Forecasting Crude Oil Price Movements with Oil-Sensitive Stocks

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Abstract

This paper uses monthly data from 1984:M10 to 2012:M8 to show that oil-sensitive stock price indices, particularly those in the energy sector, have strong power in predicting nominal and real crude oil prices at short horizons (one-month-ahead predictions), using both in- and out-of-sample tests. In particular, the forecasts based on oil-sensitive stock price indices are able to outperform significantly the no-change forecasts. For example, using the NYSE Arca (AMEX) oil index as a predictor, the one-month-ahead forecasts for nominal crude oil prices reduce the mean squared prediction error by between 22% (for the West Texas Intermediate oil price) and 28% (for the Dubai oil price). Moreover, we find that the directional forecast based the AMEX oil index is significantly better than a 50:50 coin toss. The novelty of this analysis is that it proposes a new and valuable predictor that both reflects timely market information and is readily available for forecasting the spot oil price.

Keywords: oil-sensitive stock prices; oil prices; out-of-sample prediction

JEL classification: G17; Q43; Q47; C53

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1 Introduction

This paper uses monthly data from 1984:M10 to 2012:M8 to investigate the predictive content of oil-sensitive stock price indices for both nominal and real spot crude oil prices in both in- and out-of-sample tests. As stock prices are not subject to revision, the proposed variable, which reflects timely market information and is readily available, can potentially be a valuable predictor, and thereby help to improve the accuracy of forecasts of the price of crude oil.

Given that crude oil price is one of the key variables in forecasting macroeconomic aggregates, including real GDP and inflation (see the discussion in Kilian and Vigfusson (2011a,b, 2013) and Kilian and Lewis (2011)), the forecasting of crude oil prices has become the focus of many economists and decision makers (see Alquist et al. (2012)). The recent literature has already explored the forecasting ability of a number of predictors for the price of oil, including the oil futures price, oil inventories, the price of crack spread futures, the price of industrial raw materials (other than crude oil), the dollar exchange rate of major broad-based commodity exporters, U.S. and global macroeconomic aggregates, and expert survey forecasts (see Alquist and Kilian (2010), Ye et al. (2005, 2006), Murat and Tokat (2009), Reeve and Vigfusson (2011), Chen et al. (2010), Baumeister and Kilian (2012a,b, 2013), Alquist et al. (2012), and the references therein).

The novelty of this paper is to propose a new leading indicator, namely, oil-sensitive stock price indices, to forecast the price of crude oil instead. This predictor is motivated by the close link between the stock and oil markets already documented in the existing literature. Research into the oil price–stock price nexus has been increasing in recent years.[1] For

[1] Early studies analyzing the relationship between oil prices and stock market prices include Kling (1985), Jones and Kaul (1996), Sadorsky (1999), and El-Sharif et al. (2005).

example, see Driesprong et al. (2008), Nandha and Faff (2008), and Park and Ratti (2008). However, the relationship between oil prices and stock returns is unstable when one does not control for the composition of oil demand and supply shocks, as emphasized in recent work by Kilian and Park (2009). They show that the response of aggregate U.S. real stock returns may differ depending on whether the increase in the price of crude oil is driven by demand or supply shocks in the crude oil market. In other work, Apergis and Miller (2008) modify Kilian and Park (2009)'s methodology and investigate data from Australia and G7 countries. They find evidence that different oil market structural shocks play a significant role in explaining adjustments in stock returns, although the magnitude of such effects proves to be small. Elsewhere, Narayan and Sharma (2011) find evidence that lagged oil prices are able to forecast stock returns using returns for 560 U.S. companies listed on the New York Stock Exchange (NYSE), while Elyasiani et al. (2011) show that oil price fluctuations constitute systematic asset price risk at the industry level. Lastly, Scholtens and Yurtsever (2012) investigate the dynamic link between oil prices and stock returns at the industry level in the Eurozone and conclude that the oil–stock price relationship differs substantially across industries.

Most studies focus on predicting stock returns using oil prices, with only a few attempting to examine the predictive content of stock returns on the price of crude oil. Hammoudeh and Aleisa (2004) present evidence that the Saudi stock index can predict New York Mercantile Exchange (NYMEX) oil futures prices, while the empirical findings in Zhang and Wei (2011) suggest that stock market risk in some developed countries (the U.S., the U.K., and Japan) is able to forecast international crude oil returns constructed using the West Texas Intermediate (WTI) futures price.

However, to the best of our knowledge, no existing study examines the forecasting content of stock price indices on predicting spot oil prices via in- and out-of-sample tests. There are several reasons for considering stock prices as predictors of spot crude oil prices. First, as global stock markets have become more integrated, stock prices should be a reliable leading indicator of boom and bust in the economy, respectively resulting in the increasing and decreasing demand for oil. We thus expect stock prices to predict oil prices well. Furthermore, Kilian and Vega (2011) show that unlike stock prices, the price of WTI crude oil does not respond significantly to macroeconomic news in the U.S. within either the day or the month. Hence, in response to the same macroeconomic news, we expect a lead–lag relationship between stock prices and oil prices. In particular, we consider oil-sensitive stock price indices, which may be more informative in tracing future changes in crude oil prices. Finally, stock prices appear superior as a leading indicator because timely stock price data are readily available for forecasting purposes. As stock prices are not subject to revision, the proposed predictor can be used in real-time data forecasts and even extended to consider price data at higher frequencies. In this paper, we investigate oil price predictability in terms of both the nominal and real dollar prices of oil. We focus on forecasting nominal oil prices with nominal returns and on forecasting real oil prices with real returns. Just as nominal oil price forecasts are of great interest to decision makers, such as market traders and other economic agents, policy makers, such as central bankers, may also be concerned about forecasting the real price of oil.

In this paper, the in-sample tests are based on the *t*-test statistic from a one-month-ahead predictive regression model, while the out-of-sample prediction performance is measured using both the mean squared prediction error (MSPE) of the forecasts and their directional accuracy. We show that regardless of whether the forecasts are for the nominal or real dollar price of oil, energy sector stock price indices, including those for the NYSE

Arca (AMEX) Oil Index and the Morgan Stanley Capital International (MSCI) world energy sector indices (Energy, Energy Equipment & Services, and Oil & Gas) predict spot oil prices well and generally outperform the no-change forecast in pseudo out-of-sample forecast exercises. For example, the reduction in MSPE is shown to be between 22% and 28% for one-month-ahead prediction based on the AMEX oil index. Moreover, we find that the directional forecast is significantly better than tossing a coin. However, we also find that the transportation sector fails to provide informative content for the forecasting of crude oil prices. In general, the results are robust with respect to a variety of crude oil prices, including the WTI, the U.K. Brent, the Dubai, and the World Average. The findings of this paper are then of particular interest to market investors and policy makers, given that oil futures prices often fail to provide accurate predictions, as shown in Alquist et al. (2012).

The structure of the paper is as follows. Section 2 presents the empirical framework. Section 3 describes the data and the key empirical results. Section 4 provides some robustness checks. Finally, we offer a conclusion in Section 5.

