Crude Oil Return Predictability Revisited

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This Draft: January 15, 2020

Abstract

This article re-visits the evidence of crude oil return predictability resulting from the use of returns calculated from monthly averages of daily WTI crude oil prices. We show that averaging daily prices introduces spurious serial correlation in returns, and generate estimates of variance and covariance that are biased downwards, findings consistent with the predictions of Working (1934, 1960) and Schwert (1990). As a by-product, regression estimates of beta and associated standard errors are also biased leading to false inference about the true extent of crude oil return predictability. On the hand, crude oil returns calculated from end-month-prices does not suffer from these biases, and display statistically insignificant evidence of predictability reversing the conclusions of previous studies. Correcting returns for the effect of averaging using the filtering procedure in Schwert (1990) substantially weakens the evidence of predictability. The predictability that remains can be attributed to the bias in the estimates of covariance between returns and predictors that persists even after the correction.

Keywords: Crude oil; Averaged data; Serial correlation; Return predictability; False inference

JEL classification: C52, C53, Q43, Q47

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1. Introduction

Large fluctuations in crude oil prices have been shown to have a substantial impact on the real economy and financial markets (Hamilton, 1996, 2011; Baumeister and Peersman, 2013; Hou, Mountain, and Wu, 2016; Kilian and Vigfusson, 2017). For example, Hamilton (1983, 2009) show that most U.S. recessions have been preceded by large oil price increases. Reliable forecasts of crude prices are therefore important and required by institutions such as central banks and governments as they serve as a key input in inflation forecasting, play an important role in explaining fluctuations in and projecting economic activity, and are widely used by firms engaged in the production, marketing and processing of crude oil for risk management purposes (Black, 1976). It is therefore not surprising that there is a voluminous literature devoted to studying the predictability of crude oil returns, and how to improve these forecasts (Alquist and Kilian, 2010; Baumeister and Kilian, 2012; Alquist, Kilian, and Vigfusson, 2013; Baumeister and Kilian, 2014, 2015; Baumeister, Kilian, and Lee, 2014; Wang, Liu, Diao, and Wu, 2015; Yin and Yang, 2016; Zhao, Li, and Yu, 2017; Wang, Liu, and Wu, 2017; Zhang, Ma, Shi, and Huang, 2018; among others).

Many of the time series data on key financial and economic variables, including crude oil prices, widely published by popular database sources such as the Federal Reserve and it various agencies, the OECD, the Global Financial Database, and the U.S. Energy Information Administration (EIA) are time-averaged data rather than end-of-period data. This suggests different statistical properties for both series. For example, a note to the release of energy spot prices by the EIA states:

> Explanatory Notes: *Weekly, monthly, and annual prices are calculated by EIA from daily data by taking an unweighted average of the daily closing spot prices for a given product over the specified time period.*

Working (1934, 1960) and Schwert (1990) show that returns computed from month averages of daily data are spuriously autocorrelated, and estimates of variance and covariance with other variables are downward biased reducing return variability. Such data when used in regression analysis will generate biased estimates of regression coefficients and associated standard errors ultimately leading to potentially false inference in hypothesis testing. Early studies of predictability confirm these predictions. For example, Cowles and Jones (1937) analyses monthly averages of weekly stock prices from 1918 to 1938 and find evidence of predictability. The study of Kendall and Hill (1953) also find evidence of predictability using monthly averages of daily cotton prices but no evidence of predictability in wheat prices compiled without averaging. Working (1960) notes that the evidence of predictability in both studies could simply be the effect of averaging, and once this is taken into account there remains no clear evidence of predictability. Wilson, Jones, and Lundstrum (2001) confirm the predictions of Working and Schwert using U.S. S&P 500 Composite Index returns.

Notwithstanding the documented and potentially serious problems associated with the use of averaged data, which has been known, a voluminous amount of research devoted to the study of crude oil return predictability use monthly averaged data.[1] The findings from these studies are that return forecasts generated by predictive regression models of returns and their combinations significantly outperform forecasts from a simple random walk with drift (RW) benchmark model.

In this article, we comprehensively re-examine the empirical evidence of the predictability of WTI crude oil return from January 1987 to December 2018. As predictors, we use a large set of 46 popular economic and technical indicator variables studied widely in the oil forecasting literature covering the commodity, stock, bond, currency markets and the macroeconomy. We compare the estimates of autocorrelation, variance and covariance

[1] The use of monthly averages of daily prices is the convention used in much of the studies in crude oil forecasting literature. See Table 1 for a list of articles across asset markets and the price data series they used in computing returns.

between returns and predictors using monthly average return computed from daily prices, end-of-month returns[2] and monthly average return corrected for autocorrelation and bias in variance following the return filtering procedure in Schwert (1990).

We further investigate in-sample and out-of-sample oil predictability in a predictive regressions for each of the individual predictors at a time. We argue that the evidence of predictability reported in prior studies can be attributed to the aforementioned biases induced as a result of averaging. To gain power against the null hypothesis of no crude oil return predictability, we also consider forecast combination methods that combine the individual predictive model forecasts using different combining weights. Recent studies on crude oil return predictability such as Baumeister et al. (2014), Baumeister and Kilian (2015), Wang et al. (2015), Wang et al. (2017), Yin and Yang (2016), Naser (2016), and Zhang et al. (2018) also consider forecasting combination models to provide insurance against parameter instability and model uncertainty that plague individual predictive models, which affect their performance (see, for example, Stock and Watson, 2004; Baumeister and Kilian, 2015; and the references therein). As also noted by Baumeister and Kilian (2015), considering forecast combinations is useful because even when the most accurate forecasting models do not work equally well at all times.

Our results confirm the predictions of Working (1960) and Schwert (1990). There is a significantly high first-order autocorrelation in returns and estimate of variance and covariance are biased downwards compared to end-of-month returns. Filtering returns for the effect of averaging removes these two of theses biases. For example, monthly average (end-of-month) returns have a first-order autocorrelation of 0.286 (0.150) and variance of 68.59% (83.92%). Filtered returns, on the other hand, has a first order autocorrelation of 0.025 and a variance of 97.66%. However, the bias in the estimate of covariance between

[2]Returns computed from end-of-period prices is the convention used in much of of the return predictability literature. See, for example, Acharya, Lochstoer, and Ramadorai (2013), Chinn and Coibion (2014), Campbell and Thompson (2008), Neely, Rapach, Tu, and Zhou (2014), Sarno, Schneider, and Wagner (2016), Lin, Wu, and Zhou (2017), Levich and Potì (2015), and Li, Tsiakas, and Wang (2015). A comprehensive list is provided in Table 1.

filtered returns and predictors remain.

In predictive analysis, most of the individual economic and technical indicator variables we consider display statistically significant forecasting power, both in- and out-of-sample, for monthly average crude oil returns compared to forecast from the RW model. The combination forecasts of *monthly average returns* display substantial degree of predictability. However, these conclusions are completely reversed when we use end-of-month crude oil returns as the dependent variables in our forecasting models. That is, we find no evidence of predictability both in and out-of-sample forecasts from the univariate and combination models. Although filtered returns also display statistically significant evidence of predictability, this evidence, however, is much weaker. We attribute this to the bias in covariance estimate that persistent even after corrected returns for spurious autocorrelation and downward bias in variance.

We attribute the differing conclusions of predictability for the two return series to the significantly high first-order autocorrelation in and downward bias in variance estimate of *monthly average returns*. To test this hypothesis, we estimate univariate predictive regression of returns on it own lagged value, as well as multivariate regression models of returns on its own lagged value and the lag of each of the predictors at a time. The results from this test show that whereas exploiting the presence of serial correlation in monthly average return substantially improves the forecasting performance of the models relative to the RW forecast, such evidence is non-existent when we use *end-of-month returns* as the dependent variable in our forecasting models. This confirms our hypothesis that the presence of serial correlation in crude oil returns, which is severe in the *monthly average returns*, is what account for the evidence of predictability reported in the majority of the extant literature on crude oil return predictability.

The rest of the paper is organised as follows. Section 2 describes the oil price data used in computing returns, the predictor variables used in investigating return predictability, and offers preliminary data analysis. In Section 3, we describe the methodology for predicting crude oil returns. The empirical analysis of in-sample and out-of-sample performance of crude oil return forecasts is in Section 4. Section 5 concludes.

2. Data

2.1. Crude oil returns

Daily prices and monthly averages of daily prices of WTI crude oil spot are obtained from the website of the U.S. Energy Information Administration (EIA).[3] From the daily prices, we build end-of-month price series. Real log returns at time t are computed as $r_t = \ln(Rp_t) - \ln(Rp_{t-1})$, where $Rp_t = np_t/cpi_t$ is the real price of crude oil, np_t is the nominal price of crude oil, and cpi_t is the U.S. consumer price index. We will refer to returns computed using end-of-month prices as *end-of-month returns*, and those computed using monthly average prices as *monthly average returns*. We also follow the filtering procedure in Schwert (1990) to correct monthly average returns for spurious autocorrelation and biased variance. Schwert (1990) first estimates a first-order moving average (MA(1)) process,

$$R_t = \mu + \theta\varepsilon_{t-1} + \varepsilon_t, \tag{1}$$

where R_t is the monthly average returns and θ is the moving average parameter. The author notes that θ should be about 0.3 since the first-order autocorrelation from an MA(1) process is $\theta/(1+\theta^2) = 0.27$. An estimate of return is then given by $\hat{R}_t = \hat{\mu} + \hat{\varepsilon}_t$. This new estimate has the same mean as the original monthly average returns, but no first-order correlation and a variance estimate that is biased downward compared to that of original data series. To solve for the downward bias in the estimate of variance, Schwert (1990) propose to multiply the errors $\hat{\varepsilon}_t$ by a factor $[1.2(1+\theta^2)^{1/2})]$ which results in standard deviation 20% larger than the standard deviation of the original series. The

[3]https://www.eia.gov/

new estimate of return, which we denote as *filtered returns* is

$$\hat{R}_t = \hat{\mu} + \hat{\varepsilon}_t[1.2(1 + \hat{\theta}^2)^{1/2}], \tag{2}$$

where $\hat{\mu}$, $\hat{\theta}$ and $\hat{\varepsilon}_t$ are from (1).

Our analysis focus on monthly crude oil returns from January 1987 to December 2016 period. This sample covers the period used by many of the crude oil return predictability studies we cite in this paper. Because the data used in our analysis differs from the dataset used in existing studies of crude oil return predictability, it is worth highlighting the main differences. The main difference is what price series are used in computing returns. Studies such as Baumeister and Kilian (2012), Baumeister and Kilian (2014), Wang et al. (2017), Zhang et al. (2018), and the references therein, use monthly crude oil returns computed from monthly averages of daily prices of WTI crude oil spot obtained from the website of the EIA. We compute crude oil returns using end-of-month prices extracted from daily oil prices. Our approach therefore follows the convention in most of the studies on stock, bond, currency, and commodity return predictability. Table 1 lists articles and the price series used in computing returns across the various asset markets.

[Insert Table 1 about here]

The reasons provided for the use of *monthly average returns* are first, the average price mitigates one-day market perturbations resulting from rumours, and is less noisy; second, average returns generates better results; and third, the high correlation between monthly average and *end-of-month returns* (Ye, Zyren, and Shore, 2006). Over the sample period under consideration, the correlation between the *monthly average returns* and *end-of-month returns* was 0.72. Although this correlation is quite high, it is not nearly perfect. As such, it is likely that the analysis of returns may lead to different inferences being drawn about the degree of return predictability. We are of the view that using *monthly average returns* is erroneous from the point of view of both forecasting and making inferences about key macroeconomic variables. For the purposes of budgeting, the consumers may wish to know how much they are likely to pay for their crude oil needs on average, in which case the average price may be of interest. However, for policy makers, central banks, and firms involved in the marketing and production of crude oil, and for risk management purposes, the end-of-period price may be the most appropriate. A further criticism from using the monthly average price is that it is not realizable and may not have been available to both consumers and forecasters in real time. Notwithstanding the limitations from using *monthly average returns*, we are of the view that it serves as a good lower bound on the degree of return predictability that is attainable inline with the second reason provided for their use.

Panel A of Table 2 presents descriptive statistics for the three return series. The mean of *monthly average returns* is almost twice that of the *end-of-month returns* with much lower standard deviation. Filtered returns has the same mean as monthly average returns but a higher standard deviation of about 20% larger. The last three columns of Table 2 reports the results for the correlation between returns and predictor variance. As can be seen, filtering returns for the effect of averaging has a little effect on the covariance estimates. These three findings are consistent with the predictions of Working (1960) and Schwert (1990).

Figure 1 plot the time series of the two return series which shows very similar volatility patterns. *Monthly average returns* are also more left skewed and fat-tailed than the *end-of-month returns*. *Monthly average returns* have first-order autocorrelation of 0.30 compared to 0.15 for the *end-of-month returns*. Figure 2 plots the sample autocorrelation function up to 36 lags with 95% confidence bands for the three return series. As shown by the autocorrelation plots, filtering returns remove autocorrelation as none is significant up to 36 lags. Figure 3 also plots the autocorrelation function of squared returns. The figure shows substantial evidence of autocorrelation of squared returns suggesting that the data is heteroskedastic, and therefore test statistics that account for this feature of the data as well as autocorrelation should be used.

[Insert Table 2 about here]

[Insert Figure 1 about here]

[Insert Figure 2 about here]

[Insert Figure 3 about here]

2.2. Predictor variables

We consider a set of 46 predictor variables: 28 economic variables and 18 technical indicators that have been used in studies on crude oil return predictability (see, for example, Fama and French, 1987; Bessembinder, 1992; Gargano and Timmermann, 2014; Hong and Yogo, 2012; Chen, Rogoff, and Rossi, 2010; Groen and Pesenti, 2011; Basu and Miffre, 2013; Baumeister, Kilian, and Zhou, 2017; among others). They include commodity market, financial market, treasury and corporate bond markets, and macroeconomic variables.[4]

2.2.1. Economic variables

1. Commodity market variables: The first set of 10 predictors are variables selected from the commodity return predictability literature, and are analysed in studies such as Fama and French (1987), Bessembinder (1992), De Roon, Nijman, and Veld (2000), Coppola (2008), Hong and Yogo (2012), Basu and Miffre (2013), Gorton, Hayashi, and Rouwenhorst (2013), Kilian and Murphy (2014), Baumeister et al. (2017), among others. The consideration of this set of predictors is motivated by the fact that they are related to the classical commodity pricing theories of storage and normal backwardation. For

[4] Further details and the rational for considering these predictors for commodity returns are provided in the Appendix.

example, the theory of storage of Kaldor (1939), Working (1948), and Brennan (1958) explain the dynamics of the commodity futures prices by linking basis, the difference between the contemporaneous spot and futures price, to the cost of storage and the risk premium for holding inventory. When inventories are high, basis is low since futures prices are expected to fall with maturity leading to high expected returns. The theory of normal backwardation of Keynes (1930), Hicks (1939), and Cootner (1960) on the hand posits that hedgers use the futures market to transfer risk to speculators in the process paying a significant risk premium to them. The net position of hedgers or a measure of supply-demand imbalances in the commodity futures markets, also known as hedging pressure, is what dictates, in equilibrium, the compensation to be paid. When hedgers are net long, futures prices are expected to decrease leading to high expected returns. The variables are: *Futures return*, *basis*, *hedging pressure* (HP), *price pressure* (PP), *open interest growth* (OI), *crude oil crack spread* (SCS), *Gasoline spot spread* (GSS), *Heating oil spot spread* (HSS), *global crude oil inventory* (GOI), and *global crude oil production* (GOP).

