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FORECASTING THE PRICE OF CRUDE OIL WITH MULTIPLE PREDICTORS

Hüseyin KAYA*

Abstract

For the price of crude oil, this paper aims to investigate the predictive content of a variety of variables including oil futures prices, exchange rates of particular countries and stock-market indexes. Out-of-sample forecasting results suggest that oil futures prices have marginal predictive power for the price of oil at a 1-month forecast horizon. However, they generally lose their forecasting power at higher forecast horizons. The results also suggest that exchange rates help predicting oil prices at higher forecast horizons. The paper also considers forecast averaging and variable selection methods, and finds that forecast averaging significantly improves the forecasting performances.

Keywords: Forecast, oil price, exchange rate, stock-market index, forecast averaging

JEL Codes: C53, Q40, C11

* Assoc. Prof., Istanbul Medeniyet University, Department of Economics, huseyin.kaya@medeniyet.edu.tr

HAM PETROL FİYATININ ÇOK TAHMİNCİ İLE TAHMİNİ

Özet

Bu makale petrol futures fiyatları, belirli ülkelerin döviz kurları ve borsa endeksleri gibi birçok değişkenin ham petrol fiyatlarını tahmin etme yeteneğini araştırmayı amaçlamaktadır. Elde edilen örneklem-dışı tahmin sonuçları petrol futures fiyatlarının bir aylık dönemde marjinal bir tahmin gücü olduğunu ancak daha uzun dönemlerde tahmin gücünün kaybolduğunu göstermektedir. Diğer yandan, döviz kurlarının tahmin gücünün daha uzun dönemli olduğu tespit edilmiştir. Ayrıca bu makalede tahmin ortalamaları ve değişken seçimi yöntemleri de kullanılmış ve tahmin ortalama yöntemlerinin tahmin performansını artırdığı bulunmuştur.

Anahtar Kelimeler: Tahmin, petrol fiyatı, döviz kuru, borsa endeksi, tahmin ortalaması

Introduction

During the last decade the price of oil and its fluctuations have reached record highs. In 2002, the West Texas Intermediate (WTI), one of the most important benchmarks for crude oil prices, averaged around 26 $/b, while in 2013 the WTI price was around 98 $/b. For this period the variation in the WTI price was around 40% of the average.

These rises and fluctuations in the price of oil have renewed interest in producing reliable forecasts of oil price because the future price of oil is one of the key variables for economic agents in making business decisions, generating projections, and assessing the macroeconomic risk. While many institutions, including the European Central Bank and the International Monetary Fund, rely on oil futures prices as the predictor of future spot prices, recently Alquist et al. (2013), using a variety of methods based on oil futures prices, find that there is no evidence of significant forecast accuracy gains at shorter horizons and that oil futures prices are clearly inferior to the no-change forecast at long forecast horizons. They also show that the forecasting models based on the Hotelling Model (1931), which claims that the future oil price should be the current spot price adjusted for the interest rate, and a variety of simple time series regression models do not provide significantly better forecasts than the no-change model. In addition, expert survey forecasts of the nominal price of oil are found to be no more accurate than those of the no-change model in general. Similarly, Chinn and Coibion (2014) consider a number of commodity futures' predictive content using a futures-spot spread model which uses the spread between the current futures prices and the spot prices to predict movements in the price of oil. They find that forecasts based on oil futures prices are not better than a random walk. They also show that oil futures fare worse in predicting subsequent price changes than other commodities. Consequently, Reitz et al. (2009) argue that as a consequence of difficulties in foreseeing oil prices many research institutes do not forecast oil price in their macroeconomic models anymore and instead they assume that the price of oil follows a random walk.

Chen et al (2010) argue that exchange rate is fundamentally a forward-looking variable that likely embodies information about future commodity price movements. They show that exchange rates of a number of commodity exporters have predictive power over global commodity prices. Alquist et al. (2013) consider forecasting power of exchange rates of Canada, Australia, South Africa and New Zealand and show that the Australian exchange rate has significant predictive power for sign of the change in the nominal price of oil, but not at all horizons. However, they use forecasting models that are too restrictive and examine whether the no-change forecasts are improved upon by extrapolating today's oil price at the most recent growth rate of exchange rate.

