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Oil prices and UK industry-level stock returns

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In this article, we study whether the behaviour of oil prices can be used as a reliable predictor for the disaggregated industry-level stock market indices. We find strong evidence for the relevance of changes in oil price as a predictor for the returns of UK industry portfolios, while this relevance is heterogeneous across industries. In an out-of-sample framework, we find that both the contemporaneous and lagged oil price changes do predict UK industry stock market returns. The predictive power is more transient for the latter case, and mostly appearing after allowing for time variation in the relative performance. In addition, we find some evidence of asymmetry in the oil-stock price relationships.

Keywords: Oil price shocks; UK stock returns; industry-level; Out-of-sample forecast; Asymmetric effect

JEL classification: C22; C53, G12; Q43

1. Introduction

Oil is an important source of energy that drives modern economies. A central question for economists and financial analysts is: how does the economy respond to changes in the price of oil? The answer to this question is critical for many decisions including the formulation of macroeconomic policy, asset pricing, risk management and portfolio management. Despite a large body of literature on examining the effects of oil price shocks on the economy, less attention has been paid on studying the dynamic effects of oil price shocks on stock markets and especially on issues such as whether oil prices have any predictive power. Exceptions are, for example, Jones and Kaul (1996) and Driesprong et al. (2008), who show evidence on predictability of oil price changes on the aggregate stock market indices returns. However, the main focus of these studies is concerned with examining in-sample predictive power of oil price changes on the aggregate market
indices. Much remains unknown on the ability of oil prices to predict stock returns at disaggregate levels in an out-of-sample framework.

In this article, we extend the literature on studying whether oil prices can predict the movements in the disaggregate UK industry-level stock market indices. We perform out-of-sample forecasting exercises to test the predictive content of oil prices for each industry separately, as well as to allow for time variation in the model’s relative predictive performance\(^1\). Furthermore, despite there being considerable empirical evidence on the presence of an unstable relationship between oil price shocks and the economy, little attention has been paid on formally testing whether potential instabilities affect the forecast performance of the oil price model. We perform the fluctuation test (FT) proposed by Giacomini and Rossi (2010) to compare the out-of-sample forecasting performance in the presence of possible instabilities. In addition, we consider two asymmetric models to further study the response of stock prices to oil price increases and decreases separately.

Our findings are as follows. First, we show the existence of a strong relevance between changes in oil prices and UK industry portfolios. In particular, higher oil prices lead to a higher return for Oil & Gas industry and an adverse effect for other oil user industries. Second, in an out-of-sample framework, when using contemporaneous oil price changes to predict UK industry stock market returns, the predictive ability is strongly significant and robust to the choice of the in-sample window size. Third, based on the Giacomini and Rossi’s (2010) FT, we find that oil price model forecasts are significantly superior to the no-change benchmark models after 2008. On the other hand, the predictive ability of lagged realized oil price changes is more transient, and allowing for time variation in the relative performance is crucial to show that lagged oil prices can be a statistical significant predictor of Consumer Goods, Health Care and Oil and Gas industry indices out-of-sample. Finally, we show some evidence of asymmetry in the oil-stock price relationships.

\(^1\) Note that the performance of the out-of-sample forecasts can differ on how a given data set is split into estimation and forecasting periods; we use various window sizes to test the robustness of the results.
The rest of the article is organized as follows. Section II reviews the existing literature. Section III discuss our data and model and presents the results on whether oil price changes predict stock returns across UK industries. Section IV presents the out-of-sample forecast results for oil price models. Section V reports the empirical results for more general oil price models that allow for asymmetries and threshold effects. Section VI details the main conclusions.

II. Review of Prior Research

According to the equity pricing model, oil price changes can affect stock prices through their effects on the expected cash flows and expected discount rate channels. First, the price of oil is one of the important input costs faced by many firms, so a higher oil price can drive up firms’ marginal cost of production. Second, oil price changes can affect the firm’s future cash flows from the demand side. For example, consumers may increase their precautionary savings and smooth their consumptions in response to positive oil price shocks as they perceive a greater chance of future unemployment (Kilian, 2008); large oil prices volatility can raise uncertainties about future energy market conditions and affect consumers’ consumption and investment behaviour, often resulting in reduced or postponed investments and purchases on goods and services (Edelstein and Kilian, 2009). Furthermore, oil price shocks can adversely affect stock prices through the discount rate channel as monetary policy makers tend to raise interest rates in anticipation of the higher inflation triggered by higher oil prices (Bernanke et al., 1997). A rise in interest rate implies a higher required rate of return and consequently, negatively affects stock prices.

The empirical literature focuses on studying the oil-stock relationships that falls into two main categories depending on the level of aggregation: aggregate level and disaggregate level. The empirical evidence is mixed at the aggregate stock market index level. For example, Huang et al. (1996) fail to find any relationship between returns on oil future prices and U.S. stock returns using both a regression model and a VAR model. Sadorsky (1999) uses a VAR model and find that both oil prices and its volatility play important roles in affecting U.S. real stock returns. Huang and Guo
(2008) show the existence of a negative relationship between oil price shocks and Japanese stock market index returns based on a VAR model. Park and Ratti (2008) employ VAR models and find a positive response of real stock returns to an oil price increase for Norway, but negative responses for 12 other European countries. One possible explanation for the mixed findings may be because these studies do not distinguish the underlying causes of a higher oil price. Recent studies by Kilian and Park (2009) and Abhyankar et al. (2013), use structural VAR models to study the relationship between oil prices and returns to aggregate U.S. and Japan stock market indices, respectively. They use short-run exclusion restrictions to separately study the effects on stock market index returns of oil shocks arising from oil market supply shocks, surges in aggregate demand due to increased global economic activity, and oil market specific demand shocks. In contrast to previous literature, they find that an increase in the price of oil is not always bad news for the stock market (e.g. Huang and Guo, 2008; Park and Ratti, 2008). More specifically, higher oil prices due to an increase in the global aggregate demand for industrial commodities result in higher stock prices in U.S. and Japan. Oil price shocks are bad news for the stock only when high oil prices arise from oil-market specific demand shocks related to shifts in the precautionary demand for crude oil in response to concerns about shortfall in future production. In contrast to prior research, they found that the supply shocks arising from unexpected oil production disruption played a less important role in explaining changes in stock prices compared to global aggregate demand shocks and oil-market specific demand shocks.

In addition, some studies examine whether oil price shocks have nonlinear effect on aggregate stock market returns. Odusami (2009), for example, uses an asymmetric Generalized Auto-Regressive Conditional Heteroskedasticity (GARCH) – jump model and detects nonlinear causality from unanticipated crude oil shocks to the aggregate U.S. stock market returns. He finds that both contemporaneous and lagged returns on crude oil futures have significant negative effects on jump distribution in the U.S. stock market returns. Rafailidis and Katrakilidis (2014) employ the TAR and momentum TAR models to investigate the long-run and short-run dynamics between the
aggregate U.S. stock prices and oil prices. They find that the stock returns react to oil-price changes only in deviations from the long-run equilibrium below a threshold value.

