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Can U.S. EIA Retail Gasoline Price Forecasts Be Improved Upon?

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Abstract

Perhaps the most widely followed price in the market is the price of crude oil. The volatility of this commodity is evident to consumers through the gasoline prices that consumers see on the retail side. The U.S. Energy Information Agency provides widely followed forecasts for the retail gasoline price (along with other energy products) produced with their short-term energy outlook (STEO) model. The purpose of this research is to compare a number of forecasts using different techniques to the STEO model. This is accomplished through the use of Holt Winters, structural, ARIMA, and vector error-correction models. We also construct a composite forecast by averaging the respective forecasts from the four models. From the empirical analysis, we find evidence from the structural model and the vector error-correction model that the movement in the gasoline prices can be explained by the West Texas Intermediate (WTI) benchmark and the spread between BRENT and WTI benchmarks. In terms of forecasting performance, the additive Holt Winters model outperforms the other models within sample. Out sample, the composite forecast is the best performing model. The composite forecast has a MAPE of 6.3% versus a MAPE of 8.1% from the STEO model.

Key Words: Retail Gasoline Prices, Forecasting, short-term energy outlook model; Holt-Winters model; ARIMA model; structural model; vector error-correction model

JEL Classification: Q47

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1. Introduction

Crude oil is not only one of the most actively traded commodities but is also a vital component of the world economy. The importance of the price of oil to the U.S. economy is clear in that 10 out of 11 of the postwar U.S. recessions were preceded by a large increase in the price of crude oil (Hamilton, 2011, p. 264). As the main input into gasoline, changes in the price of crude oil are important. At the consumer level the most immediate and visible aspect of oil price fluctuations is the volatility in gasoline prices seen at gas stations. An example of a less obvious effect on the consumer's budget is the change in the prices of used vehicles in response to changes in the prices of gasoline at a six-month delay (Allcott and Wozny, 2014). To reiterate crude oil is a volatile commodity that affects the bottom line of businesses and consumers and accurate price predictions are a necessity.

The U.S. Energy Information Administration (EIA) is the main and most widely followed source of forecasts for the energy sector. Focusing specifically on U.S. refiner wholesale gasoline prices, in August 2016 the EIA forecast for 2017 an average of \$1.97/gal in the first quarter, \$2.35/gal in the second quarter, \$2.41/gal in the third quarter, and \$2.30/gal in the fourth quarter (EIA, 2016). These numbers are in comparison to a fourth quarter average of \$1.95/gal in 2016.

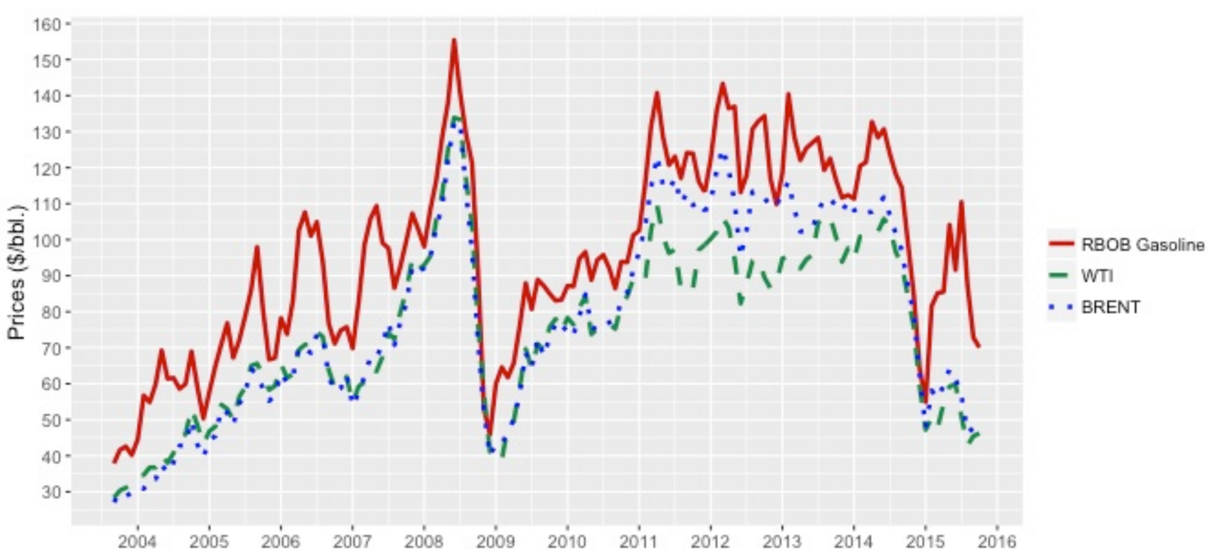

Fig. 1. Crude Oil and Gasoline Spot Prices in Dollar per Barrel from Sep 2003 to Oct 2015

The Energy Information Administration (EIA) estimates that about two-thirds of the price of gasoline is attributable to the cost of crude oil.[1] As Fig. 1 demonstrates, fluctuations on gasoline prices tend to track fluctuations in crude oil prices very closely. The U.S retail gasoline price is determined by four elements: the price of crude oil, refining costs and margins, retail and distribution costs and margins, and taxes. All but the first element tend to be relatively stable and easier to forecast. The majority of volatility in gasoline prices is from the crude oil component.

The principal aim of this research is to determine the best method to provide forecasts of gasoline prices by comparing forecasts from Holt Winters, structural, ARIMA, and vector error-correction models. We also construct a composite forecast by averaging the respective forecasts from the four models. Forecast accuracy is compared using RMSE, MAE, MAPE, and percent correct direction of change. From the empirical analysis, we find evidence from the structural model and the vector error-correction model that the movement in the U.S. gasoline spot prices can be explained by the West Texas Intermediate (WTI) benchmark and the spread between the BRENT and WTI benchmarks[2]. In terms of forecasting performance, the Holt Winters model outperforms other models within sample. Out sample, the composite forecast provides the most accurate forecasts. The composite forecast has better performance based upon MAE, MAPE, and correct direction of change relative to forecasts form the EIA.