2. Currency market variables: The second set of predictors consist of 4 "commodity currencies" studied in Chen et al. (2010), Groen and Pesenti (2011), and Gargano and Timmermann (2014).[5] Chen et al. (2010), for example, exploit the notion that changes in commodity currencies are correlated with commodity prices. Therefore the movement in the currencies of major commodity exporting countries where commodities represent a quarter to one-half of their total export earnings should be informative commodity returns. We consider the log exchange rate of the currencies of following countries against the US dollar obtained from Bloomberg: *Australia* (AUS), *Canada* (CAN), *New Zealand* (NZ), and *South Africa* (SA).

3. Stock, treasury and corporate bond market variables: The third set of 9 predictors

[5]Commodity currencies, as defined in Chen et al. (2010), refer to the few floating currencies that co-move with the world prices of primary commodity products, due to the countries' heavy dependence on commodity exports.

is drawn from the stock and bond return predictability literature. The fact that most of these variables are economic activity variables and therefore track the business-cycle, and have been shown to explain expected returns on stocks and bonds (Fama and French (1989)) is the reason why we consider them. These variables are also chosen based on recent evidence in Irwin and Sanders (2011), Tang and Xiong (2012), and Hamilton and Wu (2015) of the financialization of commodities that has increased their correlation with stocks and bonds. As such, by considering this set of variables, we are essentially imposing the assumption of market integration. The predictors are *S&P 500 stock index return* (S&P 500 return), *3-month treasury bill rate* (TBL), *change in treasury bill rate* (CTBL), *yield spread* (YS), *default yield spread* (DFY), *1-year term spread* (TMS1Y), *2-year term spread* (TMS2Y), *5-year term spread* (TMS5Y), and *VIX*.

4. Macroeconomic variables: The final set of predictors include 7 macroeconomic variables that measure the broad state of the economy. These variables are analysed in studies such as Pagano and Pisani (2009), Kilian (2009), Hong and Yogo (2012), Groen and Pesenti (2011), Gargano and Timmermann (2014), Baumeister and Kilian (2015), among others. The variables we consider are *global real economic activity index* (REA), *Baltic Dry Index* (BDI), *inflation* (INFL), *degree of capacity utilization in US manufacturing* (CUTIL), *industrial production growth* (INDPRO), OECD *composite leading indicator* (CLI), and OECD *business confidence index* (BCI).

2.2.2. Technical indicators

We investigate the predictive ability of 18 popular technical indicator variables (Sullivan, Timmermann, and White, 1999; Miffre and Rallis, 2007; Szakmary, Shen, and Sharma, 2010; Fuertes, Miffre, and Rallis, 2010; Neely et al., 2014; Yin and Yang, 2016) based on three trading rules, namely moving-average (MA) rule, momentum (MOM) rule, and on-balance volume (VOL) rule.

The MA rule generates a buy or sell signal, ($s_{i,t} = 1$ or $s_{i,t} = 0$, respectively) at the end of t by comparing the averages:

$$s_{i,t} = \begin{cases} 1, & \text{if } \mathrm{MA}_{k,t} \geq \mathrm{MA}_{l,t}, \\ 0, & \text{if } \mathrm{MA}_{k,t} < \mathrm{MA}_{l,t}, \end{cases} \tag{3}$$

where

$$\mathrm{MA}_{j,t} = (1/j) \sum_{j=0}^{j-1} P_{t-1}, \quad \text{for } j = k, l; \tag{4}$$

$P_{i,t}$ is the level of crude oil prices, and $k(l)$ is the length of the short (long) MA$(k < l)$. The MA indicator with length k and l is denoted by MA(k, l). The MA rule detects movements in prices. We should therefore expect the short MA to be more sensitive to recent movements in crude oil prices compared to the long MA. In our empirical analysis, we consider MA rules with $k = 1, 2, 3$ and $l = 9, 12$.

The MOM rule generates a buy or sell signal, ($s_{i,t} = 1$ or $s_{i,t} = 0$, respectively) at the end of t by comparing the current oil to its level m periods ago:

$$s_{i,t} = \begin{cases} 1, & \text{if } P_t \geq P_{t-m}, \\ 0, & \text{if } P_t < P_{t-m}, , \end{cases} \tag{5}$$

Intuitively, if the current crude oil price is higher than its level m periods ago indicates “positive" momentum and relatively high expected excess returns, thereby generating a buy signal. We denote the momentum indicator that compares P_t to P_{t-m} by MOM(m), and we compute monthly signals for $m = 1, 2, 3, 6, 9,$ and 12

The VOL rule employ volume data together with past prices to identify crude oil market trends. Define on-balance volume (OBV) as

$$\mathrm{OBV}_t = \sum_{k=1}^{t} \mathrm{VOL}_k D_k \tag{6}$$

where $\mathrm{VOL}_k D_k$ is a measure of trading volume during period k and D_k is a binary variable that takes a value 1 if $P_k - P_{k-1} \geq 0$ and -1 otherwise. We then form a trading signal, ($s_{i,t} = 1$ or $s_{i,t} = 0$, respectively) at the end of t, from OBV_t by comparing two moving averages as

$$s_{i,t} = \begin{cases} 1, & \text{if } \mathrm{MA}_{k,t}^{\mathrm{OBV}} \geq \mathrm{MA}_{l,t}^{\mathrm{OBV}}, \\ 0, & \text{if } \mathrm{MA}_{k,t}^{\mathrm{OBV}} < \mathrm{MA}_{l,t}^{\mathrm{OBV}}, \end{cases} \tag{7}$$

where

$$\mathrm{MA}_{j,t}^{\mathrm{OBV}} = (1/j) \sum_{i=0}^{j-1} \mathrm{OBV}_{t-i}, \quad \text{for} \quad j = k, l. \tag{8}$$

The intuition behind this rule is that recent high volume together with recent price increases, for example, indicate a strong positive market trend and therefore generates a buy signal. We analyse VOL rules with $k = 1, 2, 3$ and $l = 9, 12$.

Following Yin and Yang (2016), we use the closing price of the 1-month to maturity WTI crude oil futures (contract 1) traded on the New York Mercantile Exchange (NYMEX). The data is downloaded from the EIA database. The volume data for the same contract is obtained from the commitments of traders report published by the U.S. Commodity Futures Trading Commission. These price and volume data are used in Equations (3), (5), and (7).

Panel B of Table 2 reports summary statistics for the predictor variables. First-order autocorrelation of around -0.037 to 0.99 with of the predictors showing strong persistent.

3. Prediction models for crude oil returns

In this section, we introduce the return prediction models and describe the estimation method and the statistical tests used in evaluating out-of-sample crude oil return forecasts.

We consider 48 individual predictive models and 28 forecast combination models based on the 28 and 18 economic and technical indicator variables, respectively, described in the previous section.

3.1. Individual predictive models

Consider the following univariate predictive regression model for excess commodity returns,

$$r_{t+1} = \alpha_i + \beta_i x_{i,t} + \varepsilon_{i,t+1}, \tag{9}$$

where r_{t+1} is the realized log return on crude oil from time t to $t+1$, $x_{i,t}$ is a predictor available at time t, and $\varepsilon_{i,t+1}$ is a zero-mean error term. By replacing $x_{i,t}$ with $s_{i,t}$ from Equations (3), (5) and (7) yields the predictive model of crude oil returns based on the individual technical indicator variables.

The step-ahead forecast of log returns is given by

$$\hat{r}_{t+1} = \hat{\alpha}_t + \hat{\beta}_t x_{i,t}, \tag{10}$$

where $\hat{\alpha}_i$ and $\hat{\beta}_i$ are the OLS estimates of α_i and β_i in Equation (9), respectively.

3.2. Forecast combination models

In light of the poor out-of-sample forecasting performance of individual predictive model forecast of asset returns as a results of structural instability of the underlying models (Welch and Goyal, 2008; Baumeister and Kilian, 2012), we also consider forecast combination methods. Combination forecasts incorporate information from many predictors and therefore should provide insurance against model uncertainty and parameter instability of the individual predictive models. Our combination forecasts differ in the way we compute weights assigned to the individual predictive model forecasts. Forecast combination methods have been shown in oil return predictability studies such as Baumeister et al. (2014), Baumeister and Kilian (2015), Naser (2016), Drachal (2016), Zhang et al. (2018), among others, to lead to improved forecasts. As noted by Timmermann (2008), which combination method is ex ante optimal is an empirical question and justifies why we consider different forecast combination methods.

Let $\hat{r}_{i,\,t+1}$ denote the pseudo out-of-sample forecast of the realization r_{t+1} computed at time t based on the ith predictor variable as given by Equation (10). Most of the forecast combination methods we consider take the following form:

$$\hat{r}_{t+1}^{\text{CF}} = \sum_{i=1}^{N} w_{i,\,t} \hat{r}_{i,\,t+1}, \tag{11}$$

where $\hat{r}_{t+1|t}^{\text{CF}}$ is the combination forecast and $w_{i,\,t}$ is the weight assigned to the ith forecast with $\sum_{i=1}^{N} w_{i,\,t} = 1$.

The first set of combining methods we consider use simple averaging schemes: mean, trimmed mean, median, and weighted-mean forecasts. Rapach, Strauss, and Zhou (2010), for example, find that simple methods work well for forecasting the U.S. equity risk premium. The mean combination forecast, $\hat{r}_{t+1}^{\text{Mean}}$, is the average of the N individual forecasts that assign equal weights, $w_{i,\,t} = 1/N, i = 1, ..., N$, to each forecast defined in Equation (10):

$$\hat{r}_{t+1}^{\text{Mean}} = \frac{1}{N}\hat{r}_{1,\,t+1} + \frac{1}{N}\hat{r}_{2,\,t+1} + ... + \frac{1}{N}\hat{r}_{N,\,t+1}. \tag{12}$$

The trimmed mean forecast, $\hat{r}_{t+1}^{\text{Trimmed mean}}$, sets the $w_{i,\,t} = 0$ for the smallest and largest forecasts, and $w_{i,\,t} = 1/(N-2)$ for the remaining individual forecasts in Equation (11). The median combination forecast, $\hat{r}_{t+1}^{\text{Median}}$, is the sample median of the N individual predictive model forecasts. The weighted-mean forecast ($\hat{r}_{t+1}^{\text{Weighted-mean}}$) proposed by Bates and Granger (1969) specifies the combination weights to be proportional to the inverse of the estimated residual variance, $\sigma_{i,\,t}^2$, for the individual predictive regression models given by Equation 9,

$$\hat{r}_{t+1}^{\text{Weighted mean}} = \frac{1/(\hat{\sigma}_{1,\,t}^2)}{\sum_{i=1}^{N} 1/(\hat{\sigma}_{i,\,t}^2)}\hat{r}_{1,t+1} + \frac{1/(\hat{\sigma}_{1,\,t}^2)}{\sum_{i=1}^{N} 1/(\hat{\sigma}_{i,\,t}^2)}\hat{r}_{2,t+1} + ... + \frac{1/(\hat{\sigma}_{1,\,t}^2)}{\sum_{i=1}^{N} 1/(\hat{\sigma}_{i,\,t}^2)}\hat{r}_{N,t+1}, \quad (13)$$

The second set consist of various performance-based combination forecasts. First, we compute the discounted mean squared forecast error (DMSFE) combination forecast following Stock and Watson (2004). Here, the combining weights are specified as functions of the historical performance of the individual predictive model forecasts over a holdout out-of-sample period,

$$w_{i,\,t}^{\text{DMSFE}} = \frac{\phi_{i,\,t}^{-1}}{\sum_{j=1}^{N} \phi_{j,\,t}^{-1}}, \quad \phi_{i,\,t} = \sum_{s=1}^{t-1} \theta^{t-1-s} \left(r_{s+1} - \hat{r}_{i,\,s+1}\right) \quad (14)$$

where θ is the discount factor.[6] When $\theta < 1$, greater importance is attached to the individual predictive model forecast with lower mean square forecast error (MSFE). That is, the individual predictive model that generates the least MSFE is assigned a greater weight because it signals better forecasting performance. In the special case where there is no discounting ($\theta = 1$) and forecasts are uncorrelated leads to the optimal combination weights proposed by Bates and Granger (1969) given by Equation (13). We consider θ values of 0.7 and 0.9. Rapach et al. (2010) also show that the DMSFE combination forecasts of US equity risk premium consistently outperforms a constant expected return benchmark forecast. Second, we consider Approximate Bayesian Model Averaging (ABMA) combination forecast following Garratt, Lee, Pesaran, and Shin (2003) and choose the combining weights as follows:

$$w_{i,\,t}^{\text{ABMA}} = \frac{\exp(\triangle_{i,t})}{\sum_{j=1}^{N} \exp(\triangle_{i,t})}, \quad (15)$$

where $\triangle_{i,t} = \text{AIC}_{i,t} - \max_j(\text{AIC}_{j,t})$ and $\text{AIC}_{i,t}$ is the Akaike Information Criterion of

[6] The DMSFE combination forecast require a holdout evaluation period to estimate the combining weights. However, note that the first out-of-sample forecast of this method is simply calculated as the mean combination forecast because there is no past individual forecast used to form the DMSFE weight at this time point.

model i. The ABMA thus gives higher weight to models with better historical fit as measured by the AIC. The Bayesian model has the advantage that, in addition to dealing with structural instability and model uncertainty, it also deals with estimation errors surrounding the parameters of the predictive models. Third, Elliott, Gargano, and Timmermann (2013, 2015) propose a new class of combination forecast which they call Subset regression forecast. Their approach uses equally weighted combination of forecasts based on all possible predictive regression models that include a subset of the predictor variables. As noted by the authors, by keeping the number of predictors to be included in the predictive model fixed, they are able to control estimation error by trading off the bias and variance of the forecast errors similarly to generating the mean-variance efficient frontier of individual assets in portfolio theory. Suppose the number of potential predictors that enter a regression is K. A subset regression is then defined by the set of regression models that include a specified number of regressors, $k \leq K$. The $k \leq K$ dimensional subset forecasts are then averaged to generate the forecasts. In our analysis, we use a maximum K value of 7. Given K regressors in full and k regressors chosen for short models, one has to average over $C_k^K = K!/(k!(K-k)!)$ subset regression forecasts. As a special case, when $k = 1$ results in the mean combination forecast given by Equation (12). Generally, the subset regression forecast is given by

$$\hat{r}_{t+1}^{\text{Subset}} = \frac{1}{C_k^K} \sum_{i=1}^{C_k^K} \hat{\beta}_{i,t} x'_{i,t}, \tag{16}$$

where $\dim(x_{i,t}) = k$.