Several authors employ regression analysis using disaggregate industry or firm-level data, and the general conclusion is that oil price shocks affect specific industry groups in different ways (e.g. see Lee and Ni, 2002; El-Sharif et al., 2005; Arouri and Nguyen, 2010; Narayan and Sharma, 2011). To be more specific, each industry is heterogeneous in the sense of having different market structure, level of competition and concentration, and whether oil is acting as an input or key output of the industry. Therefore, the effect of oil price shocks on their stock prices can vary due to the nature of the industry and its capability to transfer oil price shocks to other entities. For example, in oil-related industries such as the oil and gas sector where oil is a key output, an increase in oil price leads to higher expected cash flows and to positive changes in stock returns subsequently. In contrast, for oil-consuming industries such as automobiles, leisure and travel, higher oil prices are negatively related to stock prices. Furthermore, Fukunaga et al. (2010) suggest that the response of stock returns of industry portfolios depends not only on the nature of the industry but also the specific underlying causes of the oil price shocks based on the structural VAR models.

Another strand of the research investigates whether oil prices predict stock returns. Most studies focus on the in-sample predictability of oil prices on the aggregate stock market indices. Jones and Kaul (1996), for example, test whether the reaction of international stock markets to oil shocks can be justified by current and future changes in real cash flows and/or changes in expected returns using Campbell’s (1991) return decomposition. Their results for Japan, UK and U.S. show the substantial negative impact of oil shocks on stock returns. In particular, they find that the negative impact is most dramatic in the case of Japan with the adjusted $R^2$ over 25%. Driesprong et al. (2008) use regression models to examine whether changes in oil prices predict stock returns by using stock market data from 48 countries and find a significant predictability in 12 out of the 18 developed markets, with emerging markets showing the same effect although less significantly. Yet, very few studies have tested whether oil price changes predict stock prices by sector. Exceptions
are, for example, Fan and Jahan-Parvar (2012), who test whether U.S. industry returns are predicted by oil price changes based on regression models and show oil predictability is concentrated in a relatively small number of the U.S. industry portfolios. To be more specific, they find that less than 20% of the 49 U.S. industry portfolio prices can be predicted using the WTI spot prices and this predictability almost disappears when they use the NYMEX light sweet crude futures prices. They did not test whether oil prices have a significant predictive content in an out-of-sample framework. Arouri and Nguyen (2010) study the relationship between oil price changes and stock returns at the disaggregated sector level in European using GARCH models. In contrast to Fan and Jahan-Parvar (2012), they find that augmenting the market model with oil price changes leads to better forecasting of most European sector indices returns. A possible reason behind the contradictory findings maybe because Arouri and Nguyen (2010) include the additional contemporaneous aggregate stock market index in their forecasting models, while Fan and Jahan-Parvar (2012) only make use of lagged oil price changes. Furthermore, Arouri and Nguyen (2010) employ unexpected changes in oil price in their forecasting exercises, which is the difference between the observed contemporaneous oil price changes and the expected oil price changes computed from an AR model.

In this article, we focus on whether the behaviour of oil prices can be used as a reliable predictor for the UK industry stock market indices returns in an out-of-sample forecasting framework. We focus on the UK industry portfolios for two main reasons. First, the UK is the largest producer of oil among EU member countries, and the energy industry has been acting as a major contributor to the UK’s Balance of Payments through the exports of crude oil and oil products over the last four decades (e.g. DUKES, 2014; EIA, 2014). Thus, oil plays a crucial role in the UK’s economy. Second, there is limited research on studying the implications of oil price shocks on the UK industry stock returns. Exceptions are, for example, El-Sharif et al. (2005), and Nandha and Faff (2008), but the main focus is to model the oil price sensitivity to the stock market returns and none of them examine whether oil prices have any predictive power.
III. Oil and The Stock Market

The aim of this article is to look into the short-term predictive power of oil prices on the UK stock market returns. We use daily stock market and crude oil data, and our sample period starts from 04 January 1988 and ends in 01 February 2013. For the stock market data, we use Datastream’s FTSE All-share industries indices\(^2\) as a proxy for the UK sector stock market. Our measure of oil price changes is based on the price of Brent Crude which is a blended crude oil stream produced in the North Sea Region. We express Brent oil prices in pound using exchange rates from DataStream.

[INSERT FIG 1. HERE]

Fig.1 depicts the behaviour and dynamics of the price of Brent Crude. We note that daily spot prices of Brent Crude seem to have been greatly influenced by exogenous events. First, geopolitical events such as the Persian Gulf War in 1990 and Iraq war in 2003 that disrupt supply and increase uncertainty about future oil supplies tend to drive up oil prices. Second, changes in quotas or production policies often result in changes in oil prices, for example, OPEC cut its production target to 1.7 million barrel per day in 1999 and 4.2 million barrel per day in 2009. Third, global macroeconomic conditions seem to influence the price of oil greatly. There was a sharp drop in the price of oil following the Asian crisis from 1997 to 1998; a persistent rise during 2003-2008 associated with booming global economies; and the recent credit crunch saw prices fall in late 2008 to 2009. Finally, adverse weather conditions and natural disasters such as the Hurricane Katrina in August 2005 and the earthquake and accompanying tsunami in Japan in March 2011 tend to add upward pressures on oil prices.

We begin our analysis taking the presence of unit root in the data. We apply ADF, Phillips-Perron (PP) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests. We determine the optimal lag length using the Schwarz-Bayes Information Criterion for the ADF test, and use the Newey-West

\(^2\) We use the FTSE All-Share index as it represents 98-99% of UK market capitalization; it is the aggregate of the FTSE100, FTSE250 and FTSE Small Cap indices. FTSE calculates the disaggregate-level indices followed by the Industry Classification Benchmark (ICB) in a 4-tier hierarchy (10 industries, 18 super-sectors, 39 sectors and 104 subsectors). We use 10 FTSE All-Share industry indices. We use both UK pound and US dollar returns, but as results tend to be similar and we only report results for the local currency returns.
automatic bandwidth parameter methods for PP and KPSS tests. Table 1 reports the results of the ADF, PP and KPSS tests for each series. All the series appear to be integrated of order one.

[INSERT TABLE 1 HERE]

Table 2 reports relevant descriptive statistics for UK stock market variables and Brent oil prices (both in first logarithmic differences). The top performing industries are Utilities (0.034%) and Oil and Gas (0.027%), while the bottom industry is the Consumer Services (0.015%). Although oil prices have an average returns more than UK stock prices over our sample period, they are more volatile than the stock returns. Industries such as Basic Materials (1.63%) and Technology (1.62%) are more volatile than other industries. Apart from the relatively high kurtosis, most return series are well behaved in that not many series are significantly skewed. Furthermore, we find significant first-order autocorrelations on Oil & Gas, Health Care, Telecom, Utilities and the FTSE All-share market returns, but the magnitude tends to be small. Based on these basic characteristics, it seems justified to use heteroscedasticity and autocorrelation consistent (HAC) covariance matrix estimators to adjust for the high level of kurtosis. Finally, we report the correlations between oil price changes and UK sector returns. Correlations between oil price changes and UK industry returns are positively significant except for Health Care. The Oil & Gas industry has the highest correlation with oil price movements (22%), followed by Basic Materials (16%). Correlations between the UK aggregate stock market index (FTSE All-Share index) and industry returns are positive and high on average.

[INSERT TABLE 2. HERE]

Simple Oil Price Model

In order to test for the existence of an oil effect, we incorporate an oil variable, $R_{oil,t-i}$, in the following simple oil price model:

$$R_{i,t} = \alpha + \beta_i R_{oil,t-i} + \epsilon_{i,t}, \quad t = 1, ..., T$$  \hfill (1)
where $R_{t,i}$ is the first difference of the logarithm of the FTSE All-share index industry $i$, $R_{\text{oil},t-1}$ is the log return in Brent oil price, $\varepsilon_{t,i}$ is the error term and $T$ is the total sample size. Using this model, we test whether the coefficient $\beta_i$ is significantly different from zero. The statistical inference is based on HAC covariance matrix estimator from Newey and West (1987), with an optimal lag selected as in Newey and West (1994).