2 Econometric Framework

2.1 In-Sample Predictive Regression Models

In this paper, we intend to use monthly data to investigate nominal (real) crude oil price predictability based on nominal (real) oil-sensitive stock prices. We consider the following one-month-ahead predictive regression model for in-sample tests:

$$y_{t+1} = \alpha + \beta x_t + u_{t+1}. \tag{1}$$

When investigating nominal oil price predictability, let $y_t = (op_t - op_{t-1})/op_{t-1}$ be the percentage change in nominal oil prices, where op_t is the spot crude oil price. Moreover, let $x_t = (sp_t - sp_{t-1})/sp_{t-1}$ be the nominal stock return, where sp_t is the stock price index. When the focus is on forecasting real prices of oil, we construct $y_t = (rop_t - rop_{t-1})/rop_{t-1}$ and $x_t = (rsp_t - rsp_{t-1})/rsp_{t-1}$, where $rop_t = op_t/cpi_t$ and $rsp = sp_t/cpi_t$ are real oil and real stock prices, respectively. The term cpi_t represents the U.S. consumer price index.

We conduct an in-sample test as a test of the null hypothesis of no predictive power for future oil price movements: $\beta = 0$ against the alternative hypothesis, $\beta \neq 0$. Thus, we evaluate the predictability of the stock return, x_t using a t-statistic corresponding to $\hat{\beta}$ with Newey–West heteroscedasticity and autocorrelation consistent (HAC) standard errors.

2.2 Out-of-Sample Forecasts

We now move focus to out-of-sample tests to evaluate oil price predictability. Instead of forecasting the percentage change in the oil price, the out-of-sample oil price predictability is now evaluated in terms of the (nominal or real) dollar price of oil as in Baumeister and Kilian (2012a,b, 2013) because the level of the oil price is the one that matters most in decision making.[2] The total sample of T observations is divided into in- and out-of-sample portions. There are R in-sample observations, $t = 1, ..., R$, and P out-of-sample observations, $t = R+1, ..., R+P$. Obviously, $R+P = T$. Consider the following predictive regression model for the percentage change in the nominal oil price:

$$y_{t+h} = \alpha + \beta x_t + u_{t+h}, \quad t = R, R+1, \ldots, T-h, \tag{2}$$

where:

$$y_{t+h} = \frac{op_{t+h} - op_t}{op_t}, \quad x_t = \frac{sp_t - sp_{t-1}}{sp_{t-1}}.$$

[2]The results are quantitatively similar when considering forecasts of the percentage change in the oil price.

The h-step-ahead pseudo out-of-sample forecast of the crude oil return is obtained by:

$$\hat{y}_{t+h} = \frac{\widehat{op}_{t+h} - op_t}{op_t} = \hat{\alpha}_t + \hat{\beta}_t x_t,$$

where $\hat{\alpha}_t$ and $\hat{\beta}_t$ are estimated by a recursive scheme. Hence, the forecast of the nominal spot price of crude oil is then constructed by:

$$\widehat{op}_{t+h} = (1 + \hat{\alpha}_t + \hat{\beta}_t x_t) \times op_t. \tag{3}$$

To forecast the real spot price of crude oil, we reconstruct y_{t+h} and x_t accordingly as:

$$y_{t+h} = \frac{rop_{t+h} - rop_t}{rop_t}, \quad x_t = \frac{rsp_t - rsp_{t-1}}{rsp_{t-1}}.$$

The forecast horizon h is 1, 3, 6, 9, and 12 months.

The benchmark for forecasts based on the price of oil-sensitive stock is provided by the no-change forecast (the driftless random walk model), which suggests that the best forecast of the spot oil price is simply the current spot price; that is:

$$\widehat{op}_{t+h} = op_t, \tag{4}$$

and

$$\widehat{rop}_{t+h} = rop_t, \tag{5}$$

for the nominal and real prices of oil, respectively.

To evaluate the out-of-sample forecasting accuracy, we use the MSPE as a measure of prediction performance. Letting $\mathcal{M}^{NC}$ and $\mathcal{M}^{SP}$ denote the no-change forecast and the predictive regression model based on the oil-sensitive stock price, respectively, we compute the MSPE ratio as:

$$\frac{\text{MSPE}(\mathcal{M}^{SP})}{\text{MSPE}(\mathcal{M}^{NC})}.$$

Clearly, if the oil-sensitive stock price has a lower MSPE than the no-change forecast, the MSPE ratio will be less than one. To assess whether the difference between MSPE($\mathcal{M}^{SP}$)

and MSPE($\mathcal{M}^{NC}$) is statistically significant, we formally test the null hypothesis of equal forecasting accuracy that MSPE($\mathcal{M}^{SP}$) = MSPE($\mathcal{M}^{NC}$) against the alternative hypothesis that the candidate model is more accurate than the no-change forecast: MSPE($\mathcal{M}^{SP}$) $<$ MSPE($\mathcal{M}^{NC}$), using the bootstrap Diebold and Mariano (1995) test statistic and the bootstrap Clark and West (2007) MSPE-adjusted test statistic.

In addition to examining the MSPE ratio, we also consider the directional accuracy of the forecasts, as measured by the success (hit) ratio indicating the relative frequency with which the predictive regression model based on the oil-sensitive stock price is able to predict correctly the sign of the change in the oil price. The success ratio is formally evaluated using the test proposed by Pesaran and Timmermann (2009).

3 Data and Empirical Results

3.1 Data

We employ monthly data from 1984:M10 to 2012:M8 given considerations of data availability. The oil-sensitive stock price index with the longest sample period available is the AMEX oil index, which is a price-weighted index of the leading companies involved in the exploration, production, and development of petroleum. The components of the index are listed in Table 1.[3]

Moreover, to show the usefulness of the oil-sensitive stock prices for forecasting crude oil prices, we use the S&P 500 price index for the purpose of comparison. Finally, as a sensitivity analysis, we have also considered the oil-sensitive stock prices obtained from the MSCI World Sector Indices, which are constructed using the Global Industry Classifi-

[3]We employ a series of stock returns without any adjustment for dividends and stock splits because the adjusted data for AMEX oil index are not available. We compute the return as the exact percentage change in the stock price.

cation Standard (GICS) with a shorter sample period starting from 1995:M1.[4] The MSCI World Index, covering over 6,000 securities in 24 developed markets and spanning large, medium, small and micro-cap securities, is generally considered representative of global market conditions. The oil-sensitive sectors that we include are: (1) Energy sector with subitems (1.1) Energy Equipment & Services and (1.2) Oil & Gas, as well as (2) Transportation sector with subitems (2.1) Air Freight & Logistics, (2.2) Airlines, (2.3) Marine, and (2.4) Road & Rail. The Energy Sector comprises companies whose businesses are dominated by energy activities:

1. Manufacturers of oil rigs and drilling equipment, and providers of drilling services.
2. Manufacturers of equipment for and providers of services to the oil and gas industry not classified elsewhere, including companies providing seismic data collection services.
3. Integrated oil companies engaged in the exploration, production, refinement, and distribution of oil and gas products.
4. Companies engaged in the exploration and production of oil and gas not classified elsewhere.
5. Companies engaged in the refining, marketing and/or transportation of oil and gas products.

The Transportation Sector comprises companies whose businesses are dominated by transportation activities:

1. Companies providing airfreight transportation, courier and logistics services, including package and mail delivery and customs agents.
2. Companies providing primarily passenger air transportation.
3. Companies providing goods or passenger maritime transportation.

[4]The MSCI World Sector Indices are not used for the baseline results because the sample span is smaller.

4. Companies providing primarily goods and passenger rail transportation.
5. Companies providing primarily goods and passenger land transportation, including vehicle rental and taxi companies.