On the other hand, Lee et al. (2012) show that stock price changes in Germany, the UK and the US lead to oil price changes, but oil price shocks do not significantly impact stock prices in the G7 countries. Hence, the presence of causality running from stock prices to oil price may indicate that stock prices have predictive power for oil prices. While many studies have focused on the effect of oil price shocks to economies (Kling 1985, Jones and Kaul 1996, Hamilton, 1996, 2011; Barsky vd., 2004, Kilian, 2008a, 2008b, Lippi and Nobili, 2012), the studies that consider the link from stock prices to oil prices are rather few (Lee et al. 2012). As discussed in Kilian and Park (2009), while existing works on the link between oil prices and stock prices usually regard oil price as exogenous, it has become widely accepted in recent years that the price of oil has responded to some of the same factors that drive stock prices. Considering this evidence and the fact that stock market indexes are forward-looking variables that likely embody information about the future state of economies, one can argue that stock prices may be useful in predicting future oil prices.

In this study I examine the predictive content of oil futures prices, exchange rates and stock-market indexes for oil prices. I first test the existence of a predictive relationship between these variables and oil prices using the Granger causality test. To examine the forecasting ability of futures prices, exchange rates and stock-market indexes I use a range of out-of-sample forecasting statistics and investigate a variety of forecast averaging and variable selection methods.

The rest of the paper is organized as follows. Section 2 describes the forecasting models and data. Section 3 provides Granger non-causality test results. Section 4 provides forecast evaluation methods and Section 5 documents the forecasting results when a single predictor is used. Section 6 describes forecast averaging methods and forecasting results. Section

7 provides variable selection methods and forecasting results. Section 8 concludes.

1. Forecasting Model and Data

I consider the following dynamic regression of the form[1]

$$\Delta y_{t+h} = \alpha + \sum_{i=1}^{p} \varphi \Delta y_{t-(i-1)} + \Delta x_t \beta + \varepsilon_{t+h} \quad (1)$$

where y_{t+h} is the price of oil, $y_{t-(i-1)}$ are the p own lags of the oil price, x_t is a vector of predictors, and ε_{t+h} is a Gaussian forecast error with zero mean and variance σ^2. All the variables are transformed to logarithms. Δ denotes the first-difference.

To forecast the price of oil I use three groups of variables; 1- Oil Futures Prices, 2-Bilateral dollar exchange rates, and 3-Stock-market indexes. I use the crude oil price of WTI Cushing, Oklahoma and collect it from Federal Reserve Economic Data (FRED). All data used are monthly and observed for the period 1990M1-2013m10.

For the oil futures prices, I use the price of the NYMEX light sweet crude contracts. These contracts are the most liquid and the largest volume market for crude oil trading. I use end-of-month values for oil futures and consider 12 futures which are available at 1 to 12-month horizons. The prices of NYMEX oil futures are collected from Bloomberg (the ticker is CL). Figure 1 shows the WTI prices and three futures prices. The current nominal price of the futures contract that matures in *h* periods is denoted by *oilfth*.

Figure 1: WTI and Selected Oil Futures Prices

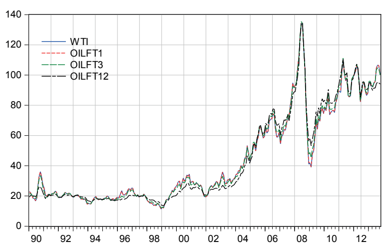
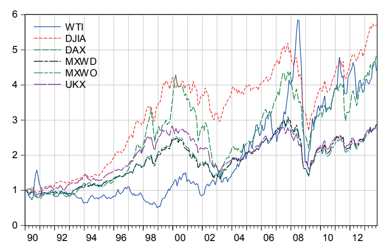


Figure 2: WTI and Selected Exchange Rates



[1] Since Alquist et. al (2013) and Chinn and Coibion (2014) have recently considered several forecast models based on oil futures prices and document the results, in this paper I use a general model for all predictors including oil futures prices.

