Forecasting motor gasoline consumption in the United States

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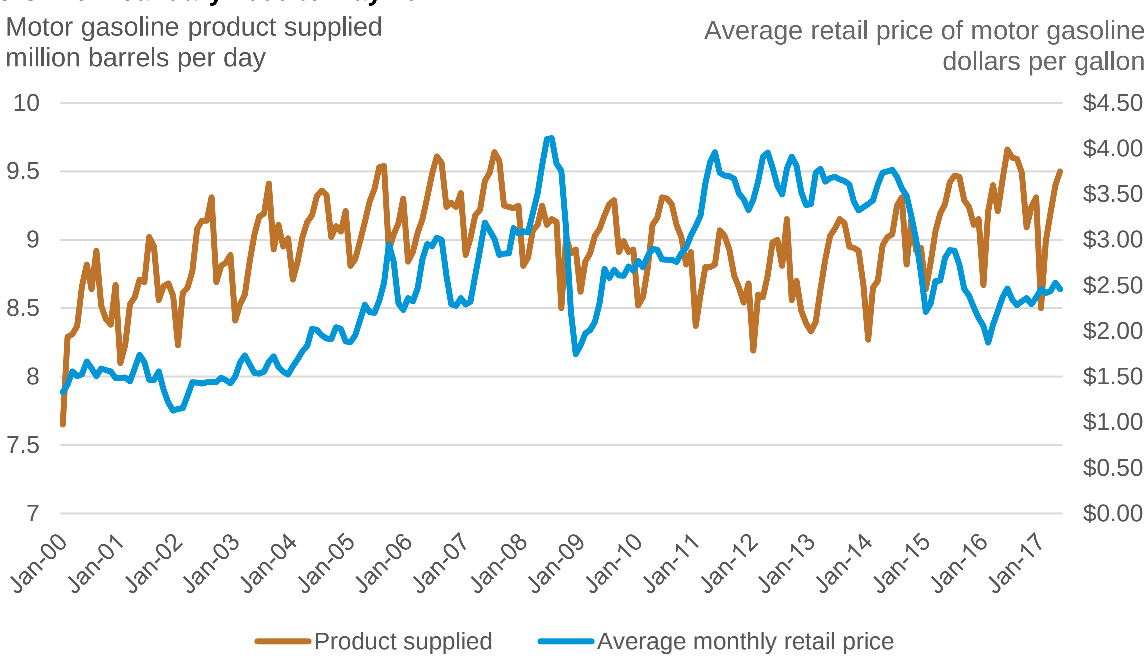
1. Introduction

Motor gasoline consumption forecasts are important to numerous stakeholders. State and federal governments rely on motor gasoline forecasts for planning purposes to estimate income from motor gasoline tax revenues. Government officials and researchers also use motor gasoline consumption forecasts to analyse potential policy scenarios. However, accurately forecasting motor gasoline consumption can be a challenge and recent changes in oil prices, macroeconomic indicators, and consumer preferences have not made it easier.

Over the last two decades motor gasoline consumption has oscillated between growth, contraction, and is currently in a period of growth again (Figure 1). In the early to mid-2000s there was a general fear of reaching peak supply as motor gasoline demand and prices continued to creep upward. The storyline changed to reaching peak demand in the late 2000s and early 2010s during the Great Recession and the corresponding high gasoline prices during the recovery. Now, neither of those market observations may hold. What was thought to be a regime switch to lower VMT and more fuel efficient vehicles might have been a consequence of high oil prices and the Great Recession and not a fundamental change in consumer preferences. Now, with fuel prices remaining low and consumption creeping up, the question becomes are we back on the pre-Great Recession trajectory; have we entered a third gasoline consumption regime; or have all the changes experienced in the last two decades been explainable through changes in macroeconomic indicators and prices and not changes in consumer preferences resulting in no regime changes. Knowing that we have entered a new regime or returned to the pre-Great Recession regime could be beneficial when developing a forecast model. However, this is typically determined after the fact and could slow down the inclusion of new market dynamics that could improve a models ability to predict future motor gasoline demand.