We obtain the AMEX oil index, and the S&P 500 price index from Yahoo Finance. The MSCI World Sector Indices are from Datastream. The crude oil price data that we consider are for the prices of WTI, U.K. Brent, United Arab Emirates Dubai, and World Average oil, all of which are available from the International Financial Statistics (IFS) published by the International Monetary Fund. The world average crude price is an equal-weighted average of the U.K. Brent (light), Dubai (medium), and WTI prices. The U.S. consumer price index is from the Federal Reserve Economic Data (FRED). Table 2 details the variable names, data codes, and sample periods. The three measures of crude oil prices are shown in Figure 1. Figure 2 depicts the AMEX oil index and the S&P 500 price index, and 3 plots all of the MSCI world sector indices.

3.2 In-Sample Predictive Regression Results

The estimates of the predictive regression model in equation (1), including coefficient estimates, t-statistics, and p-values, are reported in Tables 3 and 4 for nominal and real prices of crude oil, respectively. The Newey–West HAC standard errors employ the Bartlett kernel. The truncation parameter m is determined by $m = 0.75T^{1/3}$, rounded to the nearest integer.

According to the baseline results, the estimates of β for the AMEX oil index are all positive and statistically significant, which suggests that higher values of oil-sensitive stock returns predict the higher growth rate of crude oil prices. Different forecasting objectives (nominal vs. real) and different measures of crude oil prices provide similar results. The positive dynamic correlation is consistent with our expectations. That is, as stock prices are strongly forward looking, expected positive shocks (for instance, good news about future global demand or macroeconomic conditions) that induce higher oil demand will increase current oil-sensitive stock returns and thus result in a higher oil price. That is, the empirical results presented here are dominated by the flow demand shock (shock to the amount of oil being consumed) discussed in Kilian and Park (2009) and Kilian and Murphy (2012a,b). The evidence of significant predictive power for future oil price movements is consistent with the findings of Kilian and Vega (2011) in that there is no systematic feedback from news about a wide range of U.S. macroeconomic aggregates to the price of oil between one day and one month, whereas stock prices incorporate information about future macroeconomic conditions instantaneously. Hence, in response to the same macroeconomic news, we should expect that the stock price leads the crude oil price and that such a lead–lag relationship may be more prominent when the stock considered is oil sensitive. As a comparison, we observe that the S&P 500, a non-oil-sensitive stock price index, does not have any significant in-sample predictive power.

Moreover, investigating each MSCI stock return in turn shows that the MSCI world energy sector indices (Energy, Energy Equipment & Services, and Oil & Gas) produce consistently strong results across the crude oil prices considered, while one of the transportation sector indices (Marine) provides somewhat weaker evidence. In contrast, three MSCI world transportation sector indices (Transportation, Air Freight & Logistics and Road & Rail) do not have significant predictive power. It is then natural to ask: why does the Energy sector provide strong predictive power while the Transportation sector does not, and under the Transportation sector, why does the Marine sector provide some predictive power while the Air Freight & Logistics and Road & Rail sectors do not? Possible explanations for the sectoral differences may be as follows. First, the companies comprising the Energy, Energy Equipment & Services, and the Oil & Gas sectors represent the supply side of the oil market, whereas the companies comprising Transportation industries mostly represent the demand side of the market. While on the one hand, future booms in global oil demand, which push up oil prices, may stimulate the stock prices of both the energy and transportation industries (positive impacts), on the other hand, we also expect the higher oil price to erode profits in transportation industries and thereby to lower their stock prices (negative impacts). Hence, the positive and negative effects may cancel each other out in the Transportation sector, and we may find that the Transportation sector as a whole has insignificant forecasting power. Moreover, within the Transportation sector, the reason that the Marine sector can better forecast spot oil prices may be because the transports of crude oil and refined product heavily rely on marine transportation, which suggests that the positive impact from increased oil demand may dominate the results for the Marine transportation sector.

Two other remarks are worth noting. First, we augment the simple predictive regression model in equation (1) with autoregressive terms to obtain an autoregressive distributed lag (ARDL) predictive regression model:

$$y_{t+1} = \alpha + \sum_{j=0}^{p} \beta_j x_{t-p} + \sum_{j=0}^{p} \gamma_j y_{t-p} + u_{t+1},$$

as a robustness check of the empirical results. We select the number of lags p using the Akaike Information Criterion. The in-sample predictive ability is assessed by testing H_0: $\beta_0 = 0$, and the findings are similar to those in Tables 3 and 4. Second, it is of interest to confirm whether the relationship between oil-sensitive stock prices and spot oil prices has changed over the sample periods that we consider in this analysis. The Andrews–Quandt tests developed by Andrews (1993) suggest no evidence of the presence of structural breaks at an unknown date within the sample period considered. Using the relationship between nominal WTI oil price and the nominal AMEX oil index as an example, the Andrews–Quandt test statistic is 5.12 with a p-value of 0.54, suggesting that we cannot reject the null hypothesis of no structural change .[5]

In sum, we find that oil-sensitive stock returns, particularly the U.S. AMEX Oil Index and the MSCI world energy sector provide useful information for forecasting the percentage changes in crude oil via in-sample predictive regressions. The empirical evidence on the predictability of the oil-sensitive stock is robust with respect to different forecasting objectives (nominal vs. real), different measures of crude oil prices, and different model specification. Moreover, the predictive relationship between the oil-sensitive stock return and the percentage change in the crude oil price is stable over time.

3.3 Out-of-Sample Forecasting Performance

We now turn to the evidence obtained from the out-of-sample forecasting tests. As well documented in the literature, in-sample predictability does not necessarily translate into out-of-sample forecasting ability (see Inoue and Kilian (2004)). Accordingly, we would like to appreciate whether the in-sample oil price predictability found above holds in an out-of-sample forecasting exercise.

Recall that R represents the sample size for in-sample estimation (model specification/estimation/training period), and P is the number of out-of-sample observations (model comparison/evaluation/validation period). The out-of-sample results are obtained by setting the out-of-sample period to 1991:M1–2012:M8, so that the starting date for the forecast evaluation matches what Alquist et al. (2012) and Baumeister and Kilian (2012b) use. Initially we use 75 observations to estimate the predictive regression model. The

[5] Detailed results supporting both of the above remarks are available upon request.

out-of-sample forecast results are obtained based on the recursive estimation scheme.[6]

Table 5 shows that at short horizons (one and three months), the forecasts for nominal crude oil price levels based on the AMEX oil index produce lower MSPEs than the no-change forecast. For example, the one-month-ahead forecasts for nominal crude oil prices reduce the MSPEs by between 22% (for the WTI price of oil) and 28% (for the Dubai price of oil). These results are statistically significant at the 5% level. For the three-month forecast horizon, the reductions in MSPE are somewhat smaller (between 5% and 8%), but still statistically significant. However, for the longer forecast horizons of 6, 9, and 12 months, the oil-sensitive stock price fails to beat the benchmark no-change forecast.

Regarding the accuracy of the directional forecasts, the success ratios are all superior to tossing a coin (50%) at all horizons considered. For example, the probability of correctly predicting the direction of change at horizons of 1, 3, 6, 9, and 12 months is 63%, 57%, 54%, 53%, and 53%, respectively, for the WTI price of oil, though statistically significant directional accuracy is only obtained at the one-month horizon. Different measures of the crude oil price provide similar evidence. According to the bottom panel in Table 5, the out-of-sample test results for real oil prices generally exhibit patterns similar to the results from forecasting the nominal price of oil. That is, we may conclude that the oil-sensitive stock price contains out-of-sample forecasting power for nominal as well as real prices of crude oil at short horizons (one month).