Panel A in Table 3 reports the empirical results for the simple oil price model. For Oil & Gas industry, the effect of oil prices on returns is positive (0.060) and highly statistically significant. In the absence of oil price changes the average daily return for Oil and Gas index is 0.027%; a 1 SD increase in oil prices (2.32%, see Table 2) in 1 day increases the expected return in the next day to 0.17%. This is mainly because oil acts as the major output for oil-related industry such as Oil & Gas, and the demand for their products are relative inelastic with respect to the oil price fluctuations. Therefore, any positive changes in oil prices can be considered as beneficial for their cash flows and lead to positive changes in their stock returns. Nevertheless, higher oil prices affect oil user industries’ future stock returns negatively by harming their current and future earnings from both supply and demand side. The magnitudes of the coefficients range between -0.010 and -0.028 and values in bold are significant at the 10% level: Consumer Goods (-0.021), Health Care (-0.028), Consumer Services (-0.017), Utilities (-0.014) and Financials (-0.018). In sum, our findings are consistent with conventional wisdom in which the effect of oil price shocks on stock returns varies due to the nature of the industry and its capability to transfer oil price shocks to other entities.

One possible explanation for a lagged effect of oil prices on industry returns is related to the underreaction hypothesis. Investors tend to overreact to private information and underreact to public information (Daniel et al., 1998). Oil price movements can be observed almost in real time without cost. Thus, underreaction to oil price news is likely to occur in the stock market. Another channel in which underreaction can potentially take place is via the gradual information diffusion hypothesis.
proposed by Hong and Stein (1999). They show that each news watcher possess some private information, but fails to extract information from prices of other news watchers. This leads to a gradual diffusion of information across the investing public and price underreacting in the short run. We further test how long the lagged oil price changes retain their predictive power for the stock returns. We include the oil price changes lagged for 3 days:

\[ R_{it} = \alpha + \sum_{j=1}^{3} \beta_j R_{oil,t-j} + \varepsilon_{it}, \ t = 1,...,T \]  

(2)

where \( R_{oil,t-1} \) to \( R_{oil,t-3} \) are the lagged oil price returns in day \( t-1 \) to \( t-3 \). We report the results for this regression in Panel B of Table 3. We show strong evidence of oil price for having a statistically significant effect on stock returns with lags and we notice that the most common lag at which oil price has a statistically significant negative effect for most industries is three. Our findings are consistent with Driesprong et al. (2008), who also find stock market investors react with a delay to information in oil price changes; Narayan and Sharma (2011) find strong evidence of lagged effect of oil price on firm returns.

Robustness Check

This section tests the robustness of this lagged effect of oil price on stock returns in conjunction with a set of additional factors \( Z \) such as the daily aggregate stock returns, daily global economic activity growth rates and daily changes in commodity index (Goyal and Welch, 2008). We include one additional factor at a time and employ the following regression model:

\[ R_{it} = \alpha + \beta_i R_{oil,t-1} + \gamma_i Z_{t-1} + \varepsilon_{it}, \ t = 1,...,T \]  

(3)

We test whether the \( \beta_i \) is significantly different from zero in the presence of \( Z_{t-1} \).

Table 4 shows the empirical results by adding lagged UK aggregate stock returns together with the lagged oil price changes. Values in bold are significant at 10%. Compared with Table 3,
the $\beta_i$ coefficients slightly increase in magnitude for the Oil & Gas industry index and decrease for some other industries. By including $Z_{t-1}$, $\beta_i$ is significant at the 10% level for all industries except for the Basic Materials and Telecom. The last column in Table 4 reports the $p$-values for the null hypotheses of $\beta_i = \gamma_i = 0$. We find that all the $p$-values are below 10% except for the Basic Materials, which suggest that oil price changes retain their predictive ability when an additional factor is included. It also suggests that when the lagged aggregate returns are combined with the lagged oil price changes, two factors complement each other in predicting industry stock returns. For the Basic Materials, we find that both factors are insignificant. To save space, we do not report the results when adding additional factors (e.g. global economic activity growth rates, changes in commodity index), but the main conclusion is that the link between the oil price changes and future stock returns remains robust over our sample period, even after including other factors.

[INSERT TABLE 4. HERE]

IV. Out-of-sample Forecast Analyses of UK stock Returns

Out-of-sample Forecasts with Contemporaneous Brent Oil Price Changes

In this section, we perform an out-of-sample forecast exercise to examine whether contemporaneous oil prices have predictive content for UK industry stock returns. We focus on the simple oil price model to produce a one-step-ahead pseudo out-of-sample forecast on the returns of each industry $i$:

$$\hat{R}_{i,t+1} = \hat{\alpha}_{i,t} + \hat{\beta}_{i,t} R_{o,t+1}, \ t = \lambda, \lambda + 1, ..., T - 1$$

(4)

where $\lambda$ is the in-sample estimation window size, $\hat{\alpha}_{i,t}$ and $\hat{\beta}_{i,t}$ are the parameter estimates obtained from a rolling sample of observations $t = t - \lambda + 1, t - \lambda + 2, ..., t$. Note that we consider the realized oil price changes as a predictor for the changes in the stock prices, and the underlying reason is because it is very difficult to obtain a model that can accurately predict daily future changes in the
oil prices (e.g. Alquist et al., 2011; Ferraro et al., 2011). If we were to include past values of oil prices in our experiment, and the lagged oil prices changes were not good forecasts of future oil price changes, we may wrongly reject the predictive power of oil prices even though the reason for the lack of predictive ability is not the absence of a relationship between oil prices and stock prices, but the poor forecasts that lagged price changes generate for future oil price changes. To avoid this problem, we first condition the forecast on the realized future changes in oil prices (Ferraro et al., 2011). Notice also that the performance of the out-of-sample tests can depend on how a given data set is split into an estimation period and an out-of-sample evaluation period (Rossi and Inoue, 2011). Therefore, we vary our in-sample window (λ) from 10 to 90% of the sample size to test the robustness of the results to the choice of the rolling window size, and report the results on the out-of-sample predictive ability of oil price changes for industry index using Diebold and Mariano’s (1995) (DM) test over different rolling in-sample windows (see Appendix for detailed descriptions on the DM test). We use the no-change random walk (RW) without drift and RW with drift\(^3\) as the benchmark models against the simple oil price change model.

Figure 2(a) to 2(j) report the empirical results for the out-of-sample forecast for 10 UK industries’ returns with varying in-sample estimation window size respectively. The size of the in-sample estimation window relative to the total sample size is reported on the x-axis (from 10 to 90%). Each figure reports the results of whether the oil price model is superior to the two benchmark models: the RW without drift (solid line with circles) and with drift (solid line with diamonds); the continuous lines represent the critical value of the DM statistic. Note that the negative values indicate that the oil price model is superior and, when the DM statistic is less than -1.96, we reject the null hypothesis of equal performance and conclude that the oil price model outperforms the benchmark models. Our results suggest that no matter the size of the in-sample window, the contemporaneous oil price changes do predict daily returns of UK industry indices, and their predictive ability is strongly significant. Except for the Health Care industry, the oil price

\(^3\) It is according to which the returns are forecasted to be zero.
model is superior to the benchmark models when the in-sample window size is relative large (see Fig. 2(e)).

