Inside the Crystal Ball:
New Approaches to Predicting the Gasoline Price at the Pump

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Abstract

Although there is much interest in the future retail price of gasoline among consumers, industry analysts, and policymakers, it is widely believed that changes in the price of gasoline are essentially unforecastable given publicly available information. We explore a range of new forecasting approaches for the retail price of gasoline and compare their accuracy with the no-change forecast. Our key finding is that substantial reductions in the mean-squared prediction error (MSPE) of gasoline price forecasts are feasible in real time at horizons up to two years, as are substantial increases in directional accuracy. The most accurate individual model is a VAR(1) model for real retail gasoline and Brent crude oil prices. Even greater reductions in MSPEs are possible by constructing a pooled forecast that assigns equal weight to five of the most successful forecasting models. Pooled forecasts have lower MSPE than the EIA gasoline price forecasts and the gasoline price expectations in the Michigan Survey of Consumers. We also show that as much as 39% of the decline in gas prices between June and December 2014 was predictable.

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1. Introduction

There is arguably no retail price in the U.S. economy that is more closely watched than the price of gasoline. Fluctuations in gasoline prices not only directly affect the pocketbook of consumers, but also affect which cars consumers choose to buy and how close they choose to live to their workplace. Gasoline prices even have been shown to affect home prices and home foreclosure rates (see Hamilton 2009; Ravn and Shan 2013). Central bankers in turn are concerned with the effects of gasoline prices on inflation expectations, consumer spending, and consumer confidence (see, e.g., Yellen 2011). Being able to predict the price of gasoline matters not only to consumers, automobile manufacturers, and central bankers; gasoline price forecasts also help predict the revenue from ad valorem gasoline taxes, and they are considered useful more generally for assessing the outlook for inflation and economic growth. Finally, gasoline price predictions play an important role in microeconomic models of automobile markets and in the analysis of environmental policies (see, e.g., Busse, Knittel and Zettelmeyer 2012, 2013; Allcott and Wozny 2014).

In fact, gasoline price forecasts are considered so important by the government that the U.S. Energy Information Administration (EIA) issues regular forecasts of the retail price of gasoline that are closely monitored and widely discussed by the media. The government is not the only producer of gasoline price forecasts, however. For example, on December 1, 2014, the American Automobile Association (AAA) released its own prediction that gasoline prices at the pump would drop this holiday season, and later elaborated that it expected the price of gasoline to drop by 50 cents by the end of the year. There are even websites solely devoted to providing daily forecasts of the local price of gasoline for consumers (e.g., www.gaspredictor.com). In addition, the Michigan Survey of Consumers regularly inquires about consumers' expectations about future retail gasoline prices (see Anderson, Kellogg, and Sallee 2013).

Perhaps surprisingly, the accuracy of retail gasoline price forecasts has not received much attention by academic researchers. One recent exception is Anderson, Kellogg, Sallee and Curtin (2011). This study investigates the ability of U.S. consumers to forecast the price of gasoline, as measured by responses in the Michigan Survey of Consumers. Another is an evaluation of the accuracy of EIA gasoline price forecasts by Sanders, Manfredo and Boris (2009). Neither study, however, addresses the question of how to construct gasoline price forecasts. There are a number of model-free methods and of regression-based methods that can be used for constructing gasoline price forecasts. The literature has largely ignored these methods to date.[1] One reason may have been the perception that forecasting gasoline prices beyond a few days is next to impossible, given publicly available information. In this view, there is no rhyme or reason to private sector gasoline price forecasts, and for all practical purposes we can think of the current gasoline price as the best predictor of the future price.

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[1] A rare exception is the work of Bastianin, Galeotti, and Manera (2015), which in turn builds on preliminary analysis in Bachmeier and Griffin (2003). Bastianin et al. investigate the extent to which allowing for asymmetries in the relationship between oil and gasoline prices improves the accuracy of regression-based forecasts for the price of gasoline. These studies, however, are not concerned with the question of whether either model forecasts more accurately than the no-change forecast or how they compare with other forecasts.

Until recently, this no-change forecast (or random walk forecast) was also considered the best possible forecast of the price of crude oil, but a rapidly expanding literature has overturned this consensus. It is well established now that one can forecast the price of crude oil in real time more accurately than the no-change forecast.[2] Because gasoline is a product obtained from refining crude oil, gasoline prices are closely tied to the evolution of the price of crude oil with both prices moving together in the long run (see, e.g., Kilian 2010). Hence, one might expect the ability to forecast oil prices to extend to gasoline price forecasts, but such a conclusion is less than obvious upon reflection. Unlike oil prices, gasoline prices are subject to changes in gasoline taxes and environmental regulations and are affected by refinery shutdowns as a result of routine maintenance, accidents and hurricanes (see, e.g., Kilian 2010). Moreover, the link between oil and gasoline prices has been affected by important changes in the structure of the refining market in recent years (see, e.g., Borenstein and Kellogg 2014; Kilian 2014). Finally, the evolution of gasoline prices is also affected by changes in the market power of refiners (see, e.g., Borenstein and Shepard 2002; Sweeney 2015).

This paper provides a comprehensive analysis of the forecastability of the real U.S. price of gasoline, drawing on state-of-the-art regression-based forecasting methods. Our objective is to provide a benchmark for future studies and to document the merits of alternative forecasting models. The analysis is conducted in real-time, taking account of the delays in the availability of some data and subsequent revisions when data become available. We focus on the problem of forecasting the average monthly U.S. retail price of gasoline, as defined by the EIA, at horizons up to 24 months.

Our analysis addresses several questions. First, how accurate are retail gasoline price forecasts based only on their own past? We consider autoregressive, autoregressive-moving average and exponential smoothing forecasts. Second, we examine the predictive content of financial market predictors. Specifically, we quantify the predictive content of gasoline futures prices and we examine the predictive power of the spread of the gasoline spot price relative to the spot price of crude oil. Third, we investigate the predictive power of bivariate vector autoregressive (VAR) models including both retail gasoline prices and crude oil prices. Our analysis examines in detail the impact of the lag structure, of imposing cointegration restrictions on the VAR model, and of the definition of the price of crude oil. We abstract from asymmetric VAR models, given the evidence provided by Bachmeier and Griffin (2003) and Bastianin et al. (2015) in favor of the linear VAR model. Fourth, we consider models of the gasoline market linking gasoline prices to changes in U.S. gasoline consumption. We also explore the use of single-equation factor forecasting models and of factor augmented VAR (FAVAR) forecasting models linking the price of gasoline to U.S. real economic activity. Fifth, building on recent developments in the literature on oil market forecasting models, we explore larger-scale VAR models that jointly model the global market for crude oil and the U.S. gasoline market.

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[2] Examples include Alquist, Kilian and Vigfusson (2013), Baumeister, Guérin and Kilian (2015), Baumeister and Kilian (2012, 2014a, 2015), Baumeister, Kilian and Lee (2014), Bernard, Khalaf, Kichian, and Yelou (2015), and Chen (2014).

Our key finding is that substantial reductions in the mean-squared prediction error (MSPE) of gasoline price forecasts are feasible in real time at horizons up to two years, as are substantial increases in directional accuracy. The most accurate individual model is a simple bivariate VAR(1) model for real retail gasoline and Brent crude oil prices. This model generates MSPE reductions at all horizons ranging from 10% to 26% and at some horizons has statistically significant directional accuracy as high as 68%. These results are robust to the use of Bayesian estimation methods as proposed in Giannone, Lenza, and Primiceri (2015). Even more reliable overall is a pooled forecast that assigns equal weight to the five most successful individual forecasting models. The accuracy of this pooled forecast also is more stable over time than that of the VAR(1) model. Moreover, the implied nominal gasoline price forecast has lower MSPE than the gasoline price forecasts of the U.S. Energy Information Administration and the gasoline price expectations in the Michigan Survey of Consumers. Finally, we show that as much as 39% of the widely discussed decline in the retail price of gasoline after June 2014 was predictable, but only by one of the models in the forecast combination.

The remainder of the paper is organized as follows. Section 2 reviews the forecasting environment and discusses the gasoline price data. In section 3, we motivate and describe each of the alternative forecasting methods and discuss their performance. Section 4 provides additional sensitivity analysis. We assess the role of seasonality in the monthly gasoline price data, we assess the stability over time of the accuracy of our preferred gasoline price forecast, we examine the potential benefits from pooling the most successful forecasting models, and we extend the analysis to quarterly forecasts. Section 5 discusses how to recover nominal price forecasts from real gasoline price forecasts. We compare the pooled forecast with the gasoline price expectations in the Michigan Survey of Consumers and with quarterly EIA forecasts of the nominal price of gasoline. In section 6, we investigate how much of the recent decline in gasoline prices was predictable as of the end of June 2014. The concluding remarks are in section 7.

2. The Forecasting Environment

All forecasting models are estimated at monthly frequency. We consider monthly forecast horizons up to two years. Forecasts at the corresponding quarterly horizons are obtained by averaging the monthly forecasts at quarterly frequency, as recommended in Baumeister and Kilian (2014a). The regression models underlying the gasoline price forecasts are re-estimated recursively in real time, as more data become available. This approach has been shown in the oil price forecasting literature to be much more accurate than relying on rolling regressions (see, e.g., Baumeister and Kilian 2014a). Our analysis is conducted in real-time, taking account of the delays in the availability of some data and subsequent revisions when data become available.

2.1. Real-Time Data

We rely on data from a suitably updated real-time database developed in Baumeister and Kilian (2012, 2014a) and extended in Baumeister, Kilian and Zhou (2014) and Baumeister, Kilian and Lee (2014). The reader is referred to these references for a detailed description of the data sources and definitions. This database consists of different data sets for each month in the sample. Each data set is referred to as a vintage and contains only the data that were known to the forecaster at each point in time. Missing observations at the end of each data set are nowcast based on data in this vintage.

We add to this database real-time data for U.S. gasoline consumption and for the nominal volume-weighted average U.S. retail price of gasoline. The price of gasoline is reported in column 4 of Table 9.4 of the *Monthly Energy Review*. This gasoline price series is backcast from January 1978 to October 1973 using EIA data on the price of leaded regular gasoline, as in Kilian (2010). There are no revisions in the nominal gasoline price data, but there is a delay in their release. We nowcast the missing observations at the end of each vintage based on the monthly average of the weekly releases of the nominal retail gasoline price in the *Weekly Petroleum Status Report*. Gasoline consumption data are constructed as the sum of commercial, industrial and transportation sales, following Kilian (2010). Gasoline consumption data are subject to revisions. The real-time data were manually compiled from past issues of the *Monthly Energy Review*. Percent changes in gasoline consumption were nowcast at their average rate of growth in the preceding five years based on a moving-average model, taking into account seasonal variation in the form of seasonal dummies.

2.2. Evaluation Criteria

The evaluation period is January 1992 through March 2014 (or equivalently the first quarter of 1992 through the first quarter of 2014). The length of the initial recursive estimation period differs depending on data availability. No data prior to October 1973 is used in estimation. Our objective is to forecast the level of the ex-post revised real price of gasoline, as measured by the observations in the September 2014 vintage of the real-time database.

The real-time forecasts are evaluated based on their recursive MSPE and their directional accuracy, as measured by the success ratio. The success ratio is the fraction of times that a method correctly predicts the direction of change in the real price of gasoline. Success ratios above 0.5 indicate an improvement relative to the no-change forecast. The MSPE results are normalized relative to the no-change forecast, with a ratio below 1 indicating a gain in accuracy. Where appropriate, we assess the statistical

significance of the MSPE reductions based on the test of Diebold and Mariano (1995) for nonnested models without estimation uncertainty. We also examine the stability of our results across horizons, across specifications and over time. The statistical significance of the success ratios is assessed based on the test proposed in Pesaran and Timmermann (2009).

