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Predicting gasoline prices using Michigan survey data

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ABSTRACT

This study investigates the predictive power of Michigan Surveys of Consumers (MSC) data for gasoline prices. Specifically, we utilize the MSC data on both expected inflation and consumer sentiment to construct a vector autoregressive (VAR) model for forecasting gasoline prices for 2003–2014. Our findings indicate that the VAR forecasts are superior to the comparable benchmark forecasts obtained from a univariate integrated moving average (MA) model in terms of both predictive information content and directional accuracy. As such, we conclude that the MSC data on both expected inflation and consumer sentiment have significant predictive information for gasoline prices. Further inspection reveals that the VAR forecasts are particularly accurate for the period since 2008, reinforcing the notion that consumers are “economically” rational.

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1. Introduction

Existing studies have shown that energy prices do not display purely random walk behavior (Baker et al., 1998; Hamilton, 2008). As such, various techniques have been proposed to forecast energy prices (Alquist et al., 2011; Yu et al., 2008). This study contributes by investigating the predictive power of Michigan Surveys of Consumers (MSC) data for gasoline prices. Reliable forecasts of gasoline prices, in particular, are important in accurately projecting the demand for both gasoline and energy-using durable goods such as automobiles (Allcott and Wozny, 2014; Busse et al., 2009; Kahn, 1986). Such forecasts are also important in modeling energy-related investment decisions including investment in new energy production (Anderson et al., 2011; Kellogg, 2014). The success of such regulatory policies as automotive fuel standards and gasoline taxes in dealing with carbon emissions and climate change also critically hinges on the quality of predictions about future gasoline and energy prices (Alquist et al., 2011; Davis and Kilian, 2010; Goldberg, 1998).

Given the importance of gasoline price forecasts, the MSC asks consumers to report their beliefs about future retail gasoline prices. In a recent study, Anderson et al. (2011) show that, on average, the MSC forecasts are as accurate as the no-change forecasts of gasoline prices. They further conclude that “there is evidence that the MSC forecasts outperform the no-change forecast during the late-2008 economic crisis, when the MSC forecast more closely follows the futures market” (p. 114). We add to the literature by utilizing the MSC data on both expected inflation and consumer sentiment to construct a vector autoregressive (VAR) model for forecasting the spot price of gasoline for the period 2003–2014. Our findings indicate that the VAR forecasts of gasoline prices are superior to the comparable benchmark forecasts obtained from a univariate integrated moving average (MA) model. In particular, the VAR forecasts are both unbiased and embody useful predictive information above and beyond that contained in the MA forecasts. In addition, unlike the MA benchmarks, the VAR forecasts are directionally accurate and generally imply asymmetric loss in the sense that they are of value to a user who assigns high (low) cost to incorrect upward (downward) predictions.

With such findings, we conclude that the MSC data on both expected inflation and consumer sentiment have significant predictive information for gasoline prices for 2003–2014. Further inspection reveals that the VAR forecasts are particularly accurate in capturing the large fluctuations in the actual gasoline price change for the period since 2008. One explanation is that consumers are “economically” rational (Baghestani, 1992). That is, in generating the optimal forecast, “economically” rational agents balance the predictive benefit against the cost of gathering and processing information. As such, one can argue that, due to the

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2008 economic crisis, the marginal predictive benefit exceeds the cost of gathering and processing additional information and, thus, the MSC data have been more informative.

The format of this study is as follows: Section 2 discusses both the data and the forecasts. Section 3 presents the forecast evaluation test results. Section 4 concludes.

2. Data and forecasts

We measure the monthly price of gasoline (Pg_t) by the New York Harbor conventional gasoline regular spot price (FOB, dollars per gallon).[1] The MSC provides the monthly data on both expected inflation and consumer sentiment. Specifically, every month since January 1978, the MSC probes at least 500 randomly selected consumers on various aspects of consumer attitudes and expectations. One question on the survey states, "During the next 12 months, do you think that prices in general will go up, or go down, or stay where they are now?" and "By what percent do you expect prices to go up, on the average, during the next 12 months?" Using the individual responses, the MSC calculates and reports the consensus (median) response which we employ as the measure of expected inflation. In measuring consumer sentiment, we employ the MSC Index of Current Economic Conditions (ICC) derived from the following two questions. First, "We are interested in how people are getting along financially these days. Would you say that you (and your family living there) are better off or worse off financially than you were a year ago?" Second, "About the big things people buy for their homes—such as furniture, a refrigerator, stove, television, and things like that. Generally speaking, do you think now is a good or bad time for people to buy major household items?"[2]

