as shown in Figure 1. The price fluctuation has been more severe after 2008. For example, the average annual price volatilities of urea are 23.3%[2] between 2003 and 2007, while between 2009 and 2014 it increases to 36.1% (*Fertilizer Week* 2014). This high price volatility and the relatively slow transportation in the urea fertilizer industry make production planning and inventory management difficult.

To manage the urea fertilizer price volatility, a price risk management tool is required. Futures contracts have been tried for fertilizer, but were unsuccessful due to high basis risk since transportation cost occupies a large portion of the fertilizer price. Often purchases are conducted in advance of the sale in order to take advantage of backhauls. The fertilizer cash market is also not active enough to support a futures contract. Moreover, fertilizer is provided by a few private companies and there exists only limited market information. Forward contracts are available and there is a swaps market in France, but these risk management tools can be expensive.

[1] Urea occupies the highest proportion in nitrogen fertilizer and nitrogen shows the highest consumption of plant nutrients in the U.S. (USDA 2013a).
[2] The annualized price volatilities are calculated as the standard deviation of monthly returns multiplied by the square root of the number of trading month in the year.

In this situation, an accurate urea price forecast is useful. Now, some commercial publications such as *Fertilizer Week*[3] by CRU group and *FMB* by Argus Media are meeting this need by providing fertilizer price forecasts. However, there exists little academic literature regarding forecasting urea prices.

The objectives of this study are to suggest an appropriate forecasting model for granular urea price in the U.S. New Orleans market. The procedures to achieve the goal are (1) to construct forecasting models using various methods and check properties for optimal forecast, (2) to evaluate the selected model compared to that of *Fertilizer Week*, and (3) to check the possibility to improve forecasting accuracy using the composite model by combining our forecasts and those of *Fertilizer Week*.

Methodology

Model Identification

Autoregressive Moving Average Models

For short-term forecasting, the autoregressive moving average model (ARMA) is commonly used (Whitle 1951; Box and Jenkins 1976):

(1) $$y_t = \mu + v_t,$$
(2) $$v_t = \sum_{m=1}^{M} \varphi_m v_{t-m} - \sum_{s=1}^{S} \eta_s \epsilon_{t-s} + \epsilon_t,$$
(3) $$\epsilon_t \sim IN(0, \sigma^2),$$

where y_t, μ and v_t indicate the dependent variable, the intercept, and the mean equation error, respectively, φ_m and η_s are the coefficients of AR and MA terms, m and s indicate the lag number for autoregressive and moving average terms, and ϵ_t is normally and independently distributed with a mean of 0 and a variance of σ^2. The autoregressive moving average model only uses its own past information. However, there might be other appropriate time series data which capture the influence of external factors and increase forecast accuracy. To consider the other pertinent time series in our forecasting model, an autoregressive moving average model with exogenous variables (ARMAX) is used. The ARMAX model can be expressed by adding the exogenous variables to the mean equation in (1) as:

(4) $$y_t = \mu + \boldsymbol{x}_t'\boldsymbol{\beta} + v_t,$$

where $\boldsymbol{x}_t$ is a vector of explanatory variables. There is a possibility of seasonality. To account for possible seasonality, a seasonal autoregressive moving average (SARMA) model is estimated, which can be expressed by redefining equation (2) as

(5) $$v_t = \sum_{m=1}^{M} \varphi_m v_{t-m} - \sum_{s=1}^{S} \eta_s \epsilon_{t-s} + \sum_{i=1}^{I} \psi_i (v_{t-i*w} - \varphi_1 v_{t-i*w-1}) - \sum_{j=1}^{J} \xi_j \left(\epsilon_{t-j*h} - \eta_1 \epsilon_{t-j*h-1}\right) + \epsilon_t,$$

[3] *Fertilizer Week* is a kind of commercial publications by CRU group which provides fertilizer prices and market information and also forecasts monthly fertilizer prices.

where ψ_i, and ξ_j are the coefficients of seasonal AR and seasonal MA terms, w and h are the seasonal length for autoregression and moving average terms.