3. Forecast Evaluation

This section provides a systematic evaluation of the accuracy of forecasting methods for the monthly retail price of gasoline. We focus on forecasts of the real price of gasoline because for many economic questions it is the real price rather than the nominal price that matters. Moreover, many of our forecasting models are motivated by economic models relating to the determination of the real price of gasoline.[3] The question of how to construct quarterly forecasts is addressed in section 4; extensions to nominal gasoline price forecasts are discussed in section 5. Before considering forecasting models motivated based on economic theory, it is useful to assess the forecast accuracy of simple time series models for the real price of gasoline.

3.1. Forecasting the real retail price of gasoline based on its own past

It is well established that parsimonious autoregressive-moving average (ARMA) time series models often provide more accurate forecasts than multi-equation forecasting models (see Box and Jenkins 1970). A natural starting point is the ARMA(1,1) model for the real price of gasoline in logs, r_t^{gas}, with logs denoted by lower case letters. The ARMA(1,1) model is estimated by the method of maximum likelihood. Forecasts $\hat{r}_{t+h|t}^{gas}$ of the log of the real price of gasoline are constructed iteratively from the estimated ARMA model conditional on the most recent data and converted to levels, $\hat{R}_{t+h|t}^{gas}$, with upper case denoting dollar prices, resulting in the forecast $\hat{R}_{t+h|t}^{gas} = \exp(\hat{r}_{t+h|t}^{gas})$, where h is the forecast horizon. The first column of Table 1 shows that this ARMA(1,1) model has systematically higher MSPE than the no-change forecast and cannot be recommended.

One concern with this specification is that we cannot rule out a priori that the log of the real price of gasoline is a unit root process because this process appears highly persistent (see Figure 1). Indeed, a unit root test would not be able to reject the null of a unit root, suggesting that an alternative specification of the model as an MA(1) process in percent changes (IMA(1)) may be more appropriate (see Diebold and Kilian 2000). The second column of Table 1 demonstrates that this alternative specification obtained by imposing the unit root on the ARMA(1,1) process if anything has even higher MSPE ratios. This evidence suggests that the process actually is not well characterized as a unit root process or near unit root process, mirroring similar results for the price of crude oil in Alquist et al. (2013). Finally, relaxing the dynamic specification by specifying an ARMA(1,1) model in first differences (ARIMA(1,1)), further increases the MSPE ratios. Apart from some directional accuracy at horizon 1 for all three specifications, none of these ARMA models is able to beat the random walk benchmark. This evidence adds credence to the view that standard time series forecasting models that perform well in a wide range of macroeconomic applications are not suitable for forecasting the real price of gasoline.

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[3] Throughout the paper all real prices are obtained by deflating the nominal price by the seasonally adjusted U.S. consumer price index for all urban consumers. Real-time data for the monthly seasonally adjusted U.S. consumer price index for all urban consumers can be obtained from the Economic Indicators published by the Council of Economic Advisers. These data are available in the FRASER database of the Federal Reserve Bank of St. Louis. Additional real-time U.S. consumer price index data were obtained from the macroeconomic real-time database of the Federal Reserve Bank of Philadelphia.

An alternative approach is to rely on purely autoregressive forecasting models for the log-level of the real price of gasoline. Forecasts are constructed iteratively and converted to levels according to $\hat{R}_{t+h|t}^{gas} = \exp(\hat{r}_{t+h|t}^{gas})$. Autoregressive models may be estimated by unconstrained least-squares methods or by Bayesian shrinkage estimation methods. Bayesian shrinkage estimators allow the forecaster to reduce the variance of the forecast at the cost of increasing its bias. These methods have been shown to be successful in reducing the MSPE of autoregressive forecasts in a wide range of macroeconomic applications. Our application relies on state-of-the-art data-driven Bayesian forecasting methods that only rely on real-time information (see Giannone et al. 2015).

An important question in specifying autoregressive (AR) or Bayesian autoregressive (BAR) models is the lag order. BAR models are likely to be preferable when working with less parsimonious models with many autoregressive lags. Table 1 shows results based on a fixed lag order of 12, which has also been shown to work well in forecasting the real price of oil (see Alquist et al. 2013). Further analysis revealed that allowing for larger fixed lag orders or, for that matter, reducing the lag order, does not improve on this baseline model. Table 1 shows that this model with the exception of horizon 6 produces no reductions in the MSPE compared to the no-change forecast, although it shows some signs of significant directional accuracy at horizons up to 18 months. There is little difference between the AR(12) and BAR(12) specification. An alternative approach to lag order selection is to select the lag order of the forecasting model at each point in time, allowing the lag order to vary across the recursive sample. We follow standard practice in choosing the lag order based on the Akaike Information Criterion (see, e.g., Marcellino, Stock, and Watson 2006). Table 1 indicates that this approach produces similar results to the model with fixed lag order.

A very different forecasting approach is recursive exponential smoothing. Exponential smoothing involves converting the observed series, $\left\{ r_t^{gas} \right\}_{t=1}^T$, into a smoothed series $\left\{ \overline{r}_t^{gas} \right\}_{t=1}^T$. Forecasts are formed as $\hat{r}_{T+h|T}^{gas} = \overline{r}_T^{gas}$ and converted to levels by exponentiating. It can be shown that exponential smoothing delivers a one-sided moving average model with exponentially declining weights. This approach is designed for series that are not trending over time. Because the log level of the real price of gasoline in Figure 1 has no pronounced trend, it is a natural candidate for the application of exponential smoothing. Given $\overline{r}_1^{gas} = r_1^{gas}$, the smoothed series is constructed recursively from

$$\overline{r}_t^{gas} = a\, r_t^{gas} + (1-a)\overline{r}_{t-1}^{gas}, \quad t = 2,...,T,$$

where the smoothing parameter $a \in [0,1]$. The smaller a, the smoother $\overline{r}_t^{gas}$. For econometric applications, it is common to choose large values of a (see, e.g., Faust and Wright 2013). The results in Table 1 are based on $a = 0.8$. The qualitative results are reasonably robust to changing this parameter.

The second-to-last column of Table 1 shows that exponential smoothing performs very poorly at horizons 1 and 3, but greatly improves on the accuracy of the no-change forecast at longer horizons. The MSPE reductions at these horizons range from 8% to 22%, depending on the horizon. Because exponential smoothing forecasts are not subject to estimation uncertainty, the statistical significance of

the MSPE reductions can be assessed using the test of Diebold and Mariano (1995). Table 1 shows that several of the MSPE reductions are statistically significant at the 5% level or the 10% level. Exponential smoothing forecasts have no directional accuracy, however, at any horizon.

The last column focuses on an unobserved components stochastic volatility (UC-SV) forecasting model. This UC-SV model was originally proposed by Stock and Watson (2007) in the context of forecasting inflation. The model treats the log of the real retail price of gasoline as the sum of a permanent component and a serially uncorrelated transitory component. Both components are allowed to be time-varying, making the model equivalent to a time-varying IMA(1) model for the growth rate of the real price of gasoline.[4] Rather than using the Kalman filter, the model is estimated using the efficient Markov Chain Monte Carlo (MCMC) sampler proposed in Chan (2013), building on Chan and Jeliazkov (2009). We adopt the same diffuse prior specification as Chan (2013). Table 1 shows that the UC-SV model is quite accurate at longer horizons reaching reductions in the MSPE up to 22% accompanied by mostly statistically insignificant directional accuracy. We also experimented with an UC model without stochastic volatility in the permanent component. The results are uniformly less accurate than for the UC-SV model and hence are not shown.

3.2. Forecasts based on Spot and Futures Market Prices

A natural question is whether information from financial markets about spot and futures prices may be used to improve the accuracy of forecasts of the real price of gasoline. For example, in the absence of a risk premium, standard arbitrage arguments imply that the gasoline futures prices should be the conditional expectation of the spot price of gasoline. This line of reasoning suggests constructing a forecast of the real retail price of gasoline as

$$\hat{R}_{t+h|t}^{gas} = R_t^{gas}\left(1 + f_t^h - s_t - E_t(\pi_{t+h}^h)\right),$$

where f_t^h is the log of the current gasoline futures price for maturity h, s_t is the log of the corresponding spot price of gasoline, and $E_t(\pi_{t+h}^h)$ is the expected inflation rate over the next h periods. The latter expectation is estimated recursively and in real time using the inflation gap model proposed in Faust and Wright (2013). We follow Faust and Wright in postulating an AR(1) model for the deviation between current monthly inflation and long-run inflation expectations, as measured by the 5-10 year ahead Blue Chip inflation forecast. The slope coefficient of this model is fixed at 0.429. This estimate is obtained from fitting an AR(1) model to the 1991.12 vintage of CPI inflation data from 1947.2 to

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[4] More formally, let $r_t^{gas} = \tau_t + \eta_t$, where $\eta_t = \sigma_{\eta,t}\zeta_{\eta,t}$ is the transitory component and the stochastic trend component, τ_t, evolves according to $\tau_t = \tau_{t-1} + \varepsilon_t$, where $\varepsilon_t = \sigma_{\varepsilon,t}\zeta_{\varepsilon,t}$. The log-variances of η_t and ε_t evolve as independent random walks $\ln\sigma_{\eta,t}^2 = \ln\sigma_{\eta,t-1}^2 + \nu_{\eta,t}$ and $\ln\sigma_{\varepsilon,t}^2 = \ln\sigma_{\varepsilon,t-1}^2 + \nu_{\varepsilon,t}$, $\zeta_t = \left(\zeta_{\eta,t}, \zeta_{\varepsilon,t}\right)$ is i.i.d. $N(0, I_2)$, $\nu_t = \left(\nu_{\eta,t}, \nu_{\varepsilon,t}\right)$ is i.i.d. $N(0, \gamma I_2)$, where γ is a scalar parameter, and ζ_t and ν_t are independent. The parameter γ is estimated recursively in real time, and the forecast of the real price of gasoline is constructed as $\hat{R}_{t+h|t}^{gas} = \exp\left(\hat{r}_{t+h|t}^{gas}\right)$, where the expectation is estimated by Monte Carlo integration.

1991.12.[5] Forecasts are constructed by iterating the gap model forward and adding the predicted inflation gaps to the expected trend inflation rate.

Monthly gasoline futures price data for our evaluation period are available only up to a horizon of 6 months, limiting the applicability of this approach. Moreover, the first column of Table 2 shows that the futures-based forecast has systematically higher MSPE than the no-change forecast. The high MSPE of these forecasts does not come as a surprise given recent evidence in favor of a time-varying risk premium in the market for crude oil (see Baumeister and Kilian 2014b). It would not be surprising if there were such as risk premium in the gasoline market as well. Although not useful from an MSPE point of view, futures-based forecasts show some evidence of statistically significant directional accuracy at horizons 3 and 6.

An alternative approach is the use of product spread regressions, as discussed in Baumeister, Kilian and Zhou (2014) in the related context of oil price forecasting. This approach exploits the fact that the nominal spot prices of gasoline and crude oil are cointegrated. Under the maintained hypothesis of cointegration, current deviations of the spot price of gasoline from the spot price of crude oil would be expected to have predictive power for cumulative changes in the nominal spot price of gasoline:

$$\Delta s_{t+h|t}^{h,gas} = \alpha + \beta \left[s_t^{gas} - s_t^{oil} \right] + \varepsilon_{t+h}$$

where the s_t^{gas} is the log of the nominal U.S. spot price of gasoline, s_t^{oil} is the log of the nominal spot price of crude oil, and $\Delta s_{t+h|t}^{h,gas}$ denotes the cumulative change in s_t^{gas} over the next h months. Analogous predictive regressions have become standard tools in financial economics (see, e.g., Mark 1995). Given recursive estimates of this relationship, one can construct the forecast of the real retail price of gasoline as

$$\hat{R}_{t+h|t}^{gas} = R_t^{gas} \exp \left\{ \hat{\alpha} + \hat{\beta} \left[s_t^{gas} - s_t^{oil} \right] - E_t(\pi_{t+h}^h) \right\},$$

where $E_t(\pi_{t+h}^h)$ is estimated as described earlier. As shown in Baumeister, Kilian and Zhou (2014), restricting α to zero may in practice reduce the MSPE of the forecast based on product spread models. Table 2 considers both versions of the model.