Figure 1. Monthly motor gasoline product supply and average motor gasoline retail price in the U.S. from January 2000 to May 2017.



Source: U.S. Energy Information Administration, Short-term Energy Outlook

The purpose of this study is to determine the forecast model or pooled forecast model that best predicts monthly motor gasoline consumption in the United States. Multiple forecasting models and levels of aggregation are considered to determine which model best forecasts motor gasoline consumption for up to 24 months. This study contributes to the literature since it is one of the first studies since the downturn in oil prices to analyze motor gasoline consumption and may help researchers understand the changes in motor gasoline consumption that have happened since 2014.

Section 2 contains a brief literature review of relevant articles for motor gasoline forecasting. Section 3 contains an overview of the methods and data used in the analysis. Section 4 summarizes the results. And section 5 contains the conclusion.

2. Literature Review

There is no shortage of papers trying to determine the price and income elasticities of motor gasoline consumption as evidenced by Dahl (2012). In this study Dahl reviewed 240 motor gasoline demand studies that covered more than 70 countries. Even though elasticities can be used to forecast motor gasoline consumption, there are substantially less papers whose primary or sole purpose is to forecast motor gasoline consumption.

Because numerous studies have conducted thorough literature reviews of motor gasoline consumption, this paper does not intend to do so. Instead, the literature review section below highlights forecasts that have been used by state agencies and variables that are commonly used in structural models. While the purpose of this study is to determine the best model to forecast motor gasoline consumption and not to determine elasticities of motor gasoline consumption or create a model to conduct what-if scenarios, a review of the literature is still important. Because a single variable forecast model cannot perfectly forecast motor gasoline consumption having an understanding of what variables should be considered for inclusion in a multivariate forecast model is important.

Many states rely on short and long run motor gasoline consumption forecasts to determine tax revenue. Many of these studies have used auto-regressive integrated moving average (ARIMA) models to determine state level motor gasoline consumption forecasts (Cervero, 1985; Wachs & Heimsath, 2015; Washington State Department of Transportation, 2010). They find that ARIMA models are beneficial due to the limited data needed to forecast motor gasoline consumption. However, using the ARIMA model may not be advisable past a couple years.

While time series analysis is beneficial for forecasting short-run motor gasoline consumption, econometric regression analysis is more commonly seen in the literature. This is because econometric regression analysis can help researchers determine the price and income elasticities of motor gasoline consumption as well as conduct what-if scenarios. Since ARIMA models only rely on lagged observations of the dependent variable these type of analyses are not possible using an ARIMA model.

Price and income are the most commonly used explanatory variables in motor gasoline consumption analysis. However, the income variable enters the model in several different ways depending on aggregation level of the data, data availability and beliefs of the researcher

(Energetics Incorporated, 2017 (forthcoming)). The most common income variables are real disposable income per capita and GDP per capita. Several studies have also used income per household, real aggregate personal income, and nominal income.

Vehicle related variables are also commonly included. These variables include vehicle stock, vehicle fuel efficiency, vehicle price and vehicle miles traveled (Energetics Incorporated, 2017 (forthcoming)). Other variables include price of substitutes – diesel and public transportation; price of consumer goods; private consumption expenditures; consumer sentiment; road saturation; and urbanization. Population based variables are also popular and have included number of households, proportion of people of driving age, and population by age cohort (Energetics Incorporated, 2017 (forthcoming)).

Employment variables are also commonly used but may be highly correlated with income data. Due to high correlation between employment and income variables and because many researchers want to determine elasticities and conduct what-if scenarios income is typically the variable that is used. However several studies have chosen to use employment based variables to help determine motor gasoline consumption (Arizona Department of Transportation, 2016; Eltony, 1993; Sillence, 2014; Wachs & Heimsath, 2015; Washington State Department of Transportation, 2010).