As our finally combination method, we generate out-of-sample forecast by estimating a predictive regression based on diffusion index that assumes a latent factor structure following Stock and Watson (2002a,b):

$$\hat{r}_{t+1}^{\text{PC}} = \hat{\alpha} + \sum_{k=1}^{K} \hat{\beta}_{k,t} F_{k,t}, \tag{17}$$

where $F_{k,t}$ is the kth principal component extracted from the 28 predictor variables. Diffusion indices provide a convenient way of extracting common factor from a large number of potential predictor variables. Neely et al. (2014), for example, show that this approach improves US equity premium forecasting. We consider models where the principal components are selected via the Akaike information criterion (AIC),[7] the Bayesian information criterion, and the adjusted R^2 statistical model selection criterion. We set the maximum number of principal components to 4.

3.3. Random walk with drift model

The random walk with drift (RW) forecast is a popular benchmark forecast that has been used widely in studies on commodity return predictability (see, for example, Alquist and Kilian (2010), Chinn and Coibion (2014), Ahmed and Tsvetanov (2016) and the references therein). The use of the RW return forecast as the benchmark is consistent with the hypothesis that commodity futures prices follow a random walk so returns are unpredictable. Under the null hypothesis of no predictability, the model assumes a constant return:

$$r_{t+1} = \alpha + \varepsilon_{t+1}, \tag{18}$$

where r_{t+1} is log real return on crude oil. We use the forecast from this model as the benchmark forecast against which all other forecasts are compared to in assessing crude oil return predictability.

[7] The Akaike information criterion (similarly to the adjusted R^2 selection criterion), unlike the Bayesian information criterion (BIC), is not statistically consistent in the sense of selecting the "true" model as the sample size increases without bounds. However, Pesaran and Timmermann (1995) note that in the context of forecasting asset returns where the correct list of regressors is unknown and may be changing over time, the consistency property of a model selection criterion is not as important as it may first appear. They suggest that of greater importance is to select a forecasting model that could be viewed at the time as being a reasonable approximation to the data generating process. Although AIC is statistically inconsistent, it has the property of yielding an approximate model. Shibata (1976), for example, shows that AIC strikes a good balance between giving biased estimates when the order of the model is too low, and the risk of increasing the variance when too many regressors are included.

4. Empirical results

This section describes our empirical results. We first report results based on full-sample estimates followed by an out-of-sample analysis of the statistical evidence of return predictability.

4.1. Full-sample estimation results

Table 3 reports ordinary least-square estimates for the oil return prediction models using the lag values of each of the individual economic and technical indicator variables at a time. The table also reports the associated Newey and West (1987) heteroskedasticity-consistent t-statistics and R^2 statistics. Results are reported for the full-sample period (1987:01-2013:12). From Panel A, 15 of the 28 economic variables, namely Futures return, Basis, HP, PP, SCS, AUS, CAN, NZ, SA, CTBL, BDI, CAPUTIL, CLI and BCI, display statistically significant forecasting power at conventional levels for monthly average crude oil returns. The t-statistics for the significance of the slope coefficient, β, range from 1.83 to 9.38. The R^2 statistics for the same 15 variables also range from 1.95% to 34.50%. Although some of the R^2 values may seem small, these are typical values reported in return predictability literature. Campbell and Thompson (2008), for example, notes that R^2 values as low as 0.5% could still represent economically significant degree of return predictability. Most of the R^2 values exceed this 0.5% threshold. Turning to the results for the *end-of-month returns*, only 6 of the 28 economic variables, namely Futures return, SCS, GSS, CTBL, CLI and BCI, display significant forecasting power for crude oil returns although the degree of predictability reported is not as strong compared to those based on the *monthly average returns*. The results for the filtered return series is displayed in the last three columns of the table. Clearly, filtering returns for the effect of averaging reduces the performance of the forecasting models substantially and in some cases leads to insignificant results. For example, the futures return predictor which display evidence of predictability for monthly average returns with an R^2 of 8.74% is insignificant in the case of filtered returns. Another example, is the basis predictor with a significant R^2 of about 35% for monthly average returns but reduces to 18% when filtered returns are instead used in the forecasting model.

The results based on the technical indicator variables are reported in Panel B of Table 3. Similar conclusions to the analysis based on the economic variables can be drawn. Whereas some of the 9 of the 18 technical indicators, namely MA$(1, 9)$, MA$(1, 12)$, MOM(1), MOM(2), MOM(6), MOM(12), VOL$(1, 9)$, VOL$(1, 12)$ display forecasting power *monthly average returns*, non of these variables have forecasting power for *end-of-month returns*, with performance further reduces in the case of filtered returns.

[Insert Table 3 about here]

4.2. Analysis of out-of-sample crude oil return forecasts

The full-sample tests of predictability reported in Table 3 are not based on truly ex-ante measures of future expected crude oil returns and would not have been available to a forecaster in real-time. That is, a forecaster could only have used prevailing information to estimate the parameters of the predictive models and not the full-sample. In the sections that follow, we analyse out-of-sample forecasts of crude oil returns to gauge the value of the forecasting models in real-time.

4.2.1. Calculating out-of-sample return forecasts

We conduct our out-of-sample experiment using a recursive (expanding window) estimation approach as follows. Suppose T observations are available for r_t and $x_{i,t}$ ($s_{i,t}$). We use the first $n = 120$ observations (1987:01-1996:12)[8] as the initial in-sample estimation

[8]The choice of length of the in-sample estimation period enables us to have a sufficiently long out-of-sample forecasts evaluation period. Hansen and Timmermann (2012), for example, show that using a relatively large proportion of the available sample for forecast evaluation provides better size properties of the test statistics of predictive ability.

period and the remaining $T - n = 204$ observations (1997:01-2013:12) as the out-of-sample forecast evaluation period. The parameters of the models are updated recursively as new data becomes available. Meaning that the estimation sample always starts in 1987:01 and we expand the estimation window by one month as additional observations become available. Only data up to month t is therefore used to estimate the model parameters and generate the pseudo out-of-sample forecast of crude oil returns corresponding to each predictor variable for the month $t + 1$ as

$$\hat{r}_{t+1} = \hat{\alpha}_t + \hat{\beta}_t \, x_{i,\,t}, \tag{19}$$

where $\hat{\alpha}_t$ and $\hat{\beta}_t$ are the OLS estimates of α and β in Equation (9), respectively, from regressing $\{r_s\}_{s=2}^{n}$ on a constant and $\{x_{i,\,s}\}_{s=1}^{n-1}$.

4.2.2. Evaluating forecasting performance

Following the convention in the return predictability literature, we evaluate the out-of-sample predictive accuracy of the forecast from individual and combination models relative to the forecast from the RW return model using the Campbell and Thompson (2008) out-of-sample R^2 statistic, R^2_{OOS}, given by:

$$R^2_{\text{OOS}} = 1 - \frac{\text{MSFE}(\hat{r}_t)}{\text{MSFE}(\bar{r}_t)} = 1 - \frac{\sum_{t=n+1}^{T} (r_t - \hat{r}_t)^2}{\sum_{t=n+1}^{T} (r_t - \bar{r}_t)^2}, \tag{20}$$

where r_{n+1} is the realized log oil return at time $n + 1$ and $\hat{r}_{n+1}(\bar{r}_{n+1})$ is an alternative, individual or combination, forecast (RW forecast). The R^2_{OOS} statistic measures the proportional reduction in mean square forecast error (MSFE) for an alternative forecast relative to the RW forecast. Positive values of this statistic suggest evidence of time-varying return predictability, and implies that the alternative forecast, because it has a lower MSFE, outperforms the RW forecast.

We evaluate the statistical significance of the R^2_{OOS} statistic using the p-value of the

MSFE-adjusted statistic of Clark and West (2007). The statistic tests the null hypothesis of equal out-of-sample predictive ability of the alternative model forecasts against the RW model forecast. That is, the null hypothesis of $R^2_{\text{OOS}} \leq 0$ against the alternative hypothesis that $R^2_{\text{OOS}} > 0$. Under the null of no crude oil return predictability, the RW return forecast is expected to have a lower MSFE. The Clark and West (2007) procedure accounts for the fact that under the null of equal predictive accuracy, the MSFE of the RW model is expected to be lower compared to the alternative individual or combination models. This is because the alternative model introduces noise into its forecasts by attempting to estimate parameters whose population values are zero. As such, finding that the RW model forecast has a lower MSFE is not clear evidence against the alternative model. Clark and West propose to adjust the MSFE to account for the noise associated with the alternative models' forecast as follows:

$$\text{MSFE-adjusted} = \frac{1}{F}\sum_{t=n+1}^{T}(r_t - \hat{r}_t)^2 - \frac{1}{F}\sum_{t=n+1}^{T}(\bar{r}_t - \hat{r}_t)^2\,, \tag{21}$$

where F is the number of forecasts. They also note that the computationally most convenient way of testing the null of equal MSFE is to define:

$$\hat{f}_t = (r_t - \bar{r}_t)^2 - [(\bar{r}_t - \bar{r}_t)^2 - (\bar{r}_t - \hat{r}_t)^2] \tag{22}$$

and to regress $\hat{f}_t$ on a constant and using the resulting t-statistic for a test of zero coefficient. Although the asymptotic distribution of this test statistic is non-normal, Clark and West (2007) argue that standard normal critical values provide a good approximation. They recommend to reject the null of equal MSFE if the test statistic has critical values greater than 1.282 for a one-sided 10% test, 1.645 for a one-sided 5% test, and 2.326 for a one-sided 1% test.

Table 5 reports R^2_{OOS} values for each of the individual predictive regression and the combination model forecasts of crude oil returns relative to the random walk with drift

(RW) forecast. The statistical significance of the R^2_{OOS} statistics is based on the test of equal predictive accuracy of Clark and West (2007). Columns 1-3 of Panel A show that 12 of the 30 economic variables display significant predictive ability for monthly average crude oil returns. These variables are the same variables that displayed predictive power when estimating the models using the full sample. The R^2_{OOS} values range from 0.76% for hedging pressure (HP) to 26.72% for futures return which are statistically significant at conventional levels. Conversely, we find no statistically significant predictive power of the economic variables for the *end-of-month returns*, except 3 of the variables namely change in 3-month treasury bill rate (CTBL), composite leading indicator (CLI) and business confidence index (BCI). Similar results are obtained for the combination forecasts reported in Panel B. All the combination forecasts of *monthly average returns* add substantial improvements in out-of-sample predictive performance over the RW forecast, consistent with the findings in studies such Baumeister et al. (2014), Baumeister and Kilian (2015), Wang et al. (2017), among others. Apart for the Mean combination forecast which records an R^2_{OOS} value of 1.46% and significant at the 5% level, all the other combination forecasts record R^2_{OOS} values well above 5% with the highest value of 22.31% recorded for the Subset combination forecast which consider up to 7 predictors at a time. All the R^2_{OOS} values are statistically significant at the 1% level. Turning to the results for the *end-of-month returns* reported in columns 4-6, we can see that non of the combination forecasts of end-of-month crude returns display statistically significant forecasting power, as they fail to add any improvement to the forecast from the RW model.

The univariate and combinations forecast based on the technical indicator variables are reported in Table 6. Similarly to the out-of-sample results reported for the economic variables, and consistent with their in-sample results, both individual and combination forecasts of *monthly average returns* are statistically significant at conventional levels, and outperformance the RW forecast. The R^2_{OOS} are significantly greater than zero, and combining information from the individual technical indicators lead to sizeable improvements in forecasting performance. These results are also consistent with the findings in Yin and Yang (2016) who find that exploiting information from individual technical indicators or their combinations outperform a no-change forecast of crude oil returns. Turning to the *end-of-month returns*, however, we find that all the individual and combination forecasts of *end-of-month returns* fail to beat the forecast from RW model. Similar to the in-sample results, the use of filtered returns reduce substantially the evidence of predictability. For example, the statistical significance of out-of-sample R^2 statistics reduce by more than 50%.

In summary, we find that whereas individual and combination forecasts of monthly average crude oil return based on both economic and technical indicator variables display significant evidence of predictability consistent with the voluminous studies on crude oil return predictability, such conclusions are completely reversed when we perform the same forecasting exercise using *end-of-month returns*. Individual and combination forecasts of end-of-month oil returns add no improvement to the forecasting performance of the random walk model. Correcting returns for spurious first-order autocorrelation, and the downward bias in estimate of variance and covariance substantially weakens the evidence of predictability. The predictability that remain, however, can be attributed to the bias in covariance between returns and predictors that persist even after the correction.

Taken together, the in-sample and out-of-sample results confirm the predictions of Working (1960) and Schwert (1990), and is still consistent with the findings of Wilson et al. (2001). The evidence of crude oil predictability reported in prior studies can be attributed to the aforementioned biases introduced as result of averaging prices.

[Insert Table 5 about here]

[Insert Table 6 about here]

4.2.3. Exploiting the first-order autocorrelation in crude oil returns

It is of interest to check whether the significant first-order autocorrelation reported in Table 2 could potentially be exploited to increase the power of the forecasting models against the null hypothesis of no return predictability. Performing this analysis should provide a quantitative explanation and shed more light on our thesis that the statistical evidence of crude oil return predictability reported in the vast majority extant literature could be overstated, and that such evidence would not have existed if *end-of-month returns* were used in the forecasting models.