A potentially important question is which measure of the price of crude oil to use in the spread model. Traditionally, this question made little difference in that different measures of the price of crude oil generally moved in parallel. This is no longer true. Since 2011, the price of West Texas Intermediate (WTI) crude oil has fallen below global benchmarks such as Brent. Borenstein and Kellogg (2014) and Kilian (2014) observe that the price of gasoline in the United States in recent years has been determined by the price of crude oil imported by East Coast refineries or equivalently by the price of U.S. exports of gasoline. This suggests that the Brent price of crude will be a better proxy in constructing the gasoline

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[5] Prior to 1979, long-run survey inflation expectations data do not exist, so we use an exponential smoothing estimate of trend inflation as a crude proxy instead.

spot price spread than the price of WTI crude oil. Table 2 shows both versions of the model. It shows that there is little to choose between these specifications. Both models have higher MSPE than the no-change forecast. In both cases, imposing $\alpha = 0$ in the interest of greater parsimony reduces the MSPE ratios, but without generating systematic improvements relative to the no-change forecast.

One concern in the literature has been that product spread models may have time-varying coefficients. One reason is that gasoline is jointly produced along with other refined products such that the marginal market for refined products tends to shift over time. Another reason is that the spread model does not account for a range of global and domestic disturbances to the refining market including, for example, changes in environmental regulation and refinery outages. We therefore follow Baumeister, Kilian and Zhou (2014) in first recursively estimating the time-varying regression spread model

$$\Delta s_{t+h|t}^{h,gas} = \alpha_t + \beta_t \left[s_t^{gas} - s_t^{oil} \right] + \varepsilon_{t+h}.^6$$

Given the TVP estimates, we then construct the TVP model forecast:

$$\hat{R}_{t+h|t}^{gas} = R_t^{gas} \exp\left\{ \hat{\alpha}_t + \hat{\beta}_t \left[s_t^{gas} - s_t^{oil} \right] - E_t(\pi_{t+h}^h) \right\}$$

by Monte Carlo integration as the mean of the forecasts simulated based on 1,000 Gibbs iterations conditional on the most recent data.[7] We also explore the effects of restricting $\alpha_t = 0$. Table 2 shows that for most specifications allowing for time variation in the parameters results in MSPE ratios below 1 at horizon 1. Although the restricted TVP Brent spot price model in the last column shows some promise at longer horizons and produces larger MSPE reductions than any of the other spread models, overall spread models cannot be recommended.[8]

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[6] In estimating the model, we postulate that $\varepsilon_{t+h} \ \square \ NID(0, \sigma^2),$ while the time-varying coefficients $\theta_t = [\alpha_t \quad \beta_t]'$ evolve according to a random walk as $\theta_t = \theta_{t-1} + \xi_t,$ and ξ_t is independent Gaussian white noise with variance $Q.$ This state-space model is estimated using a Gibbs sampling algorithm. The conditional posterior of θ_t is normal, and its mean and variance can be derived via standard Kalman filter recursions (see Kim and Nelson 1999). Conditional on an estimate of θ_t, the conditional posterior distribution of σ^2 is inverse Gamma and that of Q is inverse Wishart.

[7] Our forecasts take into account that the model parameters continue to drift over the forecast horizon according to their law of motion. The first 30 observations of the initial estimation period are used as a training sample to calibrate the priors and to initialize the Kalman filter.

[8] Building on the analysis in Baumeister, Kilian and Zhou (2014), we also experimented with models including both the gasoline spot price spread and the heating oil spot price spread, which allow for interaction between the diesel/heating oil and gasoline retail markets. The results were similar to the gasoline spot spread model overall.

3.3. Bivariate VAR Models of the Real Retail Price of Gasoline and the Real Price of Crude Oil

Given the close relationship between gasoline and oil prices, at least in the long run, a natural extension of the univariate autoregressive forecasting models in Table 1 is a VAR model of the form:

$$B(L) y_t = v + u_t$$

where $y_t = \left[r_t^{oil}, r_t^{gas} \right]'$ refers to a vector including the log of the real price of crude oil and the log of the real U.S. retail price of gasoline, v denotes the intercept, $B(L) = I_4 - B_1 L - ... - B_p L^p$ denotes the autoregressive lag order polynomial, p is the autoregressive lag order, L is the lag operator, and u_t is a white noise innovation. As in the univariate case, forecasts $\hat{r}_{t+h|t}^{gas}$ are generated recursively and subsequently converted to levels. We consider forecasts both from the unrestricted least-squares estimator (denoted as VAR in the tables) and the Bayesian estimator of Giannone et al. (2015) (denoted as BVAR).

For expository purposes, Table 3 focuses on the Brent price of crude oil. Using a proxy for the global price of oil avoids the structural instability in the relationship between the U.S. prices of crude oil and gasoline discussed in Borenstein and Kellogg (2014) and Kilian (2014). Table 3 investigates the effect of changing the lag order on the accuracy of the forecast of the level of the real price of gasoline. The baseline is the model with a fixed lag order of 12. This model clearly outperforms the no-change forecast at horizons of 1, 3 and 6, with MSPE reductions between 5% and 26% and statistically significant directional accuracy as high as 0.70. Because this model nests the AR(12) in Table 1, we conclude that past information about the real price of crude oil improves forecast accuracy.

There is no reason for this model to be optimal, however. Reducing the autoregressive lag order to 6, results in MSPE reductions at all forecast horizons and statistically significant directional accuracy at horizons as high as 18 months. Further investigation reveals that the most accurate MSPE results are in fact obtained for the VAR(1) model. There is nothing to choose between the Bayesian and the unrestricted estimator of this model specification. Re-estimating the lag order recursively based on the AIC does not systematically improve the MSPE ratios compared with the VAR(1) model. We conclude that substantial improvements on the accuracy of real gasoline price forecasts are possible with a very simple bivariate model.

An obvious question is whether the MSPE reductions for the VAR(1) model are statistically significant. This question cannot be answered because none of the currently available tests of the null hypothesis of equal MSPEs are appropriate in our context. For example, the test of Diebold and Mariano (1995) does not apply in this setting. This problem is not specific to this paper. Sometimes, related studies have reported p-values based on the test of no predictability proposed by Clark and West (2007) for nested model comparisons with estimation uncertainty. Although all of the MSPE reductions for the VAR(1)

model in Table 3 are statistically significant based on the test of Clark and West (2007), we choose not to report these results because applying this test often results in statistically significant rejections even when the MSPE ratios exceed one. For example, for the AR(12) model in Table 1, the Clark and West (2007) test suggests a statistically significant reduction in the MSPE for $h = 1,$ notwithstanding an MSPE ratio of 1.0217. This contradiction arises because this test is biased toward rejecting the null of equal MSPEs because it tests the null of no predictability in population rather than the null of equal out-of-sample MSPEs (see Kilian 2015). It also ignores the real-time nature of the data used in our forecasting exercise (see Clark and McCracken 2013). Nor is it designed for iterated forecasts, rendering it invalid in the current setting. This criticism applies generically to similar tests of no predictability commonly used in applied work. Any such test results have to be interpreted with caution. These problems are compounded when dealing with forecasts based on model selection procedures or forecast combinations. For further discussion of the problem of out-of-sample inference see Kilian (2015).[9]

Table 4 takes the lag structure as given and re-examines the sensitivity of the forecast accuracy results to the definition of the real price of crude oil. It considers four alternative definitions of the underlying nominal oil price: (1) the WTI price of crude oil, (2) the U.S. refiners' acquisition cost for crude oil imports with nowcasts based on the growth rate of the WTI price, (3) the U.S. refiners' acquisition cost for crude oil imports with nowcasts based on the growth rate of the Brent price of oil, and (4) the Brent price of crude oil. Specifications (2) and (3) have been used in the related literature on modelling the global market for crude oil. Table 4 confirms that the choice of the oil price series matters. As expected, the WTI specification yields the highest MSPE ratios, whereas the Brent specification yields the lowest MSPE ratios. This result is consistent with the economic arguments in Borenstein and Kellogg (2014) and Kilian (2014) that the U.S. price of gasoline is determined by the price of crude oil in global markets rather than the WTI price. At some horizons, the reduction in the MSPE ratio can be as high as 0.08. Thus, for the remainder of the paper, we focus on the Brent price only.

Table 5 returns to the question of whether the real prices of gasoline and crude oil should be modelled in log-levels or not. Because oil and gasoline prices move together in the long run, as illustrated in Figure 2, a VAR model under the unit root null hypothesis must treat them as cointegrated. In this case, a VAR model for variables in percent changes would be invalid. In contrast, the VAR model in log-levels remains valid, but there is a possible efficiency gain from imposing cointegration in estimating the VAR model. The implied vector error correction (VEC) representation of this model can equivalently be

expressed in triangular form as a VAR model for $y_t = \left[\Delta r_t^{gas}, r_t^{gas} - r_t^{oil} \right]'$. This model is labelled VEC or

BVEC in Table 5, depending on whether the model is estimated by unrestricted least squares or by Bayesian methods.

Whether imposing cointegration reduces the MSPE of the out-of-sample forecasts is an empirical question (see, e.g., Christoffersen and Diebold 1998). The first two columns of the table provide the earlier VAR(1) and BVAR(1) results as a benchmark. Fitting a VEC(1) or BVEC(1) model generates no reductions in the MSPE at any horizon. Allowing for six lags improves the MSPE ratios at horizons up to 9

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[9] It should be noted that the alternative test of Giacomini and White (2006), which allows for some of these complications, does not apply either in our context because it does not allow for recursive estimation.

months. Further improvements are obtained with 12 lags, which turns out to be the most accurate VEC specification overall. The use of Bayesian estimation methods makes little difference for this model. Even the most accurate VEC model is not as accurate as the VAR(1) model in levels, however. Thus, the possibility of cointegration may for all practical purposes be ignored in forecasting the real price of gasoline.

3.4. Models of the U.S. Retail Gasoline Market

Rather than linking the monthly real retail price of gasoline to the price of crude oil in global markets, another strategy is to model its connections to the state of the domestic economy. A common monthly measure of U.S. real activity is the Chicago Fed National Activity Index (CFNAI). The CFNAI is a weighted average of 85 monthly indicators of U.S. real economic activity. These indicators are drawn from four broad categories of data: production and income; employment, unemployment, and hours; personal consumption and housing; and sales, orders, and inventories. The index corresponds to the leading common factor contained in the growth rates of these 85 series and has been shown to be a useful gauge on current and future economic activity and inflation in the United States. As is standard, we rely on the smoothed version of the CFNAI based on a one-sided moving average filter.[10] Vintages for this index are available from January 2001 onwards; earlier vintages are constructed as pseudo real-time data taking account of the 1-month delay in the availability of the index. Nowcasts are constructed using exponential smoothing with weight $a = 0.95$.

A natural conjecture is that the demand for gasoline and hence the real price of gasoline responds to changes in the U.S. business cycle. One way of capturing this intuition is to construct a parsimonious factor forecasting model

$$r_{t+h|t}^{h,gas} = \alpha + \beta\, cfnai_t + \varepsilon_{t+h},$$

where $r_{t+h|t}^{h,gas}$ denotes the cumulative percent change in the real price of gasoline expressed as a fraction such that $\hat{R}_{t+h|t}^{gas} = \exp\left(r_t^{gas} + \hat{r}_{t+h|t}^{h,gas} \right)$, and $cfnai_t$ the common factor. Table 6 shows that this model does not improve on the MSPE of the no-change forecast at any horizon and lacks directional accuracy at all horizons. An alternative strategy is to construct a factor-augmented VAR (FAVAR) model including the real retail price of gasoline and the CFNAI. Among all such models the specification involving 12 lags performed best. Even this specification offers little improvement, however. Although it has some non-negligible statistically significant directional accuracy at horizons 1 through 9, as shown in Table 6, it tends to have higher MSPE than the no-change forecast and cannot be recommended. The same is true for Bayesian estimates of the FAVAR model, denoted by BFAVAR in Table 6.