In addition to the discussion in the literature on including income variables versus employment variables, there is a discussion on the symmetry of the price variable. Dahl (2012) believed that there would be more response to increases in price than decreases in price. However, studies that have addressed asymmetric prices have found mixed results.

3. Methodology, Data, and Testing

In order to determine the best motor gasoline consumption forecast model or pooled forecast models several models and aggregation levels of data are tested. This study uses two forecast models that fall into two model categories –ARIMA model and vector autoregressive (VAR) model. Both of these models have benefits and downsides for forecasting.

The first model considered is the ARIMA model. The ARIMA model has a couple advantages. First, the model only relies on the lagged dependent variable for an input. This can eliminate the need for other forecasted variables that may be biased (i.e. macroeconomic variables during the recovery). Second, because it only relies on the lag of the dependent variable, it can potentially pick up changes in the trend more quickly than other forecasting models that use multiple input variables.

The ARIMA model can be written as

$$\textbf{Eq. 1} \quad \boldsymbol{y_t = \gamma + \theta_1 y_{t-1} + \cdots + \theta_p y_{t-p} - \varphi_1 e_{t-1} - \cdots - \varphi_q e_{t-q}}$$

where y_t is the d^{th} difference of the dependent variable y in period t; γ is a trend; θ is the coefficient estimate for the lagged dependent variable; p is the number of autoregressive terms; e is the moving average; φ is the coefficient estimate on the moving average; and q is the number of lagged forecast errors. For brevity the ARIMA model is typically written as ARIMA(*p,d,q*).

Two levels of aggregation are tested using the ARIMA model. The first uses nationwide data, while the second uses Petroleum Administration Defense Districts (PADD) level data. Several tests were conducted to determine if the data exhibits a unit root and to determine the number of lags that should be included in the ARIMA model. The Augmented Dickey-Fuller test was used to determine if the national and regional data exhibit a unit root. Both the national and regional data exhibit a unit root when the data is examined in levels. However, the data is stationary when the first-difference is examined.

Two common tests used to determine the number of lags to include in the ARIMA model are the autocorrelation function (ACF) and the partial autocorrelation function (PACF). The ACF determines the level of correlation of y between two periods. The PACF determines the correlation between y at two periods that is not explain by the correlation of lower order lags. Based on the ACF the regional and national data should include two lags. With the exception of PADD 3, the regional and national data exhibit annual seasonality.

A second set of models were tested using a VAR model specification. Unlike ARIMA models, VAR models rely on multiple lagged independent variables. There are several advantages to using the VAR model. First, changes in other variables may precede changes in motor gasoline consumption which could lead to an early response in motor gasoline consumption. Second, VAR models allow for analysis of what affects changes in motor gasoline consumption which can be beneficial when analyzing what-if scenarios.

A VAR model can be written as

Eq. 2 $\boldsymbol{X} = \boldsymbol{A} + \boldsymbol{BZ} + \boldsymbol{U}$

where $\boldsymbol{X}$ is a s x 1 vector of dependent variables; s is the number of explanatory variables; $\boldsymbol{A}$ is a s x 1 vector of constant terms; $\boldsymbol{B}$ is a t x s matrix of coefficient estimates; t is the number of lags; $\boldsymbol{Z}$ is a s x 1 vector of lagged explanatory variables; and $\boldsymbol{U}$ is a s x 1 vector of error terms. In addition to lagged dependent variables, a vector of explanatory variables can also be added to the equation.

A couple VAR models are tested. The first VAR model assumes that there are no asymmetric price responses. The second model assumes an asymmetric price response. In addition to the price variable, both models include historic vehicle miles travelled (VMT) from the U.S. Department of Transportation Federal Highway Administration (Federal Highway Administration, 2017) and a macroeconomic indicator from the Federal Reserve Bank of Chicago (Federal Reserve Bank of Chicago, 2017).