[INSERT FIGS. 2(a) to 2(j). HERE]

The conventional wisdom in the stock return predictability literature is that if daily returns are very slightly predictable by a slow-moving variable, then predictability adds up at longer horizons (e.g. Fama and French, 1988; Campbell et al., 1997; Cochrane, 2001). Our empirical results show the existence of a short-term relationship at the daily frequency between changes in oil price and changes in the UK industry stock prices. We further examine whether this out-of-sample predictive ability will hold over longer horizons. However, we fail to find any systematic oil-stock price relationships at monthly or quarterly frequencies. Our findings are consistent with Ang and Bekaert (2007), who find that return predictability is concentrated at short horizons using the nonlinear present value models; Ferraro et al. (2011) find the effects of commodity price changes on exchange rate changes break down for monthly and quarterly data. A possible reason behind weaker oil-stock relationship at lower frequencies could be because the effects of changes in oil prices are translated into changes in UK industry portfolio prices quickly and, as such, do not necessarily portend further changes, after removing the slow-moving component in the oil prices by differencing the series (Ferraro et al., 2011). In sum, our results suggest that the effects of oil price changes on stock price changes are short-lived and the frequency of the data is crucial to capture them.

Fluctuation Test

The common overall predictive ability tests such as Diebold and Mariano (1995) and Clark and McCracken (2001), compare the relative performance of competing forecasting models on average over the forecasting sample. Giacomini and Rossi (2010) point out that in the presence of structural instability, the relative performance of the two models may itself be time-varying and thus averaging this evolution over time will result in a loss of information. In fact, there is considerable

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4 To save space, we did not report these results.
empirical evidence on changing relationship between the oil prices and the economy over time (e.g. Edelstein and Kilian 2009; Baumeister and Peersman, 2013). Lee and Chiou (2011) also find that in a regime of high oil price fluctuations there is a negative association with the stock market, which is not observed in a regime of lower oil price fluctuations. Yet, limited attention has been paid on formally testing whether the model’s relative performance has actually changed over time. In this article, we examine whether the oil price models’ relative superiority over the benchmark models has been stable over time.

We use the FT procedure proposed by Giacomini and Rossi (2010), which relies on a measure of the local relative forecasting performance of the models estimated over rolling windows of data. The FT is a rescaled version of mean squared error functions and is computed as follows for one-step ahead forecasting:

\[
FT^{OOS}_{1,m} = \sigma^{-1}m^{-1/2} \left( \sum_{j=t-m/2}^{t+m/2} (e^1_{i,t+j})^2 - \sum_{j=t-m/2}^{t+m/2} (e^2_{i,t+j})^2 \right)
\]  \hspace{1cm} (5)

for \( t = \lambda + 1 + m/2, \ldots, T - m/2 + 1 \), where \( \lambda \) is the in-sample estimation period and \( m \) is the rolling windows, \( e^1_{i,t+j} \) and \( e^2_{i,t+j} \) are the errors from models 1 and 2, respectively, \( \hat{\sigma} \) is a HAC estimator of the asymptotic variance \( \sigma = \text{var} \left( P^{-1/2} \sum_{j=1}^{T} (e^1_{i,t+1})^2 - (e^2_{i,t+1})^2 \right) \), where \( P = T - \lambda \). We formally test whether the model’s forecasting performance is the same at each point of time for each industry \( i \).

The null and alternative hypotheses can be written as

\[
H_0 : E(e^1_{i,t+1}^2) - (e^2_{i,t+1}^2) = 0, t = \lambda + 1, \ldots, T
\]  \hspace{1cm} (6)

\[
H_1 : E(e^1_{i,t+1}^2) - (e^2_{i,t+1}^2) \neq 0, t = \lambda + 1, \ldots, T
\]  \hspace{1cm} (7)

We reject the null hypothesis at the 5% significance level against the two-sided alternative when
\[ \max |F^\text{OOS}_{t,m}| > 3.179 \text{ and } m/P \approx 0.2^5. \]

Figure 3 (a-j) reports the relative performance measured by FT statistics for the oil price model against two benchmark models, together with the 5% critical values. We find for most industries that the values of the statistics are below the negative critical levels at some point in time. Therefore, we reject the null hypothesis of equal predictive ability at each point in time and conclude that the oil price model forecasts more accurately in some periods. In particular, we find that the oil price model performs significantly better than the RW models more recently. This finding is interesting as it is not unusual to find forecasting models that perform well during regular times, only to break down during times to market turmoil. In contrast, the oil price model’s relative accuracy actually increases noticeably during the financial crisis period. These accuracy gains arise because the oil price models include forward-looking information in the form of the oil price changes (Baumeister and Kilian, 2012). A recent study by Ferraro et al. (2011) also finds that their oil price model is superior to the no-change RW models for forecasting the exchange rate after 2005.

[INSERT FIGS. 3(a) to 3(j). HERE]

**Out-of-sample Forecasts with Lagged Oil Price Changes**

In the previous section, we use the contemporaneous value of oil price changes to predict stock returns. The results confirm the existence of predictive ability of oil prices on stock returns using daily data. Here we test whether lagged oil price changes have predictive power for future stock returns: \( \hat{R}_{t+1} = \hat{\alpha}_{t,i} + \hat{\beta}_{t,i} R_{\text{oil},t} \), where \( t = \lambda, \ldots, T-1 \). \( \hat{\alpha}_{t,i} \) and \( \hat{\beta}_{t,i} \) are the parameter estimates obtained from a rolling sample of observations. We estimate the parameters of model with rolling in-sample windows and produce a sequence of one-step-ahead pseudo out-of-sample forecasts conditional on the lagged value of oil price. Next, we compare the performance of our model to the two no-change benchmark models: RW with drift and RW without drift using the DM test.

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3 Giacomini and Rossi (2010) provide critical value for various significance levels, window and sample sizes.
Figure 4 (a-j) reports the empirical results for the out-of-sample forecasting for 10 UK industries’ returns with varying in-sample estimation window size. The size of the estimation window relative to the total sample size is reported on the x-axis. We find that predictability depends on the estimation of window size. For example, we find that when the in-sample window size is relatively small, the DM statistic is negative and smaller than -1.96 for the daily returns of the Oil & Gas industry, suggesting that the oil price model forecasts better than both the RW with and without drift – see Fig. 4(a). With respect to the Consumer Goods and Health Care industries, we find that the oil price model is statistically superior than the RW models when in-sample window size is relatively large – see Figs. 4(d) and 4(e). This finding is in fact consistent with the in-sample forecasting, oil price changes coefficients are highly significantly different from zero for these three industries (Consumer Goods, Health Care and Oil and Gas) – see Table 3 for details.

[INSERT FIGS. 4(a) to 4(j). HERE]

Figure 5(a-j) reports the empirical results for the FT in daily data for each industry. It shows that once we allow the relative performance of the models to be time-varying, we find evidence in favour of the lagged oil price model, especially around the 2005 to 2007 period, both against the RW with and without drift.

[INSERT FIGS. 5(a) to 5(j). HERE]

V. Nonlinearity in the Predictive Regressions

In studying the effects of oil price shocks, a natural baseline is the hypothesis that firms respond proportionately to a percent change in oil prices, regardless of the magnitude (Kilian, 2008). Recent studies suggest an asymmetric transmission of oil price shocks to the macroeconomic fundamentals. For example, Mork (1994) and Hamilton (1996) find the asymmetric effect for which the positive shocks have a statistically significant impact on the U.S. economy. Jimenze – Rodriguez and Sanchez (2005) compare both linear and nonlinear approaches to test the impact of an oil price shock on the main industrialized countries. Ramos and Veiga (2013) find evidences to support the
presence of asymmetric effects of oil price shocks on stock markets only for oil-importing countries. Therefore, we further study whether it is possible to improve the predictability by taking account of the asymmetric effects of oil prices.