Generalized Autoregressive Conditional Heteroskedasticity Models

ARMA models assume homoskedasticity which means the variance does not change over time. However, variance of time series data is often non-constant. To account for the heteroskedasticity, the generalized autoregressive conditional heteroskedasticity (GARCH) model by Bollerslev (1986) is used. In a GARCH model, the conditional variance is a function of the past values of squared errors and lagged conditional variances. The distribution of the error term in equation (3) can be redefined as

$$(6) \qquad \begin{aligned} &\epsilon_t|\Psi_{t-1}\sim N(0,\sigma_t^2) \\ &\sigma_t^2=\alpha_0+\textstyle\sum_{i=1}^{q}\alpha_i\epsilon_{t-i}^2+\sum_{j=1}^{p}\rho_j\sigma_{t-j}^2+\sum_{k=1}^{m}\eta_k T_{k(t)} \\ &\frac{\epsilon_t}{\sqrt{\sigma_t^2}}\sim IN(0,1), \end{aligned}$$

where Ψ_{t-1} denotes all available information at time $t-1$, σ_t^2 is the conditional error variance, $T_{k(t)}$ indicates year dummy variables. The coefficients in equation (6) should be positive to obtain a positive conditional variance.

Rolling Window Regression

In time series data, structural change is frequently observed. To account for the possibility of structural change, rolling window regression is applied with various window sizes at the estimation step. Rolling window regression is a recursive regression to generate estimates for every window of a given size in the series as

$$(7) \qquad y_{t(\lambda)}=\boldsymbol{x}'_{\boldsymbol{t}(\lambda)}\boldsymbol{\beta}+v_{t(\lambda)} \quad \lambda=1,\cdots,n-w+1$$

where λ is the ordinal number of w-time unit window, and n indicates the total number of observations. The coefficient β is often used to assess the stability of a model over time. For example, if β is non-constant it shows an unstable market. There is a trade-off relationship between sensitivity and volatility of the parameters in window size. The considered windows, w, are 36, 48, 60, 72, and 81[4] months.

Properties for Optimal Forecast

Diebold and Lopez (1996) suggest four criteria for optimal forecast models, but only two are relevant here since only one-step-ahead forecasts are considered. The two relevant properties are unbiasedness and efficiency of forecasting error (Granger and Newbold 1986). A forecast is unbiased if its average deviation from the actual value is zero. Unbiasedness can be identified with the significance of the mean forecast error by using a regression of the error on a constant term (Holden and Peel 1990) as

[4] 81 months is the longest possible window size since the time span of in-sample is 81 months.

(8) $$\epsilon_t = \gamma + e_t,$$

where ϵ_t is forecast error, γ indicates a constant term, and e_t is white noise error term. The null hypothesis of an unbiased forecast is $\gamma = 0$. When the null hypothesis is rejected with $\gamma > 0$, the forecast overestimates all actual series and vice versa. Forecast efficiency implies that the forecast error is not related to information available at the time the forecast is made (Nordhaus 1986; Holden and Peel 1990; Barrionuevo 1996). This condition is tested by measuring the correlation between the forecast term and its error term, and between the forecast error at the current period and that at the previous period (Pons 2000) as

(9) $$\epsilon_t = \alpha_1 + \beta F_t + e_t,$$

(10) $$\epsilon_t = \alpha_2 + \rho\epsilon_{t-1} + e_t,$$

where F_t denotes the forecast at time t. When β=0 in equation (9) and ρ=0 in equation (10), forecast efficiency holds. There exist three inefficient cases: when β≠0 and ρ=0 the inefficiency is caused by the fact that the forecast is not the minimum variance model, when β=0 and ρ≠0, the inefficiency arises because the past errors repeat in the present, and when β≠0 and ρ≠0 the inefficiency is partly from the fact that the forecast does not use all useful information when it is conducted and partly from the errors of the past are repeated in the present (Pons 2000).

Adjustment of Heteroskedasticity and Different Forecast Horizons

Since the urea price volatility has increased overtime, a heteroskedasticity adjustment is needed. To adjust the heteroskedastic error terms of all models conditional error variance from a GARCH (1, 1) model with a random walk assumption[5] as

(11) $$e_{t(H)} = \frac{e_t}{\sigma_t},$$

where, $e_{t(H)}$ and e_t indicate the adjusted error term and the error term from an forecast model, respectively, σ_t denotes the conditional error variance.

When one forecast has a different forecast horizon, the forecast error should be adjusted to compare its forecasting performance with the other models. The adjustment of different forecast horizons is conducted as

(12) $$e_{t(adj)} = e_{t(H)} * \sqrt{\frac{1}{k}},$$

[5] A random walk model assumes no difference between the values at t and t-1 as $y_t - y_{t-1} = \epsilon_t$, where ϵ_t indicates a white noise error term. Hyndman and Koehler (2006) also use the weighted error terms based on the random walk assumption to get a measure of forecast accuracy such as mean absolute scaled error.

where, k denotes the proportion of the forecast horizon out of the standard forecasting horizon. For example, if the forecast horizon is 2 weeks and the standard forecasting horizon is 4 weeks then k is equal to 0.5.