The best measure of VMT would only include miles traveled by motor gasoline fueled vehicles however this variable contains all on-road VMT. While over the course of two years (the forecast period) the trends in motor gasoline versus non-motor gasoline fueled travel should not greatly vary, throughout the year there could be significantly different ratios of travel by fuel type due to increased heavy-duty trucking during certain months. Despite this potential issue the variable is included based on results from past research.

As discussed above, there are different opinions in the literature as to what macroeconomic variables should be included in a motor gasoline consumption analysis. To circumvent some of this debate a macroeconomic indicator is used in this model. The Federal Reserve Bank of Chicago macroeconomic indicator known as the Chicago Fed National Activity Index (CFNAI) takes into account – production and income; personal consumption and housing; employment, unemployment and hours; and sales orders and inventories. Both VMT and CFNAI are not forecasted and must be forecasted within the VAR to determine motor gasoline consumption.

To determine the appropriate number of lags to include in the VAR analysis several different tests were conducted. The first test is the likelihood ratio test. The second test determines the Akaike and Bayesian Information Criteria (AIC and BIC). Based on the likelihood ratio test and AIC test 12 lags is the optimal number of lags.

A third structural model similar to those used in most motor gasoline consumption literature was also analyzed at the national and regional level. The model is

Eq. 3 $$\log(\boldsymbol{consumption}) = \boldsymbol{\alpha} + \boldsymbol{\beta_1}\log(\boldsymbol{price}) + \boldsymbol{\beta_2}\log(\boldsymbol{income}) + \boldsymbol{\beta_3}\log(\boldsymbol{employment}) + \boldsymbol{\beta_4 HHD}$$

where consumption is either the national or regional motor gasoline consumption; price is the national or regional motor gasoline price; income is gross domestic product (GDP) in the national model and gross state product (GSP) at the regional level; employment is the civilian unemployment rate at the national level and non-farm employment at that regional level; HHD is the heating degree days; α is a constant term; and β are the coefficient estimates. The regional and national variables differ due to availability of data at the regional versus national level. As discussed above, income and employment are correlated but are both included in this model since changes in income and employment may have different effects on motor gasoline consumption.

The structural model is the most data intense of the three models. Because it is not a forecast model, all the independent variables must be known or forecasted separately to determine a forecast of motor gasoline consumption.

All three models have their benefits and downfalls when it comes to forecasting. For this reason a pooled forecasting model is also tested. Though the effect of changes in price and macroeconomic variables may be hidden in the pooling of the forecast, the overall forecast may be more robust.

Most of the data used in the analysis come from the Energy Information Administration (EIA) Short-term Energy Outlook (U.S. Energy Information Administration, 2017). The dependent variable is monthly product supply at the national and PADD level. Product supply is used as a proxy for product consumed since there is no comprehensive motor gasoline consumption dataset. Due to the short storage time of finished products, this is likely a good proxy.

In the discussion that followed each model above, the independent variables considered include average retail price of gasoline across all products, real GDP, real GSP, non-farm employment, civilian unemployment rate, heating degree days, VMT, and CFNAI. Heating degree days is included since motor gasoline consumption typically decreases during the winter and this is a monthly forecast.

Variables like vehicle stock and fuel efficiency are common in structural models in the literature however are not included in this analysis. Over the long run these variables are important in determining motor gasoline consumption however because this analysis is only concerned with up to two years of motor gasoline consumption the change in stock and fuel efficiency is not large. This is because there is a slow turn-over in the vehicle stock.

The regional analysis is conducted at the PADD level however the macroeconomic and weather variables are at the EIA census division level. There are nine census divisions and they do not perfectly overlap with the PADDs. PADD 1 is the only PADD that perfectly aligns with a grouping of census divisions – New England, Middle Atlantic, and South Atlantic (Table 1). Because PADD level is the most granular level of motor gasoline consumption data available, when regional analysis is conducted, variables for all census divisions that are contained in a PADD are included in the analysis.