Recall that we found the autocorrelation for the *monthly average returns* to be more than twice the autocorrelation of the *end-of-month returns.* To exploit this feature of the data, we modify the univariate models to include the lagged return on crude oil and the predictor. This leads to the following multivariate predictive model

$$r_{t+1} = \alpha_i + \beta r_t + \gamma_i x_{i,t} + \varepsilon_{i,t+1}, \tag{23}$$

where r_{t+1} is the realized log return on crude oil from time $t-1$ to t, $x_{i,t}$ is a predictor available at time t, and $\varepsilon_{i,t+1}$ is a zero-mean error term. By replacing $x_{i,t}$ with $s_{i,t}$ from Equations (3), (5) and (7) yields the predictive model of crude oil returns based on the individual technical indicator variables. From the individual predictive forecasts, we then generate the combination forecasts as described in Section 3.2. We use the same forecast evaluation metrics detailed in Section 4.2.2. As before, the benchmark forecast is the random walk with drift (RW) forecast. As a special case, we also estimate a version of the model in (23) which excludes the economic and technical indicator variables and use only the lagged returns.

The out-of-sample forecasting for the three return series using their lagged as predictors are reported in Table 4. As can be seen only lagged *monthly average returns* have predictive power for next period returns. This is consistent with the significantly high first-order autocorrelation documented earlier. Not surprisingly, *end-of-month returns* and *filtered returns* have very low and almost first-order autocorrelation, respectively, display no statistical evidence of predictability from their lagged values.

Table 7 reports results for the forecasting models in Equation (23) and their combinations. As seen from the table, the predictive performance of the multivariate models of returns that include its own lagged value and the lagged values of each of the economic variables at a time improves substantially over the result reported in Table 5. The R^2_{oos} values for both the multivariate and combination forecasts are greater than 30% and significant at the 1% level based on the tests of equal predictive accuracy of Clark and West (2007). However, predictability is largely absent when we use *end-of-month returns.* Non of the multivariate and combination forecasts for *end-of-month returns* display significant forecasting ability.

The results based on the technical indicators are reported in Table 8. Again, all forecasts based on the *monthly average returns* display statistically significant predictive ability with improved results over those presented in Table 6. Predictability is, however, absent when we use *end-of-month returns* as the dependent variable in the forecasting models. All the multivariate and combination model forecasts of *end-of-month returns* fail to beat the RW forecast.

Figures 4, 5, 6 and 7 reinforce the results in Tables 7 and 8. Figures 4 and 6 report t-statistics computed recursively for the *monthly average returns* based on economic and technical indicator variables, respectively. As seen from graph, the t-statistics of the coefficient of lagged return in multiple regressions is well above the standard 2.0 cut-off required to proclaim results as significant, whereas the t-statistics on the lagged predictors are statistically insignificant. The t-statistics based on lagged returns and economic and technical indicator variables are statistically insignificant. The results are displayed in Figures 5 and 7.

Overall, our results show that whereas exploiting the presence of serial correlation in monthly average return magnifies the forecasting performance of the models relative to the RW model forecasts, such evidence is absent when we use *end-of-month returns* and *filtered returns* as the dependent variable in our forecasting models. The results confirm our earlier predictions that hypothesis that the spurious serial correlation and downward bias in the estimate of variance of crude oil returns, which is severe in the *monthly average returns*,is what partly accounts for the evidence of predictability reported in majority of the studies on crude oil return predictability.

[Insert Table 4 about here]

[Insert Table 7 about here]

[Insert Table 8 about here]

5. Conclusion

This study comprehensively re-examines the evidence of crude oil return predictability based on individual predictive regression models and forecast combination methods that pool information from a large set of 46 economic and technical indicator predictor variables. Existing studies that examine the predictability of crude oil returns use monthly averages of daily prices of WTI crude oil spot in computing returns. These studies find evidence of return predictability from time-varying forecasting models when compared to forecasts from a simple random walk with drift benchmark model. Following the convention in the return predictability literature, we examine oil return predictability using *end-of-month returns* and compare our results to the extant literature that uses *monthly average returns.*

Using WTI crude oil returns data from January 1987 to December 2017, we find that most of the individual economic and technical indicator variables and their combinations display statistically significant forecasting power for *monthly average returns* both in- and out-of-sample compared to forecast from a simple random walk with drift model consistent with the results in the extant literature. However, these conclusions are completely reversed when we use *end-of-month returns* as the dependent variables in our forecasting models. We attribute the differing inference about predictability for the two return series to the spurious first-order autocorrelation and the downward bias in estimates of variance and covariance induced by averaging leading to biased estimates of beta and associated standard errors. These findings are consistent with the studies of Working (1934, 1960), Schwert (1990) and Wilson et al. (2001). In addition, correcting returns for the effect of averaging using the filtering procedure in Schwert (1990) substantially weakens the evidence of predictability. The predictability that remains can be attributed to the bias in the estimates of covariance between returns and predictors that persists even after the correction.

As a further test of the effect of spurious autocorrelation on predictability, we estimate multivariate regression models with lagged oil return and each of the predictors at a time as independent variables. The results from this test shows that whereas exploiting the presence of serial correlation in *monthly average returns* substantially magnifies the forecasting performance of our models relative to the RW forecast, such evidence is still non-existent when we perform the same exercise with *end-of-month returns*. This confirms our hypothesis that the presence of serial correlation in monthly average crude oil returns, together with other biases, induced by averaging is what accounts for the evidence of predictability.

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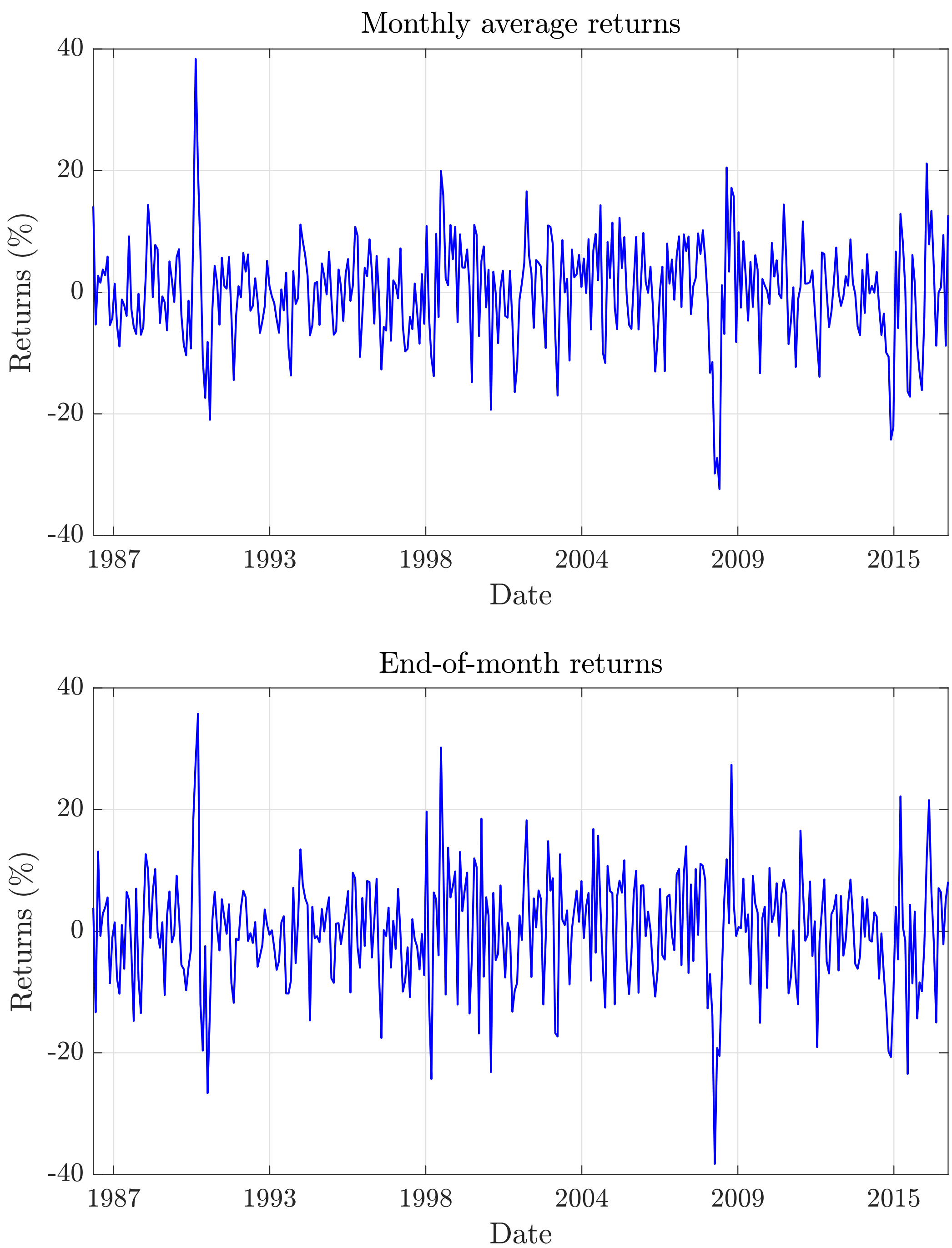
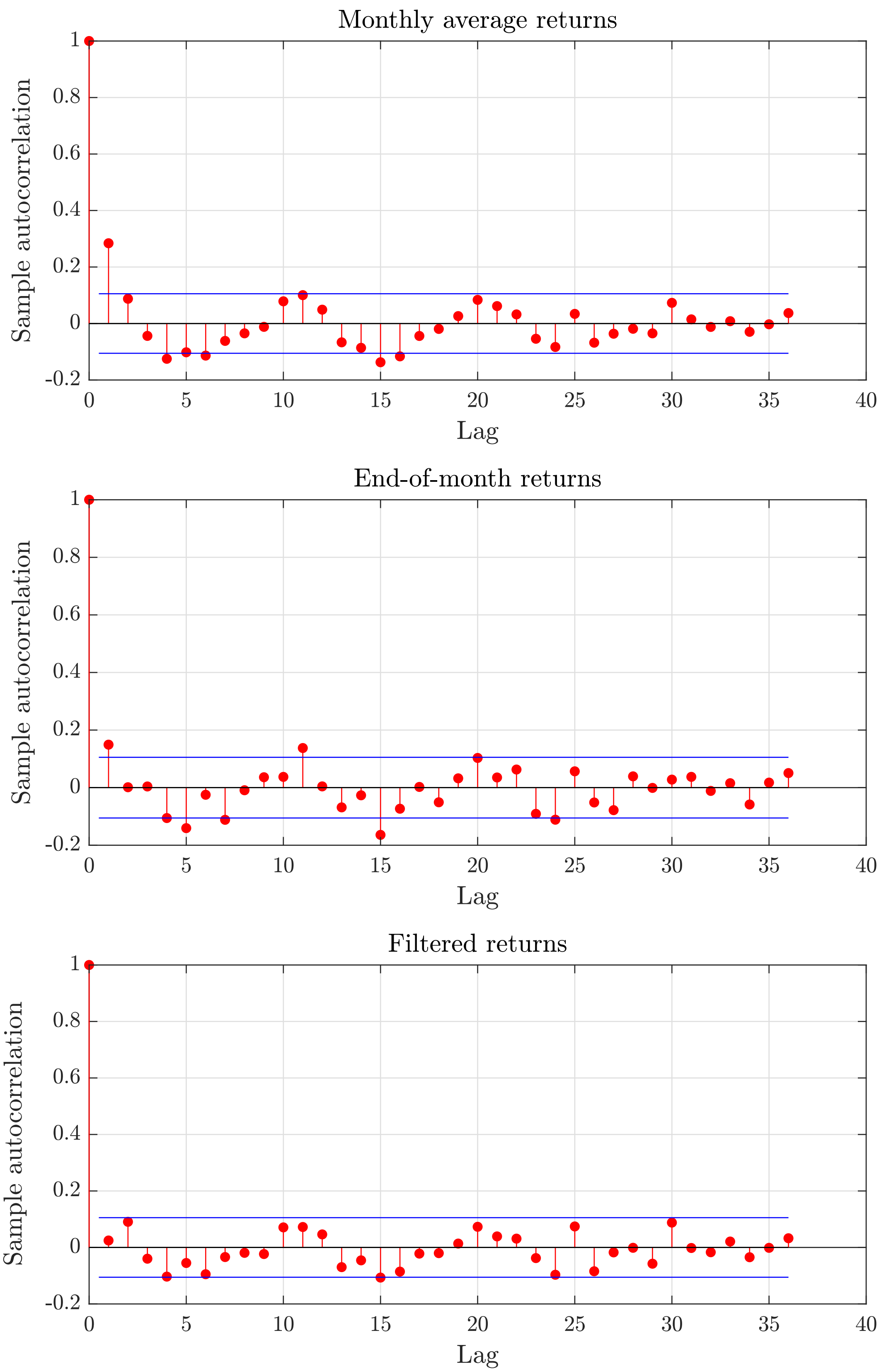
Figure 1: Crude Oil Returns