Measures of Forecast Accuracy

To evaluate the performance of the constructed forecasting models, two different statistical measures were applied: mean absolute error (MAE) and root mean squared error (RMSE). Those forecast accuracy measures are defined as

(13) $$MAE = \frac{1}{n}\sum_{t=1}^{n}\left|e_{t(adj)}\right|,$$

(14) $$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n} e_{t(adj)}^{2}},$$

Modified Diebold Mariano Test

To test the null hypothesis of no difference in the accuracy of two competing forecasts Diebold and Mariano (DM) (1995) suggest a parametric test. Given two time series errors, $\varepsilon_{0,t}$ and $\varepsilon_{1,t}$, the specified loss functions, $g(\varepsilon_{0,t})$ and $g(\varepsilon_{1,t})$, and the loss differential $d_t = g(\varepsilon_{0,t}) - g(\varepsilon_{1,t})$, the null hypothesis of equal expected forecast accuracy is

(15) $$H_0: E[d_t] = E\left[g(\varepsilon_{0,t}) - g(\varepsilon_{1,t})\right] = 0,$$

and the test statistic is

(16) $$DM = \frac{\bar{d}}{\sqrt{\hat{V}(\bar{d})}},$$

where $\hat{V}(\bar{d})$ is an estimate of the asymptotic variance of $\bar{d}$. Diebold and Mariano propose estimating the variance using the truncated kernel with a bandwidth of $(h-1)$ for h-step-ahead forecasts. Failing to reject the null hypothesis can be interpreted as the two models are not statistically different. On the other hand, the smaller loss model is the better. The asymptotic variance is estimated as

(17) $$\hat{V}(\bar{d}) = \frac{1}{T}[\hat{\gamma}_0 + 2\sum_{k=1}^{h-1}\hat{\gamma}_k],$$

where $\hat{\gamma}_k$ is an estimate of the k-th autocovariance of d_t, given by

(18) $$\hat{\gamma}_k = \frac{1}{T}\sum_{t=k+1}^{T}(d_t - \bar{d})(d_{t-k} - \bar{d}).$$

The DM test statistic has an asymptotic standard normal distribution. Harvey, Leybourne, and Newbold (1997) suggest the modified Diebold Mariano (MDM) test to improve small sample properties with a t-distribution, rather than the standard normal. The MDM statistic is obtained as

(19) $$MDM = \frac{\sqrt{T+1-2h+\frac{h(h-1)}{T}}}{T} DM.$$

Forecast Encompassing Test

Even though one forecast will be superior to the others based on forecast accuracy measures, it is useful to test whether competing forecasts may be combined to construct a composite forecast superior to all the original forecasts (Diebold 2007). The forecast encompassing can be examined following Harvey, Leybourne, and Newbold (1998) as

(20) $$\varepsilon_{0,t} = \phi + \lambda_t(\varepsilon_{0,t} - \varepsilon_{1,t}) + \tau_t,$$

where $\varepsilon_{0,t}$ and $\varepsilon_{1,t}$ are the forecast error terms of the hypothesized model and the competing one, λ_t indicates the weight, which the alternative should hold in constructing a composite forecast and minimizes the mean squared forecast error and vice versa for $1 - \lambda_t$ (Sanders and Manfredo, 2004). A failure to reject the null hypothesis ($\lambda_t = 0$) implies the hypothesized forecast encompasses the competing one.

Data

To choose appropriate explanatory variables for constructing a urea price forecasting model, three factors are considered: supply, demand, and transportation. Natural gas price is selected as a supply factor since the raw material of urea is natural gas. In detail, urea is a composite between carbon dioxide and ammonia which is extracted from natural gas. Corn price is considered as the demand factor since corn production is the largest use of urea[6]. The U.S. is one of the largest urea importing countries with about 80%[7] of the imported volume coming from overseas using marine transportation. This form of transportation mainly uses intermediate fuel oil (IFO). Based on this fact, oil price is used for the transportation cost factor.