First, we include positive changes for the oil price shocks to account for the asymmetric effects of oil prices:

$$R_{i,t} = \alpha + \beta_{i} R_{oil,t} + \gamma_{i}^{+} R_{oil,t}^{+} + \epsilon_{i,t}, t = 1,...,T$$  \(\text{(8)}\)

where $R_{oil,t} = \max(0, R_{oil,t})$, $\gamma_{i}^{+}$ are $i$th industry coefficients corresponding to positive movements in the oil price and other notations are the same as equation (1).

Second, we include a threshold model which considers the large changes in oil prices and our model can be stated as follows:

$$R_{i,t} = \alpha + \beta_{i} R_{oil,t} + \gamma_{i}^{+} R_{oil,t}^{+} + \epsilon_{i,t}, t = 1,...,T$$  \(\text{(9)}\)

where $R_{oil,t}^{\gamma_{i}} = R_{oil,t}$, if $R_{oil,t} > 80^{th}$ or $< 20^{th}$ percentile of $R_{oil}$; 0 otherwise; the percentile of oil price changes are computed over the full sample; $\gamma_{i}^{+}$ are $i$th industry coefficients corresponding to positive movements in the oil price and other notations are the same as Equation (1).

Panel A in Table 5 reports the empirical results of the in-sample estimations of the models for equation (8). First, we find that the oil price changes ($\beta_{i}$) are statistically significant for all industries except Basic Materials. We find that the coefficients $\gamma_{i}^{+}$ designed to capture the potential asymmetric effects are never statistically significant from zero for all industries except the Technology industry. We show the empirical results for the threshold models for equation (9) in Table 5, Panel B. We evidence for asymmetric effects for Oil & Gas, Industrials and Health Care industries. A recent study by Arouri and Nguyen (2010) also find Health Care industries respond to oil price changes asymmetrically in Europe. Ramos and Veiga (2011) find that the oil & gas industry responds asymmetrically to changes in oil prices.
Next, we perform the out-of-sample test to check whether the asymmetric model and threshold mode provide additional predictive power to the simple oil price model. We focus on the models with contemporaneous predictors. Figure 6(a-j) reports the empirical results for both the asymmetric and threshold models for 10 UK industry stock returns with varying in-sample estimation window size, whose size relative to the total sample size is reported on the x-axis. Negative values in the plot indicate that the asymmetric model equation (8) and threshold model equation (9) are better than the simple oil model equation (1). In general, we find that the simple oil price model outperforms the asymmetric model. However, we have some mixed results for the threshold model. We find that threshold models are statistically better than the oil price models when the in-sample window size is large, whereas the result is the opposite when it is small.

[INSERT FIGS. 6(a) to 6(j). HERE]

Finally, we test whether forecast instabilities are important by carrying out the FT. Figure 7(a-j) shows the results of the FT for both the asymmetric and threshold models against the simple oil price model equation (1), together with the 5% critical values. We find that asymmetric models are never statistically better than the simple oil model, and the linear model is significantly better than the asymmetric model for some window sizes. For the threshold model, we find evidence in favour of the model with threshold oil prices around 2010 against the linear oil model.

[INSERT FIGS. 7(a) to 7(j). HERE]

VI. Conclusions

One of the key objectives of this article is to show that the use of a different fundamental, namely, oil prices, can be used as a reliable predictor for the UK industry-level stock market indices’ returns. We find strong evidence for the relevance of changes in oil price as a predictor for the returns of UK industry indices. Consistent with our prior belief, the effect of oil prices on industry returns is heterogeneous, both in terms of sign and magnitude. We find a positive impact on the oil-
related industry such as *Oil & Gas* industry, and an adverse effect on other oil-consuming industries. Using an out-of-sample forecasting framework, we find that the predictive power of oil price is strongly significant and robust to the choice of the in-sample window size when using contemporaneous daily oil price to predict industry indices. We also find evidence that the oil price model forecasts are significantly superior to the benchmark models after 2008 based on Giacomini and Rossi’s (2010) FT. Nevertheless, the predictive power of the lagged oil price changes is more transient and, allowing for time variation in the relative performance, we find *Consumer Goods, Health Care* and *Oil & Gas* industry stock returns outperformed the no-change benchmark models. Finally, we find some evidence to support the view that oil price has asymmetric effects when the in-sample window size is large.

In sum, our findings provide useful information from the risk assessment, stock selection and portfolio management’s point of view. By identifying the heterogeneity of industry sensitivities to oil price changes implies that some industries can provide a channel for diversification during large swings in oil prices. For example, if the oil price is expected to increase in the future, investors may use this information to devise their investment strategies such as taking short positions in *Consumer Goods, Consumer Services* stocks and long positions in *Oil and Gas* firms. In addition, to hedge oil price risk, one could include some assets with a positive impact from oil price changes, such as *Oil and Gas* stocks, or oil-based derivatives. Furthermore, one could set up trading strategies based on oil price changes. One interesting question will be to find out whether the UK industry stock returns respond to oil price shocks arising from oil market supply shocks, surges in aggregate demand due to increased global economic activity or oil market-specific demand shocks differently. If yes, is it possible to improve the predictability by taking account of the effects of supply or demand oil price shocks separately? However, this requires one to estimate a measure of aggregate demand shock which may be hard to come by on a daily frequency (Kilian, 2009). We shall leave these issues for future work.
Acknowledgment

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REFERENCES


http://www.eia.gov/countries/analysisbriefs/United_Kingdom/uk.pdf


**Fig. 1** Daily Brent Crude Price changes

Fig. 1 plots daily spot prices of Brent Crude expressed in British Pounds from 1st January 1988 to 1st February 2013, using data from the DataStream. The price of oil seems to react to a variety of geopolitical and economic events.
Fig. 2 Out-of-sample analysis using realized oil price changes

Figs. 2(a) to 2(j) report the rolling Diebold-Mariano (1995)’s (DM) test results for 10 UK industries stock returns with varying in-sample estimation window size. The size of the in-sample estimation window relative to the total sample size is reported on the x-axis of each figure (i.e., from 10% to 90%). Each figure reports the DM statistic for comparing forecasts of oil price model with realized oil price changes to two benchmark models: RW with drift and RW without drift.

Note that, the continuous lines represent the critical value of the DM statistic. The negative values indicate oil price model is better, and when the DM statistic is less than -1.96, we reject the null hypothesis of equal performance and conclude that the oil price model performs better than its competitors.

Fig. 2(a) *Oil & Gas* stock returns

![Diebold-Mariano rolling test – Oilgas](image)

Fig. 2(b) *Basic Materials* stock returns

![Diebold-Mariano rolling test – Basicmats](image)

Fig. 2(c) *Industrial* stock returns

![Diebold-Mariano rolling test – Industrial](image)
Fig. 2(d) *Consumer Goods* stock returns

Fig. 2(e) *Health Care* stock returns

Fig. 2(f) *Consumer Services* stock returns

Fig. 2(g) *Telecom* stock returns
Fig. 2(h) *Utilities* stock returns

![Diebold–Mariano rolling test – Utilities](image)

Fig. 2(i) *Financial* stock returns

![Diebold–Mariano rolling test – Financials](image)

Fig. 2(j) *Technology* stock returns

![Diebold–Mariano rolling test – Technology](image)
**Fig. 3** Fluctuation Test for out-of-sample analysis using realized oil price changes

Figs. 3(a) to 3(j) report the fluctuation test (FT) proposed by Giacomini and Rossi’s (2010). The estimation window is one-half of the total sample size and out-of-sample period equals to five hundred days. Each figure reports the FT statistic for comparing forecasts of oil price model with realized oil price changes to two benchmark models: RW with drift and RW without drift.