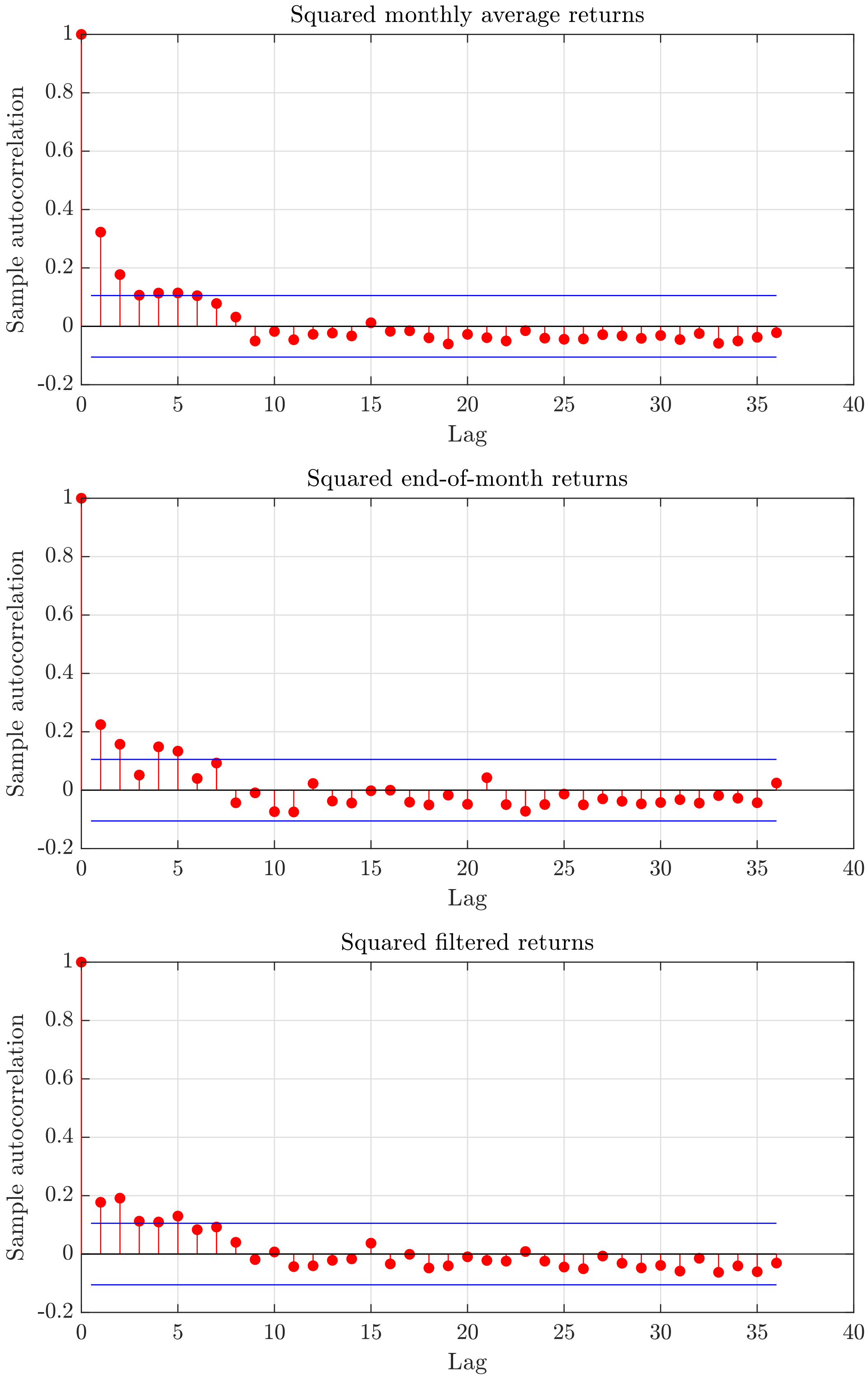
Notes. This figure plots the time series of monthly WTI crude oil returns (percentage terms) for two return series: average monthly and end-of-month returns, respectively. Average monthly returns are computed from monthly prices which are averages of daily prices. The end-of-month returns are computed using end-of-month prices. The sample period is from January 1987 to December 2016.

Figure 2: Sample Autocorrelation Function of Crude Oil Returns



Notes. This figure plots the the sample autocorrelation function of monthly WTI crude oil returns (in percent) for three return series: monthly average, end-of-month, and filtered returns. Monthly average returns are computed from monthly averages of daily prices, end-of-month returns from end-of-month prices, and filtered returns using the filtering procedure in Schwert (1990). The sample period is 1987:01-2016:12.

Figure 3: Sample Autocorrelation Function of Squared Crude Oil Returns



Notes. This figure plots the the sample autocorrelation function of squared monthly WTI crude oil returns (in percent) for three return series: monthly average, end-of-month, and filtered returns. Monthly average returns are computed from monthly averages of daily prices, end-of-month returns from end-of-month prices, and filtered returns using the filtering procedure in Schwert (1990). The sample period is 1987:01-2016:12.

Table 1: Price Series used in Computing Returns in the Return Predictability Literature

Article	Journal published	Price series used in computing returns	Evidence of Predictability
	Panel A: Crude oil return predictability		
Baumeister, Kilian, and Zhou (2018)	Macroeconomic Dynamics	Monthly average of daily prices	Yes
Zhang et al. (2018)	Energy Economics	Monthly average of daily prices	Yes
Wang et al. (2017)	Energy Economics	Monthly average of daily prices	Yes
Yin and Yang (2016)	Energy Economics	Monthly average of daily prices	Yes
Naser (2016)	Energy Economics	Monthly average of daily prices	Yes
Drachal (2016)	Energy Economics	Monthly average of daily prices	Yes
Wang et al. (2015)	Energy Economics	Monthly average of daily prices	Yes
Baumeister and Kilian (2015)	Journal of Business and Economic Statistics	Monthly average of daily prices	Yes
Baumeister and Kilian (2014)	International Economic Review	Monthly average of daily prices	Yes
Baumeister et al. (2014)	Enery Economics	Monthly average of daily prices	Yes
Alquist et al. (2013)	Handbook of Economic Forecasting	Monthly average of daily prices	No
Baumeister and Kilian (2012)	Journal of Business and Economic Statistics	Monthly average of daily prices	Yes
Alquist and Kilian (2010)	Journal of Applied Econometrics	End-of-month	No
Ye et al. (2006)	Energy Policy	Monthly average of daily prices	Yes
Ye, Zyren, and Shore (2005)	International Journal of Forecasting	Monthly average of daily prices	Yes
	Panel B: Other commodity return predictability		
Gargano and Timmermann (2014)	International Journal of Forecasting	End-of-month	Yes
Chinn and Coibion (2014)	Journal of Futures Markets	End-of-month	Yes
Acharya et al. (2013)	Journal of Financial Economics	End-of-month	Yes
Gorton et al. (2013)	Review of Finance	End-of-month	No
Hong and Yogo (2012)	Journal of Financial Economics	End-of-month	Yes
Chen et al. (2010)	The Quarterly Journal of Economics	End-of-month	Yes
Bessembinder and Chan (1992)	Journal of Financial Economics	End-of-month	Yes
	Panel C: Equity risk premium predictability literature		
Choi, Jacewitz, and Park (2016)	Journal of Econometrics	End-of-month	No
Rapach, Ringgenberg, and Zhou (2016)	Journal of Financial Economics	End-of-month	Yes
Neely et al. (2014)	Management Science	End-of-month	Yes
Rapach, Strauss, and Zhou (2013)	Journal of Finance	End-of-month	Yes
Ferreira and Santa-Clara (2011)	Journal of Financial Economics	End-of-month	Yes
Rapach et al. (2010)	Review of Financial Studies	End-of-month	Yes
Campbell and Thompson (2008)	The Review of Financial Studies	End-of-month	Yes
Welch and Goyal (2008)	Journal of Financial Economics	End-of-month	No
Lanne (2002)	The Review of and Economics Statistics	End-of-month	No
	Panel D: Bond return predictability		
Zhong and Wang (2018)	Journal of Empirical Finance	End-of-month	Yes
Lin et al. (2017)	Management Science	End-of-month	Yes
Sarno et al. (2016)	Journal of Empirical Finance	End-of-month	Yes
Lin, Wang, and Wu (2014)	Journal of Financial Markets	End-of-month	Yes
Greenwood and Hanson (2013)	The Review of Financial Studies	End-of-month	Yes
Ludvigson and Ng (2009)	The Review of Financial Studies	End-of-month	Yes
Cochrane and Piazzesi (2005)	American Economic Review	End-of-month	Yes
	Panel E: Currency return predictability		
Anatolyev, Gospodinov, Jamali, and Liu (2017)	Journal of Empirical Finance	End-of-month	Yes
Ahmed, Liu, and Valente (2016)	International Journal of Forecasting	End-of-month	No
Li et al. (2015)	Journal of Financial Econometrics	End-of-month	Yes
Levich and Potì (2015)	International Journal of Forecasting	End-of-month	Yes
Rossi (2013)	Journal of Economic Literature	End-of-month	Yes
Molodtsova and Papell (2009)	Journal of International Economics	End-of-month	No
Della Corte, Sarno, and Tsiakas (2008)	The Review of Financial Studies	End-of-month	Yes

Notes. This table list the articles on studies of return predictability across commodities, stock, bond and currency markets, the journals that published the articles, the prices series used in computing returns (monthly averages of daily prices or end-of-month prices) in the articles, and whether or not they found evidence of return predictability.

Table 2: Summary Statistics

Variable	Mean	Std. dev.	Skew	Kurt	Auto	Cov(y_1, x)	Cov(y_2, x)	Cov(y_3, x)
Panel A: Returns								
Monthly average (y_1)	0.107	8.282	−0.237	4.993	0.286***			
End-of-month (y_2)	0.087	9.161	−0.101	4.505	0.150**			
Filtered (y_3)	0.119	9.882	−0.001	4.274	0.025			
Panel B: Predictors (x)								
Panel B1: Economic variables								
Futures return	0.317	9.177	−0.147	4.592	0.156	54.729	83.931	64.648
Basis	−0.011	0.494	2.486	21.850	0.184	0.498	0.403	0.476
HP	4.067	9.516	0.563	3.167	0.882	13.570	14.653	16.124
PP	0.073	4.729	−0.010	4.827	−0.215	10.502	18.232	16.174
OI	0.784	6.741	0.279	5.718	−0.133	6.631	7.578	9.501
SCS	0.304	9.265	−0.126	4.592	0.162	55.518	84.818	65.412
GSS	−0.015	2.548	−0.645	10.403	−0.224	−0.496	2.254	−1.703
HSS	−0.009	1.991	1.541	21.658	−0.276	2.661	3.715	2.980
GOI	0.103	1.119	0.267	3.275	−0.051	−0.710	−0.805	−0.553
GOP	0.103	0.989	−0.560	9.768	−0.070	−0.761	−0.179	−0.960
AUS	0.022	3.339	−0.573	5.307	0.028	6.200	10.056	6.982
CAN	0.008	2.217	−0.606	8.084	−0.064	4.572	7.284	4.946
NZ	0.078	3.432	−0.446	5.095	−0.033	6.192	7.811	6.628
SA	−0.510	4.021	−0.448	4.491	0.018	6.594	7.270	6.331
S&P 500	0.715	4.325	−0.809	5.640	0.073	1.510	2.885	1.571
TBL	3.225	2.518	0.124	1.798	0.998	0.815	0.685	0.735
CTBL	−0.014	0.187	−1.069	5.997	0.476	0.170	0.229	0.163
YS	4.236	1.508	0.116	2.539	0.985	−0.918	−0.906	−0.874
DFY	0.975	0.385	3.081	16.730	0.962	−0.341	−0.267	−0.298
TMS1Y	0.343	0.269	0.062	2.846	0.944	−0.065	−0.093	−0.067
TMS2Y	0.621	0.500	0.165	1.785	0.982	−0.056	−0.038	−0.057
TMS5Y	0.549	0.422	0.236	1.930	0.984	−0.135	−0.155	−0.147
VIX	20.120	7.755	1.860	8.365	0.816	−7.351	−9.048	−7.208
REA	0.799	27.248	−0.111	4.792	0.947	22.358	18.632	18.492
BDI	0.088	18.663	−1.417	13.006	0.138	30.519	34.936	31.035
INFL	0.218	0.274	−1.176	10.929	0.410	0.174	0.042	−0.044
CAPUTIL	−0.018	0.743	−0.723	4.961	0.229	1.004	1.179	1.068
INDPRO	−0.053	2.194	−8.768	95.279	0.017	0.793	0.798	0.598

Table 2: *continued*

Variable	Mean	Std. dev.	Skew	Kurt	Auto	Cov(y_1, x)	Cov(y_2, x)	Cov(y_3, x)
				Panel B1: Technical indicator variables				
MA(1, 9)	55.556	49.760	−0.224	1.050	0.639	183.154	176.071	179.338
MA(1, 12)	56.389	49.659	−0.258	1.066	0.728	166.439	152.668	162.207
MA(2, 9)	56.667	49.623	−0.269	1.072	0.751	142.284	104.807	127.106
MA(2, 12)	58.611	49.321	−0.350	1.122	0.782	117.192	79.506	103.747
MA(3, 9)	57.500	49.503	−0.303	1.092	0.772	90.081	41.095	71.943
MA(3, 12)	57.500	49.503	−0.303	1.092	0.806	66.077	28.814	47.564
MOM(1)	53.889	49.918	−0.156	1.024	−0.031	217.869	349.762	267.145
MOM(2)	54.444	49.871	−0.178	1.032	0.315	270.462	263.338	288.747
MOM(3)	56.111	49.694	−0.246	1.061	0.537	213.713	198.499	203.033
MOM(6)	56.944	49.584	−0.280	1.079	0.659	150.368	139.273	151.460
MOM(9)	58.611	49.321	−0.350	1.122	0.656	92.429	103.990	89.828
MOM(12)	57.778	49.460	−0.315	1.099	0.697	122.135	118.317	123.612
VOL(1, 9)	59.167	49.221	−0.373	1.139	0.424	167.753	182.022	166.528
VOL(1, 12)	60.833	48.880	−0.444	1.197	0.545	159.945	157.998	159.432
VOL(2, 9)	58.889	49.272	−0.361	1.131	0.678	130.873	85.340	113.103
VOL(2, 12)	58.333	49.369	−0.338	1.114	0.794	114.931	91.840	103.146
VOL(3, 9)	58.056	49.415	−0.326	1.107	0.726	63.639	43.784	42.740
VOL(3, 12)	58.333	49.369	−0.338	1.114	0.840	79.780	62.358	65.642

Notes. This table reports the summary statistics for monthly WTI crude oil returns (in percent) and predictor variables (in percent) used in this article. We report the mean, standard deviation, skewness, kurtosis, and first-order autocorrelation (Auto), and the covariance between returns and the predictors. Returns are generated using monthly averages of daily prices (monthly average returns), end-of-month prices extracted from daily prices (end-of-month returns), and the returns corrected for autocorrelation and bias in variance estimates using the filtering procedure in Schwert (1990) (filtered returns). **, and *** indicate statistical significance at the 5% and 1% levels, respectively. The sample period is 1987:01-2016:12.