To construct a urea price forecasting model, the monthly average prices of granular urea, Henry Hub natural gas, Brent oil, and the U.S. average corn price are used (see Figure 2). The free-on-board (FOB) bulk price of granular urea traded in the U.S. New Orleans spot markets were purchased from *Fertilizer Week.* The prices of the natural gas and Brent oil were gathered from the U.S. EIA (2015a and b) and the U.S. average corn price was obtained from the USDA's (2015a) Agricultural Prices. To compare the performance of our forecast model the forecasted price from *Fertilizer Week* is used. It includes some missing values since CRU Group did not issue forecasts for parts of the time period[8]. Also, *Fertilizer Week* is issued at the end of previous month or early in the month, implying the forecasting horizon is shorter than one month. For example, *Fertilizer Week* for June 2014

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6 The average proportion of nitrogen fertilizer consumption for corn, wheat, and cotton are 42.1%, 12.1%, and 3.5% from 2006 to 2010 (USDA 2013a).

7 The U.S. imported 7.65 billion tons in 2012. In detail, the overseas countries export urea to the U.S.as much as 6.06 billion tons and Canada and Mexico do as much as 1.58 billion ton (USDA 2014a).

8 *Fertilizer Week* issued its forecast of the urea price from April to September 2008, November 2008, from January to May 2009, from July 2009 to June 2010, and April 2013 to the present.

was issued on June 3, 2014. To account for the different forecast horizon of *Fertilizer Week* to those of the constructed forecasts, the forecast horizon adjustment is conducted.

To test for unit roots in price levels and log difference of all data, the augmented Dickey-Fuller (ADF) test is used. The ADF test failed to reject the null hypothesis of a unit root at the 5% significance level for all price level data[9]. However, the null hypothesis of a unit root is strongly rejected at the 1% level for the monthly log difference. Monthly log differences of all data are used from August 2001 to June 2014. In-sample and out of sample are decided based on the point when *Fertilizer Week* started to issue its urea forecast, May 2008.

Summary statistics for all time-series data are presented in Table 1. The means and standard deviations are measured as the percentage change of price from the prior month. Brent oil indicates the highest mean as much as 1.0%, but *Fertilizer Week* shows the lowest mean of -1.6%. *Fertilizer Week* forecasts are the most volatile with a standard deviation of 14.7% and the corn price is relatively stable with a standard deviation of 5.5%. Urea indicates the highest percentage change of price as much as -56.6%.

Results

To choose the optimal lags for constructing forecasting models the corrected Akaike information criterion (AICC) and Schwarz Bayesian Criteria (SBC) are considered and the alternative lags are up to 12 months for autoregressive moving average terms and explanatory variables and 36 months for seasonal autoregressive moving average terms. The optimal lags for each model which indicate the lowest criterion are shown in Table 2.

Tables 3, 4, and 5 indicate the test results for unbiasedness and efficiency as optimal forecast properties. The mean forecast error, γ, is shown in Table 3 and the results indicate all forecasts are unbiased. Also, there is no overestimation/underestimation pattern. In Tables 4 and 5, there are the results for the efficiency tests of the forecasts. From the results for β in Table 4, forecasts incorporate all available information at the time the forecast is conducted (β=0) at the 5% level. However, ARG with window size 36 and ARGX with window size 48, 60, 72, and 81 are inefficient since the past errors are repeated in the present ($\rho \neq 0$) as shown in Table 5.

Table 6 illustrates the comparison of MAE, a mean-type forecasting accuracy measure, compared to a naïve no-change forecasting model only when *Fertilizer Week* is not issued in out-of-sample period. All models are superior to the naïve model with MAE less than 0.766. The models with exogenous variables show smaller MAE compared to the model without exogenous variables and it means the exogenous variables improve forecasting accuracy. The appropriate window sizes are 48 months for the models with exogenous variables and 72 months for the AR and the SAR models, and 60 months for the ARG model. The most appropriate forecasting model is the SARX with a window size of 48 months with a MAE of 0.553.

[9] Given a unit root in price level data, the cointegration test is conducted among urea price and explanatory variables, but the null hypothesis of cointegration is rejected.

Table 7 indicates the comparison of RMSE, a variance-type forecasting accuracy measure, compared to a naïve no-change forecasting model only when *Fertilizer Week* is not issued in out-of-sample period. The lowest RMSE of 0.795 is for the ARX model with the window size of 48 months. Comparing pair forecasts with/without exogenous variables such as AR versus ARX or SAR versus SARX, the models with exogenous variables indicate lower RMSE and it means the inclusion of exogenous variables reduces forecast error variance. Based on the results in Table 6 and Table 7, the SARX and ARX with a window size of 48 months are chosen as the competitive models to *Fertilizer Week* forecasting model.

