US Industry-Level Returns and Oil Prices

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Abstract

This paper empirically investigates the oil price puzzle documented in Driesprong et al. (2008) using industry level data. We find empirical support for the oil effect in the US industry level returns. With percentage changes in oil spot prices as predictor, oil effect predictability for one fifth of industries in sample can not be statistically ruled out. On the other hand, statistical support for predictability based on changes in oil future prices is weak. Using measures for net oil price changes along the lines of Hamilton (1996), we find additional support for predictability at the industry-level, as well as a categorization of predictable returns based on their sensitivity to net oil price increase or decrease. We find an approximate two trading week delay in reaction to oil price changes which is consistent with Hong and Stein (1996)'s underreaction hypothesis. These results are robust to various alternative specifications, and are shown to be unrelated to time varying risk premia.

Keywords: Industry-level returns, Market efficiency, Oil prices, Return predictability, Underreaction.
JEL classification: G11, G14, and G17.

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1 Introduction

Driesprong et al. (2008) show that changes in oil prices can predict index returns of developed and emerging international financial markets. They document the relatively short duration of this effect, its independence from time-varying risk premia, and gains from an oil-based active trading strategy in the presence of reasonable trading costs for developed markets.[1] Driesprong et al. show that this remarkable finding is due to delayed reaction by a significant number of market participants in response to changes in oil prices. The fact that oil prices, which are widely and freely available and are closely followed by market participants and scholars, contain information which can be used to predict index returns and generate significant gains in active trading, is an interesting result for both practitioners and financial researchers and hence deserves further investigation.

In our work, using industry-level returns data for US, we show that this predictability is statistically significant for approximately one fifth of industry returns in our sample. A delayed reaction of approximately two trading weeks, or between seven and eight trading days, is detectable in the data, which confirms the findings of Driesprong et al. We also show that the negative impact of oil price changes at industry-level can not be statistically ruled out for the cross section of these returns. Based on this finding, we document the potential gains from an oil-based strategy in comparison with buy and hold, in presence of reasonable trading costs. These results are robust to inclusion of usual financial and economic factors, as well as various specifications of the estimated models.

Since Driesprong et al. findings imply gains from active trading using oil-based strategies, it is necessary to know which industry returns are predictable using oil price changes. This would isolate the source of predictability at the aggregated, index-level returns studied by Driesprong et al. for further research or decision making. Detailed industry-level data are not available for all markets studied by Driesprong et al., but they are available for the US. We use forty nine US industry-level return series to extend and re-examine Driesprong et al. 's study to find the source of predictability observed at the aggregate level.

Second, to exploit the oil effect in research or in practice, it is necessary to know which measure of oil price changes has reasonable prediction power at the disaggregated level. The study by Driesprong et al. focuses on two measures, percentage changes in spot oil prices and percentage changes in futures prices for sweet crude oil. We find that spot oil price changes have significant and superior prediction power compared to changes in oil future prices. Using measures of net oil price changes along the lines of Hamilton (1996), we find additional supporting evidence in favor of predictability. Moreover, using these measures as predictors, we can categorize industry returns based on their predictive sensitivity to net price increase or decrease measures.

[1] Driesprong et al. (2008) find oil predictability effect to be in place for approximately one month. We find a similar duration.

Third, Driesprong et al. justify their findings based on a variation of Hong and Stein (1996)'s underreaction hypothesis. Specifically, they use an empirical testing procedure based on Hong et al. (2007) delayed reaction to newly available information. We follow Driesprong et al. testing procedure to show that our results are consistent with the underreaction hypothesis empirically. In particular, we document evidence in support of an approximate eight day, or two trading week, delay in reaction to changes in oil prices by a significant number of market participants.

Our findings contribute to the literature on equity return predictability. In general, models with even modest predictability are studied seriously in the financial literature, since they can potentially lead to significant profits. Our results provide additional support for Driesprong et al. "oil effect" and the return predictability literature on one hand, and provide a link between two other strands of literature, oil and macroeconomy and return predictability based on macroeconomic factors, on the other hand.

Finance research devotes considerable energy to the study of returns predictability based on business cycle variables. Many studies in macroeconomics investigate the power of changes in oil prices in predicting business cycle fluctuations. Hence, it is natural to study whether an important business cycle factor has meaningful and exploitable predictive power for equity returns.