The empirical results from the MSCI indices with shorter sample span (limited to 1995:M1–2012:M8) are reported in Tables 6 and 7. The forecast evaluation period is 2002M1–2012M8 so that initially we have 84 observations to estimate the model parameters. Tables 6 and 7 show that for the one-month forecast horizon ($h = 1$), the MSCI world

[6]Using a rolling estimation scheme does not substantially alter the empirical results.

energy sector indices and the MSCI marine index outperform the no-change forecast with statistical significance in terms of the MSPE criterion and the forecasting performance of the directional change in the price of oil. These results are robust, regardless of whether the focus is on the nominal or real price of oil. However, the evidence supporting a forecast horizon longer than one month exhibits patterns similar to those obtained in Table 5 and indicates no predictive power as based on the MSCI indices.

In sum, we have found strong evidence that the U.S. AMEX Oil Index and the MSCI world energy sector stock price index help to forecast crude oil prices (nominal and real) out-of-sample at short horizons (one month).

4 Robustness Checks

To check the robustness of our empirical results, we consider the following modifications of the forecasting exercise. First, we consider different forecasting validation periods; i.e., different P/R ratios. Second, we include additional data in the form of the MSCI Energy Sector Indices for All Country World, Europe, and Emerging Markets. Finally, we include the oil futures–spot spread to see whether stock returns contain additional information beyond that in futures prices. In this section, we only report the results for the one-month-ahead forecasts ($h = 1$) as the model does not have significant predictive power for longer forecasting horizons, as shown previously.

4.1 Alternative Forecasting Validation Periods

In the baseline out-of-sample forecasting exercise, the forecast evaluation period is 1991:M1–2012:M8, which implies $P/R \approx 3.55$, where P is the number of out-of-sample observations and R is the sample size for the in-sample estimation. We now consider $P/R = 0.5$, 1.0, 1.5, 2.0, and 3.0, and thus the corresponding starting dates for the evaluation are 2003:M6, 1998:M11, 1996:M1, 1994:M3, and 1991:M11, respectively. Table 8 reports the results and shows that our earlier conclusions are robust with respect to different P/R ratios.

4.2 Alternative Stock Price Indices

We examined oil-sensitive stock returns using the MSCI World Sector Index, which only includes developed markets. To check for robustness, we further consider the following indices: (1) the MSCI All Country World Index (ACWI), which incorporates both developed and emerging countries, (2) the MSCI Europe Index, which measures the equity market performance of developed markets in Europe, and (3) the MSCI Emerging Markets (EM) Index, which covers over 2,700 securities in 21 markets currently classified as EM countries.

For the in-sample predictive regressions, we report the t-statistics for testing $\beta = 0$ in equation (1). For the out-of-sample forecasting tests, we report the MSPE ratio and the success ratio. The results reported in Tables 9 and 10 show that for both the in-sample predictive regressions and the out-of-sample forecast comparisons, our previous conclusions remain strong and significant.

4.3 Adding Information from Oil Futures Prices

As the prices of oil futures contracts are widely used in the existing literature to forecast future spot oil prices, we question whether the strong predictive power of oil-sensitive stock returns suggested in this analysis remain after accounting for the forecasting content in futures prices. That is, we would like to know what, if any, additional information oil-sensitive stock prices contain beyond the futures prices of crude oil. We consider the following regression model:

$$y_{t+1} = \alpha + \beta x_t + \theta \xi_t + u_{t+1}, \tag{6}$$

where $\xi_t = (f_{t,t+1} - op_t)/op_t$ represents the oil futures–spot spread, and $f_{t,t+1}$ denotes the current price of an oil futures contract that matures in one month (the one-month-ahead futures price). We use the NYMEX one-month-ahead crude oil futures price data for the WTI (Light-Sweet, Cushing, Oklahoma) available from the U.S. Energy Information Administration.

For forecasting the one-month-ahead nominal WTI price of oil using the AMEX oil index as a predictor from 1984:M10 to 2012:M8, we find that the t-statistics is 3.89 for the in-sample test. The MSPE ratio is 0.78, which suggests a 22% reduction in MSPE. The success ratio equals 0.62 and shows that the directional forecast is better than a coin toss. Both the MSPE and success ratios are statistically significant at the 5% level. Clearly, in both in- and out-of-sample tests, the AMEX oil index has strong predictive power for the spot oil price, even after conditioning on the price of oil futures contracts.

5 Conclusion

This paper focuses on the dynamic relationship between crude oil prices and oil-sensitive stock prices. We investigate the predictive content of oil-sensitive stock price indices for crude oil prices using in- and out-of-sample tests. The baseline findings with monthly data from 1984:M10 to 2012:M8 show that the AMEX oil index indeed provides useful information in forecasting crude oil prices via in-sample predictive regressions. Moreover, using both MSPE and directional forecast accuracy as criteria of forecasting performance, the AMEX oil index outperforms the no-change forecasts in the pseudo out-of-sample forecast exercises at horizon one (the one-month-ahead forecast). The MSPE reductions are between 22% to 28% for forecasting nominal oil price, while the reductions are up to 26% for forecasting real oil prices. Moreover, the one-month-ahead forecasts based on the AMEX oil index have higher directional accuracy than tossing a coin. Both the MSPE reductions and the directional accuracy are statistically significant. We have also examined the MSCI world sector indices with a shorter sample span from 1995:M1 to 2012:M8 as a sensitive analysis and found that the MSCI world energy sector indices (Energy, Energy Equipment & Services, and Oil & Gas) have strong in-sample and out-of-sample predictive power. However, the evidence also shows that the transportation sector stock price does not forecast oil prices well.

Our results are quite robust with respect to different measures of crude oil prices (WTI, Brent, Dubai, and World Average), a variety of model validation periods, diverse estimation schemes, and a range of sample periods. Finally, we find that oil-sensitive stock prices contain substantial additional information beyond that found in oil futures prices.

The novelty of the current paper is that it proposes a new and valuable predictor, which reflects timely market information and is readily available, for forecasting short-run oil price movements. As stock prices are not subject to revision, the proposed predictor can be used in real-time data forecasts and can be extended to incorporate even higher frequencies. The evidence provided in the current paper is thus of particular interest to market investors and policy makers given that oil futures prices typically fail to provide accurate predictions.