Table 8 shows the results for forecast accuracy measures and for two kinds of MDM tests only when *Fertilizer Week* is issued. The forecast accuracy measures indicate *Fertilizer Week* is outperforming than the ARX and SARX. However, the results of two MDM tests show no statistical difference between *Fertilizer Week* and the two models. Based on the forecast accuracy measures and MDM tests, the ARX with window size of 48 months is chosen as a candidate for constructing a combination model with *Fertilizer Week*.

The forecast encompassing regression (Table 9) shows significant estimated weight for both *Fertilizer Week* and the ARX, indicating that neither forecast encompasses the other, and each contains unique information at the 1% level. The results imply that forecasting accuracy can be improved by using both *Fertilizer Week* and ARX rather than either alone. For example, the combined model using 66.8% of *Fertilzer Week* and 33.2% of the ARX brings about the minimum forecast error.

Table 10 indicates results for forecasting accuracy measures and MDM tests for the composite model using *Fertilizer Week* and the ARX with a window size of 48 months. As indicated in Table 8 and Table 10, the composite model outperforms *Fertilizer Week* based on the forecasting accuracy measure. In addition, the MDM test based on the squared-error loss function supports that the composite model is statistically different to *Fertilizer Week* and encompasses *Fertilizer Week* at the 10% level.

Conclusion

This study constructs various forecasting models for the free-on-board (FOB) bulk price of granular urea traded in the U.S. New Orleans spot markets using a variety of methods and rolling window sizes, tests the optimal forecasting properties such as unbiasedness and efficiency, and evaluates the performance for the constructed models, *Fertilizer Week*, and the combination model based on forecasting accuracy measures, two types of MDM tests, and encompassing tests.

Using the tests for the optimal forecasting conditions, forecasts from all constructed models and *Fertilizer Week* are unbiased and incorporate all available information at the time the forecasting is made. However, inefficiency is observed in ARG model with a window size of 36 and ARGX model with a window size 48, 60, 72, and 81 at the 5% level since forecast errors are autocorrelated.

Based on the comparison among the constructed models using forecasting accuracy measures, the SARX for MAE and the ARX for RMSE with a window size of 48 months show the lowest values. The models with exogenous variables provide smaller accuracy measures than models without exogenous variables. All models show the MAE and RMSE values less than that of no change naïve model indicating they are superior to a no change naïve model.

In comparison between the constructed models and *Fertilizer Week* even though the forecast accuracy measures indicate *Fertilizer Week* outperforms ARX and SARX with window size 48, the two MDM tests show no statistical difference between *Fertilizer week* and the two models. The ARX is chosen as a candidate for constructing a combination model with *Fertilizer Week* based on the forecast accuracy measures. Neither of *Fertilizer Week* and ARX forecast encompasses the other and each contains unique information. The results imply the desirability of a combination model using both *Fertilizer Week* and the ARX rather than either alone. When comparing the combination model to *Fertilizer Week* the combination model shows lower forecast accuracy measures and the MDM test based on squared-error loss supports that the composite model is statistically different and it shows improved forecasting performance at the 10% level.

The combination forecast model can explain about half of the variability of percentage changes. Therefore, the forecasting model can successfully reduce the risk faced by those in the fertilizer industry.

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Table 1. Descriptive Statistics from September 2001 to June 2014

	Urea	Brent Oil	Natural Gas	Corn	*Fertilizer Week*
N	154	154	154	154	34
Mean	0.008	0.010	0.003	0.006	-0.016
St. dev.	0.109	0.086	0.132	0.055	0.147
Max.	0.371	0.180	0.380	0.144	0.428
Min.	-0.566	-0.311	-0.407	-0.154	-0.532

Table 2. Optimal Lags for AR Terms, Explanatory Variables, ARCH, and GARCH Terms

Model	Autoregressive	Explanatory Variable			ARCH	GARCH
		Natural Gas	Brent Oil	Corn		
AR	(1, 3, 6, 12)	.	.	.	.	.
ARX	(1, 2, 4, 6, 12)	1, 6	1, 3	6	.	.
SAR	(1, 3, 6)*, (12)**	.	.	.	.	.
SARX	(1, 2, 4, 6)*, (12)**	1, 6	1, 3	6	.	.
ARGARCH	(1, 3, 6, 12)	.	.	.	1	1
ARXGARCH	(1, 2, 4, 6, 12)	1, 6	1	6	1	1

Note: *, ** indicate the autoregressive lags and seasonal autoregressive lags, respectively.