Table 3: In-sample Univariate Model Estimation Results

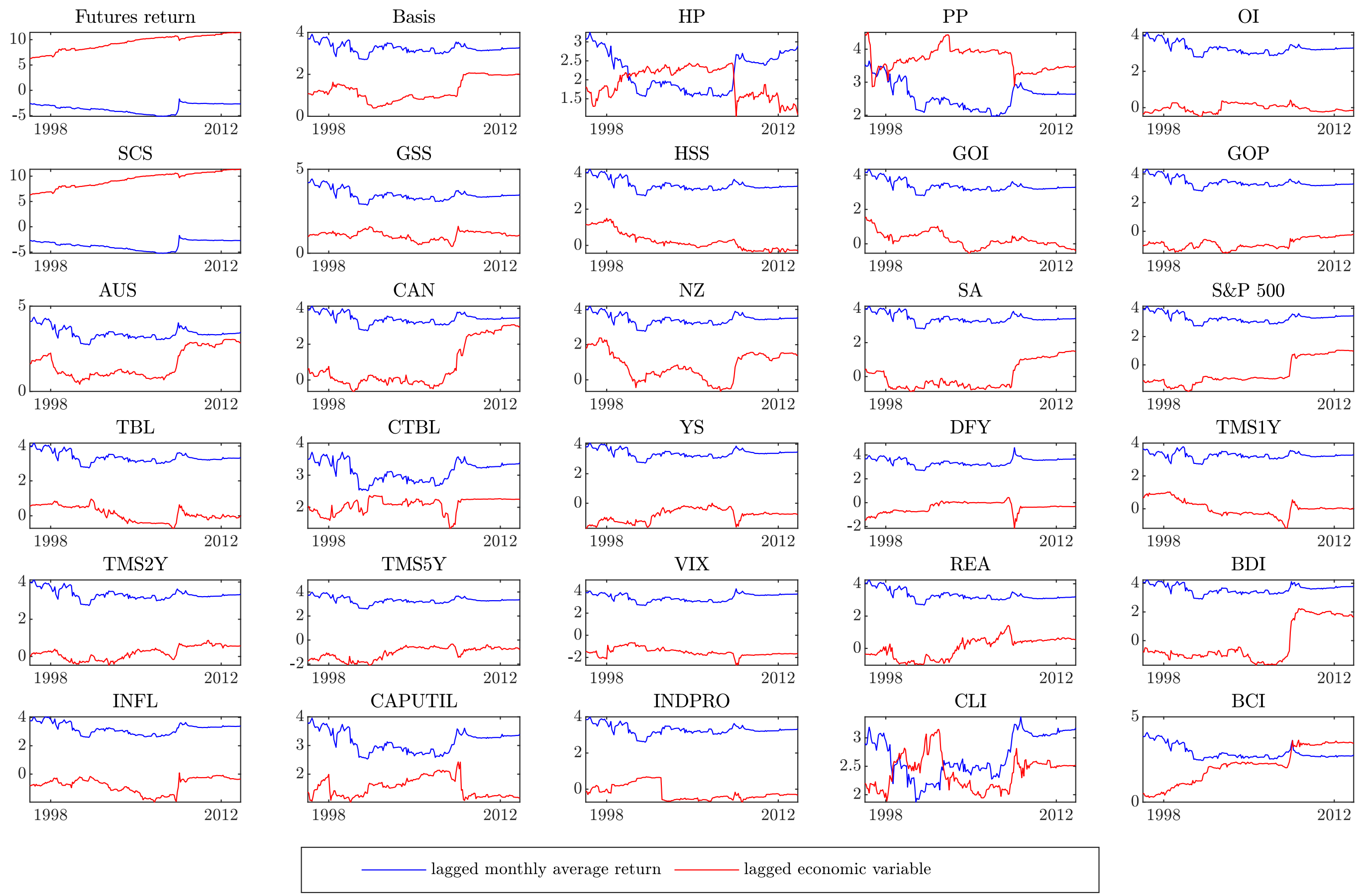
	Monthly average returns			End-of-month returns			Filtered returns		
Predictor	β	t-stats	R^2 (%)	β	t-stats	R^2 (%)	β	t-stats	R^2 (%)
Panel A: Economic variables									
Lagged return	0.30	4.45***	8.74	0.16	2.42**	2.67	0.03	0.39	0.07
Futures returns	0.54	11.09***	35.29	0.16	2.36**	2.54	0.47	7.58***	18.38
Basis	3.04	2.33**	3.22	2.50	2.03**	1.79	3.25	2.07**	2.58
HP	0.03	0.73	0.14	−0.04	−0.85	0.19	0.00	−0.05	0.00
PP	0.40	4.62***	5.14	0.16	1.59	0.68	0.31	2.91***	2.15
OI	0.05	0.79	0.18	0.00	0.02	0.00	0.01	0.12	0.00
SCS	0.54	11.04***	35.06	0.16	2.39**	2.59	0.46	7.51***	18.17
GSS	0.15	0.84	0.20	−0.29	−1.57	0.66	0.25	1.24	0.42
HSS	0.30	1.16	0.49	−0.10	−0.45	0.05	0.16	0.56	0.10
GOI	−0.12	−0.34	0.03	0.52	1.13	0.39	−0.04	−0.09	0.00
GOP	−0.56	−1.15	0.43	−1.16	−1.72	1.54	−0.43	−0.89	0.18
AUS	0.57	3.66***	5.08	0.19	1.01	0.45	0.53	3.01***	3.12
CAN	0.89	3.86***	5.57	0.20	0.82	0.24	0.83	3.10***	3.42
NZ	0.31	2.01**	1.61	0.04	0.27	0.03	0.23	1.31	0.61
SA	0.31	2.41**	2.21	0.12	0.81	0.26	0.28	1.90*	1.27
S&P 500	0.11	0.77	0.30	0.08	0.54	0.15	0.11	0.70	0.23
TBL	0.12	0.61	0.12	0.10	0.47	0.07	0.10	0.45	0.06
CTBL	7.58	2.49**	2.87	8.37	2.52**	2.89	8.18	2.40**	2.36
YS	−0.41	−1.09	0.55	−0.34	−0.95	0.31	−0.40	−0.91	0.36
DFY	−0.78	−0.38	0.13	−0.22	−0.12	0.01	−0.42	−0.17	0.03
TMS1Y	−0.27	−0.15	0.01	0.01	0.01	0.00	−0.11	−0.05	0.00
TMS2Y	0.01	0.01	0.00	0.08	0.07	0.00	0.09	0.08	0.00
TMS5Y	−1.11	−1.09	0.31	−1.00	−0.92	0.21	−1.13	−0.91	0.23
VIX	−0.13	−1.42	1.34	−0.10	−1.17	0.70	−0.12	−1.26	0.91
REA	0.01	0.64	0.17	0.01	0.45	0.07	0.01	0.36	0.05
BDI	0.08	2.48**	3.56	0.05	1.36	0.96	0.08	2.12**	2.22
INFL	0.60	0.28	0.04	0.12	0.06	0.00	0.86	0.34	0.06
CAPUTIL	0.88	1.10	0.61	0.18	0.22	0.02	0.56	0.60	0.18
INDPRO	−0.01	−0.08	0.00	0.04	0.26	0.01	−0.05	−0.35	0.01

Table 3: *continued*

Predictor	Monthly average returns			End-of-month returns			Filtered returns		
	β	t-stats	R^2 (%)	β	t-stats	R^2 (%)	β	t-stats	R^2 (%)
Panel B: Technical indicator variables									
MA(1, 9)	0.03	3.07***	2.63	0.00	−0.11	0.00	0.01	1.35	0.52
MA(1, 12)	0.03	3.26***	3.01	0.01	0.88	0.22	0.02	1.73*	0.86
MA(2, 9)	0.02	1.93*	1.10	0.00	0.01	0.00	0.01	0.74	0.16
MA(1, 12)	0.01	1.23	0.45	0.00	−0.36	0.04	0.00	0.24	0.02
MA(3, 9)	0.00	0.05	0.00	0.00	−0.35	0.03	−0.01	−0.68	0.13
MA(3, 12)	0.00	0.10	0.00	0.00	−0.27	0.02	0.00	−0.37	0.04
MOM(1)	0.07	8.44***	16.90	0.01	1.06	0.32	0.06	5.57***	8.09
MOM(2)	0.05	6.30***	10.19	0.01	1.19	0.39	0.04	3.36***	3.11
MOM(3)	0.04	4.42***	5.29	0.01	1.25	0.43	0.03	2.45**	1.67
MOM(6)	0.02	2.10**	1.29	0.00	−0.38	0.04	0.01	0.66	0.13
MOM(9)	0.02	1.90*	1.02	−0.01	−0.52	0.07	0.01	1.06	0.32
MOM(12)	0.02	2.60**	1.92	0.01	0.75	0.16	0.02	1.44	0.59
VOL(1, 9)	0.03	3.48***	3.62	0.00	0.01	0.00	0.02	1.95*	1.14
VOL(1, 12)	0.03	2.98***	2.78	0.01	0.50	0.08	0.02	1.53	0.74
VOL(2, 9)	0.01	1.26	0.48	0.00	−0.06	0.00	0.00	0.19	0.01
VOL(2, 12)	0.02	2.15	1.41	0.01	0.55	0.09	0.01	1.23	0.46
VOL(3, 9)	0.01	0.72	0.15	0.00	−0.20	0.01	0.00	0.33	0.03
VOL(3, 9)	0.01	1.43	0.62	0.00	0.37	0.04	0.01	0.85	0.21

Notes. This table reports the in-sample estimation results for the predictive regression models of crude oil returns and the predictor variables individually: $r_{t+1} = \alpha + \beta x_{i,t} + \varepsilon_{i,t+1}$, where r_{t+1} is the realized log crude oil return, $x_{i,t}$ is a predictor available at time, and $\varepsilon_{i,t+1}$ is a zero-mean error term. $x_{i,t}$ ($s_{i,t}$) is an economic (technical indicator) variable. Returns are generated using monthly averages of daily prices (monthly average returns), end-of-month prices extracted from daily prices (end-of-month returns), and the returns corrected for autocorrelation and bias in variance estimates using the filtering procedure in Schwert (1990) (filtered returns). To the right of the slope coefficient, β, is the the t-statistics calculated using Newey and West (1987) heteroskedasticity and autocorrelation consistent standard errors, and the R^2 statistics. Results are computed for the full sample period 1987:01-2016:12. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Figure 4: Plot of t-statistic of the coefficient of lagged returns and economic variables for monthly average crude oil returns

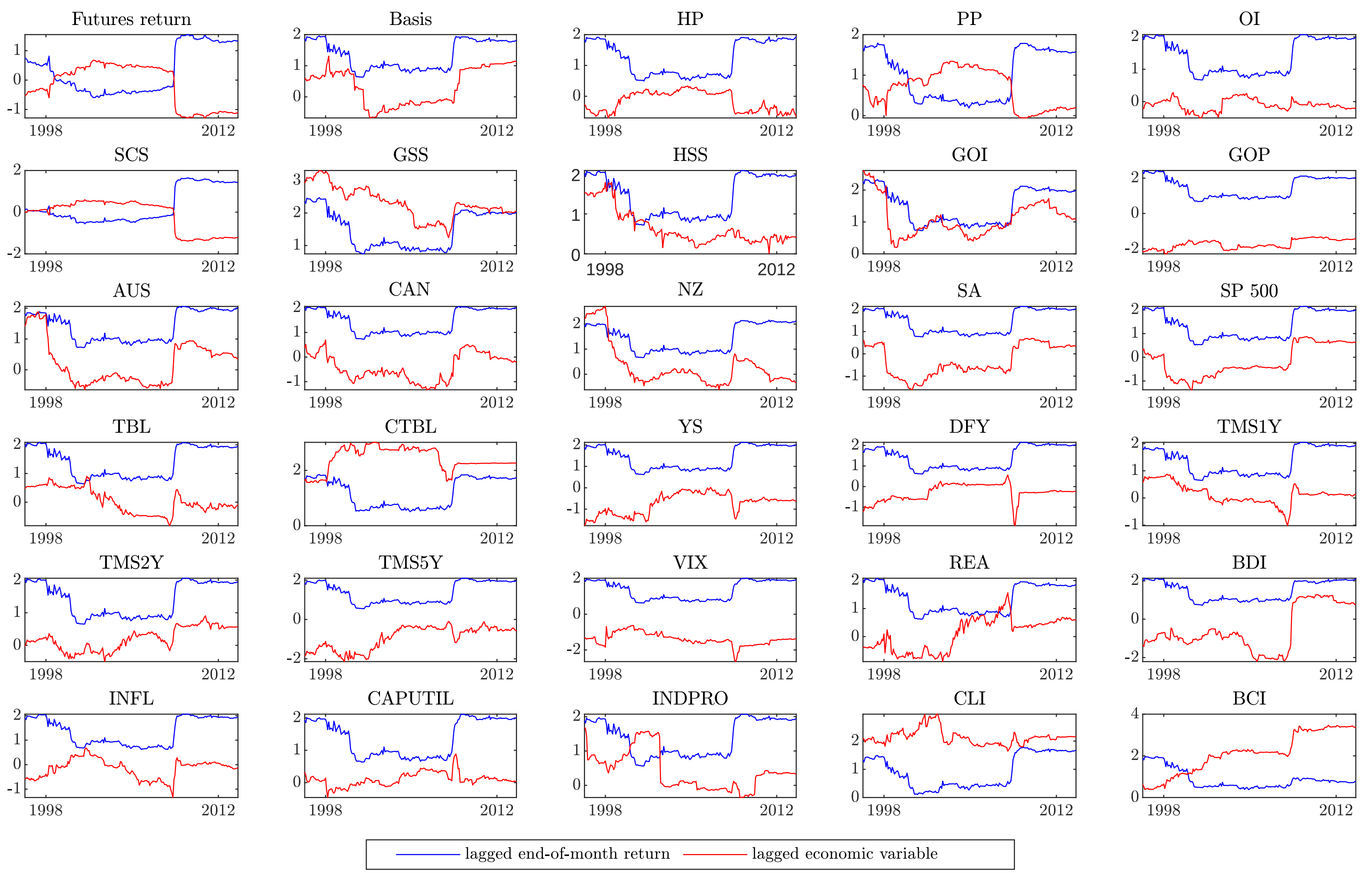


Notes. This figure plots the out-of-sample t-statistics of the coefficients of the independent variables in the following multiple predictive regression:

$$r_{t+1} = \alpha_i + \beta r_t + \gamma_i x_{i,t} + \varepsilon_{i,t+1},$$

where r_{t+1} is the realized log monthly average returns from time $t-1$ to t, $x_{i,t}$ is an economic available at time t, and $\varepsilon_{i,t+1}$ is a zero-mean error term. Results are reported for the full out-of-sample forecast evaluation period 1997:01-2013:12.