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Table 1: AMEX Oil Index Components

Company Name	Symbol
Anadarko Petroleum Corporation	APC
BP plc	BP
ConocoPhillips	COP
Chevron Corporation	CVX
Hess Corporation	HES
Marathon Oil Corporation	MRO
Occidental Petroleum Corporation	OXY
Petr	PBR
Phillips 66	PSX
Total SA	TOT
Valero Energy Corporation	VLO
Exxon Mobil Corporation	XOM

Table 2: Description of Data

Variables	Code	Source
Baseline (1984M10–2012M8)		
WTI	11176AAZZFM17	IFS
Brent	11276AAZZF...	IFS
Dubai	46676AAZZF...	IFS
World Average	00176AAZZF...	IFS
AMEX Oil Index	ˆXOI	Yahoo Finance
S&P 500	ˆGSPC	Yahoo Finance
U.S. Consumer Price Index	CPIAUCSL	FRED
MSCI World Sector Index (1995M1–2012M8)		
(1) Energy	M1DWE1$	Datastream
(1.1) Energy Equipment & Services	M3DWES$	Datastream
(1.2) Oil & Gas	M3DWOG$	Datastream
(2) Transportation	M2DWTR$	Datastream
(2.1) Air Freight & Logistics	M3DWAF$	Datastream
(2.2) Airlines	M3DWAL$	Datastream
(2.3) Marine	M3DWMA$	Datastream
(2.4) Road & Rail	M3DWRR$	Datastream

Table 3: In-sample Predictability of Nominal Oil Prices

	WTI			Brent		
	$\hat{\beta}$	t-stat	p-value	$\hat{\beta}$	t-stat	p-value
Baseline (1984:M10–2012:M8)						
AMEX Oil Index	0.43	3.95	**0.00**	0.48	3.95	**0.00**
S&P 500	0.01	0.07	0.95	0.03	0.14	0.89
MSCI (1995:M1–2012:M8)						
Energy	0.28	2.51	**0.01**	0.36	3.17	**0.00**
Energy Equip. & Services	0.22	2.82	**0.00**	0.27	3.28	**0.00**
Oil & Gas	0.26	2.36	**0.02**	0.34	3.03	**0.00**
Transportation	0.16	0.95	0.34	0.25	1.49	0.14
Air Freight & Logistics	0.05	0.46	0.65	0.09	0.80	0.43
Airlines	0.10	1.03	0.30	0.19	1.99	**0.05**
Marine	0.20	1.69	0.09	0.23	1.92	**0.05**
Road & Rail	0.03	0.19	0.85	0.10	0.63	0.53

	Dubai			Average		
	$\hat{\beta}$	t-stat	p-value	$\hat{\beta}$	t-stat	p-value
Baseline (1984:M10–2012:M8)						
AMEX Oil Index	0.51	4.53	**0.00**	0.47	4.20	**0.00**
S&P 500	0.03	0.15	0.88	0.02	0.11	0.92
MSCI (1995:M1–2012:M8)						
Energy	0.34	3.25	**0.00**	0.32	2.99	**0.00**
Energy Equip. & Services	0.25	3.33	**0.00**	0.25	3.17	**0.00**
Oil & Gas	0.33	3.11	**0.00**	0.31	2.85	**0.00**
Transportation	0.22	1.39	0.16	0.20	1.28	0.20
Air Freight & Logistics	0.09	0.83	0.41	0.08	0.69	0.49
Airlines	0.17	1.91	0.06	0.15	1.63	0.10
Marine	0.22	1.93	**0.05**	0.22	1.87	0.06
Road & Rail	0.07	0.47	0.64	0.06	0.42	0.67

Note: The predictive regression model is $y_{t+1} = \alpha + \beta x_t + u_{t+1}$, where y_t is the percentage change in nominal crude oil prices, and x_t represents the nominal oil-sensitive stock return. Values in bold type indicate statistical significance at the 5% level; 0.00 indicates the value is smaller than 0.005.

Table 4: In-sample Predictability of Real Oil Prices

	WTI			Brent		
	$\hat{\beta}$	t-stat	p-value	$\hat{\beta}$	t-stat	p-value
Baseline (1984:M10–2012:M8)						
AMEX Oil Index	0.42	4.00	**0.00**	0.47	4.03	**0.00**
S&P 500	0.00	0.03	0.98	0.02	0.12	0.90
MSCI (1995:M1–2012:M8)						
Energy	0.26	2.41	**0.02**	0.34	3.15	**0.00**
Energy Equip. & Services	0.21	2.79	**0.01**	0.26	3.29	**0.00**
Oil & Gas	0.24	2.23	**0.03**	0.33	3.00	**0.00**
Transportation	0.14	0.89	0.37	0.24	1.50	0.13
Air Freight & Logistics	0.04	0.40	0.69	0.09	0.79	0.43
Airlines	0.09	1.00	0.32	0.18	2.01	**0.04**
Marine	0.20	1.71	0.09	0.23	1.96	**0.05**
Road & Rail	0.01	0.06	0.95	0.09	0.58	0.56

	Dubai			Average		
	$\hat{\beta}$	t-stat	p-value	$\hat{\beta}$	t-stat	p-value
Baseline (1984:M10–2012:M8)						
AMEX Oil Index	0.49	4.64	**0.00**	0.45	4.29	**0.00**
S&P 500	0.02	0.11	0.91	0.01	0.08	0.94
MSCI (1995:M1–2012:M8)						
Energy	0.32	3.22	**0.00**	0.30	2.95	**0.00**
Energy Equip. & Services	0.24	3.32	**0.00**	0.24	3.17	**0.00**
Oil & Gas	0.31	3.07	**0.00**	0.29	2.79	**0.01**
Transportation	0.20	1.37	0.17	0.19	1.25	0.21
Air Freight & Logistics	0.09	0.80	0.43	0.07	0.66	0.51
Airlines	0.16	1.91	0.06	0.14	1.63	0.10
Marine	0.22	1.96	**0.05**	0.21	1.90	0.06
Road & Rail	0.05	0.38	0.70	0.05	0.33	0.74

Note: The predictive regression model is $y_{t+1} = \alpha + \beta x_t + u_{t+1}$, where y_t is the percentage change in real crude oil prices, and x_t represents the real oil-sensitive stock return. Values in bold type indicate statistical significance at the 5% level; 0.00 indicates that the value is smaller than 0.005.

Table 5: Out-of-sample Predictability Test Results: The AMEX oil Index as the Predictor

	Forecasting Nominal Crude Oil Prices							
	WTI		Brent		Dubai		Average	
Horizon	MSPE Ratio	Success Ratio	MSPE Ratio	Success Ratio	MSPE Ratio	Success Ratio	MSPE Ratio	Success Ratio
$h = 1$	**0.78**	**0.63**	**0.76**	**0.62**	**0.72**	**0.61**	**0.74**	**0.63**
3	**0.95**	0.57	**0.94**	0.57	**0.92**	0.60	**0.94**	0.57
6	1.02	0.54	1.01	0.56	1.00	0.55	1.01	0.55
9	1.04	0.53	1.01	0.55	1.01	0.56	1.02	0.54
12	1.04	0.53	0.99	0.54	0.98	0.58	1.00	0.56
	Forecasting Real Crude Oil Prices							
	WTI		Brent		Dubai		Average	
Horizon	MSPE Ratio	Success Ratio	MSPE Ratio	Success Ratio	MSPE Ratio	Success Ratio	MSPE Ratio	Success Ratio
$h = 1$	**0.80**	**0.62**	**0.79**	**0.65**	**0.74**	**0.63**	**0.77**	**0.63**
3	**0.95**	0.54	**0.94**	0.53	**0.93**	0.55	**0.94**	0.52
6	1.01	0.52	1.00	0.51	0.99	0.51	1.00	0.52
9	1.03	0.54	1.01	0.55	1.00	0.58	1.01	0.57
12	1.03	0.58	0.99	0.58	0.98	0.57	1.00	0.57

Note: The forecast evaluation period is 1991:M1–2012:M8, and the initial estimation window is 1984:M10–1990:M12. A recursive estimation scheme is used. The MSPE ratio represents $\frac{\text{MSPE}(\mathcal{M}^{SP})}{\text{MSPE}(\mathcal{M}^{NC})}$, where $\mathcal{M}^{NC}$ and $\mathcal{M}^{SP}$ denote the no-change forecast and the predictive regression model based on the oil-sensitive stock price, respectively. The success ratio is constructed using the proportion of forecasts that correctly predict the sign of the change in the oil price. The statistical significance of the MSPE ratio is inferred from pairwise tests of the null hypothesis of equal predictive accuracy with the no-change forecast. Values in bold type designate that both the bootstrap Diebold–Mariano test and bootstrap Clark–West test statistics indicated statistical significance at the 5% level. The sign test for the success ratio is based on Pesaran and Timmermann (2009). The values in bold type again indicate statistical significance at the 5% level.