Note: In Figure 2 series are divided by their first observation for graphical purposes.

The forecasting ability of the nominal dollar exchange rates of Australia, New Zealand, Chile, Canada, Germany, UK and Japan are examined. The first four currencies are selected by following Chen et al. (2010). Considering their shares in total world trade and production, I also take into account Germany, UK and Japan. The exchange rate data are obtained from the FRED. Figure 2 shows the WTI prices and exchange rates of the first four countries.

The stock-market indexes I use are the most observed and traded indexes in the world. Table 1 provides the stock-market indexes and their descriptions. Index data and descriptions are collected from Bloomberg.

Table 1: Stock-Market Indexes

Index Ticker	Description	Country
DJIA	The Dow Jones Industrial Average is a price-weighted average of 30 blue-chip stocks that are generally the leaders in their industry.	United States
SPX	Standard and Poor's 500 Index is a capitalization-weighted index of 500 stocks.	United States
DAX	The German Stock Index is a total return index of 30 selected German blue-chip stocks traded on the Frankfurt Stock Exchange.	Germany
CAC 40	The CAC 40, the most widely-used indicator of the Paris market, reflects the performance of the 40 largest equities listed in France.	France
AS30	The Australian All Ordinaries Index is a capitalization weighted index. The index is made up of the largest 500 companies as measured by market cap that are listed on the ASX.	Australia
FTSE100	The FTSE 100 Index is a capitalization-weighted index of the 100 most highly capitalized companies traded on the London Stock Exchange.	United Kingdom
NIKKEI	The Nikkei-225 Stock Average is a price-weighted average of 225 top-rated Japanese companies listed in the First Section of the Tokyo Stock Exchange.	Japan

MXWD	MXWD is the MSCI ACWI Index that captures large, mid, small and micro cap size segments for 23 Developed and 21 Developing markets countries. MXWD represents the performance of stocks in the world.	23 Developed and 21 Developing Countries
MXWO	MXWO is the MSCI World Index that captures large and mid cap representation across 23 developed world markets. MXWO represents the performance of stocks in developed market countries	23 Developed Countries

Figure 3: WTI and Selected Stock-Market Indexes

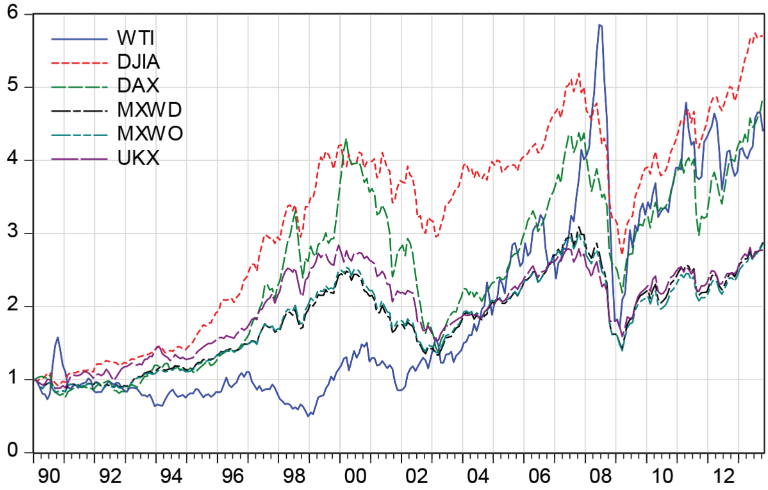


Figure 3 shows the WTI and five stock-market indexes. Market indexes seem to have a similar pattern over time and usually they move together. Especially after 2002, stock prices indices and WTI move in the same direction.

2. In-Sample Granger Causality

For the existence of a predictive relationship between the future prices, stock-market indexes, exchange rates and the WTI price, I use the Granger causality test. As discussed in the literature, the existence of predictability in a population is a necessary precondition for out-of-sample forecastability. I test the absence of Granger causality between percent change in the WTI price and percent change in the aforementioned variables using bivariate VAR(3) and VAR(6) models.