Table 1. Alignment of PADD and Census Divisions

PADD	Census Division	States
PADD 1	New England	Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, Vermont
	Middle Atlantic	New Jersey, New York, Pennsylvania
	South Atlantic	Delaware, District of Columbia, Florida, Georgia, Maryland, North Carolina, South Carolina, Virginia, West Virginia
PADD 2	East North Central	Illinois, Indiana, Michigan, Ohio, Wisconsin
	East South Central	Kentucky, Tennessee
	West North Central	Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota, South Dakota
	West South Central	Oklahoma
PADD 3	East South Central	Alabama, Mississippi
	Mountain	New Mexico
	West South Central	Arkansas, Louisiana, Texas
PADD 4	Mountain	Colorado, Idaho, Montana, Utah, Wyoming
PADD 5	Mountain	Arizona, Nevada
	Pacific	Alaska, California, Hawaii, Oregon, Washington

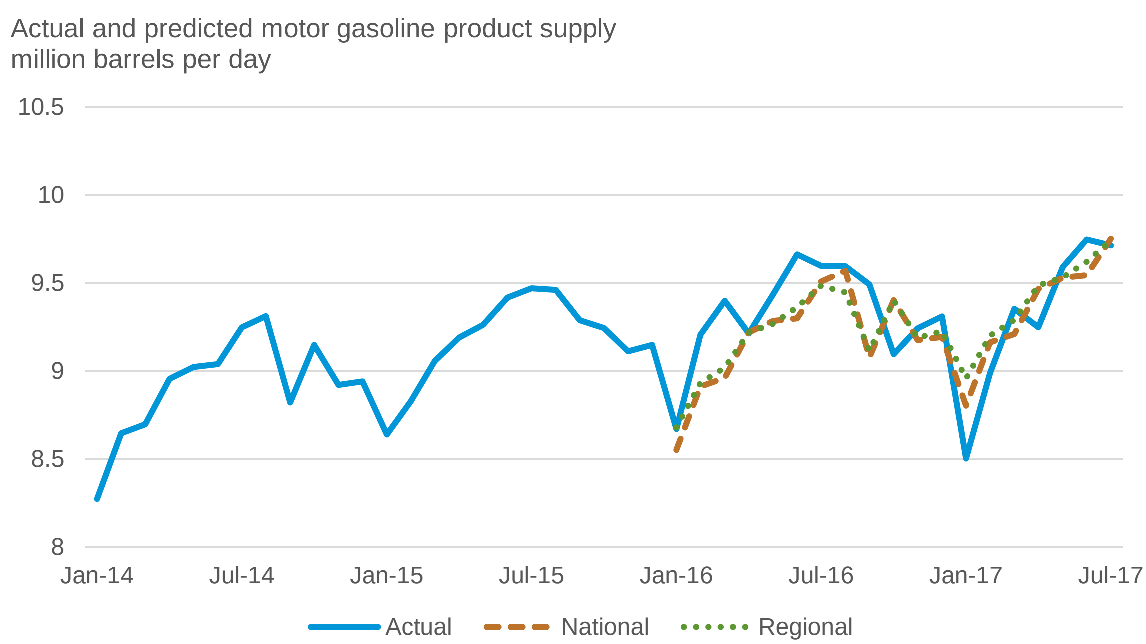
Before the Great Recession motor gasoline consumption was consistently growing year-over-year during the 2000s. After years of declining or stagnate growth during the recession and proceeding years motor gasoline consumption may be back on a similar pre-recession path. To help capture this potential trend in motor gasoline consumption, the data included in the analysis begins in January 2000. All of the variables end in July of 2017 with the exception of VMT and the Chicago macroeconomic indicator which end in May 2017. To test the forecast models the historic period is through December 2015 and the projection period begins January 2016.

4. Results

To determine the consumption of motor gasoline in the U.S. several different models were tested. ARIMA, VAR, and structural models were all used to help determine the best forecast for motor gasoline consumption.