Table 3. Forecast Bias Test on Mean Forecast Error (γ)

w	AR	ARX	SAR	SARX	ARG	ARGX	*FW*
36	-0.008	-0.007	-0.008	-0.004	-0.017	-0.021	-0.016
	(-0.64)	(-0.58)	(-0.70)	(-0.39)	(-1.09)	(-1.49)	(-0.64)
48	-0.011	-0.006	-0.012	-0.006	-0.020	-0.009	
	(-0.89)	(-0.50)	(-0.95)	(-0.56)	(-1.34)	(-0.68)	
60	-0.008	0.000	-0.009	-0.001	-0.015	-0.009	
	(-0.68)	(-0.04)	(-0.73)	(-0.12)	(-1.19)	(-0.65)	
72	-0.011	-0.007	-0.011	-0.007	-0.018	-0.014	
	(-0.88)	(-0.56)	(-0.92)	(-0.53)	(-1.36)	(-0.98)	
81	-0.012	-0.008	-0.013	-0.007	-0.019	-0.015	
	(-0.98)	(-0.60)	(-1.01)	(-0.57)	(-1.46)	(-1.06)	

Note: t-value is presented in parentheses.
None is significant at the 5% level.

Table 4. Forecast Efficiency Test (β)

w	AR	ARX	SAR	SARX	ARG	ARGX	*FW*
36	0.013	0.068	0.013	0.069	-0.266	-0.252	-0.783
	(0.10)	(0.57)	(0.10)	(0.59)	(-1.07)	(-1.71)	(-1.58)
48	-0.034	0.062	-0.001	0.053	-0.230	-0.121	
	(-0.26)	(0.50)	(0.00)	(0.43)	(-1.10)	(-0.86)	
60	-0.013	0.061	-0.009	0.067	-0.070	-0.157	
	(-0.09)	(0.46)	(-0.07)	(0.49)	(-0.53)	(-1.09)	
72	-0.005	0.050	0.020	0.057	-0.028	-0.255	
	(-0.04)	(0.35)	(0.14)	(0.39)	(-0.18)	(-1.75)	
81	-0.005	0.062	0.021	0.086	-0.027	-0.234	
	(-0.03)	(0.42)	(0.15)	(0.56)	(-0.18)	(-1.52)	

Note: t-value is presented in parentheses.
None is significant at the 5% level.

Table 5. Forecast Efficiency Test (ρ)

w	AR	ARX	SAR	SARX	ARG	ARGX	*FW*
36	0.079	-0.102	0.092	-0.063	0.304*	-0.190	0.313
	(0.69)	(-0.87)	(0.81)	(-0.55)	(2.74)	(-1.68)	(1.56)
48	0.003	-0.145	0.034	-0.149	0.189	-0.338*	
	(0.03)	(-1.26)	(0.30)	(-1.30)	(1.66)	(-3.13)	
60	-0.027	-0.187	-0.021	-0.180	-0.044	-0.358*	
	(-0.23)	(-1.64)	(-0.19)	(-1.58)	(-0.39)	(-3.34)	
72	-0.015	-0.169	-0.004	-0.156	0.014	-0.323*	
	(-0.13)	(-1.47)	(-0.04)	(-1.36)	(0.13)	(-2.95)	
81	-0.006	-0.170	0.005	-0.166	0.019	-0.319*	
	(-0.05)	(-1.49)	(0.04)	(-1.46)	(0.17)	(-2.93)	

Note: t-value is presented in parentheses.
* indicates statistical significance at the 5% level.

Table 6. MAE Only When No *Fertilizer Week* Exists

w	naïve	AR	ARX	SAR	SARX	ARG	ARXG
81	0.766	0.641	0.624	0.649	0.627	0.680	0.639
72	0.766	0.638	0.607	0.644	0.623	0.672	0.632
60	0.766	0.648	0.611	0.659	0.622	0.646	0.609
48	0.766	0.662	0.564	0.655	0.553	0.708	0.606
36	0.766	0.659	0.630	0.656	0.625	0.702	0.663

Table 7. RMSE Only When No *Fertilizer Week* Exists

w	naïve	AR	ARX	SAR	SARX	ARG	ARXG
81	1.041	0.842	0.829	0.850	0.850	0.853	0.859
72	1.041	0.838	0.809	0.849	0.830	0.853	0.847
60	1.041	0.837	0.824	0.858	0.832	0.829	0.834
48	1.041	0.848	0.795	0.845	0.808	0.866	0.830
36	1.041	0.853	0.837	0.852	0.812	0.915	0.928