Table 2 reports the p-values of the Wald test statistics. All the estimations are heteroscedasticity and autocorrelation consistent. The results suggest that almost all of the considered variables, except

$\Delta CAC40$ and exchange rate of Japan, e^{JP}, are Granger causing the oil price changes.

Table 2: Granger Causality Test

Variable	*p-value (3 lag)*	*p-value* **(6 lag)**	Variable	*p-value (3 lag)*	*p-value* **(6 lag)**
$\Delta oilft1$	**0.003**	0.158	$\Delta AS30$	0.146	**0.021**
$\Delta oilft2$	**0.061**	0.424	$\Delta CAC40$	0.227	0.210
$\Delta oilft3$	**0.005**	0.101	ΔDAX	**0.099**	**0.053**
$\Delta oilft4$	**0.000**	**0.001**	$\Delta FTSE$	**0.064**	**0.028**
$\Delta oilft5$	**0.000**	**0.000**	$\Delta DJIA$	**0.001**	**0.001**
$\Delta oilft6$	**0.000**	**0.008**	$\Delta NIKKEI$	**0.095**	0.117
$\Delta oilft7$	**0.002**	**0.027**	ΔSPX	**0.006**	**0.004**
$\Delta oilft8$	**0.000**	**0.001**	Δe^{AUS}	**0.002**	**0.001**
$\Delta oilft9$	**0.001**	**0.002**	Δe^{CAN}	**0.002**	0.121
$\Delta oilft10$	**0.004**	**0.030**	Δe^{GER}	**0.053**	**0.012**
$\Delta oilft11$	**0.000**	**0.000**	Δe^{JP}	0.654	0.423
$\Delta oilft12$	**0.001**	**0.021**	Δe^{UK}	0.181	**0.074**
$\Delta MXWD$	**0.013**	**0.009**	Δe^{NZ}	**0.026**	**0.031**
$\Delta MXWO$	**0.015**	**0.012**	Δe^{CHL}	**0.000**	**0.003**

-All the p-values less that 10% are emboldened

3. **Out-of-Sample Forecasts**

For out-of-sample forecasts, I adopt a rolling forecast scheme. As discussed in Chen et al. (2010), rolling forecasts are robust to the presence of time-varying parameters and have the advantage of not making any assumption as to the nature of the time variation in the data. I use a rolling window with size equal to half of total sample size. Specifically, the first window for the estimation is 1990:02-2001:12 with size 143. Hence, the out-of-sample forecasting exercise begins with 2002:01. I repeat the process recursively, moving the estimation window one month at a time, until I obtain the last forecast for 2013:10. I consider short-term forecasts where $h = 1,3,6,9,12$.

I use a set of alternative measures of out-of-sample predictive ability and an AR(p) model as a benchmark forecasting model. Denote the forecast error of the *AR(p)* model M_0 as ϵ_i^0, and of the model M_j as ϵ_i^j for $i = 1, \dots, N$ and $\mathrm{j} = 1, \dots, G$. Define $MSE^j = N^{-1} \sum_{i=1}^{N} \left(\epsilon_i^j\right)^2$ and similarly for MSE^0. The out-of-sample statistics for model M_j are as follows;

$$R^2 = 1 - \frac{MSE^j}{MSE^0}$$

$$\Delta MAE = \frac{1}{N} \sum_{i=1}^{N} \left(|\epsilon_i^0| - |\epsilon_i^j| \right)$$

$$\Delta RMSE = \sqrt{MSE^0} - \sqrt{MSE^j}$$

$$MSE - F = N \left(\frac{MSE^0 - MSE^j}{MSE^j} \right)$$

Higher values of all of the statistics indicate better performance of model Mj relative to the benchmark *AR(p)* model.