The remainder of the article is organized as follows. Initially, we provide a review of literature to put our research in perspective. Next, we present the theoretical aspects of the models used to make forecast gasoline prices. Then we introduce our data and perform the estimation of the respective models. After the estimation, the results are presented and the forecasts from the distinct methodologies are compared. Finally, we make concluding remarks.

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[1] https://www.eia.gov/energyexplained/index.cfm?page=gasoline_factors_affecting_prices

[2] The most popular traded grades are Brent North Sea Crude (known as Brent Crude) and West Texas Intermediate (known as WTI). Brent refers to oil produced in the Brent oil fields and other sites in the North Sea. This oil price is the benchmark for African, European and Middle Eastern crude.

2. Literature Review

An important issue in the forecasting literature revolves around the existence of long-run relationships among gasoline prices and oil prices. This issue is important to discuss even though the forecast object of this paper is the price of gasoline. Bumpass, Ginn, and Tuttle (2015) find evidence of a long run relationship between crude oil price and retail gasoline prices. In examining the long-run demand for gasoline, Akinboade, Ziramba, Kumo (2008) found long-run relationships among gasoline demand, income, and gasoline price. Zhang, Lohr, Escalante, and Wetzstein (2010) found evidence of a co-integrating (long-run) relationship between gasoline prices and oil prices. Additionally, Hammoudeh, Ewing, and Thompson (2008) found long-run relationships among majors crude oil benchmarks. These articles demonstrate the imporatance of conducting a test concerning the existence of long-term relationship among gasoline prices and oil prices and the need to consider literature forecasting the price of crude oil.

Forecasting the price of oil is accomplished through a number of methods and is widely explored in literature. Forecasts of oil prices and gasoline prices have been made using the crack spread, defined as the difference between crude oil prices and its derivative product prices (Murat and Tokat, 2009; Baumeister, Kilian, and Zhou, 2013). Alquist, Kilian, and Vigfusson (2013) compare a number of models to determine which forecasts the real price of oil most accurately. The mean squared prediction error is the main accuracy measure to judge their results. These authors find that a vector autoregression provides more accurate forecasts compared to a no change forecast when considering a time horizon of six months. The no change forecasts performs better at horizons longer than six months. This finding is in contrast to some authors such as Maslyuk and Smyth (2008), who have found evidence that crude oil prices follow a random walk process. If crude oil truly followed a random walk process than the no change forecast would have been superior even in the six-month horizon in which Alquist, Kilian, and Vigfusson (2013) found the vector autoregression to be superior. Chen (2014) uses oil-sensitive stock price indices to forecast crude oil price movements. This model is able to provide forecasts that are more accurate a no-change forecast. It seems that at least in the short run there can be information gains from trying to forecast the oil price with econometric models.

Researchers can also incorporate geological and technological constraints into econometric models in order to make forecasts of future oil prices. Benes et al. (2015) find that such a model can outperform, based on root mean squared error, a random walk in forecasting prices and outperform the EIA forecasts of oil production at horizons up to five years. The price of oil is also dependent upon the world economy. Kilian and Hick (2013) find that global growth news can predict much of the increase in the real price of oil from the middle of 2003 until the middle of 2008 (Kilian and Hicks, 2013).

Baumeister and Kilian (2015) compare the forecast performance of six different models to the EIA forecasts for the real price of oil. It is similar to this research in that two of the models used are a vector autoregression and a structural model with the gasoline and WTI spread. The authors also construct a composite forecast of different models. The composite forecast outperforms the EIA oil price forecasts based on mean squared prediction error and directional accuracy. Baumeister, Kilian, and Lee (2016) also find that a composite forecast outperforms other models when examining real-time retail gasoline prices (which take into account delays in the availability and revisions). These articles demonstrate the need to consider multiple models when making forecasts.

In addition to standard economic variables, some researchers have begun using consumer survey data to forecast gasoline prices. Anderson, Kellog, and Sallee (2013) find that the average consumer believes that the expected future price of gasoline is the current price of gasoline. Anderson et al. (2011) use consumers expected inflation from the Michigan Surveys of Consumers (MSC) to make predictions of gasoline prices. The accuracy of models incorporating this data are similar to a no change forecast on average. Some evidence did indicate that forecasts just after the late-2008 economic crisis did outperform the no-change forecasts. Baghestani (2015) uses expected inflation and consumer sentiment from the MSC in a vector autoregression to forecast gasoline prices. This author finds that the model outperforms a univariate integrate moving average model. Baghestani (2015) also finds that incorporating MSC data leads to much better forecasts just after the late-2008 economic crisis.

In addition to the literature forecasting the price of gasoline there are a number of studies that examine what factors are influencing the retail price of gasoline. Some of these variables are more obvious such as weather, income and taxes (Bello & Contin-Pilart, 2012). Lesser-known factors may include the price of gasoline in bordering countries and ease of crossing the border. Fullerton et al. (2014) include the monthly volume of passenger vehicles entering El Paso, Texas and the retail price of gasoline in Mexico as regressors in a model explaining the price of gasoline in El Paso.

The issue of whether to use a univariate model or a multivariate model for forecasting is important in the forecasting literature. Which model is better is highly dependent on the forecast object. For example, Preez and Witt (2003) find that a simple ARIMA model performs better than a multivariate time series model when forecasting tourist arrivals to the Seychelles. Bidarkota (1998) finds that an error correction model provides more accurate forecasts than a univariate model when forecasting the real interest rate. In dealing with energy market volatility, using GARCH models Wang and Wu (2012) found that multivariate models performed better when forecasting certain assets prices, but univariate models perform better forecasting crack spread volatility. Abosedra (2005) finds that a univariate forecast of crude oil prices does not perform as well as a one-month ahead futures price. Thus, it is important to test whether to use a univariate or multivariate model for each particular situation and our research is important because it will determine which is best at forecasting gasoline prices.