Table 8. Forecasting Accuracy and MDM Test Results Only When *Fertilizer Week* Exists

w	MAE			RMSE			MDM1		MDM2	
	ARX	SARX	*FW*	ARX	SARX	*FW*	ARX	SARX	ARX	SARX
48	0.690	0.692	0.495	0.955	0.962	0.695	1.287	1.284	1.031	1.072
							(0.104)	(0.104)	(0.155)	(0.146)

Note: MDM1 and MDM2 are calculated using the absolute error loss function ($g(e) = |e|$) and the squared-error loss function ($g(e) = e^2$), respectively.
p-value is presented in parentheses.
None is significant at the 10% level.

Table 9. Encompassing Regression (Preferred Model is *Fertilizer Week* to ARX)

MODEL	w	Estimated weight	
		λ	$1-\lambda$
ARX	48	0.668**	0.332**
		(7.23)	(3.59)

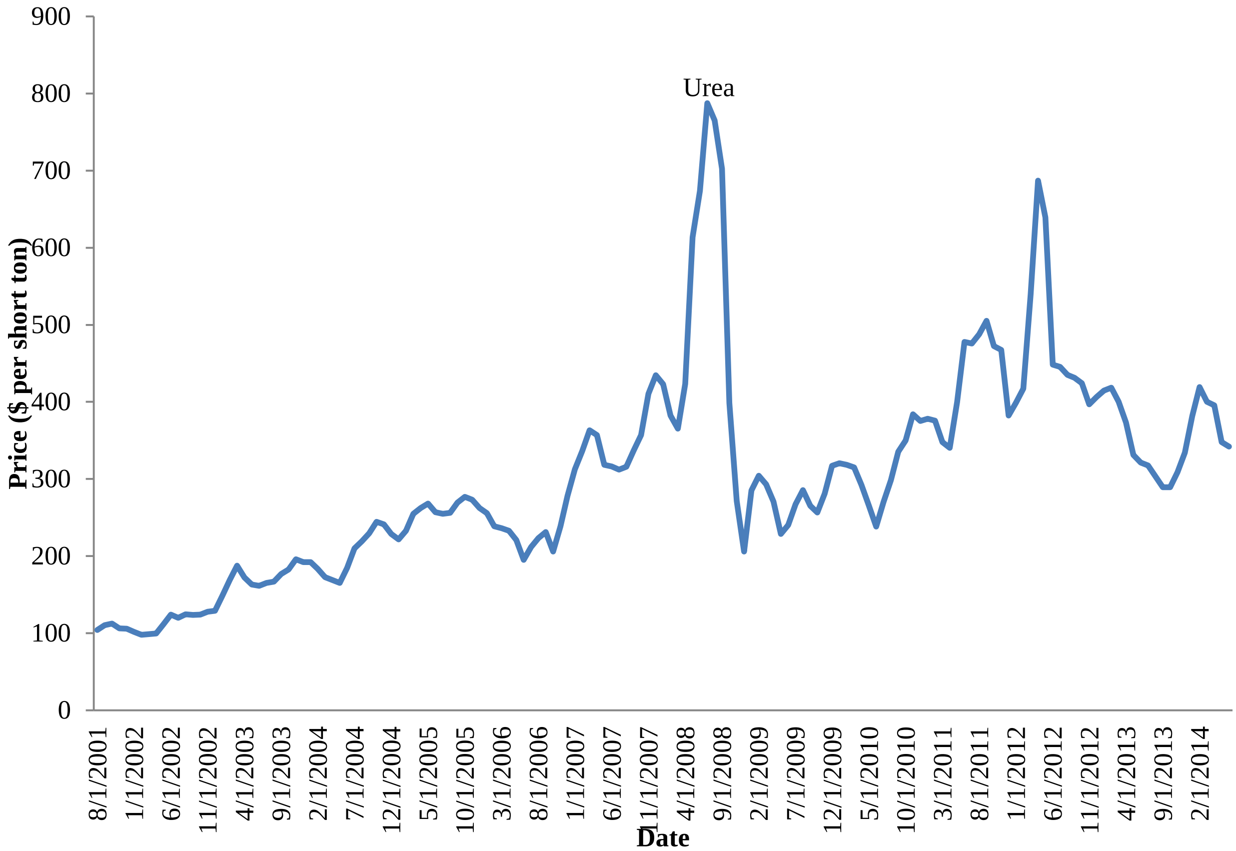
Note: The t-values for the test statistics are presented in parentheses.
** indicates statistical significance at the 1% level.