4. Forecasting Results when a Single Predictor is Used

Table 3a and 3b document the out-of-sample forecasts statistics of each variable for h=1,3,6 and 12. I use *AR(3)* as a benchmark model[2]. Most of the oil futures prices have out-of-sample forecasting power for the oil prices at a 1-month forecast horizon. However, they lose their forecasting power when higher forecast horizons are investigated. None of the stock-market indexes, except the Nikkei, has forecasting power. On the other hand, the exchange rates of Germany and Chile have forecasting power at 1 and 3 month forecast horizons. The exchange rate of Japan produces better a forecast than *AR(3)* only at a 6-month forecast horizon.

Table 3a: Forecasting Results when a Single Predictor is Used

	h=1	*benchmark model is*					*h=3*	*benchmark model is*		
	R^2	ΔMAE	$\Delta RMSE$	MSE			R^2	ΔMAE	$\Delta RMSE$	MSE
$\Delta oilft1$	-	0.000	0.000	-1.21		$\Delta oilft1$	0.018	0.001	0.000	2.59*
$\Delta oilft2$	-	0.000	0.000	-0.10		$\Delta oilft2$	-	0.000	0.000	-1.26
$\Delta oilft3$	0.021	0.000	0.000	2.98*		$\Delta oilft3$	-	0.000	0.000	-1.55
$\Delta oilft4$	*0.082*	*0.002*	*0.001*	*12.72***		$\Delta oilft4$	-	0.000	0.000	-1.97
$\Delta oilft5$	*0.135*	*0.004*	*0.001*	*22.20***		$\Delta oilft5$	-	0.000	0.000	-1.96
$\Delta oilft6$	*0.058*	*0.001*	*0.000*	*8.69***		$\Delta oilft6$	-	-0.001	0.000	-3.03
$\Delta oilft7$	*0.044*	*0.001*	*0.000*	*6.53***		$\Delta oilft7$	-	-0.001	0.000	-2.88
$\Delta oilft8$	*0.090*	*0.002*	*0.001*	*14.02***		$\Delta oilft8$	-	-0.001	0.000	-2.78
$\Delta oilft9$	*0.085*	*0.002*	*0.001*	*13.25***		$\Delta oilft9$	-	-0.001	0.000	-3.37
$\Delta oilft10$	0.032	0.000	0.000	4.69**		$\Delta oilft10$	-	-0.001	0.000	-3.68
$\Delta oilft11$	0.172	0.005	0.001	29.56**		$\Delta oilft11$	-	-0.001	0.000	-3.91
$\Delta oilft12$	-	0.000	0.000	-0.16		$\Delta oilft12$	-	-0.001	0.000	-3.99
$\Delta MXWD$	0.013	-0.001	0.000	1.84		$\Delta MXWD$	-	-0.002	0.000	-5.09
$\Delta MXWO$	0.010	-0.001	0.000	1.39		$\Delta MXWO$	-	-0.002	0.000	-5.36
$\Delta AS30$	-	-0.002	0.000	-1.43		$\Delta AS30$	-	-0.001	0.000	-4.76
$\Delta CAC40$	0.010	-0.001	0.000	1.41		$\Delta CAC40$	-	-0.002	0.000	-5.08
ΔDAX	0.001	-0.001	0.000	0.10		ΔDAX	-	-0.002	0.000	-5.38
$\Delta FTSE$	-	-0.001	0.000	-3.49		$\Delta FTSE$	-	-0.002	0.000	-4.64

2 The use of information criteria for lag selection does not improve the forecast results.

$\Delta DJIA$	0.000	-0.001	0.000	0.04	$\Delta DJIA$	-	-0.001	0.000	-3.37
$\Delta NIKKEI$	0.024	-0.001	0.000	3.57*	$\Delta NIKKEI$	-	-0.001	0.000	-2.51
ΔSPX	0.000	-0.001	0.000	0.00	ΔSPX	-	-0.002	0.000	-4.89
Δe^{AUS}	0.011	0.000	0.000	1.62	Δe^{AUS}	0.029	0.000	0.000	4.19**
Δe^{CAN}	0.004	0.000	0.000	0.54	Δe^{CAN}	-	0.000	0.000	-0.15
Δe^{GER}	0.021	0.000	0.000	3.12*	Δe^{GER}	0.035	-0.001	0.000	5.04**
Δe^{JP}	-	-0.001	0.000	-0.93	Δe^{JP}	-	0.000	0.000	-0.39
Δe^{UK}	0.006	-0.001	0.000	0.83	Δe^{UK}	-	-0.001	0.000	-2.55
Δe^{NZ}	-	0.000	0.000	-1.97	Δe^{NZ}	-	-0.001	0.000	-0.62
Δe^{CHL}	0.024	0.000	0.000	3.55*	Δe^{CHL}	0.037	0.000	0.000	5.41**

-** and * indicate better forecasts relative to the *AR(3)* model at 1% and 5% respectively.