Following the seminal work of Hamilton (1983) and the subsequent research that this study generated, the economics profession accepts a link between oil prices, macroeconomic variables, and business cycles. Examples include Lee and Ni (2002), Hamilton (2003), and Hamilton (2009), among others.[2] Moreover, macro-finance literature accepts a link between business cycles and equity returns or equity premium at the aggregate level or at the cross-section of returns, see Cochrane (2008) for a detailed discussion. As a result, it is important to study whether a variable such as oil price, which has considerable power in explaining business cycles in in the post World War II US data, has any prediction power for series such as equity returns which are very sensitive to business cycles. Moreover, there is a strong presumption in the financial press that oil prices strongly influence the stock market behavior. Yet, relatively few studies examine prediction power of oil prices for equity returns.

In general, before Driesprong et al. (2008), the empirical evidence on the impact of oil price fluctuations on stock prices was viewed as mixed. Chen et al. (1986) specifically include monthly changes of the real price of oil in their analysis, but find no evidence of a statistically significant relationship between unconditional returns and oil price changes.[3] Jones and Kaul (1996) study the reaction of stock prices to oil shocks, and find mixed evidence on the ability of the impact of

[2]Hooker (1996) argues that the oil price-macroeconomy relationship has changed and weakened in recent years.

[3]They use wholesale oil price data which is very smooth and actually remains constant for extended periods well into the 1980s. This smoothness is misleading for empirical tests concerning monthly changes in oil prices and asset returns. Thus their choice of oil price variable, in our opinion, has some problems.

oil shocks on real cash flows to explain the behavior of stock prices. Kilian and Park (2009) find that the response of aggregate U.S. real stock returns may differ greatly depending on whether the increase in the price of crude oil is driven by demand or supply shocks in the crude market. In a study similar to Driesprong et al. (2008) and ours, Hong et al. (2007) test the predictability of aggregate market returns using returns for the previous month from a variety of industries. Among other industries, they find that high returns for the petroleum industry predict lower returns for the US stock market.

Appealing to the gradual diffusion of information, or underreaction, literature pioneered by Hong and Stein (1996), Pollet (2004) investigates predictability of market returns and industry performance based on forecastable oil price movements. He states that while predictability can be compatible with market efficiency, it may be more readily explained by underreaction to information about subsequent oil price changes. His study focuses on seemingly slow diffusion of information about anticipated oil price movements. Driesprong et al. visit the underreaction issue too. They claim that sectors in which the impact of oil prices is likely to be a dominant first-order effect, show less predictability. On the other hand, they assert that sectors where oil impact seems to be a second-order impact, demonstrate a more pronounced oil effect. But they do not explore these claims any further. Documenting this latter assertion for the US data is at the heart of our contribution. We show, in detail, which US industries show predictive sensitivity to oil price changes, what is the nature and duration of this predictability, and the economic and financial significance of these findings.

The rest of the paper proceeds as follows: in Section 2, we describe and discuss the data. In Section 3, we introduce and discuss our empirical findings concerning predictability of industry-level returns using oil prices, and perform robustness checks. We discuss underreaction of market participants with respect to oil prices in Section 4. In Section 5, we discuss the returns of an oil-based trading strategy and the relation between our findings and time varying risk premia. Section 6 concludes.

2 Data

2.1 Oil Price Data

The international oil market is the most active commodity market in the world. Driesprong et al. provide a concise, yet highly informative discussion of the international oil market, pricing conventions, contracts, and market characteristics. To save space we focus on results for West Texas Intermediate (WTI) crude oil. Unlike Driesprong et al., we do not report the results based on alternative spot prices such as North Sea Brent or Arab Light. WTI data is available for a longer time period, it is highly correlated with other oil spot price measures, and is more pertinent for a study of US industries. Nevertheless, our results are empirically robust across these different oil price series. We use WTI end of the month spot and contract number 1 Cushing, Oklahoma light sweet crude oil future prices from New York Mercantile Exchange (NYMEX) and reported by the US Department of Energy's Energy Information Administration (EIA). This data is also available from usual sources such as *Rueters Thomson Datastream*. The series for WTI spot prices spans January 1979 to January 2009 period, or 360 observations. The available monthly data for light sweet crude future prices is slightly shorter, spanning February 1986 to January 2009, containing 275 observations.

Summary statistics of these series are given in Table 1. Reported statistics pertain to "oil returns" processes, i.e. log differences in oil spot or future prices between two subsequent months. Average oil price changes and standard deviations are in percentages. These series demonstrate no unconditional skewness. On the other hand, based on reported excess Kurtosis, there is moderate unconditional leptokurtotic behavior present for both series.

Two influential papers, Hamilton (1983) and Chen et al. (1986), use wholesale oil price data collected by the Bureau of Labor Statistics. While this data might be useful for examining the relationship between quarterly changes in the price of oil and real GDP, it is very smooth and actually remains constant for three, four, and even five month periods during the mid 1970s and early 1980s (as late as 1984). This smoothness is misleading for empirical tests concerning monthly changes in oil prices and asset returns.