This result is not entirely surprising upon reflection, given the fall in U.S. gasoline consumption in recent years that was not related to the U.S. business cycle so much, but to rising gasoline prices. This fact suggests specifying instead a bivariate VAR model with intercept for the log level of the real price of gasoline and the log of U.S. real gasoline consumption. The results shown in Table 6 are based on a model specification involving the log-difference of the real gasoline consumption rather than the log-

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[10] For further details see https://www.chicagofed.org/publications/cfnai/index.

level. Imposing this restriction tends to reduce the MSPE. As before, $\hat{R}^{gas}_{t+h|t} = \exp\left(\hat{r}^{gas}_{t+h|1}\right)$. Table 6 shows that the VAR(12) and BVAR(12) specification in some dimensions improve on the corresponding FAVAR(12) and BFAVAR(12) models, but not by much. Clearly, neither approach can be recommended. This result is robust to changes in the lag order. Table 6 shows two representative examples involving six autoregressive lags and one autoregressive lag.

3.5. Joint VAR Models of the U.S. Retail Gasoline Market and the Global Market for Crude Oil

In section 3.2 we showed that including the real price of oil in the same VAR model as the real retail price of gasoline greatly enhances the forecast accuracy. A natural question therefore is whether combining forecasting models of the U.S. retail gasoline market with forecasting models of the global price of crude oil may improve the accuracy of gasoline price forecasts further. Such an improvement is by no means self-evident, given the large dimensionality of models that combine both oil and gasoline market blocks.

A natural benchmark is the VAR(12) forecasting model for the real price of oil first proposed in Baumeister and Kilian (2012). This VAR model may be viewed as the reduced-form representation of the structural global oil market model developed in Kilian and Murphy (2014). It includes the percent change in global crude oil production, a measure of global real economic activity, the log of the real U.S. refiners' acquisition cost for crude oil imports as a proxy for the global price of oil, and a proxy for the change in global crude oil inventories.[11] For the purpose of the current paper, we augment the forecasting model of Baumeister and Kilian (2012) by a gasoline market block consisting of the log difference of U.S. real gasoline consumption and the log level of the real U.S. retail price of gasoline, resulting in a model with six variables.[12] We follow the oil price forecasting literature in estimating the unrestricted VAR model with 12 autoregressive lags by the method of least squares or by Bayesian methods. It can be shown that this lag order choice not only works well in forecasting the real price of oil, but also generates more accurate real gasoline price forecasts than shorter or longer lag structures. As before, forecasts $\hat{r}^{gas}_{t+h|t}$ of the log of the real price of oil are constructed iteratively from the estimated VAR model conditional on the most recent data and converted to levels, resulting in the forecast $\hat{R}^{gas}_{t+h|t} = \exp(\hat{r}^{gas}_{t+h|t})$.

The first two columns of Table 7 show that this large-scale model is surprisingly accurate at short horizons with MSPE ratios as low as 0.73 and statistically significant directional accuracy as high as 0.69. Not surprisingly, the use of Bayesian estimation methods further improves the accuracy of this high-dimensional model. The BVAR(12) model produces MSPE reductions between 3% and 28% at horizons up to nine months, accompanied by mostly statistically significant directional accuracy as high as 0.72.

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[11] The inventory data are constructed by multiplying U.S. crude oil inventories by the ratio of OECD petroleum inventories to U.S. petroleum inventories. Petroleum inventories are defined to include both stocks of crude oil and stocks of refined products. The global real activity index is constructed from data on global dry cargo ocean shipping freight rates as described in Kilian (2009).

[12] For the large-scale VAR models it can be shown that a specification in the log-level of real gasoline consumption is even more accurate by a few percentage points, but we report the results for the log-difference to maintain consistency with the earlier bivariate analysis.

Thus, at short horizons, this model is more accurate than the VAR(1) model for the real prices of gasoline and Brent crude oil in Table 3. At longer horizons, this ranking is reversed, given the greater parsimony of the VAR(1) model. The next two columns focus on a simplified version of the first model, in which the second block only includes the log of the real price of gasoline, but excludes the log of real gasoline consumption. This model is marginally less accurate than the six-variable model at very short horizons, but marginally more accurate at horizons of more than 3 months. Overall, the results are quite similar.

The remainder of Table 7 examines the robustness of these results based on another joint VAR model of the gasoline and crude oil markets proposed in Kilian (2010). The reduced-form representation of the latter model consists of the same two blocks as before, except that the oil inventory data are excluded from the first block. The next two columns of Table 7 show that similar results are obtained with this 5-variable model than with the original specification. Likewise, after dropping real gasoline consumption from this model, as shown in the last two columns, the resulting 4-variable model produces forecasts of the real gasoline price that are about as accurate as those from the earlier 5-variable model including oil inventories.

We conclude that, at short forecast horizons, high-dimensional joint forecasting models of the real price of oil and the real retail price of gasoline outperform in real time not only the no-change forecast, but the bivariate VAR(1) model forecast based on real Brent oil and gasoline prices. This result is quite striking. It demonstrates that parsimony does not always win out in forecasting.

4. Sensitivity Analysis and Refinements

This section examines the robustness of our results along four dimensions. We first assess the importance of explicitly modelling seasonality in the real price of gasoline. We then examine the robustness of the recursive MSPE rankings over time, and we explore the benefits of pooling the most successful gasoline price forecasts. Finally, we extend the analysis to quarterly gasoline price forecasts.

4.1. How Important Is Seasonality in Gasoline Prices?

It is well known that there is pronounced seasonality in the production of gasoline. It is less clear how important seasonality is in the monthly retail price of gasoline. Figure 1 does not suggest a strong seasonal pattern. Nevertheless, formal statistical tests for deterministic seasonal effects in the growth rate of the monthly real price of gasoline conducted on the full sample using fully revised data indicate statistically significant seasonal variation during some months of the year. Our analysis so far has not explicitly incorporated this seasonal variation. It can be shown that including monthly seasonal dummies in the forecasting models does not systematically improve its real-time forecast accuracy and in some cases may worsen it, indicating that the reduction in forecast bias from modelling seasonal variation is outweighed by the additional variance caused by having to estimate these additional parameters. Thus, seasonality may be ignored for the purpose of generating out-of-sample gasoline price forecasts.

4.2. How Robust Are the MSPE Reductions over Time?

The analysis so far has focused on the recursive MSPE ratio at the end of the evaluation sample. This ratio is a measure of the overall predictive power of the forecasting method. Of equal importance from the point of view of an applied user is how robust these gains in forecast accuracy have been over time. This question may be assessed by plotting the recursive MSPE ratio, as it evolves during the evaluation period. In Figure 3 we address this question for the VAR(1) model of the real prices of gasoline and Brent crude oil, which proved most accurate overall in section 3. The forecast from this model is referred as the baseline forecast in Figure 3. The last observation shown for the recursive MSPE ratio in each subplot corresponds to the entry for this horizon shown in the earlier tables.[13]

Figure 3 demonstrates that the accuracy of the VAR(1) forecasting model has been remarkably stable over time. At horizons up to 9 months, the recursive MSPE ratio has been below 1 for every month between the beginning of the evaluation period and March 2014. At horizons of 12 and 15 months, it has reduced the MSPE most of the time; even at horizons of 18 and 21 months it has remained superior to the no-change forecast more often than not; only at the horizons of 24 months, its relative accuracy has been somewhat erratic. Figure 3 establishes the robustness of the accuracy of the VAR(1) baseline forecast of the real price of gasoline price at horizons at least up to 15 months. This finding is by no means a foregone conclusion. The VAR(6) model in Table 3, for example, performs rather poorly in the first two thirds of the evaluation sample, especially at short horizons. Likewise, the accuracy of the large-

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[13] It should be noted at this point that our concern here is with demonstrating that the VAR(1) model has had lower MSPE than the no-change forecast consistently over time. We are not concerned with the question of whether there is statistically significant variation over time in the MSPE ratios. Indeed, that question is irrelevant for our analysis. Moreover, tests of the latter hypothesis, as discussed in Giacomini and Rossi (2010), rely on the framework of Giacomini and White (2006) that only applies to forecasts based on rolling windows. Such tests are not valid in our setting.

scale BVAR(12) models in Table 7 and of the bivariate VEC(12) model in Table 5 is not as stable at horizon 1 as the bivariate VAR(1) model. We conclude that the VAR(1) forecasting model based on real Brent and real retail gasoline prices is preferred over the other models not only in terms of its overall accuracy, but also its robustness.

4.3. Are there Benefits from Forecast Pooling?

Forecast combinations (also known as pooled forecasts) have a long tradition in macroeconomic forecasting (see, e.g., Timmermann 2006). They also have been shown to be helpful in forecasting energy prices. For example, Baumeister and Kilian (2014a) and Baumeister, Kilian and Lee (2014) establish that an equal-weighted combination of suitably selected oil price forecasting models is systematically more accurate than any individual forecast including the no-change forecast. It also is more accurate than forecast combinations based on recursive or rolling inverse MSPE weights. It therefore makes sense to explore the benefits of pooling in our context. Rather than pooling all gasoline price forecasts we illustrate the benefits of pooling by focusing on the five most promising forecasting approaches considered so far, which include the exponential smoothing forecast and the UC-SV forecast in Table 1, the Brent VAR(1) model in Table 3, the Brent VEC(12) model in Table 5, and the Kilian-Murphy large-scale BVAR(12) specification with the real price of gasoline added in Table 7. Table 8 shows that combining these models with equal weights of 1/5 is superior overall to relying on the most accurate individual model. The pooled forecast improves on the no-change forecast at all horizons between 1 and 24 months with MSPE ratios as low as 0.73 and success ratios as high as 0.67. It also improves substantially on the MSPE of the Brent VAR(1) model in Table 3 at some horizons and is only marginally less accurate than the VAR(1) model at the other horizons.

In addition, the accuracy of the pooled forecast is more stable over time than that of the VAR(1) model forecast. Figure 3 shows that the recursive MSPE of the pooled forecast is below that of the no-change forecast in every month of the 20-year evaluation period at all horizons except at horizon 24 and, even in that case, it dominates the no-change forecast at all but a few months of the evaluation period. Pooling forecasts systematically reduces the recursive MSPE ratio relative to the baseline VAR(1) model forecast at all horizons. We conclude that pooling the five forecasting models in question with equal weights is the preferred forecasting approach in practice.[14]

4.4. Extensions to Quarterly Forecasts of the Real Price of Gasoline

It is straightforward to derive quarterly forecasts by averaging the monthly forecasts by quarter. This approach has been shown to be considerably more accurate than relying on quarterly data in the construction of the quarterly forecasts (see Baumeister and Kilian 2014a). Figure 4 shows that the pattern of the recursive MSPE ratios of the quarterly pooled forecasts is similar to that of the monthly pooled forecasts in Figure 3. The improvements in accuracy are even higher than for the monthly

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[14] Additional reductions in the overall recursive MSPE are possible, when selecting the most accurate forecast combination for each horizon, as proposed in Baumeister and Kilian (2015). Further analysis, however, showed that the accuracy of this alternative pooled forecast is less robust over time, especially at horizons 1 and 24, than the original pooled forecast.

forecasts. The overall recursive MSPE reductions range from 15% to 31% with success ratios as high as 0.71 and statistically significant directional accuracy up to 6 quarters.[15]

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[15] The benchmark in Figure 4 is the same monthly no-change forecast as in the earlier analysis. This no-change forecast at short horizons is considerably more accurate than the quarterly no-change forecast (see Baumeister and Kilian 2014a).