Table 3b: Forecasting Results when a Single Predictor is Used

	h=6	*benchmark model is AR(3)*				*h=12*	*benchmark model is*		
	R^2	ΔMAE	$\Delta RMSE$	MSE		R^2	ΔMAE	$\Delta RMSE$	MSE
$\Delta oilft1$	-	0.000	0.000	-0.32	$\Delta oilft1$	-	0.000	0.000	-0.78
$\Delta oilft2$	-	0.000	0.000	-0.45	$\Delta oilft2$	-	-0.001	0.000	-1.91
$\Delta oilft3$	-	0.000	0.000	-0.44	$\Delta oilft3$	-	-0.001	0.000	-2.74
$\Delta oilft4$	-	-0.001	0.000	-1.62	$\Delta oilft4$	-	-0.001	0.000	-2.19
$\Delta oilft5$	-	-0.002	0.000	-2.95	$\Delta oilft5$	-	0.000	0.000	-1.49
$\Delta oilft6$	0.002	-0.001	0.000	0.25	$\Delta oilft6$	-	0.000	0.000	-1.03
$\Delta oilft7$	0.010	-0.001	0.000	1.39	$\Delta oilft7$	-	0.000	0.000	-0.28
$\Delta oilft8$	-	-0.002	0.000	-0.20	$\Delta oilft8$	0.001	0.000	0.000	0.11
$\Delta oilft9$	0.002	-0.002	0.000	0.30	$\Delta oilft9$	0.002	0.000	0.000	0.27
$\Delta oilft10$	0.020	-0.001	0.000	2.86*	$\Delta oilft10$	0.003	0.000	0.000	0.41
$\Delta oilft11$	-	-0.002	0.000	-2.34	$\Delta oilft11$	0.003	0.000	0.000	0.37
$\Delta oilft12$	0.037	-0.001	0.000	5.27**	$\Delta oilft12$	0.004	0.000	0.000	0.47
$\Delta MXWD$	-	0.000	0.000	-0.69	$\Delta MXWD$	-	-0.002	0.000	-4.02
$\Delta MXWO$	-	0.000	0.000	-0.66	$\Delta MXWO$	-	-0.002	0.000	-4.15
$\Delta AS30$	-	0.000	0.000	-0.79	$\Delta AS30$	-	-0.001	0.000	-2.73
$\Delta CAC40$	-	0.000	0.000	-1.98	$\Delta CAC40$	-	-0.001	0.000	-1.93
ΔDAX	-	0.000	0.000	-2.54	ΔDAX	-	-0.002	0.000	-4.05
$\Delta FTSE$	-	-0.001	0.000	-0.85	$\Delta FTSE$	-	-0.002	0.000	-3.55
$\Delta DJIA$	-	0.000	0.000	-0.50	$\Delta DJIA$	-	-0.001	0.000	-3.99

$\Delta NIKKEI$	-	-0.001	0.000	-1.42	$\Delta NIKKEI$	-	0.000	0.000	-0.76
ΔSPX	-	0.000	0.000	-0.17	ΔSPX	-	-0.002	0.000	-5.04
Δe^{AUS}	-	-0.001	0.000	-1.66	Δe^{AUS}	-	0.000	0.000	-0.97
Δe^{CAN}	-	0.000	0.000	-0.51	Δe^{CAN}	-	0.000	0.000	-2.78
Δe^{GER}	0.003	0.000	0.000	0.35	Δe^{GER}	0.005	-0.001	0.000	0.63
Δe^{JP}	0.026	0.000	0.000	3.59*	Δe^{JP}	0.002	0.000	0.000	0.30
Δe^{UK}	-	0.000	0.000	-1.35	Δe^{UK}	-	0.000	0.000	-0.63
Δe^{NZ}	0.009	0.000	0.000	1.29	Δe^{NZ}	-	0.000	0.000	-0.38
Δe^{CHL}	0.003	0.000	0.000	0.37	Δe^{CHL}	-	-0.002	0.000	-2.71

-** and * indicate better forecasts relative to the *AR(3)* model at 1% and 5% respectively.