Figure 5: Plot of t-statistic of the coefficient of lagged returns and economic variables for end-of-month crude oil returns

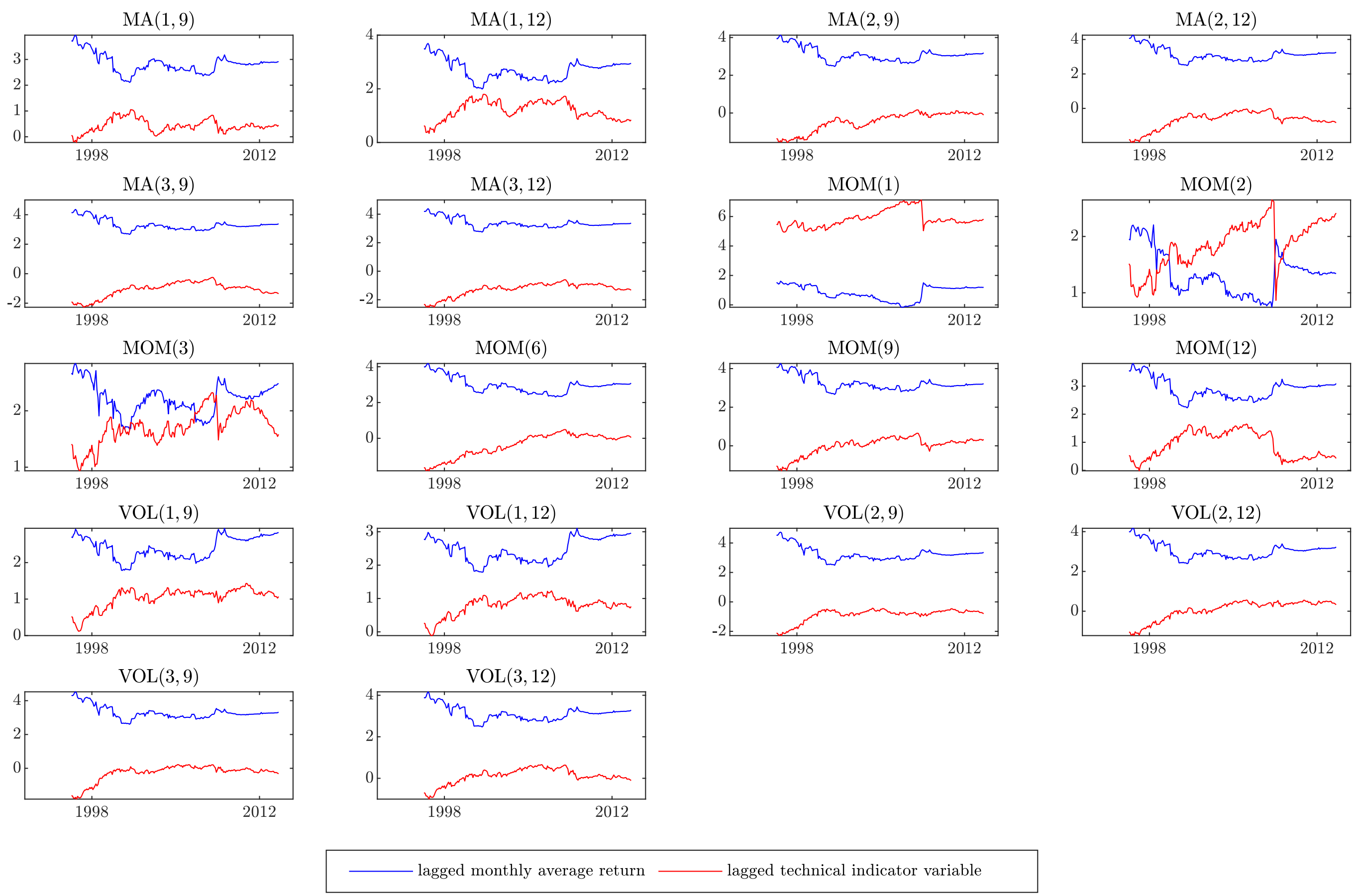


Notes. This figure plots the out-of-sample t-statistics of the coefficients of the independent variables in the following multiple predictive regression:

$$r_{t+1} = \alpha_i + \beta r_t + \gamma_i x_{i,t} + \varepsilon_{i,t+1},$$

where r_{t+1} is the realized log end-of-month returns from time $t-1$ to t, $x_{i,t}$ is an economic available at time t, and $\varepsilon_{i,t+1}$ is a zero-mean error term. Results are reported for the full out-of-sample forecast evaluation period 1997:01-2013:12.

Figure 6: Plot of t-statistic of the coefficient of lagged returns and technical indicator variables for monthly average crude oil returns

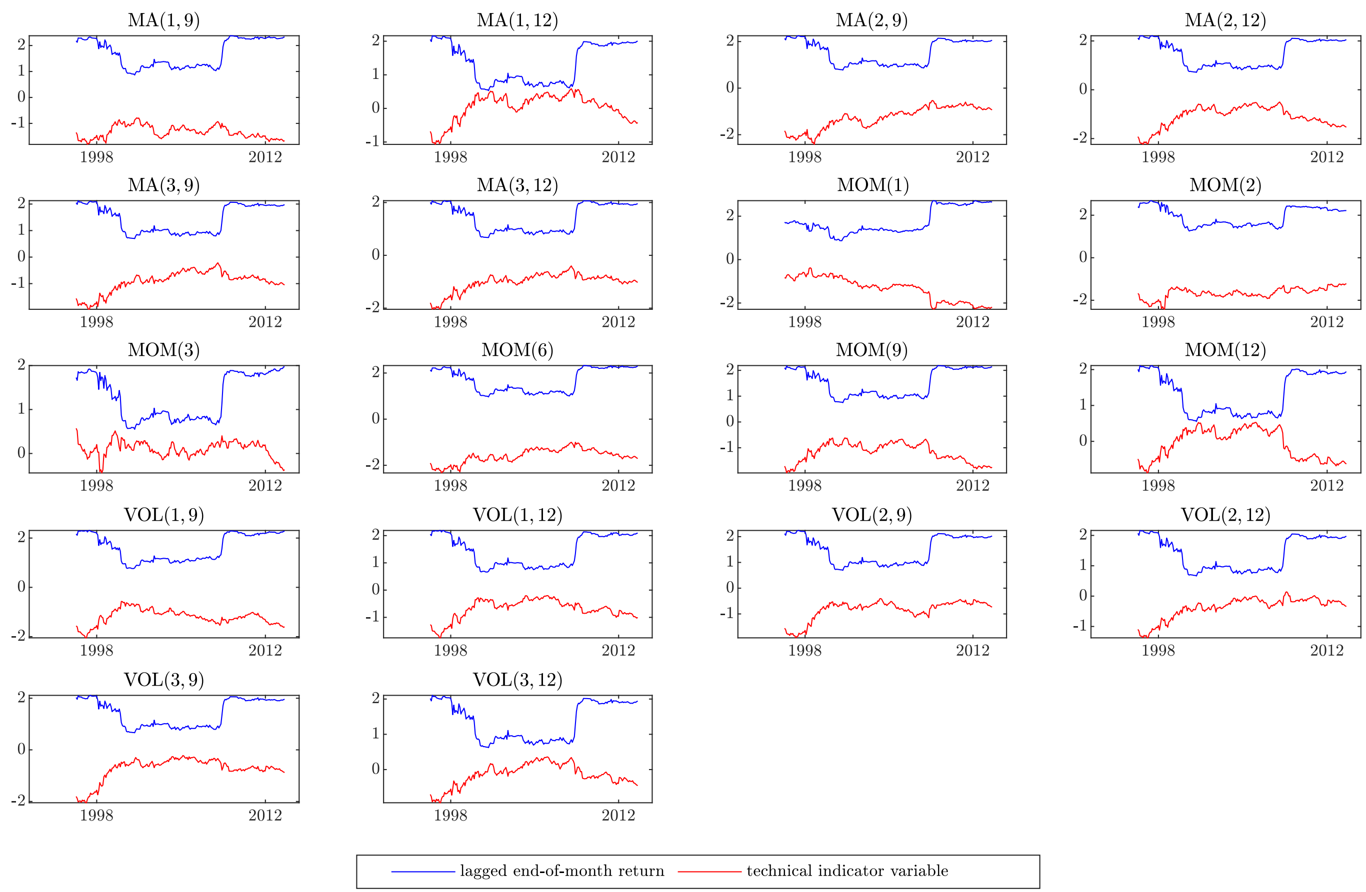


Notes. This figure plots the out-of-sample t-statistics of the coefficients of the independent variables in the following multiple predictive regression:

$$r_{t+1} = \alpha_i + \beta r_t + \gamma_i x_{i,t} + \varepsilon_{i,t+1},$$

where r_{t+1} is the realized log monthly average returns from time $t-1$ to t, $x_{i,t}$ is a technical indicator available at time t, and $\varepsilon_{i,t+1}$ is a zero-mean error term. Results are reported for the full out-of-sample forecast evaluation period 1997:01-2013:12.

Figure 7: Plot of t-statistic of the coefficient of lagged returns and technical indicator variables for end-of-month crude Oil Returns



Notes. This figure plots the out-of-sample t-statistics of the coefficients of the independent variables in the following multiple predictive regression:

$$r_{t+1} = \alpha_i + \beta r_t + \gamma_i x_{i,t} + \varepsilon_{i,t+1},$$

where r_{t+1} is the realized log end-of-month returns from time $t-1$ to t, $x_{i,t}$ is a technical indicator available at time t, and $\varepsilon_{i,t+1}$ is a zero-mean error term. Results are reported for the full out-of-sample forecast evaluation period 1997:01-2013:12.

Table 4: Statistical Evaluation of Monthly Real Crude Oil Return Predictability from lagged Returns

Predictor	RW forecast MSFE	Lagged return MSFE	R^2_{oos} (%)	MSFE-adjusted
Monthly average returns	75.51	71.38	5.47	2.58**
End-of-month returns	91.44	91.44	0.07	1.01
Filtered returns	112.75	112.78	−0.03	−0.01

Notes. This table reports out-of-sample results of log WTI crude oil returns based on lagged oil return. RW is the random walk with drift benchmark forecast. MSFE is the mean squared forecast error. The R^2_{oos} statistic measures the proportional reduction in MSFE for the competing forecasts given in the first column relative to the RW forecast. Statistical significance for the R^2_{oos} statistic is based on the p-value for the Clark and West (2007) MSFE-adjusted statistic. This statistic tests the null hypothesis that the RW forecast MSFE is less than or equal to the competing forecast MSFE against the alternative hypothesis that the HA forecast MSFE is greater than or equal to the competing forecast MSFE. Results are reported for the full out-of-sample evaluation period 1997:01-2016:12. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 5: Statistical Evaluation of Real Crude Oil Return Predictability from lagged Economic Variables

	Monthly average returns			End-of-month returns			Filtered returns		
Predictor	MSFE	R^2_{oos} (%)	MSFE-adjusted	MSFE	R^2_{oos} (%)	MSFE-adjusted	MSFE	R^2_{oos} (%)	MSFE-adjusted
RW	75.51			91.51			112.75		
Panel A: Individual predictive model forecasts									
Futures return	53.56	29.07	5.69***	91.46	0.05	0.96	99.43	11.81	4.20***
Basis	74.23	1.70	1.61*	90.61	0.98	1.13	111.76	0.87	1.41*
HP	76.79	−1.70	1.22	91.83	−0.35	−0.35	114.51	−1.56	−0.34
PP	73.47	2.69	2.84**	91.62	−0.13	0.45	114.52	−1.57	0.33
OI	75.61	−0.14	−0.28	91.89	−0.41	−1.65	113.13	−0.34	−1.42
SCS	53.82	28.72	5.67***	91.50	0.01	0.94	99.74	11.53	4.16***
GSS	77.26	−2.32	−1.44	91.17	0.36	1.06	114.83	−1.85	−0.98
HSS	75.37	0.18	0.55	91.76	−0.28	−0.36	113.04	−0.25	−0.84
GOI	75.78	−0.36	−0.89	92.14	−0.69	−0.51	113.40	−0.58	−2.16
GOP	75.67	−0.21	0.14	92.56	−1.15	0.17	112.99	−0.21	−0.18
AUS	72.03	4.61	2.60***	93.06	−1.69	−0.65	110.47	2.02	1.95*
CAN	71.23	5.67	3.20***	92.49	−1.07	−0.87	109.42	2.95	2.47**
NZ	75.30	0.27	1.11	93.87	−2.58	−1.56	113.60	−0.76	0.03
SA	74.25	1.67	2.29**	92.32	−0.89	−0.53	112.09	0.58	1.34*
S&P 500	76.96	−1.92	−0.44	92.30	−0.86	−0.22	114.43	−1.49	−0.54
TBL	76.39	−1.17	−1.34	92.44	−1.02	−1.51	113.92	−1.04	−1.65
CTBL	74.21	1.72	1.52*	89.69	1.98	1.88**	111.54	1.07	1.33*
YS	76.81	−1.72	−0.48	92.93	−1.55	−0.82	114.45	−1.51	−0.64
DFY	78.40	−3.83	−0.07	93.85	−2.57	−0.31	116.64	−3.45	−0.37
TMS1Y	76.13	−0.82	−0.75	92.17	−0.73	−1.02	113.62	−0.77	−1.04
TMS2Y	75.94	−0.58	−1.29	92.06	−0.61	−1.36	113.38	−0.56	−1.59
TMS5Y	76.74	−1.63	−0.32	92.85	−1.47	−0.60	114.31	−1.39	−0.50
VIX	75.38	0.17	0.57	92.02	−0.57	0.37	113.19	−0.39	0.37
REA	76.60	−1.45	−0.42	92.90	−1.52	−0.89	114.52	−1.57	−1.01
BDI	73.78	2.29	1.71**	92.91	−1.53	0.10	112.06	0.61	1.36*
INFL	76.61	−1.46	−0.29	92.59	−1.19	−1.10	114.15	−1.25	−0.93
CAPUTIL	76.21	−0.92	0.53	92.42	−0.99	−1.03	114.42	−1.48	−0.03
INDPRO	76.07	−0.74	−0.81	92.07	−0.61	−1.46	113.05	−0.27	−1.03
Panel B: Combination forecasts									
Mean	71.41	5.43	4.26***	91.55	−0.05	0.01	110.41	2.07	2.64***
Median	74.96	0.72	2.11**	91.55	−0.05	−0.25	112.60	0.13	0.69
Weighted mean	70.15	7.10	4.63***	91.55	−0.05	0.02	110.11	2.34	2.78***
DMSFE ($\theta = 0.9$)	70.17	7.07	4.12***	91.55	−0.05	0.03	110.67	1.84	2.41**
ABMA	72.34	4.19	3.86***	91.56	−0.06	0.01	110.68	1.83	2.49**
Subset (k = 2)	68.19	9.69	4.37***	91.71	−0.22	−0.01	108.69	3.60	2.72***
Subset (k = 3)	65.67	13.03	4.45***	91.94	−0.48	−0.04	107.45	4.70	2.77***
Subset (k = 4)	63.73	15.59	4.51***	92.24	−0.80	−0.06	106.61	5.44	2.79***
Subset (k = 5)	62.17	17.66	4.56***	92.58	−1.17	−0.08	106.01	5.98	2.83***
Subset (k = 6)	60.98	19.24	4.61***	92.99	−1.62	−0.12	105.70	6.25	2.84***
Subset (k = 7)	60.08	20.43	4.64***	93.43	−2.10	−0.15	105.53	6.40	2.86***
PC (IC = AIC)	61.99	17.90	4.66***	94.44	−3.21	0.00	109.08	3.25***	2.77
PC (IC = BIC)	62.45	17.30	4.61***	93.02	−1.65	0.17	110.44	2.05	2.37**
PC (IC = R^2)	61.61	18.41	4.71***	94.39	−3.15	0.14	108.87	3.44	2.82***