Table 6: Out-of-sample Predictability Test Results: The MSCI Sector Indices as the Predictors

	Forecasting Nominal Crude Oil Prices (Forecasting Horizon h = 1)							
	WTI		Brent		Dubai		Average	
Horizon	MSPE Ratio	Success Ratio	MSPE Ratio	Success Ratio	MSPE Ratio	Success Ratio	MSPE Ratio	Success Ratio
MSCI (1995:M1–2012:M8)								
Energy	**0.90**	**0.66**	**0.86**	**0.68**	**0.84**	**0.69**	**0.86**	**0.66**
Energy Equip. & Services	**0.89**	0.64	**0.85**	0.62	**0.83**	**0.66**	**0.85**	**0.65**
Oil & Gas	**0.91**	**0.66**	**0.87**	**0.66**	**0.86**	**0.69**	**0.88**	**0.67**
Transportation	1.00	0.60	0.97	0.60	0.98	0.63	0.98	0.61
Air Freight & Logistics	1.04	0.63	1.02	0.60	1.02	0.63	1.03	0.61
Airlines	1.02	0.66	1.01	0.59	1.00	0.66	1.01	0.64
Marine	**0.96**	0.63	**0.94**	0.60	**0.93**	0.63	**0.94**	0.63
Road & Rail	1.04	0.58	1.01	0.59	1.03	0.59	1.03	0.59

Note: The forecast evaluation period is 1991:M1–2012:M8, and the initial estimation window is 1984:M10–1990:M12. A recursive estimation scheme is used. The MSPE ratio represents $\frac{\text{MSPE}(\mathcal{M}^{SP})}{\text{MSPE}(\mathcal{M}^{NC})}$, where $\mathcal{M}^{NC}$ and $\mathcal{M}^{SP}$ denote the no-change forecast and the predictive regression model based on the oil-sensitive stock price, respectively. The success ratio is constructed using the proportion of forecasts that correctly predict the sign of the change in the oil price. The statistical significance of the MSPE ratio is inferred from pairwise tests of the null hypothesis of equal predictive accuracy with the no-change forecast. Values in bold type designate that both the bootstrap Diebold–Mariano test and bootstrap Clark–West test statistics indicated statistical significance at the 5% level. The sign test for the success ratio is based on Pesaran and Timmermann (2009). The values in bold type again indicate statistical significance at the 5% level.

Table 7: Out-of-sample Predictability Test Results: The MSCI Sector Indices as the Predictors

	Forecasting Real Crude Oil Prices (Forecasting Horizon h = 1)							
	WTI		Brent		Dubai		Average	
Horizon	MSPE Ratio	Success Ratio	MSPE Ratio	Success Ratio	MSPE Ratio	Success Ratio	MSPE Ratio	Success Ratio
MSCI (1995:M1–2012:M8)								
Energy	**0.91**	**0.65**	**0.87**	**0.63**	**0.86**	**0.66**	**0.87**	**0.65**
Energy Equip. & Services	**0.89**	0.62	**0.86**	**0.62**	**0.84**	**0.66**	**0.86**	**0.65**
Oil & Gas	**0.92**	**0.65**	**0.88**	**0.66**	**0.87**	**0.68**	**0.89**	**0.66**
Transportation	1.00	0.58	0.97	0.58	0.98	0.61	0.98	0.59
Air Freight & Logistics	1.03	0.59	1.02	0.58	1.02	0.60	1.02	0.59
Airlines	1.02	0.59	1.01	0.53	1.00	0.58	1.01	0.55
Marine	**0.96**	0.62	**0.94**	0.60	**0.93**	0.66	**0.94**	0.62
Road & Rail	1.04	0.54	1.01	0.56	1.03	0.55	1.03	0.54

Note: The forecast evaluation period is 1991:M1–2012:M8, and the initial estimation window is 1984:M10–1990:M12. A recursive estimation scheme is used. The MSPE ratio represents $\frac{\text{MSPE}(\mathcal{M}^{SP})}{\text{MSPE}(\mathcal{M}^{NC})}$, where $\mathcal{M}^{NC}$ and $\mathcal{M}^{SP}$ denote the no-change forecast and the predictive regression model based on the oil-sensitive stock price, respectively. The success ratio is constructed using the proportion of forecasts that correctly predict the sign of the change in the oil price. The statistical significance of the MSPE ratio is inferred from pairwise tests of the null hypothesis of equal predictive accuracy with the no-change forecast. Values in bold type designate that both the bootstrap Diebold–Mariano test and bootstrap Clark–West test statistics indicated statistical significance at the 5% level. The sign test for the success ratio is based on Pesaran and Timmermann (2009). The values in bold type again indicate statistical significance at the 5% level.

Table 8: Robustness Check: Out-of-sample Predictability Test Results based on the AMEX Oil Index with Different P/R Ratio

	Forecasting Nominal Crude Oil Prices (Forecasting Horizon $h = 1$)							
	WTI		Brent		Dubai		Average	
Horizon	MSPE Ratio	Success Ratio	MSPE Ratio	Success Ratio	MSPE Ratio	Success Ratio	MSPE Ratio	Success Ratio
$P/R = 0.5$	**0.76**	**0.73**	**0.74**	**0.70**	**0.69**	**0.72**	**0.72**	**0.74**
$P/R = 1.0$	**0.77**	**0.67**	**0.76**	**0.66**	**0.71**	**0.67**	**0.74**	**0.67**
$P/R = 1.5$	**0.77**	**0.65**	**0.76**	**0.64**	**0.71**	**0.63**	**0.74**	**0.66**
$P/R = 2.0$	**0.78**	**0.64**	**0.76**	**0.62**	**0.71**	**0.61**	**0.74**	**0.64**
$P/R = 3.0$	**0.78**	**0.63**	**0.76**	**0.62**	**0.71**	**0.61**	**0.74**	**0.63**
	Forecasting Real Crude Oil Prices (Forecasting Horizon $h = 1$)							
	WTI		Brent		Dubai		Average	
Horizon	MSPE Ratio	Success Ratio	MSPE Ratio	Success Ratio	MSPE Ratio	Success Ratio	MSPE Ratio	Success Ratio
$P/R = 0.5$	**0.77**	**0.73**	**0.75**	**0.73**	**0.71**	**0.74**	**0.74**	**0.75**
$P/R = 1.0$	**0.79**	**0.69**	**0.78**	**0.70**	**0.73**	**0.70**	**0.76**	**0.69**
$P/R = 1.5$	**0.80**	**0.66**	**0.78**	**0.69**	**0.74**	**0.67**	**0.77**	**0.68**
$P/R = 2.0$	**0.80**	**0.64**	**0.78**	**0.66**	**0.74**	**0.64**	**0.77**	**0.65**
$P/R = 3.0$	**0.80**	**0.62**	**0.78**	**0.66**	**0.74**	**0.63**	**0.77**	**0.64**

Note: A recursive estimation scheme is used. The MSPE ratio represents $\frac{\text{MSPE}(\mathcal{M}^{SP})}{\text{MSPE}(\mathcal{M}^{NC})}$, where $\mathcal{M}^{NC}$ and $\mathcal{M}^{SP}$ denote the no-change forecast and the predictive regression model based on the oil-sensitive stock price, respectively. The success ratio is constructed using the proportion of forecasts that correctly predict the sign of the change in the oil price. The statistical significance of the MSPE ratio is inferred from pairwise tests of the null hypothesis of equal predictive accuracy with the no-change forecast. Values in bold type designate that both the bootstrap Diebold–Mariano test and bootstrap Clark–West test statistics indicated statistical significance at the 5% level. The sign test for the success ratio is based on Pesaran and Timmermann (2009). The values in bold type again indicate statistical significance at the 5% level.