A related line of research is whether there is asymmetry in the movements of gasoline prices and crude oil prices. Bacon (1991) describes this relationship as “Rockets and Feathers.” The gasoline prices will shoot up like a rocket in response to a crude oil price increases but they fall slowly like a feather as the price of crude oil declines. A number of studies have looked at this relationship (Kristoufeka and Lunackova, 2015; Bachmeier and Griffin, 2003). The literature is still undecided on this issue (Honarvar, 2009). Some authors find that wholesale gasoline prices respond symmetrically to an oil price shock in the long-run and any evidence asymmetries is likely due to the form of cointegration in the model (Bumpass, Ginn, and Tuttle, 2015).

Table 1: Summary statistics of key nominal energy prices

	Price			Log price		
Statistic	**GASOLINE ($/gal.)**	**WTI ($/bbl.)**	**BRENT-WTI ($/bbl.)**	**GASOLINE ($/gal.)**	**WTI ($/bbl.)**	**BRENT-WTI ($/bbl.)**
Mean	2.913	76.518	3.623	1.039	4.284	0.028
Median	2.922	76.495	0.090	1.072	4.337	0.001
Maximum	4.114	133.880	27.310	1.414	4.897	0.277
Minimum	1.522	28.310	-6.880	0.420	3.343	-0.117
Std. Dev.	0.689	23.365	7.902	0.255	0.344	0.087
Skewness	-0.219	-0.102	1.174	-0.572	-0.755	0.819
Kurtosis	1.921	2.357	3.256	2.314	2.890	2.922
Jarque-Bera	7.683*	2.580	31.591**	10.070**	12.973**	15.234**

*Note: Jarque-Bera test statistic is used to test the null hypothesis of normality. * and ** denote the rejection of the null hypothesis at the 5% and 1% levels, respectively.*

Table 2: Unit root tests

	Variable Transformation	**ADF**	**KPSS**
gasoline spot	X	-2.740	1.064 **
	log(X)	-2.854 *	1.063 **
	ΔX	-7.167 **	0.111
	Δlog(X)	-7.477 **	0.119
WTI	X	-2.821	0.965 **
	log(X)	-3.155 *	0.996 **
	ΔX	-7.100 **	0.129
	Δlog(X)	-7.762 **	0.206
BRENT-WTI	X	-2.274	0.874 **
	ΔX	-9.403 **	0.111
log(BRENT)-log(WTI)	X	-2.195	0.988 **
	ΔX	-10.805 **	0.097

Note: The ADF test is used to test the null hypothesis of a unit root for the variables and their assosiated transformed variables. ; the KPSS test is applied to test for the null hypothesis of level stationarity.
** and ** denote the rejection of the null hypothesis at the 5% and 1% levels, respectively.*

Table 3: Lag Order Selection Criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
1	-612.446	671.620	3.467	9.757	10.024	9.866
2	-572.130	**76.223***	**2.126***	**9.268***	**9.736***	**9.458***
3	-564.966	13.208	2.190	9.296	9.965	9.568
4	-559.322	10.143	2.310	9.349	10.218	9.702
5	-553.836	9.599	2.445	9.404	10.473	9.838
6	-548.326	9.385	2.589	9.458	10.728	9.974
7	-544.763	5.900	2.829	9.543	11.014	10.141
8	-538.283	10.430	2.957	9.583	11.254	10.262

*Note: * indicates lag order selected by the criterion*

LR: sequential modified LR test statistic (each test at 5% level)

FPE: Final prediction error

AIC: Akaike information criterion

SC: Schwarz information criterion

HQ: Hannan-Quinn information criterion

Table 4: Johansen Test for Cointegration

Hypothesized No. of cointegrating equations	Trace statistic	Max-Eigen statistic
None	51.800*	32.575*
At most 1	19.225*	15.630*
At most 2	3.595338	3.595338

*Note: * denotes rejection of the hypothesis at the 0.05 level*

Table 5: Wald Test-Granger Causality

Null hypothesis	F-Statistic
Δgasoline does not Granger cause ΔWTI	0.983
ΔWTI does not Granger cause Δgasoline	9.942 **
ΔWTI does not Granger cause Δ(BRENT-WTI)	0.891
Δ(BRENT-WTI) does not Granger cause ΔWTI	0.320
Δ(BRENT-WTI) does not Granger cause Δgasoline	0.320
Δgasoline does not Granger cause Δ(BRENT-WTI)	0.891

*Note: The table reports Wald test statistics. ** denotes rejection of the null hypothesis at the 1% level.*

3. Empirical models

Recall that the principal aim is to determine the best method to provide forecasts of gasoline prices using Holt Winters, structural, ARIMA, and vector error-correction models. The extant literature offers little in the analyses of forecasts using separate model specifications. In this way, this research helps to fill this void. The composition of the respective models draws upon popular models discussed in the review of literature. In this section, we discuss each of the respective univariate and multivariate models. We present a general overview of the theoretical components of the models under consideration. Readers interested in more detail should refer to other sources (Chase, 2013; Greene, 2003).