Notes. This table reports out-of-sample results for the individual and combination forecasts of log WTI crude oil returns based on 28 economic variables. RW is the random walk with drift benchmark forecast. MSFE is the mean squared forecast error. The R^2_{oos} statistic measures the proportional reduction in MSFE for the competing forecasts given in the first column relative to the RW forecast. Statistical significance for the R^2_{oos} statistic is based on the p-value for the Clark and West (2007) MSFE-adjusted statistic. This statistic tests the null hypothesis that the RW forecast MSFE is less than or equal to the competing forecast MSFE against the alternative hypothesis that the RW forecast MSFE is greater than or equal to the competing forecast MSFE. Results are reported for the full out-of-sample evaluation period 1997:01-2016:12. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 6: Statistical Evaluation of Monthly Real Crude Oil Return Predictability from lagged Technical Indicators

	Monthly average returns			End-of-month returns			End-of-month returns		
Predictor	MSFE	R^2_{oos} (%)	MSFE-adjusted	MSFE	R^2_{oos} (%)	MSFE-adjusted	MSFE	R^2_{oos} (%)	MSFE-adjusted
RW	75.51			91.51			112.75		
Panel A: Individual predictive model forecasts									
MA(1, 9)	73.93	2.08	2.11**	91.93	−0.47	−0.98	112.76	−0.01	0.31
MA(1, 12)	73.83	2.22	2.15**	91.78	−0.30	−0.24	112.59	0.14	0.66
MA(2, 9)	74.87	0.84	1.28	92.33	−0.90	−0.73	113.28	−0.47	−0.64
MA(2, 12)	75.63	−0.16	0.02	92.48	−1.07	−1.15	113.91	−1.04	−1.69
MA(3, 9)	76.12	−0.81	−1.68	92.28	−0.85	−0.93	113.75	−0.89	−0.76
MA(3, 12)	76.55	−1.38	−1.90	92.61	−1.21	−1.12	114.56	−1.61	−1.26
MOM(1)	65.12	13.75	6.04***	92.13	−0.68	−0.94	107.26	4.86	3.43***
MOM(2)	68.60	9.14	4.79***	91.63	−0.13	0.02	109.83	2.59	2.64***
MOM(3)	72.73	3.68	2.88***	92.16	−0.72	−0.50	112.24	0.45	1.12
MOM(6)	74.75	1.01	1.34*	92.37	−0.94	−0.54	113.48	−0.65	−0.71
MOM(9)	74.91	0.79	1.23	92.19	−0.74	−0.84	113.01	−0.23	−0.25
MOM(12)	74.68	1.09	1.54*	91.83	−0.35	−0.71	112.89	−0.13	0.30
VOL(1, 9)	73.29	2.94	2.51**	92.03	−0.58	−0.80	112.20	0.49	1.00
VOL(1, 12)	73.97	2.04	1.99**	91.95	−0.48	−1.92	112.65	0.09	0.49
VOL(2, 9)	75.72	−0.28	−0.16	92.72	−1.33	−1.33	114.17	−1.27	−1.56
VOL(2, 12)	74.53	1.29	1.63*	92.18	−0.74	−1.58	112.88	−0.12	0.04
VOL(3, 9)	76.16	−0.87	−1.58	92.93	−1.56	−1.80	113.85	−0.98	−2.25
VOL(3, 12)	75.31	0.26	0.68	92.07	−0.61	−2.03	113.12	−0.33	−0.62
Panel B: Combination forecasts									
Mean	72.83	3.55	3.52***	92.05	−0.59	−1.98	112.09	0.59	1.35*
Median	73.91	2.12	2.36**	92.13	−0.69	−1.62	112.62	0.11	0.42
Weighted mean	72.65	3.79	3.66***	92.05	−0.59	−1.98	112.05	0.62	1.40*
DMSFE ($\theta = 0.9$)	72.80	3.59	3.42***	92.19	−0.75	−2.76	112.31	0.39	0.97
ABMA	72.99	3.33	3.39***	92.04	−0.59	−1.98	112.12	0.56	1.31
Subset (k = 2)	71.19	5.71	4.16***	92.47	−1.05	−2.40	111.67	0.96	1.57*
Subset (k = 3)	70.04	7.24	4.47***	92.84	−1.45	−2.63	111.43	1.17	1.65*
Subset (k = 4)	69.27	8.26	4.62***	93.18	−1.83	−2.67	111.36	1.23	1.68*
Subset (k = 5)	68.79	8.90	4.70***	93.53	−2.21	−2.58	111.41	1.18	1.69*
Subset (k = 6)	68.51	9.27	4.75***	93.88	−2.59	−2.42	111.56	1.05	1.69*
Subset (k = 7)	68.36	9.47	4.78***	94.25	−3.00	−2.22	111.80	0.84	1.68*
PC (IC = AIC)	67.97	9.98	5.06***	92.64	−1.24	−1.95	112.17	0.51	1.71**
PC (IC = BIC)	68.20	9.67	4.71***	92.24	−0.80	−1.34	109.90	2.53	2.38**
PC (IC = R^2)	67.58	10.49	5.21***	93.34	−2.00	−2.66	111.14	1.42	2.21**

Notes. This table reports out-of-sample results for the individual and combination forecasts of log WTI crude oil returns based on 18 technical indicator variables. RW is the random walk with drift benchmark forecast. MSFE is the mean squared forecast error. The R^2_{oos} statistic measures the proportional reduction in MSFE for the competing forecasts given in the first column relative to the RW forecast. Statistical significance for the R^2_{oos} statistic is based on the p-value for the Clark and West (2007) MSFE-adjusted statistic. This statistic tests the null hypothesis that the RW forecast MSFE is less than or equal to the competing forecast MSFE against the alternative hypothesis that the HA forecast MSFE is greater than or equal to the competing forecast MSFE. Results are reported for the full out-of-sample evaluation period 1997:01-2016:12. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 7: Statistical Evaluation of Real Crude Oil Return Predictability from Lagged Returns and Economic Variables

	Monthly average returns			End-of-month returns		
Predictor	MSFE	R^2_{OOS} (%)	MSFE-adjusted	MSFE	R^2_{OOS} (%)	MSFE-adjusted
RW	75.51			91.51		
Panel A: Individual predictive model forecasts						
Futures return	50.67	32.90	6.72***	93.29	−1.95	0.70
Basis	70.68	6.39	2.79***	90.73	0.85	1.31
HP	72.23	4.34	2.79***	91.48	0.03	1.06
PP	71.88	4.80	3.14***	91.80	−0.33	0.88
OI	71.63	5.14	2.52**	91.69	−0.20	0.89
SCS	50.89	32.61	6.71***	91.72	−0.24	1.49*
GSS	72.56	3.91	2.39**	91.29	0.24	1.37*
HSS	71.58	5.20	2.54**	91.39	0.13	1.06
GOI	71.89	4.79	2.47**	92.34	−0.91	0.68
GOP	71.47	5.34	2.54**	92.47	−1.05	0.93
AUS	69.95	7.36	2.83***	92.97	−1.61	0.40
CAN	69.45	8.02	3.04***	92.43	−1.01	0.55
NZ	71.90	4.78	2.52**	93.43	−2.11	0.21
SA	71.25	5.63	2.67***	92.45	−1.03	0.67
S&P 500 return	72.33	4.21	2.47**	92.31	−0.88	0.64
TBL	72.07	4.56	2.44**	92.26	−0.83	0.61
CTBL	70.59	6.51	2.60***	89.94	1.71	1.84
YS	72.29	4.27	2.18**	92.55	−1.14	0.50
DFY	73.55	2.60	1.90**	93.29	−1.95	0.52
TMS1Y	71.91	4.76	2.52**	92.06	−0.61	0.72
TMS2Y	71.76	4.96	2.50**	91.97	−0.51	0.75
TMS5Y	72.22	4.35	2.31**	92.51	−1.10	0.59
VIX	71.59	5.19	2.08**	92.18	−0.73	0.78
REA	72.48	4.01	2.39**	92.86	−1.48	0.49
BDI	71.14	5.78	2.54**	93.33	−1.99	0.46
INFL	72.45	4.04	2.71***	92.48	−1.06	0.52
CAPUTIL	72.26	4.30	2.28**	92.16	−0.72	0.66
INDPRO	71.57	5.22	2.53**	91.78	−0.30	0.84
Panel B: Combination forecasts						
Mean	68.29	9.55	3.19***	91.59	−0.09	0.94
Median	71.20	5.70	2.61***	91.45	0.06	1.01
Weighted mean	67.14	11.08	3.44***	91.59	−0.09	0.94
DMSFE ($\theta = 0.9$)	67.34	10.82	3.39***	91.83	−0.36	0.81
ABMA	69.17	8.39	3.00***	91.59	−0.10	0.94
Subset (k = 2)	68.00	9.95	4.24***	91.63	−0.13	0.15
Subset (k = 3)	65.48	13.28	4.34***	91.84	−0.37	0.12
Subset (k = 4)	63.51	15.88	4.44***	92.12	−0.67	0.11
Subset (k = 5)	61.95	17.96	4.54***	92.46	−1.04	0.08
Subset (k = 6)	60.74	19.56	4.61***	92.84	−1.46	0.05
Subset (k = 7)	59.72	20.91	4.69***	93.23	−1.88	0.03
PC (IC = AIC)	61.71	18.27	5.00***	94.00	−2.72	0.23
PC (IC = BIC)	62.32	17.46	4.93***	93.19	−1.84	0.40
PC (IC = R^2)	61.20	18.95	5.08***	93.75	−2.46	0.42

Notes. This table reports out-of-sample results for the individual and combination forecasts of log WTI crude oil returns based on lagged oil return and 30 economic variables. RW is the random walk with drift benchmark forecast. MSFE is the mean squared forecast error. The R^2_{OOS} statistic measures the proportional reduction in MSFE for the competing forecasts given in the first column relative to the RW forecast. Statistical significance for the R^2_{OOS} statistic is based on the p-value for the Clark and West (2007) MSFE-adjusted statistic. This statistic tests the null hypothesis that the RW forecast MSFE is less than or equal to the competing forecast MSFE against the alternative hypothesis that the HA forecast MSFE is greater than or equal to the competing forecast MSFE. Results are reported for the full out-of-sample evaluation period 1997:01-2016:12. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 8: Statistical Evaluation of Monthly Real Crude Oil Return Predictability from lagged Returns and Technical Indicators

	Monthly average returns			End-of-month returns		
Predictor	MSFE	R^2_{oos} (%)	MSFE-adjusted	MSFE	R^2_{oos} (%)	MSFE-adjusted
RW	75.51			91.51		
Panel A: Individual predictive model forecasts						
MA(1, 9)	71.57	5.22	2.55**	91.43	0.08	1.16
MA(1, 12)	71.39	5.45	2.63***	91.96	−0.50	0.72
MA(2, 9)	72.21	4.37	2.38**	92.46	−1.04	0.61
MA(2, 12)	72.55	3.92	2.33**	92.45	−1.04	0.61
MA(3, 9)	72.14	4.47	2.50**	92.27	−0.83	0.70
MA(3, 12)	72.73	3.68	2.37**	92.52	−1.11	0.58
MOM(1)	65.64	13.07	5.35***	90.67	0.91	1.52*
MOM(2)	69.27	8.26	3.62***	92.32	−0.89	0.75
MOM(3)	71.14	5.79	2.81***	91.91	−0.45	0.75
MOM(6)	72.36	4.17	2.30**	91.92	−0.45	0.95
MOM(9)	71.73	5.00	2.47**	91.90	−0.43	0.92
MOM(12)	71.48	5.33	2.57**	91.97	−0.50	0.77
VOL(1, 9)	71.12	5.81	2.64***	92.11	−0.67	0.92
VOL(1, 12)	71.41	5.43	2.55**	92.48	−1.06	0.62
VOL(2, 9)	72.75	3.66	2.28**	92.73	−1.34	0.38
VOL(2, 12)	71.87	4.82	2.43**	92.44	−1.02	0.50
VOL(3, 9)	72.31	4.24	2.36**	92.79	−1.40	0.33
VOL(3, 12)	71.80	4.91	2.48**	92.15	−0.71	0.65
Panel B: Combination forecasts						
Mean	70.91	6.09	2.74***	91.88	−0.41	0.80
Median	71.45	5.37	2.57**	92.04	−0.59	0.71
Weighted mean	70.86	6.16	2.76***	91.88	−0.41	0.80
DMSFE ($\theta = 0.9$)	70.76	6.28	2.78***	92.30	−0.86	0.57
ABMA	71.01	5.96	2.71	91.88	−0.41	0.81
Subset (k = 2)	70.83	6.19	3.94***	92.25	−0.81	−1.55
Subset (k = 3)	69.73	7.65	4.16***	92.50	−1.09	−1.44
Subset (k = 4)	69.05	8.55	4.28***	92.72	−1.32	−1.26
Subset (k = 5)	68.66	9.06	4.36***	92.91	−1.53	−1.06
Subset (k = 6)	68.47	9.33	4.41***	93.10	−1.74	−0.85
Subset (k = 7)	68.41	9.40	4.45***	93.27	−1.93	−0.64
PC (IC = AIC)	68.83	8.84***	4.82	92.39	−0.97	0.65
PC (IC = BIC)	69.12	8.46***	4.35	92.50	−1.09	0.61
PC (IC = R^2)	68.37	9.45	4.97***	92.57	−1.16	0.60

Notes. This table reports out-of-sample results for the individual and combination forecasts of log WTI crude oil returns based on lagged oil return and 18 technical indicator variables. RW is the random walk with drift benchmark forecast. MSFE is the mean squared forecast error. The R^2_{oos} statistic measures the proportional reduction in MSFE for the competing forecasts given in the first column relative to the RW forecast. Statistical significance for the R^2_{oos} statistic is based on the *p*-value for the Clark and West (2007) MSFE-adjusted statistic. This statistic tests the null hypothesis that the RW forecast MSFE is less than or equal to the competing forecast MSFE against the alternative hypothesis that the HA forecast MSFE is greater than or equal to the competing forecast MSFE. Results are reported for the full out-of-sample evaluation period 1997:01-2016:12. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.