Table 9: Robustness Check: In-sample and Out-of-sample Predictability Test Results

	Forecasting Nominal Crude Oil Prices (Forecasting Horizon h = 1)											
	In-Sample t-statistics				Out-of-Sample MSPE Ratio				Out-of-Sample Success Ratio			
	WTI	Bent	Dubai	Average	WTI	Bent	Dubai	Average	WTI	Bent	Dubai	Average
MSCI ACWI Sector Index												
Energy	**2.71**	**3.34**	**3.43**	**3.17**	**0.89**	**0.84**	**0.83**	**0.85**	**0.68**	**0.67**	**0.69**	**0.67**
Energy Equip. & Services	**2.84**	**3.29**	**3.35**	**3.19**	**0.88**	**0.85**	**0.83**	**0.85**	**0.63**	**0.64**	**0.66**	**0.65**
Oil & Gas	**2.59**	**3.23**	**3.32**	**3.06**	**0.90**	**0.85**	**0.84**	**0.86**	**0.68**	**0.69**	**0.70**	**0.68**
MSCI Europe Sector Index												
Energy	**2.62**	**3.11**	**3.33**	**3.04**	**0.90**	**0.86**	**0.84**	**0.86**	**0.64**	**0.66**	**0.67**	**0.68**
Energy Equip. & Services	**2.57**	**2.63**	**2.98**	**2.73**	**0.90**	**0.87**	**0.85**	**0.87**	**0.65**	**0.66**	**0.68**	**0.67**
Oil & Gas	**2.56**	**3.05**	**3.27**	**2.98**	**0.91**	**0.87**	**0.85**	**0.87**	**0.63**	**0.66**	**0.66**	**0.66**
MSCI Emerging Markets Index												
Energy	**2.33**	**2.67**	**2.87**	**2.62**	**0.92**	**0.86**	**0.85**	**0.87**	**0.68**	**0.70**	**0.72**	**0.72**
Energy Equip. & Services	**4.13**	**3.61**	**3.93**	**3.89**	**0.79**	**0.82**	**0.78**	**0.79**	**0.73**	**0.73**	**0.73**	**0.73**
Oil & Gas	**2.30**	**2.65**	**2.85**	**2.60**	**0.92**	**0.86**	**0.85**	**0.88**	**0.68**	**0.70**	**0.72**	**0.72**

Note: The table reports the in-sample t-statistics for testing $\beta = 0$ in the predictive regression model by equation (1). A recursive estimation scheme is used for the out-of-sample tests. The MSPE ratio represents $\frac{\text{MSPE}_{(\mathcal{M}^{SP})}}{\text{MSPE}_{(\mathcal{M}^{NC})}}$, where $\mathcal{M}^{NC}$ and $\mathcal{M}^{SP}$ denote the no-change forecast and the predictive regression model based on the oil-sensitive stock price, respectively. The success ratio is constructed using the proportion of forecasts that correctly predict the sign of the change in the oil price. The statistical significance of the MSPE ratio is inferred from pairwise tests of the null hypothesis of equal predictive accuracy with the no-change forecast. Values in bold type designate that both the bootstrap Diebold–Mariano test and bootstrap Clark–West test statistics indicated statistical significance at the 5% level. The sign test for the success ratio is based on Pesaran and Timmermann (2009). The values in bold type again indicate statistical significance at the 5% level.

Table 10: Robustness Check: In-sample and Out-of-sample Predictability Test Results

	Forecasting Real Crude Oil Prices (Forecasting Horizon $h = 1$)											
	In-Sample t-statistics				Out-of-Sample MSPE Ratio				Out-of-Sample Success Ratio			
	WTI	Bent	Dubai	Average	WTI	Bent	Dubai	Average	WTI	Bent	Dubai	Average
MSCI ACWI Sector Index												
Energy	**2.62**	**3.33**	**3.41**	**3.14**	**0.90**	**0.85**	**0.84**	**0.86**	**0.65**	**0.64**	**0.66**	**0.66**
Energy Equip. & Services	**2.82**	**3.30**	**3.34**	**3.19**	**0.89**	**0.86**	**0.84**	**0.86**	**0.62**	**0.63**	**0.66**	**0.65**
Oil & Gas	**2.49**	**3.22**	**3.29**	**3.02**	**0.91**	**0.86**	**0.85**	**0.87**	**0.66**	**0.65**	**0.66**	**0.66**
MSCI Europe Sector Index												
Energy	**2.55**	**3.12**	**3.33**	**3.02**	**0.91**	**0.87**	**0.85**	**0.87**	**0.65**	**0.63**	**0.62**	**0.64**
Energy Equip. & Services	**2.57**	**2.64**	**3.00**	**2.74**	**0.91**	**0.88**	**0.86**	**0.88**	**0.65**	**0.63**	**0.66**	**0.66**
Oil & Gas	**2.48**	**3.06**	**3.27**	**2.96**	**0.92**	**0.88**	**0.86**	**0.88**	**0.66**	**0.63**	**0.61**	**0.64**
MSCI Emerging Markets Index												
Energy	**2.30**	**2.68**	**2.87**	**2.62**	**0.93**	**0.87**	**0.86**	**0.88**	**0.67**	**0.67**	**0.72**	**0.69**
Energy Equip. & Services	**4.21**	**3.64**	**3.98**	**3.95**	**0.80**	**0.83**	**0.79**	**0.80**	**0.72**	**0.70**	**0.71**	**0.72**
Oil & Gas	**2.27**	**2.66**	**2.86**	**2.60**	**0.93**	**0.88**	**0.86**	**0.89**	**0.67**	**0.66**	**0.72**	**0.69**

Note: The table reports the in-sample t-statistics for testing $\beta = 0$ in the predictive regression model by equation (1). A recursive estimation scheme is used for the out-of-sample tests. The MSPE ratio represents $\frac{\text{MSPE}_{(\mathcal{M}^{SP})}}{\text{MSPE}_{(\mathcal{M}^{NC})}}$, where $\mathcal{M}^{NC}$ and $\mathcal{M}^{SP}$ denote the no-change forecast and the predictive regression model based on the oil-sensitive stock price, respectively. The success ratio is constructed using the proportion of forecasts that correctly predict the sign of the change in the oil price. The statistical significance of the MSPE ratio is inferred from pairwise tests of the null hypothesis of equal predictive accuracy with the no-change forecast. Values in bold type designate that both the bootstrap Diebold–Mariano test and bootstrap Clark–West test statistics indicated statistical significance at the 5% level. The sign test for the success ratio is based on Pesaran and Timmermann (2009). The values in bold type again indicate statistical significance at the 5% level.