3.1. Holt Winters model

The Holt-Winters model is a univariate forecasting approach. This method has extensions to deal with a time-series containing both trend and seasonality. The Holt-Winters method has two versions in dealing with seasonality, additive and multiplicative. Based on performance of these two versions, we use the additive version for gasoline forecasts and only present this version. The additive formulation of Holt-Winters method is given by the following set of equations:

$$l_t = \alpha(GASOLINE_t - S_{t-m}) + (1-\alpha)(l_{t-1} + b_{t-1})$$

$$b_t = \beta(l_t - l_{t-1}) + (1-\beta)b_{t-1}$$

$$s_t = \gamma(GASOLINE_t - l_{t-1} - b_{t-1}) + (1-\gamma)s_{t-m}$$

$$\widehat{GASOLINE}_{t+h|t} = l_t + b_t h + s_{t+h-m}$$

Suppose that gasoline prices in respective time periods are denoted by $GASOLINE_1, \ldots, GASOLINE_t$ (t=1,2,…,T) and the seasonal period is denoted by m (m=12 for monthly data). Let $\widehat{GASOLINE}_{t+h}$ be the h-step forecast of gasoline prices made using data to time t.

3.2. Structural model

Now turning to a multivariate approach, we introduce a structural model. This model allows us to bring in information about the current and lagged prices of crude oil, the spread between crude oil indices, and seasonality effects. The final structural model consists of the following mean and variance equations:

Mean Equation:

$$\log(gasoline_t) = \beta_0 + \sum_{i=1}^{k} \beta_i \log(WTI_{t-i+1}) + \beta_{k+1} SPREAD_t + \sum_{j=1}^{11} \beta_{k+j+1} SEAS_j + \epsilon_t$$

Variance Equation:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{k} \alpha_i \epsilon_{t-i}^2 + \sum_{i=1}^{k} \beta_i \sigma_{t-i}^2$$

3.3 ARIMA model

The ARIMA(p,d,q) is a univariate forecasting approach. The model under consideration has the following form:

$$\left(1 - \sum_{i=1}^{p} \phi_i L^i\right)(1-L)^d GASOLINE_t = \delta + \left(1 + \sum_{i=1}^{q} \theta_i L^i\right)\epsilon_t$$

where L is the lag operator ($LX_t = X_{t-1}$), p is the order of the autoregressive component, d is the degree of differencing, and q is the order of the moving average component. The differencing may be necessary so as to insure that the forecast object (gasoline prices) will be stationary. Seasonality can be incorporated into this model by using a seasonal difference (e.g., $Y_t = X_t - X_{t-12}$).

3.4. Vector Error Correction Model (VEC)

A vector autoregression (VAR) is a multivariate model that is a generalization of the univariate autoregressive model. If $GASOLINE$ prices, OIL prices, and the BRENT-WTI spread ($SPREAD$) are found to have a co-integrating relationship (as evidenced by the review of the literature), then it would be appropriate to use a vector error-correction model (VEC). Note that the variables used in VEC model must be stationary. From Table 2, the appropriate transformation for all variables is the first difference.

The general form of this VEC model is

$$\Delta OIL_t = \alpha_O + \sum_{i=1}^{k} \alpha_i \Delta OIL_{t-i} + \sum_{j=1}^{l} \beta_j \Delta GASOLINE_{t-j} + \sum_{h=1}^{m} \alpha_i \Delta SPREAD_{t-h} + \tau_{O,1} ECT1_{t-1} + \tau_{O,2} ECT2_{t-1} + \epsilon_{Ot}$$

$$\Delta GASOLINE_t = \alpha_G + \sum_{i=1}^{k} \alpha_i \Delta OIL_{t-i} + \sum_{j=1}^{l} \beta_j \Delta GASOLINE_{t-j} + \sum_{h=1}^{m} \alpha_i \Delta SPREAD_{t-h} + \tau_{G,1} ECT1_{t-1} + \tau_{G,2} ECT2_{t-1} + \epsilon_{Gt}$$

$$\Delta SPREAD_t = \alpha_S + \sum_{i=1}^{k} \alpha_i \Delta OIL_{t-i} + \sum_{j=1}^{l} \beta_j \Delta GASOLINE_{t-j} + \sum_{h=1}^{m} \alpha_i \Delta SPREAD_{t-h} + \tau_{S,1} ECT1_{t-1} + \tau_{S,2} ECT2_{t-1} + \epsilon_{St}$$

where $\epsilon_{Ot}, \epsilon_{Gt}, \epsilon_{St}$ are the stationary error terms. $ECT1_{t-1}$ and $ECT2_{t-1}$ are the error correction term. $\tau_{O,1}, \tau_{O,2}, \tau_{G,1}, \tau_{G,2}, \tau_{S,1}$, and $\tau_{S,2}$ are the adjustment coefficients.

4. Data

The data in this analysis are sourced from the U.S. Energy Information Administration. The data represents monthly average prices of gasoline and oil respectively. The 146 monthly observations run from September 2003 through October 2015. We estimate our models over the period September 2003 to December 2014, with January 2015 to October 2015 withheld to conduct ex-post forecast evaluations of accuracy. All prices used are spot prices, that is, the price for a one-time transaction for immediate delivery of a quantity of product at a specific location.

More specifically, we used price data for WTI crude oil.[3] This price deals with a crude stream produced in Texas and southern Oklahoma and is traded in the domestic spot market at Cushing, Oklahoma. For gasoline price data, we use RBOB (reformulated gasoline blend stock for oxygenate blending) gasoline for delivery in Los Angeles. The spread is the difference between BRENT and WTI crude oil prices.is the BRENT price is the price of the blended crude stream produced in the North Sea region. Each of the crude oil price series is expressed in terms of dollars per barrel. The gasoline price is expressed in terms of dollars per gallon. Table 1 presents summary statistics for each variable used in the analysis. The means and medians of the crude oil prices are very similar as expected. Note the large difference in the range (the difference between the minimum and maximum) of the respective crude oil prices. The range for WTI prices is $105.57 per barrel, and the range for BRENT prices is $105.63 per barrel. Additionally, because of the size of the standard deviations relative to the means for the crude oil prices, the coefficients of variation are above 30 (31.5 for WTI prices and 35.6 for BRENT prices), indicative of volatility in the respective oil prices. Gasoline prices run from $0.90 per gallon to $3.70 per gallon, indicative of a range of $2.80 per gallon. Gasoline prices average $2.28 per gallon over the period from September 2003 to October 2015. The coefficient of variation of gasoline prices is 28.1 indicative of less volatility compared to crude oil prices.