5. A Comparison of Econometric Gasoline Price Forecasts and Other Forecasts

A different perspective on the accuracy of pooled real-time forecasts may be obtained by comparing them to the short-term nominal gasoline price forecasts published by the EIA. The data source for the latter forecasts is the EIA's *Short-Term Energy Outlook*. These forecasts are intended to help businesses, households and governments in their decision making. A natural question is how accurate these forecasts are and whether they may be improved upon by using the pooled forecast proposed in this paper. We construct quarterly nominal pooled forecasts by averaging the monthly pooled forecasts of the real price by quarter, as in Figure 4, and inflating these forecasts based on the method of Faust and Wright (2013). The benchmark is the monthly nominal no-change forecast. Table 9 shows that the EIA forecasts are quite accurate at horizons up to 4 quarters as measured by the MSPE, which is in sharp contrast with the EIA's much less accurate oil price forecasts (see Baumeister, Kilian and Lee 2014). Nevertheless, the pooled forecast is even more accurate and hence preferable. As far as directional accuracy is concerned, both approaches yield improvements on the no-change forecast with no clear winner.

It is also of interest to compare the pooled forecast with the average expected nominal gasoline price implied by the Michigan Survey of Consumers.[16] The evaluation sample is restricted by the availability of the survey data. Table 9 shows that the MSPE of the 12-month-ahead survey forecast is larger than that of the no-change forecast and that the directional accuracy of the survey forecast is not statistically significant. The pooled forecast has a lower MSPE and higher directional accuracy than the monthly survey forecast. One interpretation of this evidence is that the simple rules of thumb used by U.S. households to form gasoline price expectations are suboptimal.

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[16] Unlike Anderson et al. (2011) we do not evaluate the implied real gasoline price forecast, but the nominal price forecast. Our survey forecast is constructed by averaging the expected change in the nominal gasoline price across households and adding it to the current nominal price of gasoline.

6. How Predictable was the Decline in Gasoline Prices in Late 2014?

There has been much public discussion about the rapid decline in the U.S. retail price of gasoline since June 2014. The question of whether this decline was predictable is of interest to economists because it helps us determine the extent to which this decline must be attributed to economic shocks occurring after June 2014. If the decline were entirely predictable as of June 2014, for example, there would be no point in searching for additional economic shocks after June 2014 to which to attribute this decline. Table 10 shows several real and nominal real-time gasoline price forecasts generated as of June 2014. It shows that about 39% of the price decline between June and December was actually predicted by the EIA in real time. Much the same result would have been obtained by forecasting gasoline prices in real time based on the Kilian-Murphy BVAR(12) model augmented by U.S. retail gasoline prices. In contrast, the pooled forecast, which overall proved clearly more accurate than the EIA forecast in Table 9, only predicted about 16% of this particular decline. This result suggests that the insurance against forecast errors provided by pooling forecasts, although effective on average, during some specific episodes may come at a high cost.

In fact, the only model contained in the forecast combination to come close to the EIA forecast is the KM-BVAR(12) model. One reason for the favorable performance of this forecasting framework primarily is that this model involves explicit forecasts of global real activity and that it anticipated falling demand for oil in the second half of 2014, consistent with an economic slowdown in Europe and Asia. In addition, the inclusion of oil inventories and global oil production can be shown to improve the accuracy of the VAR model forecast substantially. As discussed in Baumeister and Kilian (2015), VAR forecasting models motivated by structural oil market models tend to work well during times when economic fundamentals show persistent variation, but less well at other times. This fact suggests that there may be scope for using time-varying weights in the forecast combination, but there is little evidence that optimizing these weights in real time based on past data is helpful in practice. An alternative approach may be to use economic judgment and extraneous information about the state of the global economy to adjust these weights when there are large and persistent shifts in economic fundamentals, but the accuracy of such an approach would depend on the skills of the user.

7. Concluding Remarks

The price of gasoline is arguably the most closely watched retail price in the economy. The change in the gasoline price in the past has been considered essentially unforecastable based on publicly available information. Our findings challenge this conventional wisdom. We compared a wide range of alternative approaches to generating short-term forecasts of the real U.S. retail price of gasoline at horizons up to two years, drawing on insights from the related literature on forecasting the real price of crude oil. Our analysis was conducted in real-time, taking account of delays in the availability of some data and subsequent revisions when data finally become available. We identified five forecasting approaches that generate systematic real-time improvements in accuracy compared with the no-change forecast. An equal-weighted average of these five forecasts yields substantial reductions in the MSPE at all horizons up to 24 months and significant directional accuracy. The accuracy of this pooled forecast is remarkably stable over an evaluation period covering the last 20 years. We also discussed extensions of our analysis to forecasting quarterly aggregates of the real price of gasoline as well as forecasting nominal gasoline prices. In the latter case, the accuracy gains are even larger with MSPE reductions as high as 31% and directional accuracy as high as 74%. Finally, we compared our forecasts to expert and survey forecasts, and we provided evidence that about 39% of the decline in U.S. retail gasoline prices in late 2014 was predictable as of June 2014.

Our analysis provides a set of tools for forecasting gasoline prices with a wide range of applications in macroeconomics, environmental economics, urban economics, and public finance. Our results are of particular interest to central bankers, regulators, industry analysts, tax authorities, and perhaps, most importantly, consumers. There are a number of interesting extensions to be considered in future work. For example, one could extend the analysis to forecast gasoline prices at the state or regional level. One could also extend the set of predictors to include gasoline stocks, gasoline production and data on operable refining capacity, planned outages and capacity utilization (also see EIA 2014). Another question of interest would be whether pre-testing for seasonal effects and specifying a more parsimonious model of seasonal variation in gasoline prices can improve forecast accuracy. In addition, an investigation into the usefulness of gasoline price forecasts in improving inflation forecasts would be of interest to macroeconomists (see, e.g., Hendry and Hubrich 2011). Moreover, Edelstein and Kilian (2009) document that gasoline price shocks are associated with significant reductions in spending as well as in consumer confidence, suggesting that gasoline price forecasts may also help improve forecasts of U.S. economic growth.

Thomas K. Lee | U.S. Energy Information Administration | This paper is released to encourage discussion and critical comment. The analysis and conclusions expressed here are those of the authors and not necessarily those of the U.S. Energy Information Administration.

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Thomas K. Lee | U.S. Energy Information Administration | This paper is released to encourage discussion and critical comment. The analysis and conclusions expressed here are those of the authors and not necessarily those of the U.S. Energy Information Administration.

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Figure 1: Real U.S. Retail Price of Gasoline during 1973.10-2014.9
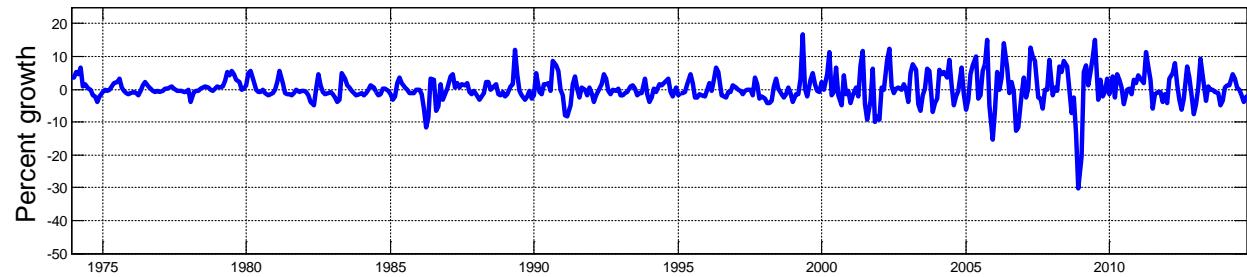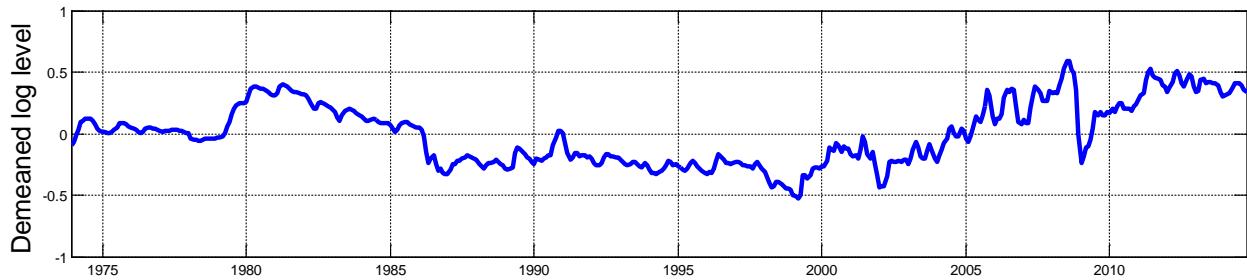
Figure 2: Real U.S. Retail Price of Gasoline and Real Brent Price during 1973.10-2014.9
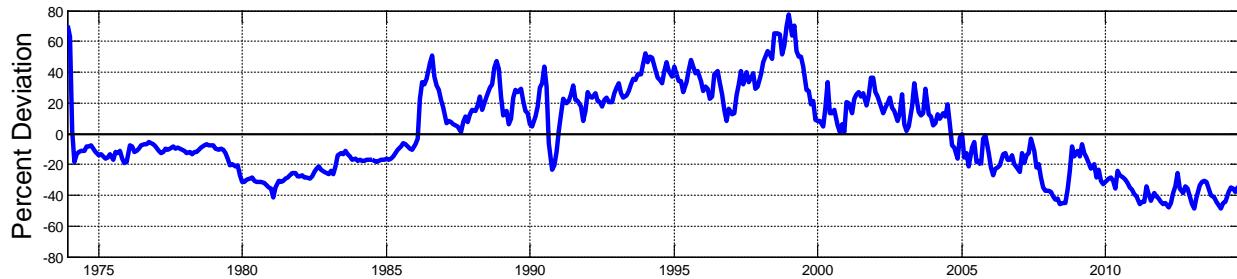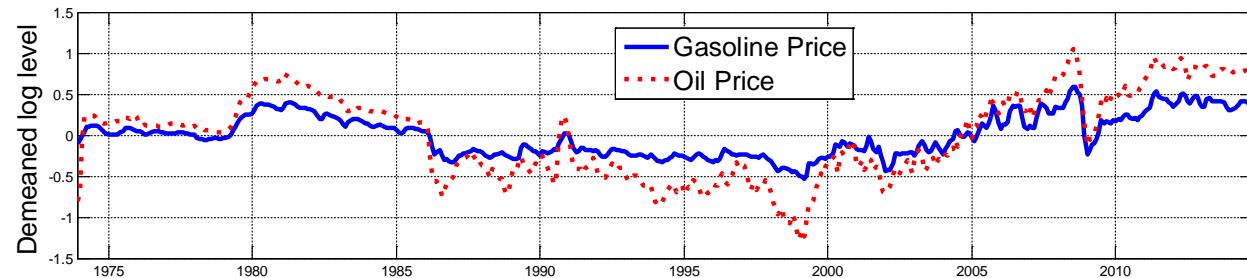
Figure 3: Evolution of the Real-Time Recursive MSPE Ratio Relative to the No-Change Forecast by Horizon
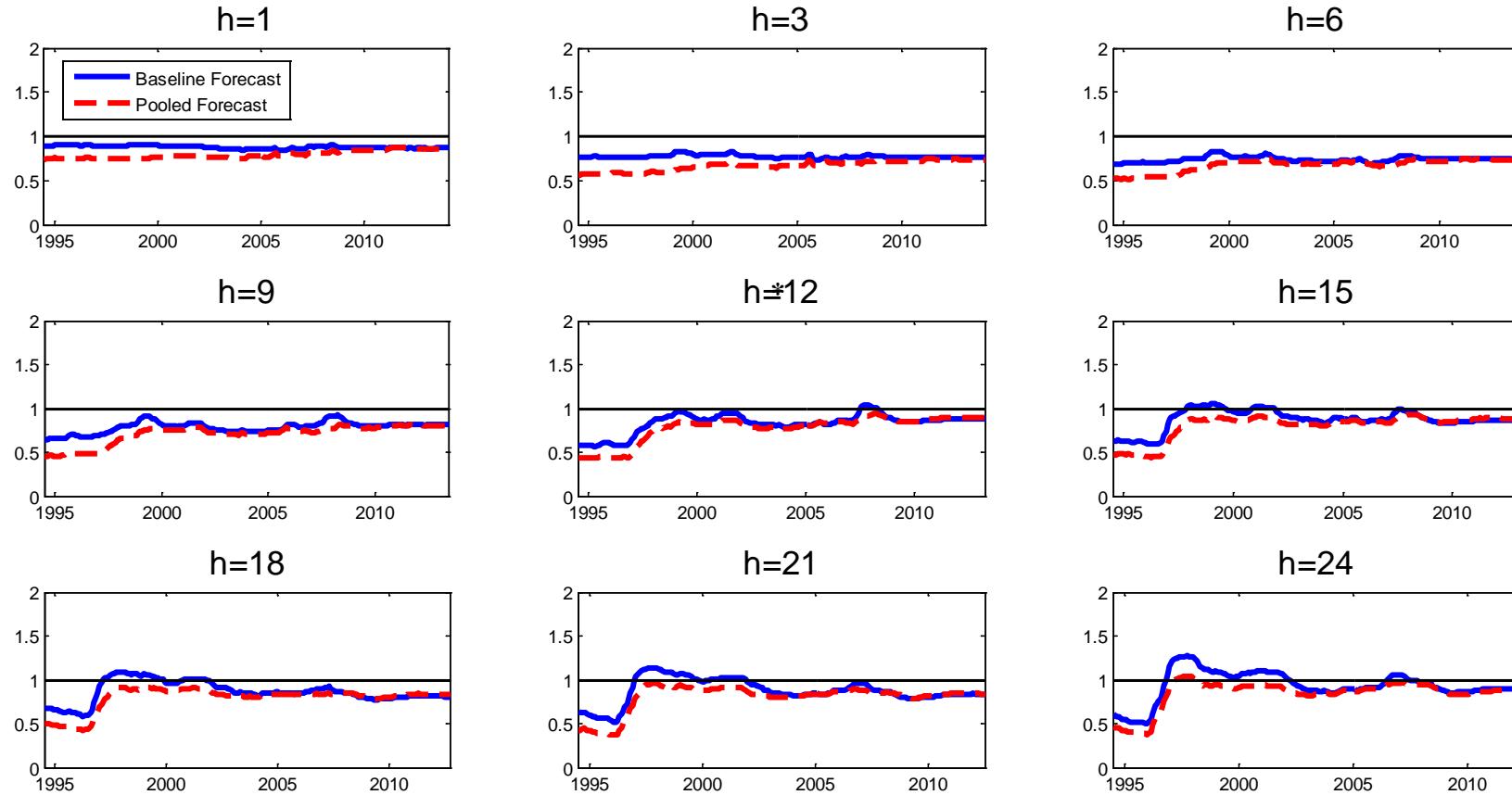
NOTES: The plot shows the evolution of the recursive MSPE ratio over time for the forecast evaluation period since the beginning of the evaluation period. The first 30 observations in each subplot have been discarded to allow the MSPE estimates to stabilize. A ratio below 1 indicates an improvement relative to the no-change forecast. The baseline forecast is from the VAR(1) model for real Brent and real retail gasoline prices in Table 3. The pooled forecast assign equal weight to the VAR(1) Brent model, the VEC(12) Brent model, the exponential smoothing forecast, the UC-SV model, and the Kilian-Murphy BVAR(12) specification with the real gasoline price added.