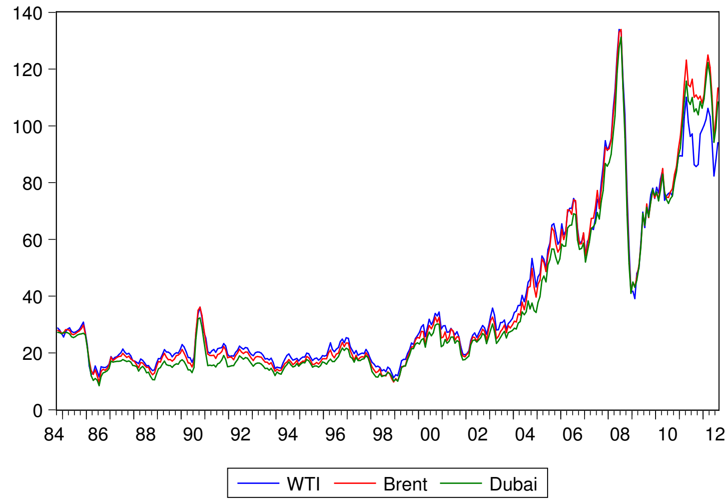

Figure 1: Crude Oil Prices. WTI, Brent and Dubai represent the West Texas Intermediate, Brent Crude, and Dubai Fateh Crude oil prices, respectively.

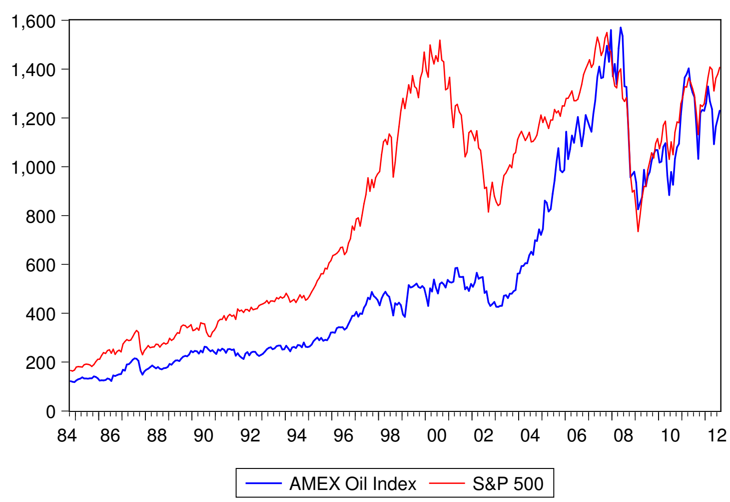

Figure 2: AMEX Oil Index and S&P 500 Index: The AMEX Oil Index is a price-weighted index of the leading companies involved in the exploration, production, and development of petroleum. S&P 500 is Standard & Poor's 500, which is a stock market index based on the market capitalization of 500 leading companies publicly traded on U.S. stock markets as determined by Standard & Poor's.

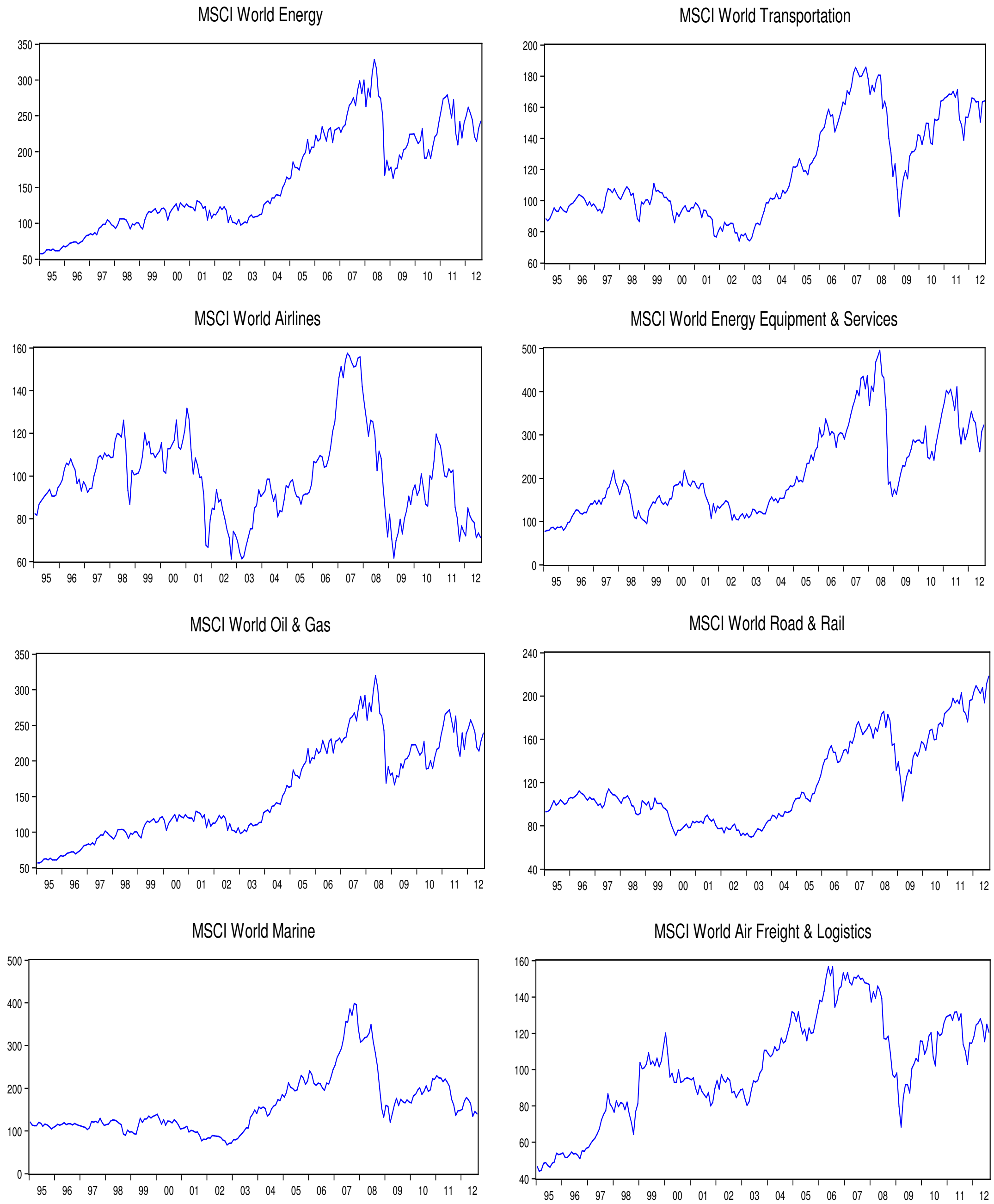

Figure 3: MSCI World Sector Indices. The MSCI World Index, covering over 6,000 securities in 24 developed markets and spanning large, medium, small and micro-cap securities, is generally considered representative of global market conditions. The oil-sensitive sectors that we include are: (1) Energy sector with subitems Energy Equipment & Services and Oil & Gas, as well as (2) Transportation sector with subitems Air Freight & Logistics, Airlines, Marine, and Road & Rail.