Note that, the continuous lines represent the critical value of the FT statistic. The negative values indicate oil price model is better, and when the FT statistic is less than the line, we reject the null hypothesis of models’ forecasting performance is the same at each point of time for industry $i$.

**Fig. 3(a) FT for Oil & Gas stock returns**

![Fluctuation Test - Oilgas](image1)

**Fig. 3(b) FT for Basic Materials stock returns**

![Fluctuation Test - Basicmats](image2)

**Fig. 3(c) FT for Industrial stock returns**

![Fluctuation Test - Industrial](image3)
Fig. 3(d) FT for Consumer Goods stock returns

Fig. 3(e) FT for Health Care stock returns

Fig. 3(f) FT for Consumer Services stock returns

Fig. 3(g) FT for Telecom stock returns
Fig. 3(h) FT for *Utilities* stock returns

![Fluctuation Test - Utilities](image)

Fig. 3(i) FT for *Financials* stock returns

![Fluctuation Test - Financials](image)

Fig. 3(j) FT for *Technology* stock returns

![Fluctuation Test - Technology](image)

Fig. 4 Out-of-sample predictability of lagged oil price changes

Figs. 4(a) to 4(j) report the rolling Diebold-Mariano (1995)’s (DM) test results for 10 UK industries stock returns with varying in-sample estimation window size. The size of the in-sample estimation window relative to the total sample size is reported on the x-axis of each figure (i.e., from 10% to 90%). Each figure reports the DM statistic for comparing forecasts of oil price model on eq. (1) to two benchmark models: RW with drift and RW without drift.

Note that, the continuous lines represent the critical value of the DM statistic. The negative values indicate oil price model is better, and when the DM statistic is less than - 1.96, we reject the null hypothesis of equal performance and conclude that the oil price model performs better than its competitors.
Fig. 4(a) *Oil & Gas* stock returns

Fig. 4(b) *Basic Materials* stock returns

Fig. 4(c) *Industrial* stock returns

Fig. 4(d) *Consumer Goods* stock returns
Fig. 4(e) *Health care* stock returns

Fig. 4(f) *Consumer Services* stock returns

Fig. 4(g) *Telecom* stock returns

Fig. 4(h) *Utilities* stock returns
Fig. 4(i) Financials stock returns

![Financials stock returns](image)

Fig. 4(j) Technology stock returns

![Technology stock returns](image)

Fig. 5 Fluctuation Test for out-of-sample analysis using lagged oil price changes

Figs. 5(a) to 5(j) report the results on fluctuation test (FT). The in-sample estimation window is one-half of the total sample size and out-of-sample period equals to five hundred days. Each figure reports the FT statistic for comparing forecasts of oil price model with realized oil price changes to two benchmark models: RW with drift and RW without drift.

Note that, the continuous lines represent the critical value of the FT statistic. The negative value indicate oil price model is better, and when the FT statistic is less than the line, we reject the null hypothesis of models’ forecasting performance is the same at each point of time for industry $i$.

Fig. 5(a) FT for Oil & Gas stock returns

![FT for Oil & Gas stock returns](image)
Fig. 5(b) FT for Basic Materials stock returns

Fig. 5(c) FT for Industrial stock returns

Fig. 5(d) FT for Consumer Goods stock returns

Fig. 5(e) FT for Health Care stock returns
Fig. 5(f) FT for *Consumer Services* stock returns

Fig. 5(g) FT for *Telecom* stock returns

Fig. 5(h) FT for *Utilities* stock returns

Fig. 5(i) FT for *Financials* stock returns
Fig. 5(j) FT for Technology stock returns

Fig. 6 Out-of-sample analysis using Asymmetric and Threshold models with realized oil prices

Figs. 6(a) to 6(j) report the rolling Diebold-Mariano (1995)’s (DM) test results for 10 UK industries stock returns with varying in-sample estimation window size. The size of the in-sample estimation window relative to the total sample size is reported on the x-axis of each figure (i.e., from 10% to 90%). Each figure reports the DM statistic for comparing asymmetric (eq. 8) and threshold (eq. 9) models to the benchmark model: simple oil price model eq. (1).

Note that, the continuous lines represent the critical value of the DM statistic. The negative values indicate oil price model is better, and when the DM statistic is less than -1.96, we reject the null hypothesis of equal performance and conclude that the oil price model performs better than its competitors.

Fig. 6(a) Oil & Gas stock returns

Fig. 6(b) Basic Materials stock returns
Fig. 6(c) *Industrial* stock returns

Fig. 6(d) *Consumer Goods* stock returns

Fig. 6(e) *Health Care* stock returns

Fig. 6(f) *Consumer Services* stock returns
Fig. 6(g) *Telecom* stock returns

Fig. 6(h) *Utilities* stock returns

Fig. 6(i) *Financial* stock returns

Fig. 6(j) *Technology* stock returns
Fig. 7 Fluctuation Test for out-of-sample analysis using Asymmetric and Threshold models

Figs. 7(a) to 7(j) report the Giacomini and Rossi’s (2010) fluctuation test (FT). The estimation window is one-half of the total sample size and out-of-sample period equals to five hundred days. Each figure reports the FT statistic for comparing asymmetric (eq. 8) and threshold (eq. 9) models with one benchmark model: simple oil price model (eq.1).

Note that, the continuous lines represent the critical value of the FT statistic. The negative value indicate asymmetric and threshold model are better, and when the FT statistic is less than the line, we reject the null hypothesis of models’ forecasting performance is the same at each point of time for industry \( i \).

Fig. 7(a) *Oil & Gas* stock returns

![Fluctuation Test – Oil & Gas](image)

Fig. 7(b) *Basic Materials* stock returns

![Fluctuation Test – Basic Materials](image)

Fig. 7(c) *Industrial* stock returns

![Fluctuation Test – Industrial](image)
Fig. 7(d) *Consumer Goods* stock returns

![Fluctuation Test - Consumer Goods](image)

Fig. 7(e) *Health Care* stock returns

![Fluctuation Test - Healthcare](image)

Fig. 7(f) *Consumer Services* stock returns

![Fluctuation Test - Consumer Services](image)

Fig. 7(g) *Telecom* stock returns

![Fluctuation Test - Telecom](image)
Fig. 7(h) *Utilities* stock returns

![Fluctuation Test - Utilities](image)

Fig. 7(i) *Financial* stock returns

![Fluctuation Test - Financials](image)

Fig. 7(j) *Technology* stock returns

![Fluctuation Test - Technology](image)
Table 1. Unit root tests

<table>
<thead>
<tr>
<th>Level</th>
<th>Return</th>
</tr>
</thead>
<tbody>
<tr>
<td>ADF</td>
<td>PP</td>
</tr>
<tr>
<td>FTSE All share market Index</td>
<td>-1.40</td>
</tr>
</tbody>
</table>