Figure 4: Evolution of the Real-Time Recursive MSPE Ratio of the Quarterly Pooled Forecast Relative to the No-Change Forecast by Horizon
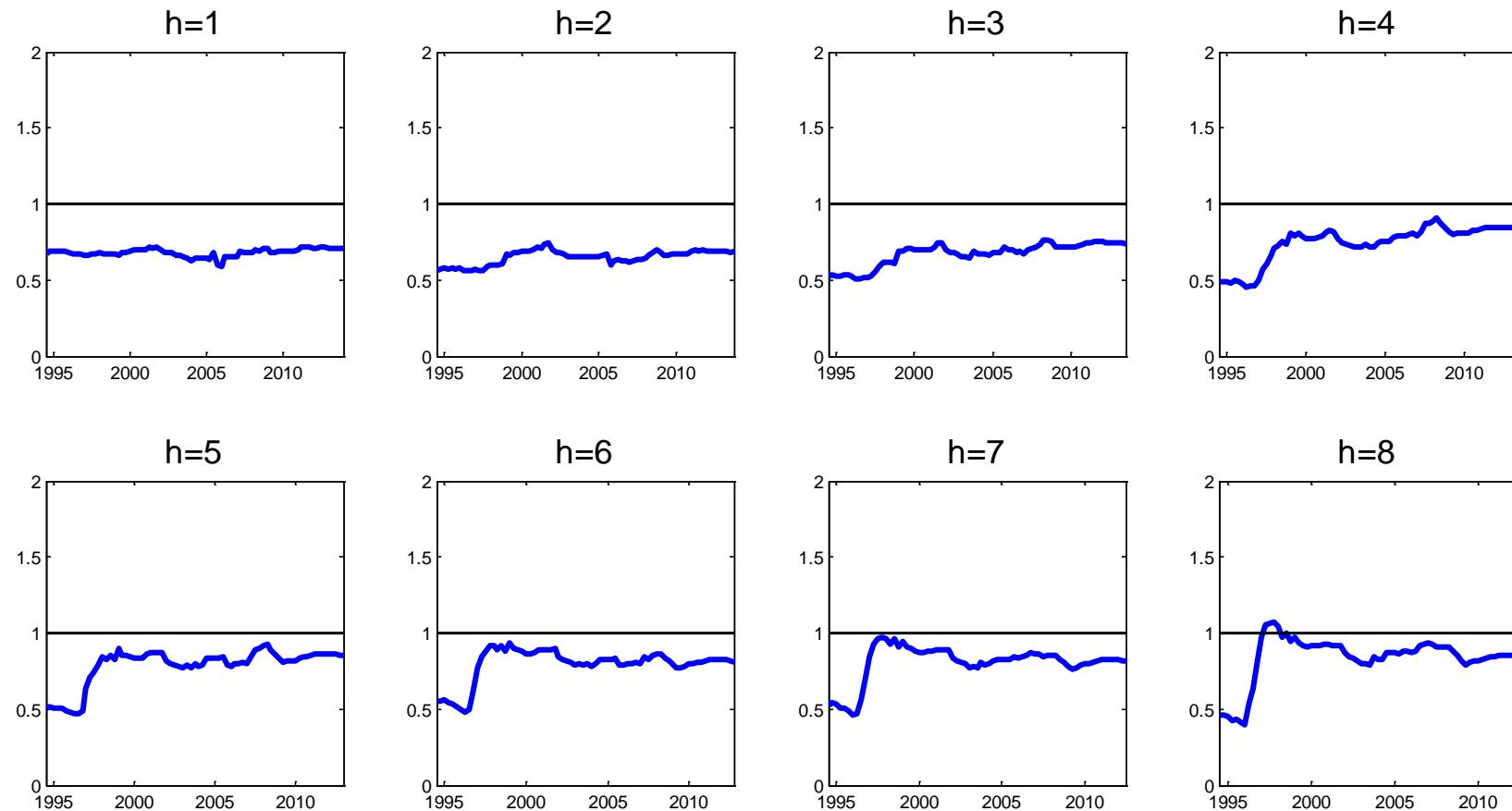
NOTES: The pooled forecast is based on an equally weighted average of five individual forecasts. The results are constructed as in Figure 3 except that the monthly forecasts are averaged by quarter, for quarters $h \in \{1,...,8\}$, as proposed in Baumeister and Kilian (2014a).

Table 1: Real-Time Forecast Accuracy of Univariate Models Evaluated on 1992.1-2014.3

Monthly Horizon	ARMA(1,1)	IMA(1)	ARIMA(1,1)	AR(12)	BAR(12)	AR(AIC)	BAR(AIC)	Exponential Smoothing	UC-SV Model
				(a) MSPE Ratios					
1	1.204	1.202	1.283	1.274	1.226	1.263	1.238	2.704	1.045
3	1.044	1.077	1.159	1.022	1.009	1.037	1.028	1.074	**0.987**
6	1.032	1.094	1.153	**0.936**	**0.931**	**0.955**	**0.950**	**0.794**[**]	**0.950**
9	1.077	1.142	1.210	1.022	1.011	1.034	1.025	**0.795**[**]	**0.921**
12	1.088	1.110	1.167	1.155	1.131	1.149	1.129	**0.922**	**0.917**
15	1.075	1.099	1.149	1.127	1.103	1.115	1.098	**0.883**	**0.910**
18	1.065	1.112	1.158	1.063	1.049	1.051	1.042	**0.818**[*]	**0.889**
21	1.112	1.128	1.179	1.111	1.098	1.095	1.087	**0.839**[*]	**0.838**
24	1.151	1.111	1.161	1.172	1.154	1.154	1.141	**0.919**	**0.776**
				(a) Success Ratios					
1	**0.644**[*]	**0.640**[*]	**0.640**[*]	**0.659**[*]	**0.663**[*]	**0.659**[*]	**0.655**[*]	0.476	0.375
3	**0.525**	**0.536**	**0.536**	**0.620**[*]	**0.611**[*]	**0.623**[*]	**0.623**[*]	**0.536**	**0.509**
6	**0.538**[*]	**0.508**	**0.508**	**0.611**[*]	**0.607**[*]	**0.607**[*]	**0.611**[*]	**0.519**	**0.534**
9	**0.502**	0.498	0.494	**0.537**[*]	**0.533**[*]	**0.517**[**]	**0.514**[**]	0.494	**0.587**[*]
12	**0.512**[**]	**0.520**	**0.520**	0.488	0.484	0.481	0.461	0.449	**0.609**
15	**0.514**	**0.510**	**0.506**	**0.534**[*]	**0.530**[*]	**0.526**[**]	**0.526**[**]	0.486	**0.577**
18	**0.524**	0.496	0.496	**0.528**	**0.536**[**]	**0.524**	**0.528**	0.536	**0.576**[**]
21	0.490	0.486	0.486	0.490	0.498	**0.514**	**0.518**	0.518	**0.587**
24	0.492	**0.508**	**0.504**	0.467	0.492	**0.504**	**0.512**	0.488	**0.562**

NOTES: BAR refers to AR models estimated using the Bayesian method of Giannone et al. (2015). The AIC lag order estimates are based on an upper bound of 12 lags. The exponential smoothing forecasts are based on a weight of 0.8. The unobserved components stochastic volatility (UC-SV) model is based on Stock and Watson (2007). All forecasts are generated recursively from data subject to real-time data constraints. Boldface indicates improvements relative to the no-change forecast. [*] denotes significance at the 5% level and [**] at the 10% level based on the Pesaran and Timmermann (2009) test for the null hypothesis of no directional accuracy and the Diebold and Mariano (1995) test of the null hypothesis of equal MSPEs where appropriate.