The national and regional ARIMA model forecasts produce similar results (Figure 2). For 10 months in 2016 both ARIMA models under predict motor gasoline consumption. However the trend disappears in the first half of 2017. Both ARIMA models under predict motor gasoline consumption in three of the first seven months in 2017. In order to compare the models the symmetric mean absolute percentage error (SMAPE) was used. Both models have an SMAPE value of approximately 2%. However, the disaggregate PADD level data has a slightly lower SMAPE score of 1.94% compared to 2.01% of the aggregate national data.

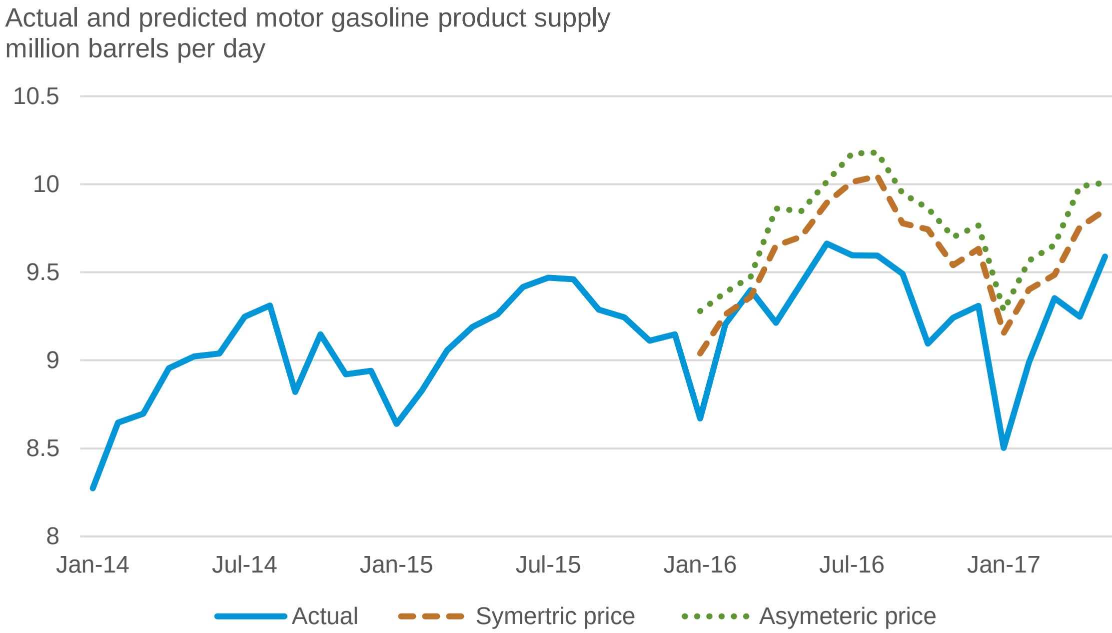
Figure 2. Actual motor gasoline product supply compared with national and regional ARIMA model forecasts



The next set of models tested are VAR models. The VAR model is beneficial when some or all explanatory variables also need to be forecasted. Two VAR models were tested. Both VAR models included vehicle miles traveled and a macro economic indicator from the Federal Reserve Bank of Chicago. Both of these variables are not forecasted by their respective institutions and must either be determined through a VAR estimation or its own ARIMA or structural equation. Price is also included in this analysis, however price is forecasted by the EIA and those forecast results are used in the analysis. Based on previous studies that finds consumers may react differently to motor gasoline price increases compared to price decreases the second model has two price variables, one for price increase and one for price decrease.