We justify using both spot and future prices data thus: we believe that spot prices reflect information available to the markets up to time t. This means that conditioning industry returns on lagged oil returns provides a semi-strong efficient prediction for industry returns. We believe that futures prices measure the sentiments of the market participants towards the short term future. Since oil markets are highly liquid, differences between oil spot and future prices are small, but non-negligible at each point in time. Thus we believe that conditioning industry returns on oil future price changes, measures the predictability content of market participants' sentiments towards the short term future.

2.2 US Industry-Level Returns

Industry level returns data is taken from Kenneth R. French's data bank.[4] We use average monthly value weighted returns on 49 industry level portfolios. The original data spans July 1926 to present. We use a subset of this data, from January 1979 to January 2009. There are 360 observations in each returns series.

According to the data definitions, each NYSE, AMEX, and NASDAQ stock is assigned to an

[4] This data set is available from `http://mba.tuck.dartmouth.edu/pages/ken.french/data_library.html`. Unfortunately, such detailed industry-level data are not available for other markets, developed or emerging, studied in Driesprong et al. Hence, we limit our study to the US industries.

industry portfolio at the end of June of year t based on its four-digit SIC code at that time. The data is constructed using Compustat SIC codes for the fiscal year ending in calendar year $t-1$. Whenever Compustat SIC codes are not available, CRSP SIC codes for June of year t are used. The monthly returns are then computed. Construction of this data bank ignores transaction costs and does not include a hold range.

Summary statistics are given in Table 2. Average sample returns and standard deviations are in percentages. None of the returns series exhibits heavy unconditional skewness. We report excess Kurtosis values in the table. Deviation from excess kurtosis greater than zero is seen in almost all industry return series. Based on sample statistics, we conclude that monthly returns demonstrate leptokurtotic behavior.

Welch and Goyal (2008) believe that many positive predictability results in the literature depend on samples which contain the oil shock of 1974. Our data starts in 1979, hence our results do not depend on, in the words of Welch and Goyal, this anomalous period.

3 Predictability of Industry-Level Returns

3.1 Basic Regression Model

We follow Driesprong et al. in testing the predictability of returns, instead of excess returns, for US industry portfolios. To test for the existence of an oil effect we incorporate an oil variable, $r_t^{oil,spot}$ or $r_t^{oil,future}$, in the regression

$$r_t^i = \mu_i + \alpha_i r_{t-1}^{oil,\cdot} + \varepsilon_t^i \tag{1}$$

where r_t^i represents the returns of industry i at time t, μ_i's are real valued constants, $r_t^{oil,\cdot}$ denotes oil 'spot' or 'future' price changes, as discussed above. For simplicity, we do not indicate 'spot' or 'future' in the notation used for the parameters. The reported results in Tables are differentiated. ε_t^i are the usual error terms for each industry. In the absence of the oil variable, this equation reduces to the random walk model for logarithmic asset returns. We test whether the coefficient on $r_t^{oil,\cdot}$, α_i, is significantly different from zero for each industry. When α_i is significant, the null hypothesis of no oil effect is rejected. We estimate these regressions individually, since our objective is a study of prediction power of oil prices for each industry-level returns series. We estimate these regressions using ordinary least squares (OLS). As discussed earlier, industry returns and oil price changes series are leptokurtotic. Hence the possibility that standard errors of the parameter estimates may not be heteroskedasticity-consistent exists. We address this potential problem by using Newey and West (1987) heteroskedasticity and autocorrelation consistent (HAC) covariance matrix estimators.[5]

[5]Driesprong et al. (2008) use the White (1980) estimator instead of the Newey-West estimator.

3.2 Empirical Evidence

Estimated values of α_i parameters in Eq. (1) are reported in Panel A of Table 3. We report industry-returns which demonstrate statistically significant predictability for the sake of brevity. Oil spot price changes have statistically significant prediction power for nine industry portfolio returns series. This translates to slightly less than 20% of industry-level returns in our sample. The null that these estimated parameters are not significantly different from zero is rejected at the 5% significance level for two industries, meals with oil spot price changes and retail with oil future price changes, and at the 10% significance level for two industries (construction and meals) using oil future price changes, and for eight industries (autos, boxes, business services, construction, personal services, retail, rubber, and telecom) using oil spot price changes. All in all, oil spot price changes can predict returns of nine out of forty nine industries in the US financial markets, or 18.36% of the total. We find the fact that auto industry shows signs of predictability puzzling at the first glance. But further investigation confirms this finding (see Table 4 and discussion of the results in Section 3.3), and we can attribute this result to our subsequent discussion of underreaction hypothesis in Section 4.