Table 2: Real-Time Forecast Accuracy of Models Based on Spot and Futures Market Prices Evaluated on 1992.1-2014.3

Monthly Horizon	Gasoline Futures	Spot Spread Model				TVP Spot Spread Model			
		WTI		Brent		WTI		Brent	
		$\hat{\alpha}, \hat{\beta}$	$\alpha = 0, \hat{\beta}$	$\hat{\alpha}, \hat{\beta}$	$\alpha = 0, \hat{\beta}$	$\hat{\alpha}_t, \hat{\beta}_t$	$\alpha_t = 0, \hat{\beta}_t$	$\hat{\alpha}_t, \hat{\beta}_t$	$\alpha_t = 0, \hat{\beta}_t$
				(a) MSPE Ratios					
1	3.831	1.094	1.035	1.055	1.016	**0.996**	**0.972**	1.034	**0.956**
3	1.455	1.054	1.022	1.078	1.013	1.017	1.007	1.098	**0.997**
6	1.258	1.208	1.026	1.206	1.015	1.127	1.116	1.050	1.037
9	-	1.320	1.042	1.288	1.038	1.157	1.128	1.017	1.005
12	-	1.312	1.035	1.233	**0.994**	1.107	1.045	**0.975**	**0.941**
15	-	1.270	1.056	1.188	1.002	1.110	1.047	1.038	**0.932**
18	-	1.174	1.105	1.202	1.046	1.141	1.154	1.072	**0.983**
21	-	1.115	1.130	1.176	1.055	1.319	1.342	1.103	1.036
24	-	1.087	1.084	1.081	**0.994**	1.604	1.587	1.034	1.032
				(a) Success Ratios					
1	0.487	0.487	**0.551**	0.494	**0.543**	0.479	0.491	0.449	0.472
3	**0.574**[*]	**0.566**[*]	0.434	**0.509**	0.404	**0.551**[*]	0.494	**0.521**[*]	**0.502**
6	**0.611**[*]	**0.603**[*]	0.424	**0.515**	0.401	**0.527**	**0.523**	0.531	0.527
9	-	**0.571**[**]	0.440	**0.552**	0.421	**0.556**	**0.557**	0.548	0.556
12	-	0.492	0.492	0.453	0.473	**0.609**	**0.606**	**0.609**	**0.609**
15	-	0.466	0.474	0.478	0.451	**0.569**	**0.569**	0.569	0.573
18	-	0.484	0.404	0.460	0.400	**0.568**	**0.564**	0.568	0.568
21	-	**0.518**	0.413	0.470	0.445	**0.583**	0.579	0.583	0.583
24	-	**0.537**	0.463	0.455	**0.557**	**0.553**	0.553	**0.570**[**]	0.562

NOTES: All forecasts are generated recursively from data subject to real-time data constraints. Boldface indicates improvements relative to the no-change forecast. [*] denotes significance at the 5% level and [**] at the 10% level based on the Pesaran and Timmermann (2009) test for the null hypothesis of no directional accuracy and the Diebold and Mariano (1995) test of the null hypothesis of equal MSPEs where appropriate.

Table 3: Real-Time Forecast Accuracy of Models for the Retail Gasoline Price and the Brent Price of Crude Oil Evaluated on 1992.1-2014.3: The Effect of the Lag Order

Monthly Horizon	VAR(12)	BVAR(12)	VAR(6)	BVAR(6)	VAR(1)	BVAR(1)	VAR(AIC)	BVAR(AIC)
				(a) MSPE Ratios				
1	**0.908**	**0.828**	**0.963**	**0.927**	**0.868**	**0.867**	**0.928**	**0.905**
3	**0.747**	**0.737**	**0.732**	**0.732**	**0.760**	**0.760**	**0.681**	**0.681**
6	**0.847**	**0.949**	**0.762**	**0.765**	**0.738**	**0.778**	**0.730**	**0.728**
9	1.013	1.154	**0.854**	**0.858**	**0.810**	**0.810**	**0.888**	**0.881**
12	1.243	1.151	**0.914**	**0.919**	**0.879**	**0.880**	1.037	1.012
15	1.264	1.069	**0.888**	**0.895**	**0.856**	**0.856**	**0.990**	**0.962**
18	1.167	1.104	**0.857**	**0.864**	**0.806**	**0.807**	**0.920**	**0.901**
21	1.169	1.192	**0.908**	**0.915**	**0.832**	**0.833**	1.003	**0.972**
24	1.266	1.024	**0.963**	**0.972**	**0.899**	**0.900**	1.072	1.035
				(b) Success Ratios				
1	**0.678**[*]	**0.697**[*]	**0.689**[*]	**0.693**[*]	**0.629**[*]	**0.633**[*]	**0.693**[*]	**0.685**[*]
3	**0.679**[*]	**0.679**[*]	**0.683**[*]	**0.676**[*]	**0.664**[*]	**0.664**[*]	**0.732**[*]	**0.725**[*]
6	**0.618**[*]	**0.622**[*]	**0.634**[*]	**0.634**[*]	**0.683**[*]	**0.687**[*]	**0.679**[*]	**0.683**[*]
9	**0.517**	**0.564**	**0.622**[*]	**0.606**[*]	**0.602**[*]	**0.602**[*]	**0.575**[*]	**0.579**[*]
12	**0.527**	0.500	**0.563**[**]	**0.559**[**]	0.559	0.555	0.500	**0.512**
15	**0.518**	**0.514**	**0.577**[*]	**0.577**[**]	**0.613**[*]	**0.613**[*]	**0.522**	**0.538**
18	**0.536**	**0.520**	**0.544**	**0.544**	**0.592**[**]	**0.592**[**]	**0.520**	**0.524**
21	**0.522**	**0.518**	**0.526**	**0.514**	**0.559**	**0.555**	**0.518**	**0.530**
24	0.484	0.471	**0.516**	**0.525**	**0.533**	**0.528**	**0.525**	**0.533**

NOTES: BVAR refers to VAR models estimated using the Bayesian method of Giannone et al. (2015). The AIC lag order estimates are based on an upper bound of 12 lags. All forecasts are generated recursively from data subject to real-time data constraints. Boldface indicates improvements relative to the no-change forecast. [*] denotes significance at the 5% level and [**] at the 10% level based on the Pesaran and Timmermann (2009) test for the null hypothesis of no directional accuracy.

Table 4: Real-Time Forecast Accuracy of Models for the Retail Gasoline Price and Alternative Oil Prices
Evaluated on 1992.1-2014.3: The Effect of the Choice of Oil Price Series

Monthly Horizon	WTI		RAC with WTI Nowcast		RAC with Brent Nowcast		Brent	
	VAR(1)	BVAR(1)	VAR(1)	BVAR(1)	VAR(1)	BVAR(1)	VAR(1)	BVAR(1)
				(a) MSPE Ratios				
1	**0.899**	**0.898**	**0.939**	**0.938**	**0.937**	**0.936**	**0.868**	**0.867**
3	**0.820**	**0.820**	**0.818**	**0.818**	**0.819**	**0.819**	**0.760**	**0.760**
6	**0.819**	**0.819**	**0.780**	**0.780**	**0.773**	**0.773**	**0.738**	**0.778**
9	**0.880**	**0.880**	**0.836**	**0.836**	**0.832**	**0.832**	**0.810**	**0.810**
12	**0.955**	**0.955**	**0.953**	**0.953**	**0.940**	**0.940**	**0.879**	**0.880**
15	**0.915**	**0.915**	**0.914**	**0.914**	**0.907**	**0.907**	**0.856**	**0.856**
18	**0.845**	**0.846**	**0.822**	**0.823**	**0.817**	**0.818**	**0.806**	**0.807**
21	**0.861**	**0.862**	**0.844**	**0.845**	**0.839**	**0.840**	**0.832**	**0.833**
24	**0.919**	**0.920**	**0.930**	**0.931**	**0.921**	**0.921**	**0.899**	**0.900**
				(b) Success Ratios				
1	**0.588**[*]	**0.588**[*]	**0.569**[*]	**0.569**[*]	**0.581**[*]	**0.581**[*]	**0.629**[*]	**0.633**[*]
3	**0.638**[*]	**0.642**[*]	**0.608**[*]	**0.611**[*]	**0.611**[*]	**0.685**[*]	**0.664**[*]	**0.664**[*]
6	**0.657**[*]	**0.657**[*]	**0.641**[*]	**0.641**[*]	**0.641**[*]	**0.641**[*]	**0.683**[*]	**0.687**[*]
9	**0.579**[*]	**0.583**[**]	**0.591**[*]	**0.591**[*]	**0.583**[*]	**0.583**[*]	**0.602**[*]	**0.602**[*]
12	**0.566**	**0.570**	**0.543**	**0.543**	**0.551**	**0.551**	**0.559**	**0.555**
15	**0.569**	**0.569**	**0.589**[**]	**0.585**[**]	**0.589**[*]	**0.585**[**]	**0.613**[*]	**0.613**[*]
18	**0.588**	**0.588**	**0.604**[*]	**0.604**[*]	**0.600**[**]	**0.600**[**]	**0.592**[**]	**0.592**[**]
21	**0.567**	**0.567**	**0.591**	**0.591**	**0.587**	**0.587**	**0.559**	**0.555**
24	**0.537**	**0.537**	**0.541**	**0.537**	**0.545**	**0.541**	**0.533**	**0.528**

NOTES: BVAR refers to VAR models estimated using the Bayesian method of Giannone et al. (2015). All forecasts are generated recursively from data subject to real-time data constraints. Boldface indicates improvements relative to the no-change forecast. [*] denotes significance at the 5% level and [**] at the 10% level based on the Pesaran and Timmermann (2009) test for the null hypothesis of no directional accuracy.

Table 5: Real-Time Forecast Accuracy of Models for the Retail Gasoline Price and the Brent Price of Crude Oil Evaluated on 1992.1-2014.3: The Effect of Imposing Cointegration

Monthly	Brent		Brent		Brent		Brent	
Horizon	VAR(1)	BVAR(1)	VEC(1)	BVEC(1)	VEC(6)	BVEC(6)	VEC(12)	BVEC(12)
				(b) MSPE Ratios				
1	**0.868**	**0.867**	1.186	1.182	1.010	**0.982**	**0.892**	**0.876**
3	**0.760**	**0.760**	1.247	1.241	**0.880**	**0.878**	**0.689**	**0.706**
6	**0.738**	**0.778**	1.341	1.334	**0.929**	**0.928**	**0.750**	**0.769**
9	**0.810**	**0.810**	1.508	1.500	**0.980**	**0.979**	**0.870**	**0.887**
12	**0.879**	**0.880**	1.519	1.511	1.008	1.005	1.010	1.012
15	**0.856**	**0.856**	1.505	1.497	1.027	1.026	**0.980**	**0.988**
18	**0.806**	**0.807**	1.523	1.515	1.018	1.019	**0.916**	**0.935**
21	**0.832**	**0.833**	1.581	1.572	1.038	1.037	**0.969**	**0.985**
24	**0.899**	**0.900**	1.600	1.591	1.059	1.056	1.038	1.044
				(b) Success Ratios				
1	**0.629**[*]	**0.633**[*]	**0.618**[*]	**0.618**[*]	**0.700**[*]	**0.689**[*]	**0.697**[*]	**0.693**[*]
3	**0.664**[*]	**0.664**[*]	**0.521**	**0.521**	**0.626**[*]	**0.619**[*]	**0.706**[*]	**0.687**[*]
6	**0.683**[*]	**0.687**[*]	**0.508**	**0.508**	**0.538**	**0.557**[*]	**0.672**[*]	**0.691**[*]
9	**0.602**[*]	**0.602**[*]	**0.529**	**0.533**	**0.552**[*]	**0.552**[*]	**0.587**[*]	**0.595**[*]
12	**0.559**	**0.555**	**0.535**	**0.539**	**0.543**[**]	**0.547**[**]	**0.543**	**0.551**[**]
15	**0.613**[*]	**0.613**[*]	**0.530**	**0.530**	**0.557**[*]	**0.553**[*]	**0.549**	**0.561**[**]
18	**0.592**[**]	**0.592**[**]	0.496	0.500	**0.592**[*]	**0.584**[*]	**0.584**[*]	**0.560**
21	**0.559**	**0.555**	0.498	0.498	**0.530**	**0.539**[**]	**0.555**	**0.534**
24	**0.533**	**0.528**	**0.525**	**0.525**	**0.537**	**0.537**	0.484	0.471

NOTES: BVEC refers to VEC models estimated using the Bayesian method of Giannone et al. (2015). All forecasts are generated recursively from data subject to real-time data constraints. Boldface indicates improvements relative to the no-change forecast. [*] denotes significance at the 5% level and [**] at the 10% level based on the Pesaran and Timmermann (2009) test for the null hypothesis of no directional accuracy.