In Fig. 2, we graphically depict the monthly price of gasoline over the period September 2003 to October 2015.

[3] These definitions are sourced from the EIA website: http://www.eia.gov/dnav/pet/TblDefs/pet_pri_spt_tbldef2.asp

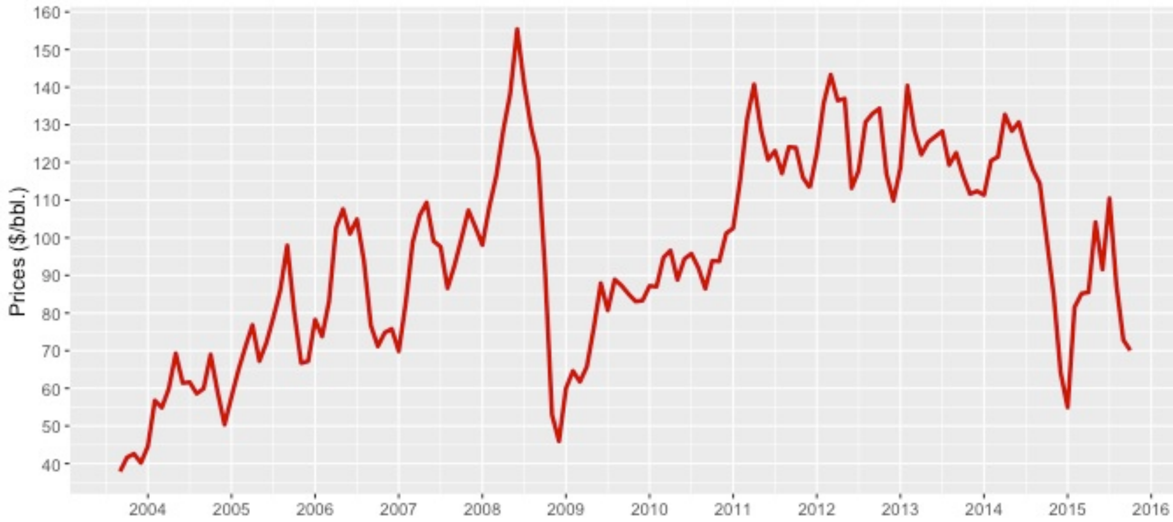

Fig. 2. Gasoline Spot Prices in Dollar per Barrel from Sep 2003 to Oct 2015

Evidence of seasonality exists based on Fig. 2. There is a large run up of gasoline prices through 2008 and then a large fall in prices due to the start of the recession in 2008-2009. Gasoline prices then experience a notable increase, followed by a period of stability, then another large fall. Variation in these prices makes it difficult to provide accurate forecasts for gasoline making this analysis pertinent.

5. Estimation Procedure

The purpose of the empirical analysis is to determine which univariate or multivariate model best captures the behavior of gasoline spot prices. The univariate models considered are Holt-Winters and ARIMA models. Based on the review of literature, the structural model is constructed to taken into account the relationship between benchmark crude oil prices and the gasoline spot prices. In addition, we consider vector autoregression and vector error-correction models. The respective models employ a logarithmic transformation to help reduce skewness of gasoline spot prices and crude oil benchmarks (Brent or WTI).

For the Holt-Winters models, we take into account the seasonality component by employing both additive and multiplicative seasonality adjustments. We find that the Holt-Winters model with additive seasonality and a logarithmic transformation outperforms other Holt-Winters models in terms of forecasting performance.

The Augmented Dickey-Fuller (ADF) test statistics provide evidence that logarithm transformation of gasoline spot prices and the crude oil benchmark results in stationarity of the series. However, for the spread between the log transformed crude oil benchmarks, the ADF test statistic suggests first differencing is necessary to remove the unit root (Table 2).

The crude oil benchmark for Brent is not directly included in this analysis. The reason that both benchmarks are not included at the same is to avoid a multicollinearity problem. In addition, we are considering U.S. gasoline spot prices, not E.U. gasoline spot prices. We construct two simple regression models with each benchmark as a single independent variable and find that the WTI price can explain gasoline spot price behavior better than the Brent price. We also construct several models using combinations of Brent or WTI and the spread between the two benchmarks. Incorporating the Brent-WTI spread to models where WTI is an independent variable significantly increases the explanatory power of the model. However, incorporating this spread to models that use Brent as an independent variable does not significantly increase the explanatory power. This is consistent with the EIA report (2014). Therefore, in the analysis that follows, we consider the WTI benchmark and the spread between WTI and Brent price series as explanatory variables in the structural specification.

It is necessary to find the optimal lag order for these models. The optimal lag suggested by the majority of model fit parameters is a lag of two. Model selection criteria for the first eight lags are presented in

Table 3. We perform pairwise Granger causality tests in order to determine precedence. Using a significance level of 0.05, appropriate for a sample size of 134 observations, we conclude that WTI Granger causes (precedes) GASOLINE. That is, WTI crude oil prices affect gasoline prices but not vice versa. These test results are presented in Table 5.

To determine whether VAR or VEC is appropriate, we use the Johansen test procedure (Table 4). The trace test and the maximal eigenvalue test are calculated at the optimal lag of two. The test includes the gasoline price, the WTI price, and the spread. Both tests indicate two cointegrating equations at the 0.05 significance level. The existence of co-integrated equations means that the VEC model is the appropriate choice over the VAR model. A seemingly unrelated regression (SUR) approach is used to estimate the VEC model.