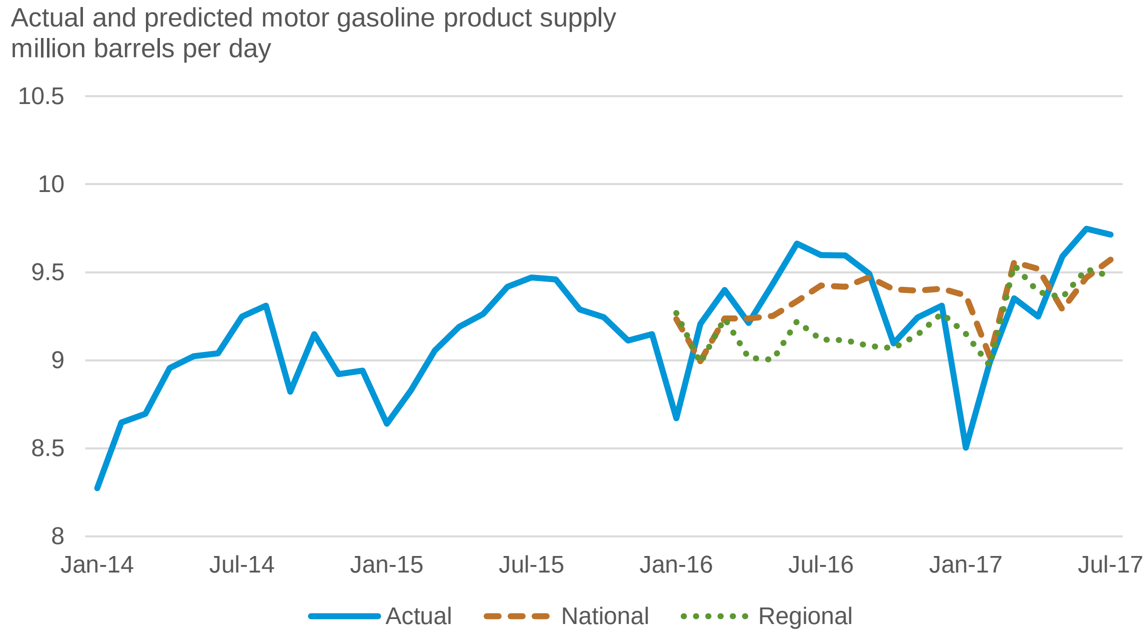
Both the VAR models – with and without symmetric motor gasoline price change – consistently over predict motor gasoline product supply (Figure 3). In addition the VAR model that allows for an asymmetric price response forecasts higher motor gasoline consumption compared to the VAR model with symmetric price response. This could imply that symmetric price should be used instead of asymmetric prices. The SMAPE scores are worse for both VAR models than for the ARIMA models. The SMAPE for the symmetric price VAR is 3.36% while the SMAPE for the asymmetric price VAR is 5.21%.

Figure 3. Actual motor gasoline product supply compared with national symmetric and asymmetric price VAR model forecasts