Table 6: Real-Time Forecast Accuracy of U.S. Gasoline Market Models Evaluated on 1992.1-2014.3

Monthly Horizon	Real Gasoline Consumption						U.S. Real Economic Activity (CFNAI)		
	VAR(12)	BVAR(12)	VAR(6)	BVAR(6)	VAR(1)	BVAR(1)	Factor Model	FAVAR(12)	BFAVAR(12)
				(b) MSPE Ratios					
1	1.260	1.187	1.267	1.211	**0.996**	**0.996**	1.008	1.276	1.189
3	**0.997**	**0.982**	1.057	1.050	**0.998**	**0.997**	1.027	1.044	1.017
6	**0.923**	**0.912**	**0.939**	**0.947**	1.002	1.001	1.027	**0.969**	**0.959**
9	1.046	1.026	1.016	1.019	1.011	1.010	1.034	1.055	1.035
12	1.194	1.157	1.076	1.071	1.026	1.025	1.039	1.172	1.135
15	1.134	1.104	1.058	1.058	1.025	1.024	1.146	1.140	1.107
18	1.060	1.040	1.029	1.032	1.021	1.019	1.056	1.081	1.063
21	1.120	1.101	1.087	1.086	1.037	1.036	1.079	1.122	1.111
24	1.187	1.164	1.136	1.136	1.058	1.058	1.105	1.172	1.156
				(c) Success Ratios					
1	**0.674**[*]	**0.678**[*]	**0.655**[*]	**0.655**[*]	**0.532**	**0.524**	**0.502**	**0.663**[*]	**0.659**[*]
3	**0.642**[*]	**0.630**[*]	**0.551**[*]	**0.566**[*]	0.491	0.494	0.468	**0.626**[*]	**0.604**[*]
6	**0.649**[*]	**0.645**[*]	**0.576**[*]	**0.542**[*]	0.470	0.473	0.489	**0.622**[*]	**0.618**[*]
9	**0.533**[**]	**0.521**	**0.510**[**]	**0.510**[**]	0.417	0.421	**0.521**	**0.541**[*]	**0.525**[*]
12	**0.504**[*]	**0.481**	**0.481**	0.496	0.414	0.414	**0.512**	0.500	0.473
15	**0.538**[*]	**0.534**[**]	**0.526**[*]	**0.510**[**]	0.407	0.419	0.490	**0.534**[*]	**0.518**
18	**0.536**[**]	**0.528**[**]	**0.524**[*]	**0.520**[**]	0.452	0.448	0.456	**0.512**	0.500
21	**0.526**	**0.518**	0.490	0.494	0.445	0.449	0.453	0.478	0.482
24	0.488	0.471	**0.529**[**]	**0.525**	0.439	0.430	0.463	0.496	0.492

NOTES: The CFNAI is the Chicago Fed National Activity Index, which refers to the leading common factor among about 85 indicators of U.S. real economic activity. FAVAR refers to a factor augmented VAR based on the real-time version of this index in addition to the real retail price of gasoline. BFAVAR refers to a FAVAR model estimated using the Bayesian method of Giannone et al. (2015). All forecasts are generated recursively from data subject to real-time data constraints. Boldface indicates improvements relative to the no-change forecast. [*] denotes significance at the 5% level and [**] at the 10% level based on the Pesaran and Timmermann (2009) test for the null hypothesis of no directional accuracy.

Table 7: Real-Time Forecast Accuracy of Joint Gasoline Market and Oil Market Models Evaluated on 1992.1-2014.3

| Monthly Horizon | Kilian and Murphy (2014) oil market model augmented with: | | | | Kilian (2009) oil market model augmented with: | | | |
| | Real gasoline price + Real gasoline consumption | | Real gasoline price only | | Real gasoline price + Real gasoline consumption | | Real gasoline price only | |
	VAR(12)	BVAR(12)	VAR(12)	BVAR(12)	VAR(12)	BVAR(12)	VAR(12)	BVAR(12)
	(a) MSPE Ratios							
1	**0.891**	**0.803**	**0.908**	**0.828**	**0.876**	**0.814**	**0.900**	**0.843**
3	**0.732**	**0.722**	**0.747**	**0.737**	**0.742**	**0.725**	**0.766**	**0.747**
6	**0.857**	**0.801**	**0.847**	**0.799**	**0.829**	**0.795**	**0.815**	**0.787**
9	1.042	**0.968**	1.013	**0.949**	1.008	**0.969**	**0.971**	**0.942**
12	1.277	1.178	1.243	1.154	1.279	1.199	1.226	1.168
15	1.277	1.160	1.264	1.151	1.246	1.173	1.222	1.160
18	1.177	1.075	1.167	1.069	1.129	1.078	1.097	1.061
21	1.178	1.111	1.169	1.104	1.184	1.126	1.156	1.110
24	1.277	1.210	1.266	1.192	1.300	1.233	1.265	1.208
	(b) Success Ratios							
1	**0.685**[*]	**0.723**[*]	**0.678**[*]	**0.697**[*]	**0.697**[*]	**0.715**[*]	**0.693**[*]	**0.708**[*]
3	**0.694**[*]	**0.694**[*]	**0.679**[*]	**0.679**[*]	**0.683**[*]	**0.691**[*]	**0.676**[*]	**0.679**[*]
6	**0.630**[*]	**0.653**[*]	**0.618**[*]	**0.622**[*]	**0.649**[*]	**0.645**[*]	**0.641**[*]	**0.630**[*]
9	**0.556**	**0.556**	**0.517**	**0.564**	**0.583**[*]	**0.568**[**]	**0.529**	**0.564**
12	**0.535**	**0.520**	**0.527**	0.500	**0.516**	**0.512**	**0.516**	**0.508**
15	**0.530**	**0.534**	**0.549**	**0.514**	**0.510**	**0.526**	**0.518**	**0.522**
18	**0.540**	**0.532**	**0.518**	**0.520**	**0.528**	**0.540**	**0.512**	**0.528**
21	**0.555**	**0.506**	**0.522**	**0.518**	0.498	0.494	0.498	**0.514**
24	0.475	0.455	0.484	0.471	0.447	0.451	0.455	0.467

NOTES: The Kilian (2009) model includes global oil production, a measure of global real activity and the real price of crude oil. The Kilian and Murphy (2014) model in addition includes a proxy for the change in global crude oil inventories.

Table 8: Real-Time Forecast Accuracy of Pooled Real Gasoline Price Forecasts
Evaluation period: 1992.1-2014.3

Monthly horizon	Equal-weighted combination of five forecasting models	
	MSPE Ratio	Success ratio
1	**0.856**	**0.588**[*]
2	**0.768**	**0.613**[*]
3	**0.735**	**0.642**[*]
4	**0.733**	**0.671**[*]
5	**0.733**	**0.662**[*]
6	**0.736**	**0.649**[*]
7	**0.742**	**0.667**[*]
8	**0.763**	**0.635**[*]
9	**0.800**	**0.606**[*]
10	**0.846**	**0.574**
11	**0.800**	**0.572**
12	**0.895**	**0.547**
13	**0.897**	**0.541**
14	**0.891**	**0.534**
15	**0.879**	**0.561**
16	**0.859**	**0.599**[*]
17	**0.839**	**0.594**[**]
18	**0.826**	**0.596**[**]
19	**0.824**	**0.594**[**]
20	**0.825**	**0.613**[*]
21	**0.838**	**0.583**
22	**0.857**	**0.553**
23	**0.855**	**0.551**
24	**0.872**	**0.541**

NOTES: The pooled forecast is an equal-weighted average of forecasts from: (1) the Brent VAR(1) model, (2) the Brent VEC(12) model, (3) the UC-SV model forecast, (4) the exponential smoothing forecast, and (5) the Kilian-Murphy BVAR(12) model specification with the real gasoline price added. All forecasts are generated recursively from data subject to real-time data constraints. Boldface indicates improvements relative to the no-change forecast. [*] denotes significance at the 5% level and [**] at the 10% level based on the Pesaran and Timmermann (2009) test for the null hypothesis of no directional accuracy. The statistical significance of the MSPE reductions cannot be assessed because none of the currently available tests of equal predictive accuracy applies in this setting.

Table 9: Real-Time Forecast Accuracy of Nominal Retail Gasoline Price Forecasts

Horizon	Quarterly Forecasts Evaluated on 1992.I-2014.I		Monthly Forecasts Evaluated on 2006.3-2014.3	
	EIA	Pooled	Michigan Survey	Pooled
	(a) MSPE Ratios			
1 quarter	**0.789**	**0.717**	-	-
2 quarters	**0.838**	**0.695**	-	-
3 quarters	**0.840**	**0.736**	-	-
4 quarters	**0.895**	**0.816**	-	-
12 months	-	-	1.051	**0.904**
	(b) Success Ratios			
1 quarter	**0.652**[*]	**0.742**[*]	-	-
2 quarters	**0.693**[*]	**0.671**[*]	-	-
3 quarters	**0.621**[*]	**0.586**[**]	-	-
4 quarters	**0.640**[*]	**0.640**[**]	-	-
12 months	-	-	**0.651**	**0.674**[*]

NOTES: The EIA real-time forecasts were compiled from the *Short-Term Energy Outlook*. The average expected change in the nominal price of gasoline in the Michigan Survey of Consumers was obtained from Soren Anderson. The pooled forecast corresponds to the model underlying Table 8. The pooled forecasts are averaged by quarter, if required, and are inflated using real-time inflation forecasts constructed as in Faust and Wright (2013). The benchmark is the monthly no-change forecast for the nominal price of gasoline. [*] denotes significance at the 5% level and [**] at the 10% level based on the Pesaran and Timmermann (2009) test for the null hypothesis of no directional accuracy and, in the case of the survey forecasts only, the Diebold and Mariano (1995) test of equal predictive accuracy. The statistical significance of the other MSPE reductions cannot be assessed because none of the currently available tests of equal predictive accuracy applies in this setting.

**Table 10: Selected Real-Time Forecast Paths for the U.S. Retail Price of Gasoline in Cents/Gallon:
How Predictable Was the Decline in Gasoline Prices after June 2014?**

Real-Time Gasoline Price Forecasts as of June 2014		2014								2015		
		May	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**	**Jan**	**Feb**	**March**
Real	*Pooled*	376	**377**	*373*	*370*	*364*	*359*	*356*	*354*	*353*	*354*	*355*
	KM-BVAR(12)	376	**377**	*376*	*370*	*359*	*346*	*334*	*326*	*324*	*326*	*328*
	EIA	376	**373**	*367*	*361*	*359*	*347*	*337*	*327*	*327*	*332*	*341*
	Actual	376	375	369	354	346	324	296	254	NA	NA	NA
Nominal	*Pooled*	374	**377**	*374*	*371*	*367*	*362*	*360*	*358*	*358*	*359*	*361*
	KM-BVAR(12)	374	**377**	*377*	*372*	*362*	*349*	*337*	*330*	*329*	*331*	*335*
	EIA	375	**373**	*368*	*363*	*361*	*350*	*341*	*331*	*332*	*337*	*347*
	Actual	375	375	369	354	346	324	295	254	NA	NA	NA

NOTES: Nowcasts are shown in bold; forecasts in italics. By construction the nominal and the real price coincide in the last nowcast period. The pooled forecast is an equal-weighted average of five individual real-time forecasts, as reported in Table 8. The KM-BVAR(12) model is augmented with the real retail price of gasoline. These forecasts are converted to nominal terms using real-time inflation forecasts constructed analogously to Faust and Wright (2013). The real price of gasoline is expressed in June 2014 dollars.