6. Empirical Results

The empirical results are presented in the following order concerning the (1) Holt-Winters model; (2) ARIMA model; (3) structural or econometric model; (4) VEC model; and (5) a composite of the respective forecasts. The composite forecast was not discussed in the theoretical section, but it is simply the average of the forecasts generated from the aforementioned four models. The composite forecast attempts to combine the best features of all the respective models into a single forecast. For the forecast analysis, the within-sample period dates from September 2003 to December 2014 (136 months), while the out-of-sample period is from January 2015 to October 2015 (10 months).

In order to make the determination of the most accurate forecasting method we use four common metrics. As discussed by Winkler and Murphy (1992), the use of multiple metrics is important because there is no "best" metric and using multiple metrics can provide greater forecasting insight. We include root mean square error (RMSE) as it is one of the most common metrics and standard in most software packages even though some authors believe it is less reliable (Armstrong and Collopy, 1992). We avoid using R-squared in order to make comparisons as a high value does not guarantee accurate forecasts (Armstrong, 2001). The other metrics we use are mean absolute percent error (MAPE), mean absolute error (MAE), and the percent correct direction of change.[4]

[4] The percent correct direction of change metric is defined as the percent of forecast predictions correctly made in direction only, not accounting for magnitude.

6.1. Additive Seasonal Holt-Winters Model

The estimation results from the additive seasonal Holt-Winters model with log(gasoline spot) as its dependent variable are provided in Table 6. The estimated coefficients confirm the presence of seasonality with the highest effect in the summer months.

6.2. ARMA Model

Several ARMA(p,q) combinations are constructed. We find that the preferred ARMA model is ARMA(1,1) model. The estimation results from ARMA(1,1) model with log(gasoline spot) as its dependent variable are provided in

Table 7. There is evidence that the variation in the current gasoline price can be explained by the price in the preceding period, since the coefficient for AR(1) is statistically significant.

6.3. Structural Model

Several structural models are constructed using combinations of benchmark crude oil (WTI) and the Brent-WTI spread. We also take into account seasonality by incorporating dummy variables for each month into the model. To take into account for dynamic effects of benchmark crude oil on gasoline prices, a polynomial distributed lag specification is incorporated into the model. To account for the presence of heteroskedasticity in the residuals, we also use GARCH model for the variance equation. In addition, we correct for serial correlation in error terms by incorporating AR and MA terms for the error term into the model.

Table 6: Holt-Winters models

Holt-Winters Additive Seasonal Model			
	Coefficient		Coefficient
Alpha	1.000	*SEAS.M05*	0.068
Beta	0.000	*SEAS.M06*	0.066
Gamma	0.000	*SEAS.M07*	0.054
Mean	1.069	*SEAS.M08*	0.047
Trend	0.006	*SEAS.M09*	0.043
SEAS.M01	-0.084	*SEAS.M10*	-0.006
SEAS.M02	-0.060	*SEAS.M11*	-0.062
SEAS.M03	-0.005	*SEAS.M12*	-0.102
SEAS.M04	0.039		

Holt-Winters Multiplicative Seasonal Model			
	Coefficient		Coefficient
Alpha	1.000	*SEAS.M05*	1.073
Beta	0.000	*SEAS.M06*	1.072
Gamma	0.000	*SEAS.M07*	1.060
Mean	1.092	*SEAS.M08*	1.055
Trend	0.006	*SEAS.M09*	1.053
SEAS.M01	0.908	*SEAS.M10*	0.998
SEAS.M02	0.934	*SEAS.M11*	0.933
SEAS.M03	0.991	*SEAS.M12*	0.886
SEAS.M04	1.038		

Table 7: ARMA model

ARMA Model	
	Coefficient
constant	1.076 **
AR(1)	0.927 **
MA(1)	0.557 **

*Note: * and ** denote rejection of the null hypothesis that the coefficient is not significant at the 5% and 1% levels, respectively.*

Table 8: Vector error correction model

ECM			
	Dependent Variable		
	$\Delta(GAS)_t$	$\Delta(WTI)_t$	$\Delta(BRENT\text{-}WTI)_t$
$ECT1_{t-1}$	0.011 **	0.186 **	
$\Delta(GAS)_{t-1}$	0.369 **		
$\Delta(WTI)_{t-1}$	0.006 **	0.354 **	
$\Delta(BRENT\text{-}WTI)_{t-1}$			0.185*

*Note: * and ** denote rejection of the null hypothesis that the coefficient is not significant at the 5% and 1% levels, respectively.*

Table 9: Structural model

Structural Model			
Mean Equation		**Variance Equation : EGARCH(1,1)**	
	Coefficient		**Coefficient**
constant	-1.953 **	*C(1)*	-0.553 *
SEAS.M01	0.032 **	*C(2)*	1.567 **
SEAS.M02	0.033 **	*C(3)*	1.121 **
SEAS.M03	0.083 **		
SEAS.M04	0.107 **		
SEAS.M05	0.112 **		
SEAS.M06	0.108 **		
SEAS.M07	0.083 **		
SEAS.M08	0.068 **		
SEAS.M09	0.075 **		
SEAS.M10	0.054 **		
SEAS.M11	0.030 **		
Δ(LOG(BRENT)-LOG(WTI))	-0.068 *		
PDL01	0.272 **		
AR(1)	0.867 **		

*Note: * and ** denote rejection of the null hypothesis that the coefficient is not significant at the 5% and 1% levels, respectively.*

Table 10: Lag Distribution of log(WTI)

Lag	Coefficient	Std. Error	t-Statistic
0	0.201	0.006	32.108
1	0.268	0.008	32.108
2	0.201	0.006	32.108
Sum of Lags	0.670	0.021	32.108

The preferred structural model is chosen based on the model selection criteria (Akaike Information Criterion (AIC), Schwarz Criterion (SIC), and Hannan-Quinn Criterion (HQC)) and the adjusted R-Squared. The final structural model consists of the following mean and variance equations:

Mean Equation:

$$\log(gasoline_t) = f(pdl(\log(WTI_t), 5,4,2)\,, D(\log(Brent_t) - \log(WTI_t)), Seasonality_i) + \epsilon_t$$

And the following variance Equation (GARCH(1,1)):

$$\sigma_t^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

for $t = 1, \ldots, 136$ **and** $i = 1, \ldots, 11$**.** Log $(gasoline_t)$ **is the log transformed U.S. nominal gasoline spot price.** Log (WTI_t) **is the log price.** Log (WTI_t) **is the log transformed U.S. crude oil benchmark.** $D(\log(Brent_t) - \log(WTI_t))$ **is the first difference of the spread first difference of the spread between the two logged crude oil benchmarks. *Seasonality* represents the monthly dummy variables. monthly dummy variables. AR(1) is the first order autoregressive process for the error term and MA(3) is the third order moving the third order moving average process for the error term. For the error terms,** ϵ_t **is the error term in the mean equation,** ϵ_{t-1}^2 **is mean equation,** ϵ_{t-1}^2 **is the ARCH term,** σ_t^2 **is the variance of the residuals, and** σ_{t-1}^2 **is the GARCH term. Note that the spread is incorporated into the model as the first difference in logarithm in order to mitigate the previously discussed unit previously discussed unit root problem (Table 2). The estimation results from the structural model with log(gasoline spot) as the log(gasoline spot) as the dependent variable are provided in**

Table 9.

The structural approach provides a number of interesting results. The estimated coefficients are positive and statistically significant for the months of February through October (the base month is December). Adjusting for other factors then, gasoline prices are significantly higher for all remaining months relative to December except for November and January. For the months of February through October relative to December, gasoline prices are higher by 10 to 20 percent. This seasonal pattern conforms to expectations that gasoline prices are higher in spring, summer, and fall relative to winter.

The sum of lags reported in Table 10 is the sum of the estimated coefficients on the distributed of current and five lags of log (WTI) on 4th degree polynomial with no endpoint constraints. It shows us that the long run effect of log (WTI) on log($gasoline$) is 0.866. This tells us that a 1% change in WTI yields a 0.866% change in gasoline prices after a period of five months. The coefficient of $D(\log(Brent_t) - \log(WTI_t))$ is 0.416 and significant. It provides evidence supporting that it is important to consider the spread when forecasting gasoline prices.

6.4. Vector Error-Correction Model

The estimation results from the VEC model are provided in Table 8. Supported by Table 2 and Table 4, the first differences of gasoline prices, WTI, and BRENT-WTI spread are used in constructing the VEC model. A few results emerge from this analysis. The first difference in the BRENT-WTI spread is only affected by the previous month's spread. The estimated coefficients on the error correction terms (i.e., $ECT1_{t-1}$ and $ECT2_{t-1}$) of the gasoline spot price and the WTI index are both statistically significant. This confirms that all of the markets adjust to their long-run equilibrium.

Using our VEC we can graph the impulse response over the forecast range for our variable of interest. From Fig. 3, when the impulse is the BRENT-WTI spread, the response of the gasoline spot price is negative for a period then positive. While the responses of both WTI and BRENT-WTI spread are positive at each time responsive period. However, the response of the spread is decreasing over time, while the response of WTI is increasing over time.

When the impulse is the gasoline spot price, the responses of all variables are positive. However, only the response of the spread is increasing over time, while the responses of the gasoline spot price and WTI are increasing to a certain point then decreasing afterward. Likewise, when the impulse is WTI, the responses of all variables are positive. Only the response of the spread is increasing over time, while the responses of the gasoline spot price and WTI are increasing to a certain point then decreasing afterward.