5. **Forecast Averaging**

A number of studies in the forecasting literature show that forecast averaging methods can improve forecast accuracy. Among many others, the following studies provide empirical evidence for this finding: Stock and Watson (2002), Kapetanios, Labhard, and Price (2008), Kascha and Ravazzolo (2010), Clark et al. (2010), and Banternghansa and McCracken (2011).

The first set of averaging methods that I consider is as follows: i) equally weighted average, ii) the median forecast and iii) the best top 10 percent. Smith and Wallis (2009), Clark et al. (2010) and Banternghansa and McCracken (2011), among others, show that these simple forms of averaging generally perform among the best methods. The equally weighted average is the simple arithmetic average of forecasts generated by 28 predictors. The median forecast is the median of 28 forecasts for each time, *t*. The best 10 percent forecast is the simple average of model forecasts in the top 10 percent of historical MSE accuracy. Thus, the average of the best three forecasts is used. I also follow Clark et al. (2010) and calculate MSE-weighted forecasts. To generate these forecasts at each forecast horizon the historical MSE of 30 forecasts are used and each forecast *i* is given a weight of $MSE_i^{-1}/\sum_i MSE_i^{-1}$.

Table 4: Forecasting Results when Forecast Averaging is Employed

	R^2	ΔMAE	$\Delta RMSE$	$MSE-F$
		Equal Weight		
h=1	0.044	0.001	0.002	6.514**
h=3	-0.007	0.000	0.000	-0.924
h=6	0.006	0.000	0.000	0.887
h=9	0.003	0.000	0.000	0.459
h=12	-0.001	0.000	0.000	-0.104
		Median		
h=1	0.022	0.000	0.001	3.196*
h=3	-0.004	0.000	0.000	-0.590
h=6	0.005	0.000	0.000	0.652
h=9	-0.007	0.000	0.000	-0.960
h=12	0.001	0.000	0.000	0.161
		Best 10 percent		
h=1	0.139	0.004	0.006	22.917**
h=3	0.048	0.000	0.002	7.130**
h=6	0.042	0.000	0.002	6.003**
h=9	0.017	0.001	0.001	2.329*
h=12	0.009	0.000	0.001	1.194
		Inverted MSE		
h=1	0.047	0.001	0.002	6.960**
h=3	-0.006	0.000	0.000	-0.842
h=6	0.007	0.000	0.000	0.933
h=9	0.004	0.000	0.000	0.551
h=12	-0.001	0.000	0.000	-0.096

-** and * indicate better forecasts relative to the *AR(3)* model at 1% and 5% respectively.

The forecasting results, when forecast averaging is employed, are reported in Table 4. At the 1-month forecast horizon all the averaging methods produce better forecasts than the AR(3) model. The best performing averaging method is the best 10 percent method. While the other three averaging methods fail to beat AR forecasts at higher forecasts horizons, the best 10 percent method produces significantly better forecasts than AR forecasts at 3, 6 and 9 month forecast horizons.

6. Variable Selection

Bayesian Variable Selection

As discussed in Korobolis (2013), when many variables are available but only a limited set is relevant for forecasting a Bayesian simulation algorithm can be used to select relevant predictors as well as model averaging based on evidence in the data. A growing number of studies confirm the usefulness of this approach including Fernandez, Ley and Steel (2001) and Korobilis (2013) for economic growth, Wright (2008) for exchange rates, Korobilis (2013) and Koop and Korobilis (2012) for inflation, and Cremers (2002) for stock returns.