Table 10. Forecasting Accuracy and MDM Test Results for the Composite Model compared to *Fertilizer Week*

w	MAE	RMSE	MDM1	MDM2
48	0.411	0.575	1.151	1.369*
			(0.129)	(0.090)

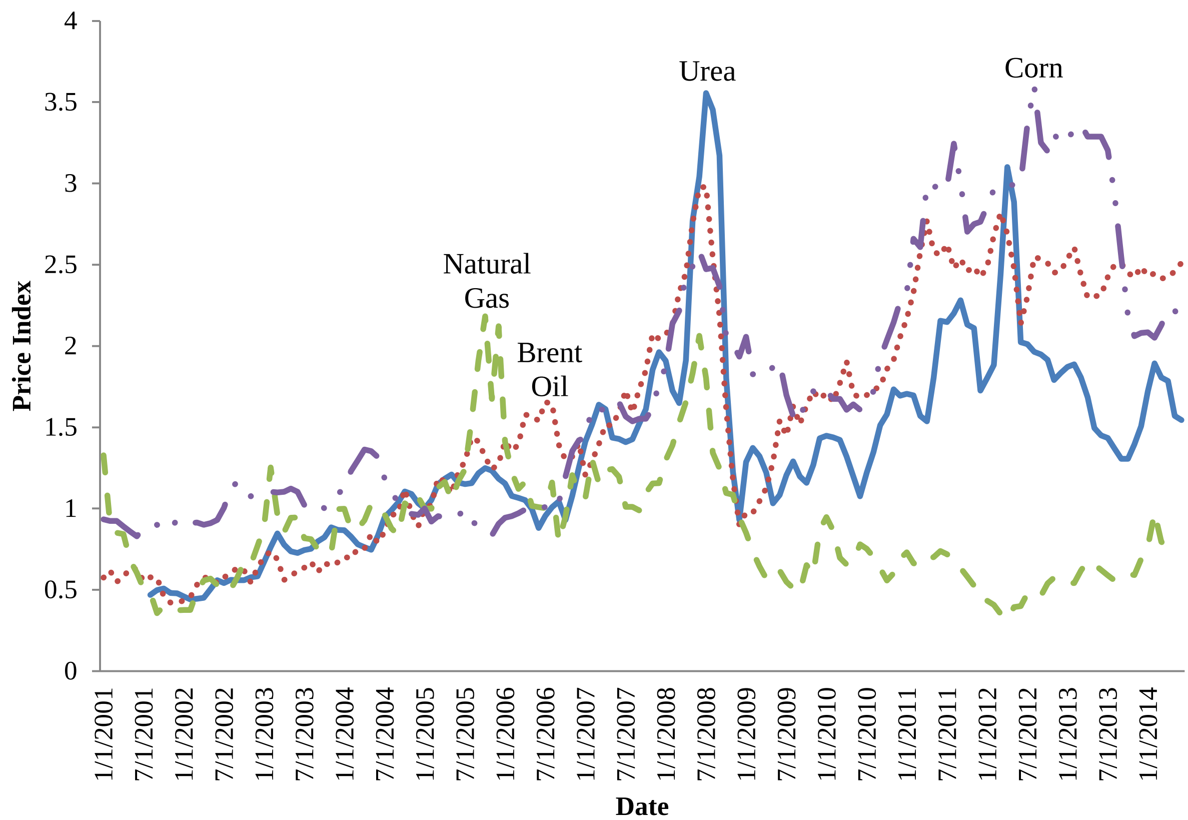
Note: MDM1 and MDM2 are calculated using the absolute error loss function ($g(e) = |e|$) and the squared-error loss function ($g(e) = e^2$), respectively.
p-value is presented in parentheses.
* indicates statistical significance at the 10% level.

Figure 1. Granular Urea Prices in New Orleans Spot Markets



Source: *Fertilizer Week* (2014)

Figure 2. Price Index for Urea, Natural Gas, Brent Oil, and Corn



Note: Price index is calculated based on the price on January, 2005.

Source: *Fertilizer Week* (2014) for urea, US EIA (2015a) for natural gas, US EIA (2015b) for Brent oil, and USDA (2015a) for corn.