Oil future price changes are far less powerful in predicting industry-level returns. Using oil future price changes as predictor yields just three predictable industries, which is barely above the variation that we expect to see in the cross-section of returns, under the null hypothesis of no predictability. Hence, we claim that changes in oil futures prices have very limited predictive power for US industry returns in the sample period.

All estimated parameters have a negative sign, regardless of their statistical significance, which is in line with the findings of Driesprong et al. This implies that a positive change in oil price growth leads to a decline in industry-level returns in the subsequent month. The values of these estimated parameters range between a low of -0.05 for telecom to a high of -0.088 for the automotive industry, using oil spot price changes as predictor. If we use oil future price changes, these values range between -0.075 (meals) to -0.095 (construction). The estimated parameter for US index returns, using WTI price changes reported by Driesprong et al., is -0.086. In this respect, our estimates are closely in line with their finding. We later show that the negative spot oil price change impact is jointly statistically significant for the cross section of the returns in the sample.

One natural question to ask is whether these negative signs of estimated parameters are driven by the positive loading on the stock market return in conjunction with the negative relationship between oil price changes and market returns documented by Driesprong et al. Our answer to this charge is that Driesprong et al. claim that oil price changes predict index returns. Index returns are almost equivalent to weighted averages of industry returns.[6] Thus, basic econometric intuition implies that predictability at the aggregate level follows from predictability at the disaggregated level. Moreover, our estimations show that all estimated coefficients of the industry returns, regardless of their statistical significance, have a negative sign. In other words, the direction of predictability relationship between spot oil price changes and returns, at aggregated and disaggregated levels, is the same. Under such conditions, we believe that the claim of negative signs for estimated parameters at the industry level due to positive loading of the market factor and the oil effect at the aggregate level, is not statistically reasonable.

Besides, we extensively studied the impact of oil price changes, both spot and future prices, on standard CAPM and three factor Fama and French settings. We included contemporaneous and lagged oil price changes in standard CAPM and three factor Fama and French regressions. The objective was to rule out the possibility that oil price change coefficients are statistically significant since oil price changes are acting as a proxy for either the market excess returns or one of the Fama-French factors. We found out that the statistical significance and the sign of lagged oil price change coefficients are robust to inclusion of market excess returns or the Fama-French factors. As a byproduct of this exercise, we can confidently rule out the interaction between positive market loadings and oil effect at the aggregate level delivering the results reported in Table 3. These results are available upon request, but are not reported to save space.

Since industry returns are correlated, we also estimate the model as a system of seemingly unrelated regressions (SUR). Our interest is in testing jointly whether the hypothesis of $\alpha_i = 0$ is rejected across industries. First, we find that the null hypothesis of no predictability is strongly rejected at conventional statistical confidence levels. We find Wald test statistics which indicate p-values smaller than 0.5%. Second, we find that joint estimation leads to a greater number of statistically significant prediction parameters for WTI spot price changes. Instead of nine predictable industries, we now have nineteen, or approximately 39% of the industries in sample. All our initial predictable industries are in this subset. Moreover, banks, building materials, clothing, coal, finance, hardware and software, lab equipment, machinery, and textiles show signs of predictability using oil spot price changes as the predictor. All estimated parameters, whether statistically significant or not, have the expected negative sign, and their sizes closely follow the estimations of Driesprong et al. In fact, they range between -0.044 to -0.089.

We then test whether α_is in the cross-section are equal, but not equal to zero. The objective is to test for differential effects across industries. Again, we strongly reject the null hypothesis of equal predictability effect across industries. The Wald test statistic indicates p-values smaller than

[6]This claim is naturally true for broad indices, such as S&P 500, Russell 3000, or MSCI indices. Driesprong et al. study MSCI US Market Index, which represents approximately 99.5% of the US equity capitalization according to MSCI-Barra index structure definitions.

0.01%. These findings confirm the evidence reported in Table 3. Our estimation results are robust to inclusion of returns from S&P 500 and Dow Jones Industrial Average indices.

Finally, we jointly test whether α_is in the cross-section are all positive. The objective is to test for statistically meaningful negative oil effects across industries. Again, we strongly reject the null hypothesis of positive oil effect across industries in a one-sided test. The Wald test statistic indicates p-values smaller than 0.01%. This result is particularly important, since we construct the "oil strategy" of Section 5.1 based on this finding.