For Bayesian variable selection, I use the method of Korobilis (2013)[3]. Considering the forecasting model, Eq. (1) assumes that intercept and coefficient of lags, $\theta=(\alpha, \varphi_1, \ldots, \varphi_p)$, as well as the variance, σ^2, admit noninformative priors of the form

$$\theta \sim N\left(0_{(p+1)\times 1}, 100 I_{p+1}\right)$$

$$\sigma^2 \sim iGamma(0.01, 0.01)$$

The semiparametric spike and slab prior for the coefficients β is of the form

$$\beta_j \sim \pi\delta_0(\beta) + (1-\pi)G$$

$$G \sim DP(\lambda G_0)$$

$$G_0 \sim N(0, \pi)$$

[3] Korobolis (2013) argues that his method, by acknowledging correlation structure in the predictors, outperforms the existing popular Bayesian variable selection algorithms.

where $\tau_a(\upsilon)$is the Dirac delta function for random variable υ which places all probability mass on the point a. G is a nonparametric density which follows a Dirichlet process with base measure G_0 and concentration parameter λ. Base measure is Gaussian with zero mean and variance τ^2.

Thus, each coefficient β_j will either be restricted to 0 with probability π or with probability $(1-\pi)$ and will come from a mixture of Gaussian densities.

The prior distributions of the hyperparameters $\lambda,\ \pi,\ \tau$ are as follows:

$$\tau^2 \sim iGamma(0.01,0.01)$$
$$\lambda \sim Gamma(1,2)$$
$$\pi \sim Beta(1,1)$$

For the estimation, Markov Chain Monte Carlo methods are implemented. After monitoring for convergence, the Gibbs sampler is run for 50,000 iterations after an initial burn-in period of 20,000 iterations.

Principal Components

When the number of candidate predictor series is large, Stock and Watson (2002) suggest using a few principal components of these series. I follow Stock and Watson (2002) and use the first three principal components of 28 predictors. Using principal components as predictors, Eq. (1) is estimated and forecasts are generated.

Table 5: Forecasting Results when Variable Selection is Employed

	R^2	ΔMAE	$\Delta RMSE$	$MSE - F$
Bayesian Variable Selection				
h=1	0.063	0.002	0.003	9.45**
h=3	-0.00	-0.000	-0.000	-0.074
h=6	-0.001	-0.000	-0.000	-0.18
h=9	-0.010	-0.000	-0.000	-1.32
h=12	0.000	0.000	0.000	0.022
Principle Components				
h=1	0.061	0.001	0.000	9.27**
h=3	-0.027	-0.003	0.000	-3.69
h=6	0.014	-0.002	0.000	1.92
h=9	-0.033	-0.022	0.000	-4.29
h=12	-0.044	-0.002	0.000	-5.53

-** indicates better forecasts relative to the *AR(3)* model at 1%.

Table 5 shows the forecasting results when variable selection is employed. At the 1-month forecast horizon both the Bayesian variable selection and principal components method perform better than the AR benchmark. However, at higher forecast horizons they are not significantly better than AR forecasts.

Conclusion

This paper aims to predict the price of crude oil using three groups of variables; i- oil futures prices, ii-bilateral dollar exchange rates of big exporters and major commodity exporters and iii- stock market indexes. In-sample Granger non-causality test statistics indicate that these variables have some predictive power over the price of crude oil. Using a general forecast model, employing rolling window estimation methodology and considering several out-of-sample forecast statistics, I find that oil futures prices have marginal predictive power at short forecast horizons. The results also suggest that exchange rates can help predicting oil prices at higher forecast horizons. Additionally, among stock market indexes only the NIKKEI index has predictive power and only at a 1-month forecast horizon. I also consider several forecast averaging and variable selection methods. All the considered methods produce better forecasts than the benchmark AR forecasts at 1-month forecast horizons. However, they generally lose their forecasting power at higher forecast horizons. There is only one exception; the best 10 percent method, which is the average of the best 3 forecasts, produces significantly better forecasts than the AR model at higher forecast horizons.

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