In formulating the univariate model, we first utilize the KPSS (Kwiatkowski et al., 1992) test to examine the stochastic behavior of $\log(Pg)_t$. Based on the Bartlett window approach with a lag truncation parameter of eight, the calculated KPSS test statistic (0.121) is above the 10% critical value (0.119), leading us to reject the null hypothesis that $\log(Pg)_t$ is stationary in favor of a unit root alternative. Using the simple and partial autocorrelation function estimates of $\Delta\log(Pg)_t$, we select the following MA model along with the estimates for 1986.06–2002.01:

$$\begin{aligned}\Delta\log(Pg)_t &= \left(1+\theta_1 B+\theta_2 B^2\right)u_t\\ \Delta\log(Pg)_t &= \underset{(1.05)}{0.075\hat{u}_{t-1}} - \underset{(3.63)}{0.258\hat{u}_{t-2}}\\ R^2 = 0.06,\quad & Q \text{ test statistic } p\text{-value} = 0.882,\quad \text{Inverted MA roots} = 0.47; -0.55\end{aligned} \tag{1}$$

where B is the backward shift operator and u_t is the error term. The numbers in parentheses are the absolute t-values, and the Ljung–Box Q test detects serial correlation up to the 12th order. As can be seen, the inverted MA roots are between zero and one in absolute value. In addition, the calculated Q test statistic p-value is far above 0.10, indicating that the residual series is white noise and thus the model is correctly specified. This specification is in line with existing studies which have shown that, unlike stock prices, commodity prices do not display purely random walk behavior; see Baker et al. (1998) and Hamilton (2008), among others.

We utilize the MA model to generate the multi-period forecasts of gasoline prices as follows. The 1986.06–2002.01 parameter estimates are used to generate the forecasts for 2002.02–2003.01. The values for 2002.04, 2002.07, 2002.10, and 2003.01 are, respectively, the three-, six-, and nine-, and twelve-month-ahead MA forecasts. Re-estimating the model for 1986.06–2002.02, we use the updated parameter estimates to generate the forecasts for 2002.03–2003.02. The values for 2002.05, 2002.08, 2002.11, and 2003.02 are, respectively, the three-, six-, nine-, and twelve-month-ahead MA forecasts. This procedure is repeated until the last set of forecasts is generated for 2014.04–2015.03 using the 1986.06–2014.03 parameter estimates. The values for 2014.06, 2014.09, 2014.12, and 2015.03 are, respectively, the three-, six-, nine-, and twelve-month-ahead MA forecasts. As such, the sample periods for the three-, six-, nine-, and twelve-month-ahead forecasts are, respectively, 2002.04–2014.06, 2002.07–2014.09, 2002.10–2014.12, and 2003.01–2015.03. For consistency, however, we use a single period (2003.01–2014.06) for evaluating the forecasts.

The VAR model contains the rate of change in gasoline prices, $\Delta\log(Pg)_t$, expected inflation, and the change in consumer sentiment.[3] Each equation in the model includes a constant and five lags of each variable. The inclusion of expected inflation follows Baghestani (2013) who shows that the MSC expected inflation rate has directional predictability for gasoline prices. Other related studies, including Barsky and Kilian (2002) and Gillman and Nakov (2009), discuss the theoretical ramifications of inflation for energy prices. The inclusion of sentiment is intended to account for optimistic or pessimistic assessment of current business conditions by consumers. Existing studies investigating the usefulness of consumer sentiment for predicting consumer spending have yet to produce a consensus; see Dees and Brinca (2013) and the references therein. In this study, however, we maintain that consumer sentiment can contain useful information for predicting gasoline prices. That is, by shifting the demand curve for gasoline, changes in consumer sentiment can influence gasoline prices.

We employ the VAR model (estimated initially for 1986.06–2002.02) to generate the three-, six-, nine-, and twelve-month-ahead forecasts of gasoline prices in the same manner outlined above for the MA model. By construction, the MA forecasts include only past information in gasoline prices, and the VAR forecasts for 2003.01–2014.06 include, in addition, past information in both expected inflation and consumer sentiment.

3. Forecast evaluation test results

Our analysis focuses on answering the following three questions:

1. Are MA and VAR forecasts unbiased?
2. Are VAR forecasts more informative than MA forecasts?
3. Are MA and VAR forecasts directionally accurate?

In answering these questions, we are mindful of the forecasting timeline presented in Fig. 1. As noted, A_{t+f} is the actual gasoline price in month $t+f$, and P_{t+f} is the forecast of A_{t+f} made at the end of month t.[4] We further denote the most recently known gasoline price at the time of the forecast by Ad_t; that is, Ad_t is the actual price in the last business day of month t. Accordingly, $(A_{t+f} - Ad_t)$ is the actual change in month $t+f$ and $(P_{t+f} - Ad_t)$ is the corresponding predicted change in gasoline prices.

3.1. Are MA and VAR forecasts unbiased?

We examine unbiasedness by estimating

$$(A_{t+f} - Ad_t) = \alpha + \beta(P_{t+f} - Ad_t) + \varepsilon_{t+f} \tag{2}$$

$$(A_{t+f} - P_{t+f}) = \alpha' + \varepsilon_{t+f} \tag{3}$$

[1] The monthly price of gasoline is obtained by averaging the daily price data available since June 1986 on the U.S. Energy Information Administration (EIA) website (http://tonto.eia.doe.gov).

[2] The MSC monthly data are available at (http://www.sca.isr.umich.edu).

[3] For the initial estimation period 1986.06–2002.01, the calculated KPSS test statistic (based on the Bartlett window approach with a lag truncation parameter of eight) is 0.094 for expected inflation and 0.256 for consumer sentiment. With the 10% critical value equal to 0.119, we reject the null hypothesis of stationarity in favor of a unit root alternative for consumer sentiment but not for expected inflation.

[4] The final survey data for month t are generally released before the end of month t to the fee-paying Thompson–Reuters subscribers.

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