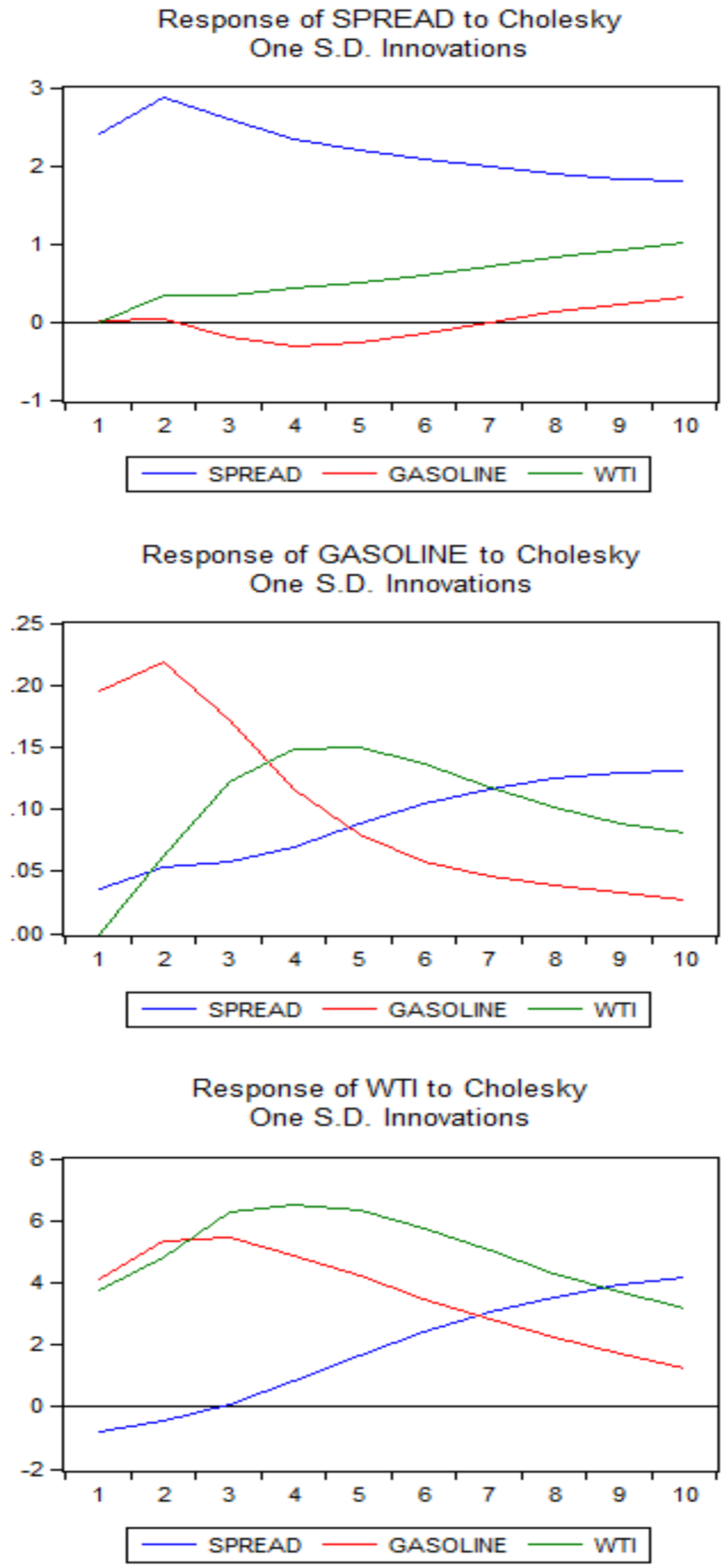

Fig. 3. Impulse Response

6.5. Comparison of Forecasts

Other than the models presented earlier, we also calculate composite forecasts by averaging the forecasts from all the preceding models. To aid in comparison across the models, we exhibit in

Table 11 the forecast measures for both the in-sample and the out-of-sample forecasts. Table 12 presents the out-of-sample forecasts of all models.

As can be seen in

Table 11, there is evidence supporting that the Holt-Winters model, regardless of how old it is, is the best model for in-sample forecasting. It performs the best in all forecast measures except MAPE. In terms of out-of-sample forecasting performance, while the Holt-Winters model performs relatively well compared to other models, the composite forecast turns out to be the best and even better than the EIA's forecasts. The composite forecast has a MAPE of 6.3% versus a MAPE of 8.1% from the EIA's STEO model. This result is similar to finding by Baumeister, Kilian, and Lee (2016) that a composite forecast outperforms other models and EIA forecasts. Moreover, the composite forecast predicts the direction of changes in gasoline prices more accurate than the STEO model.

7. Conclusions

A number of studies have investigated the relationship between crude oil prices and gasoline prices in the energy market. In this paper, we focus our attention on constructing forecasting models for forecasting retail gasoline prices. A variety of univariate and multivariate models are employed to produce forecasts. In addition, a composite forecast is created by averaging the forecasts of the models. Forecasts from each of these methods are compared forecasts to the EIA forecasts using RMSE, MAE, MAPE, and percent correct direction of change.

From the empirical analysis, we find evidence from the structural model and the vector error-correction model that the movement in the U.S. gasoline spot prices can be explained by the WTI benchmark and the spread between BRENT and WTI benchmarks. In terms of forecasting performance, we find that the additive Holt Winters model outperforms the other models within sample and the composite forecast outperforms the other models in the out sample. Our composite forecast not only has better MAE and MAPE than those of the EIA's STEO model, but also more accurately predicts the correct direction of change in gasoline prices. That the composite forecasts outperforms other models and the EIA forecasts has been documented by other authors (Baumeister, Kilian, and Lee, 2016). This paper further reinforces the necessity to consider multiple models and composite forecasts when predicting gasoline prices.

Table 11: Forecasting performance

	In-sample				Out-of-sample			
	RMSE	MAE	MAPE	Correct Direction-of-Change	RMSE	MAE	MAPE	Correct Direction-of-Change
Holt-Winters (Add)	**0.058**	**0.040**	4.239	**0.733**	**0.183**	0.176	18.559	**0.889**
Holt-Winters (Multi.)	0.059	0.042	4.394	0.696	0.209	0.203	21.626	0.778
ARIMA	0.182	0.144	4.918	0.652	0.323	0.278	10.431	0.444
Structural Model	0.117	0.085	**3.041**	0.727	0.375	0.357	13.676	**0.889**
VEC Model	0.129	0.101	3.585	0.689	0.414	0.361	13.444	0.556
Composite	0.126	0.093	3.352	0.726	0.202	**0.167**	**6.318**	**0.889**
EIA					*0.257*	*0.218*	*8.096*	*0.556*

Note: The in-sample period is Sep 2003 - Oct 2015. The out-of-sample period is Jan 2015 - Oct 2015.

Table 12: Out-of-sample forecasts

Month	Actual	Holt-Winters	ARIMA	VEC	Structural Model	Composite	EIA
2015M01	2.208	2.695	2.482	2.330	2.379	2.471	2.237
2015M02	2.301	2.776	2.450	2.193	2.133	2.388	2.215
2015M03	2.546	2.951	2.423	2.161	2.170	2.426	2.271
2015M04	2.555	3.100	2.400	2.179	2.291	2.492	2.355
2015M05	2.802	3.212	2.380	2.213	2.390	2.549	2.453
2015M06	2.885	3.223	2.363	2.243	2.509	2.585	2.466
2015M07	2.88	3.203	2.348	2.262	2.395	2.552	2.471
2015M08	2.726	3.201	2.335	2.269	2.197	2.501	2.491
2015M09	2.462	3.207	2.324	2.269	2.070	2.468	2.527
2015M10	2.387	3.072	2.315	2.267	1.989	2.410	2.502

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