Panel B: Industry Indices

<table>
<thead>
<tr>
<th>Industry</th>
<th>ADF</th>
<th>PP</th>
<th>KPSS</th>
<th>ADF</th>
<th>PP</th>
<th>KPSS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Oil &amp; Gas</td>
<td>-1.21</td>
<td>-1.19</td>
<td>9.59</td>
<td>-41.07*</td>
<td>-80.07*</td>
<td>0.07</td>
</tr>
<tr>
<td>Basic materials</td>
<td>-1.30</td>
<td>-1.16</td>
<td>7.15</td>
<td>-77.67*</td>
<td>-77.64*</td>
<td>0.05</td>
</tr>
<tr>
<td>Industrials</td>
<td>-0.76</td>
<td>-0.75</td>
<td>7.64</td>
<td>-72.59*</td>
<td>-72.76*</td>
<td>0.07</td>
</tr>
<tr>
<td>Consumer goods</td>
<td>1.05</td>
<td>0.95</td>
<td>4.79</td>
<td>-37.87*</td>
<td>-77.17*</td>
<td>0.07</td>
</tr>
<tr>
<td>Health care</td>
<td>-1.62</td>
<td>-1.45</td>
<td>8.53</td>
<td>-79.39*</td>
<td>-79.81*</td>
<td>0.22</td>
</tr>
<tr>
<td>Consumer services</td>
<td>-1.86</td>
<td>-1.87</td>
<td>4.75</td>
<td>-38.68*</td>
<td>-75.38*</td>
<td>0.09</td>
</tr>
<tr>
<td>Telecom</td>
<td>-1.82</td>
<td>-1.72</td>
<td>2.82</td>
<td>-52.59*</td>
<td>-82.64*</td>
<td>0.16</td>
</tr>
<tr>
<td>Utilities</td>
<td>-0.01</td>
<td>0.02</td>
<td>9.26</td>
<td>-79.21*</td>
<td>-79.19*</td>
<td>0.11</td>
</tr>
<tr>
<td>Financials</td>
<td>-1.70</td>
<td>-1.73</td>
<td>5.23</td>
<td>-37.52*</td>
<td>-76.99*</td>
<td>0.24</td>
</tr>
<tr>
<td>Technology</td>
<td>-2.32</td>
<td>-1.77</td>
<td>0.85</td>
<td>-71.66*</td>
<td>-72.16*</td>
<td>0.17</td>
</tr>
</tbody>
</table>

Panel C: Brent Crude Oil

<table>
<thead>
<tr>
<th>Brent Crude</th>
<th>ADF</th>
<th>PP</th>
<th>KPSS</th>
<th>ADF</th>
<th>PP</th>
<th>KPSS</th>
</tr>
</thead>
<tbody>
<tr>
<td>-0.02</td>
<td>0.05</td>
<td>7.54</td>
<td>-78.26*</td>
<td>-78.25*</td>
<td>0.06</td>
<td></td>
</tr>
</tbody>
</table>

Notes: This table reports the results of unit roots tests for our data for the period of January 1988 to February 2013. The null hypotheses for ADF and PP are ‘the series has a unit root I(1)’, while the null hypothesis of the KPSS test is ‘the series is stationary I(0)’. *Significant at 1% level.

Table 2. Descriptive statistics

<table>
<thead>
<tr>
<th>Mean (%)</th>
<th>Std. dev (%)</th>
<th>Skewness</th>
<th>Kurtosis</th>
<th>ACF(1)</th>
<th>Correlation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Market returns</td>
<td>Brent Crude</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>-----------</td>
<td>----------------</td>
<td>-------------</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Panel A: Market Index</td>
<td>FTSE All share market Index</td>
<td>0.020</td>
<td>1.03</td>
<td>-0.21</td>
<td>10.04</td>
</tr>
<tr>
<td>Panel B: Industry Indices</td>
<td>0001 Oil &amp; Gas</td>
<td>0.027</td>
<td>1.35</td>
<td>0.05</td>
<td>8.15</td>
</tr>
<tr>
<td>1000 Basic Materials</td>
<td>0.022</td>
<td>1.63</td>
<td>-0.18</td>
<td>19.09</td>
<td>0.041</td>
</tr>
<tr>
<td>2000 Industrials</td>
<td>0.018</td>
<td>1.10</td>
<td>-0.41</td>
<td>7.61</td>
<td>0.108</td>
</tr>
<tr>
<td>3000 Consumer Goods</td>
<td>0.022</td>
<td>1.15</td>
<td>0.05</td>
<td>9.98</td>
<td>0.054</td>
</tr>
<tr>
<td>4000 Health Care</td>
<td>0.025</td>
<td>1.08</td>
<td>-0.06</td>
<td>7.69</td>
<td>0.019</td>
</tr>
<tr>
<td>5000 Consumer Services</td>
<td>0.015</td>
<td>0.99</td>
<td>-0.16</td>
<td>7.92</td>
<td>0.072</td>
</tr>
<tr>
<td>6000 Telecom</td>
<td>0.019</td>
<td>1.49</td>
<td>0.03</td>
<td>7.14</td>
<td>-0.006</td>
</tr>
<tr>
<td>7000 Utilities</td>
<td>0.034</td>
<td>1.03</td>
<td>0.07</td>
<td>10.57</td>
<td>0.021</td>
</tr>
<tr>
<td>8000 Financials</td>
<td>0.019</td>
<td>1.37</td>
<td>0.04</td>
<td>12.40</td>
<td>0.048</td>
</tr>
<tr>
<td>9000 Technology</td>
<td>0.018</td>
<td>1.62</td>
<td>-0.54</td>
<td>12.11</td>
<td>0.120</td>
</tr>
<tr>
<td>Panel C: Brent Crude Oil</td>
<td>Brent Crude</td>
<td>0.032</td>
<td>2.32</td>
<td>-1.18</td>
<td>28.44</td>
</tr>
</tbody>
</table>

Notes: This table reports the descriptive statistics for our return data. ACF (1) denotes the first order autocorrelation of these series and values in bold indicate significance at 10% level. *Significant at 1% level.
Table 3. Industry stock returns and lagged oil price changes

<table>
<thead>
<tr>
<th>UK Stock Returns</th>
<th>Panel A: Simple Oil Model</th>
<th>Panel B: Oil Model with Further Lags</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\beta$</td>
<td>NW(t)</td>
</tr>
<tr>
<td>Oil &amp; Gas</td>
<td>0.060</td>
<td>6.412</td>
</tr>
<tr>
<td>Basic Materials</td>
<td>-0.010</td>
<td>-0.998</td>
</tr>
<tr>
<td>Industrials</td>
<td>-0.010</td>
<td>-1.520</td>
</tr>
<tr>
<td>Consumer Goods</td>
<td>-0.021</td>
<td>-3.010</td>
</tr>
<tr>
<td>Health Care</td>
<td>-0.028</td>
<td>-3.787</td>
</tr>
<tr>
<td>Consumer Services</td>
<td>-0.017</td>
<td>-2.780</td>
</tr>
<tr>
<td>Telecom</td>
<td>-0.010</td>
<td>-1.104</td>
</tr>
<tr>
<td>Utilities</td>
<td>-0.014</td>
<td>-2.280</td>
</tr>
<tr>
<td>Financials</td>
<td>-0.018</td>
<td>-2.157</td>
</tr>
<tr>
<td>Technology</td>
<td>-0.011</td>
<td>-1.070</td>
</tr>
</tbody>
</table>

Notes: Panel A reports the regression results on the simple oil price model eq. (1): $\Delta R_{ij,t} = \alpha + \beta_{1,t} R_{oil,t-1} + \varepsilon_{ij,t}$, where $\Delta R_{ij,t}$ is the return of FTSE All-Share index industry $i$ for day $t$, $R_{oil,t}$ is the oil price changes in day $t-1$, and $\varepsilon_{ij,t}$ is the error term. Panel B reports the in-sample results by including more lagged oil prices model eq. (2): $\Delta R_{ij,t} = \alpha + \beta_{i} \Sigma_{j=1}^{t-1} R_{oil,j-1} + \varepsilon_{ij,t}$, $t = 1, \ldots, T$. In both panels, we test whether the coefficient $\beta_{i}$ are significantly different from zero. The statistical inference is based on HAC covariance matrix estimator from Newey and West (1987), with optimal lag selected as in Newey and West (1994). We report the estimates of the slope coefficients $\beta_{i}$ and the corresponding two-sided t-statistics denoted by NW(t), these in bold are significant at 10% level.