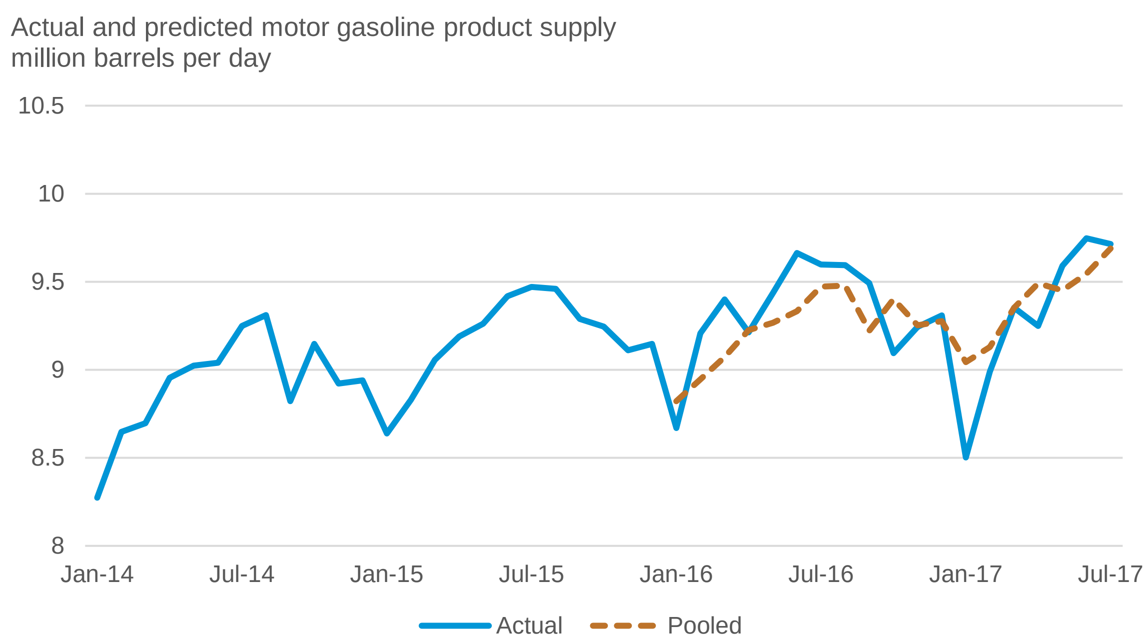
The last set of models analyzed are structural models used to determine an aggregate and disaggregate forecast of motor gasoline consumption. These models include variables for price, income, employment, and heating degree days. Both the national and regional structural models are less biased toward over or under projection compared to the ARIMA and VAR models (Figure 4). However, this model does the worst when dealing with the seasonality of motor gasoline consumption. Unlike in the ARIMA analysis, the national model does a better job forecasting motor gasoline consumption than the regional model. This could be because the PADDs and census division regions do not align well. Overall, both the national and regional levels out perform the VAR model. The SMAPE for the national model is 2.56% while the regional SMAPE is 3.02%.

Figure 4. Actual motor gasoline product supply compared with national and regional model forecasts



Due to the limitations of these models a pooled model was also analyzed. The pooled model equally weights the two ARIMA models (national and regional) and the national structural model. The pooled model has the same SMAPE as the regional ARIMA model – 1.94%. However this model is less biased toward underestimating motor gasoline consumption (Figure 5).

Figure 5. Actual motor gasoline product supply compared with national pooled forecast



5. Conclusions

Government agencies and researchers all have different motivations for using motor gasoline consumption forecasts. For the purpose of this analysis we tried to determine the best way to forecast motor gasoline consumption. The three types of models tested were ARIMA, VAR, and structural. All three models have their strengths and weaknesses. The ARIMA model is the least data intense requiring only the variable of interest – motor gasoline consumption, however what causes changes in gasoline consumption cannot be determined. The VAR model is a multivariate model that allows other variables to be considered in the analysis. The structural model is the most data intense model but can potentially give the most insight into what causes changes in motor gasoline consumption. The ARIMA model and structural model were both modeled at the national and PADD level. The VAR model considered symmetric and asymmetric price responses.

As a stand-alone model, the best model was the regional ARIMA model. It had the lowest SMAPE value. However the model was biased toward under estimating motor gasoline consumption. The national ARIMA model preformed almost as well but suffered from the same bias of underestimating motor gasoline consumption. Overall the VAR models did not perform well. Of the two models, the model with symmetric price response out preformed the model with asymmetric price response. Unlike in the ARIMA analysis, in the structural model analysis the national model out preformed the regional model. However, both of these models struggled to pick up seasonal changes in motor gasoline consumption.

Based on the strength and weaknesses of the ARIMA, VAR, and structural models a pooled forecasting model may be the best way to forecast motor gasoline consumption. The pooled forecast included both ARIMA models and the national structural model, equally weighted. The SMAPE was the same as for the regional ARIMA model but it was less biased toward underestimating motor gasoline consumption. Overall, the SMAPE of the ARIMA, structural and pooled models were all similar. Data availability and the purpose of the forecast will determine the model that should be used.

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