Table 4. Robustness check

<table>
<thead>
<tr>
<th>UK Stock Returns</th>
<th>$\beta_{i}$</th>
<th>NW(t)</th>
<th>$\gamma_{i}$</th>
<th>NW(t)</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Oil &amp; Gas</td>
<td>0.063</td>
<td>6.645</td>
<td>-0.047</td>
<td>-2.194</td>
<td>0.000</td>
</tr>
<tr>
<td>Basic Materials</td>
<td>-0.012</td>
<td>-1.290</td>
<td>0.044</td>
<td>1.158</td>
<td>0.182</td>
</tr>
<tr>
<td>Industrials</td>
<td>-0.015</td>
<td>-2.261</td>
<td>0.091</td>
<td>4.759</td>
<td>0.000</td>
</tr>
<tr>
<td>Consumer Goods</td>
<td>-0.024</td>
<td>-3.415</td>
<td>0.049</td>
<td>2.569</td>
<td>0.000</td>
</tr>
<tr>
<td>Health Care</td>
<td>-0.026</td>
<td>-3.606</td>
<td>-0.043</td>
<td>-2.363</td>
<td>0.000</td>
</tr>
<tr>
<td>Consumer Services</td>
<td>-0.020</td>
<td>-3.331</td>
<td>0.064</td>
<td>3.531</td>
<td>0.000</td>
</tr>
<tr>
<td>Telecom</td>
<td>-0.008</td>
<td>-0.872</td>
<td>-0.045</td>
<td>-2.054</td>
<td>0.097</td>
</tr>
<tr>
<td>Utilities</td>
<td>-0.013</td>
<td>-2.125</td>
<td>-0.028</td>
<td>-1.496</td>
<td>0.043</td>
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<td>-2.536</td>
<td>0.055</td>
<td>2.478</td>
<td>0.002</td>
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<tr>
<td>Technology</td>
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<td>-1.645</td>
<td>0.105</td>
<td>3.876</td>
<td>0.000</td>
</tr>
</tbody>
</table>

Notes: This table reports the regression results on eq. (3): $\Delta R_{ij,t} = \alpha + \beta_{1,t} R_{oil,t-1} + \gamma_{1} \Sigma_{i=1}^{t} Z_{i,t} + \varepsilon_{ij,t}$, where $\Delta R_{ij,t}$ is the return of FTSE All-Share index industry $i$ for day $t$, $R_{oil,t}$ is the changes in oil price in day $t-1$, and $Z_{i,t}$ is a set of additional predictors can be included into the regression – here we have $Z_{i,t}$ is the lagged UK aggregate stock market returns; and $\varepsilon_{ij,t}$ is the error term. We report the estimates of the slope coefficients $\beta_{i}$ and the corresponding two-sided t-statistics denoted by NW(t), these in bold are significant at 10%. The last column (5th) reports the joint p-values for the null hypothesis $\beta_{i} = \gamma_{i} = 0$. 

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## Table 5. Industry stock returns and oil price changes include asymmetric effects

<table>
<thead>
<tr>
<th>UK Stock Returns</th>
<th>Panel A: Asymmetric Oil Price model</th>
<th>Panel B: Threshold Oil Price model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\beta_i$</td>
<td>$\gamma_i^+$</td>
</tr>
<tr>
<td>Oil &amp; Gas</td>
<td>0.058</td>
<td>4.092</td>
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<tr>
<td>Basic Materials</td>
<td>-0.017</td>
<td>-1.024</td>
</tr>
<tr>
<td>Industrials</td>
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<td>-1.645</td>
</tr>
<tr>
<td>Consumer Goods</td>
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<td>-1.985</td>
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<tr>
<td>Health Care</td>
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<td>-2.497</td>
</tr>
<tr>
<td>Consumer Services</td>
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<td>-2.355</td>
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<tr>
<td>Telecom</td>
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<td>-1.671</td>
</tr>
<tr>
<td>Utilities</td>
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<tr>
<td>Financials</td>
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<td>-1.964</td>
</tr>
<tr>
<td>Technology</td>
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<td>-1.898</td>
</tr>
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</table>

Notes: Panel A reports the in-sample results on eq. (8): $R_{ij} = \alpha + \beta_i R_{oil,t-1} + \gamma_i^+ R_{oil,t-1}^+ + \epsilon_i$, and Panel B reports the results on eq. (9): $R_{ij} = \alpha + \beta_i R_{oil,t-1} + \gamma_i^+ R_{oil,t-1}^+ + \epsilon_i$, where $R_{ij}$ is the return of FTSE All-Share index industry $i$ for day $t$, $R_{oil,t-1}$ is the changes in oil price in day $t-1$, $\gamma_i^+$ are coefficients corresponding to positive movements in the oil price, and $\epsilon_i$ is the error term. We report the estimates of the slope coefficients and the two-sided t-statistics, these in bold are significant at 10%.

### Appendix A

We evaluate the out-of-sample predictive ability of oil price changes for each industry index $i$ using the Diebold and Mariano (1995)’s (DM) test over different rolling in-sample windows $\lambda$. Let $\hat{R}_{i,t+1}^1$ and $\hat{R}_{i,t+1}^2$ denote one-step-ahead forecasts of UK industry stock returns $R_{ij}$ from two competing models: oil price model (1) and benchmark model. In this study, we use the random walk (RW) without drift and RW with drift as the benchmark models against the oil price change model. The forecast errors for each model can be computed as follows: $\epsilon_{i,t+1}^1 = R_{ij,t+1} - \hat{R}_{i,t+1}^1$ and $\epsilon_{i,t+1}^2 = R_{ij,t+1} - \hat{R}_{i,t+1}^2$. The accuracy of each forecast is measured by a particular loss function $L(\epsilon_{i,t+1}^j), j = 1, 2$. We use the common function based on squared error loss: $L(\epsilon_{i,t+1}^1) = (\epsilon_{i,t+1}^1)^2$ and $L(\epsilon_{i,t+1}^2) = (\epsilon_{i,t+1}^2)^2$. The DM test is based on the loss differential: $d_i = L(\epsilon_{i,t+1}^1) - L(\epsilon_{i,t+1}^2)$, and the null of equal predictive accuracy is then $H_0: \bar{d} = \frac{1}{T} \sum_{t=\lambda}^{T} d_i = 0$. The DM test statistic is $S = \frac{\bar{d}}{\sqrt{\hat{f}/T}}$, where $\hat{f}$ is a consistent estimator of the variance of the sample mean loss differential. We reject the null of equal accuracy at the 5% level if $|S| > 1.96$, and suggest that one model is superior to the other.