Following the influential paper by Stambaugh (1999), many financial scholars have studied the problems of predictive regressions. A concise and lucidly written summary is given in Campbell and Yogo (2006). They also provide a pre-testing procedure for predictive regressions. We carry out these pre-tests and find that our formulation does not suffer from the overstatement of true significance by t-statistics which is documented in their study. These results are available upon request.

3.3 Robustness

In this section, we address the following concerns. First, we want to see whether predictability stems from sensitivity of industry-level returns to increase or decrease in oil price changes. Second, we want to know whether such sensitivity can provide a categorization of predictable industry returns. As a byproduct, we also study whether different measures of oil price increase and decrease can act as possible prediction tools. Third, we study robustness to different specifications for oil price changes such as shocks in prices and non-linearities. Finally, we carry out testing procedures to address questions about robustness of our reported results with respect to contemporaneous correlation of oil price changes and equity returns, longevity of the oil effect, and non-synchronous trading.

In construction of oil price increase measure, we follow Hamilton (1996) and his formulation for "net oil price increase". Very concisely, using quarterly data, Hamilton constructs this measure as the maximum of zero, and the difference between the percentage change of the crude oil price for quarter t and the maximum value for the percentage change achieved during the previous four quarters. Since we are using monthly data, our measure is constructed in a slightly different fashion. Also, we construct two measures, one for "net oil price increase" ($nopi_t$) and another for "net oil price decrease" ($nopd_t$).

In our investigation, net oil price increase ($nopi_t$) is defined as

$$nopi_t^j = \begin{cases} r_t^{oil,\cdot} - M_j, & \text{if } r_t^{oil,\cdot} > M_j; \\ 0, & \text{otherwise.} \end{cases} \tag{2}$$

where $M_j = \max\{r_{t-\tau}^{oil,\cdot}\}_{\tau=1}^{j}$ and $j = \{4, 6, 12\}$. We study M_j values that correspond to maximum value of returns in a quarter, six month, and one year, respectively. Hamilton (1996) considers net oil price increases of quarterly data over the maximum of the preceding four quarters which is equivalent in length to our $j = 12$ case.

In a similar fashion, we also construct a measure for net oil price decrease ($nopd_t$), which follows

$$nopd_t^j = \begin{cases} r_t^{oil,\cdot} - N_j, & \text{if } r_t^{oil,\cdot} < N_j; \\ 0, & \text{otherwise.} \end{cases} \tag{3}$$

Here, $N_j = \min\{r_{t-\tau}^{oil,\cdot}\}_{\tau=1}^{j}$ and j is as in Eq. (2). The difference is that instead of considering the exceedence of oil returns over a maximal measure, M_j, we look at the difference between a negative return and the minimal value attained over the last j-months, N_j.

These measures can be interpreted as either surprise return movements over the "norm" of the market over the last j-months period, or as corrections for a change in prices in the opposite direction over the past j-months, as in Hamilton (1996). Either way, they present a tool to disentangle industry returns which are sensitive to oil price increases from those which are sensitive to oil price decreases, which is one way of categorizing industry returns.

Both measures are defined for percentage changes in oil spot and future prices. We substitute oil price change measures by their corresponding net oil price change measures in Eq. (1) and estimate the resulting models. The estimated parameters are reported in Table 4. We report OLS coefficient estimates and HAC-consistent standard errors. The number of predictable industry-level returns for both reported spot oil price and future price-based measures is comparable or superior to plain percentage changes in oil prices. The reported coefficients are relatively larger than those in Table 3, and more importantly, they have an opposite sign. That is, while our results and Driesprong et al.'s findings both report a uniformly negative relationship between oil price changes and index or industry returns, we generally find a positive relationship between industry returns and net price changes. Notice that this result is not at odds with what is reported in Section 3.2 and findings of Driesprong et al. Net price change measures do not have a linear relationship with spot price or future price changes. Thus, it is not surprising that we find a different statistical relationship between these measures and industry returns.

Panel A in Table 4 reports the reaction of nine industries to net price increases compared with price changes in the preceding three months (a quarter) or six months (half a year) of WTI spot prices. Of the industries reported in Table 3, four industries appear in this panel. Construction, personal services, retail, and meals react positively to a net price increase over the preceding quarter. Moreover, Food, clothing, and aerospace show positive sensitivity to a lag in net price increase over the same period, while oil and gold industries react negatively with respect the same measure. There are no representatives of Table 3 in the second row of Panel A, which reports industries that show sensitivity to a lag price increase in WTI spot price compared with the preceding six months. Aerospace, oil and gold industries appear in this row, with the same sign as in the first row. Moreover, tobacco, soft drink, hardware, building materials, and household products seem to be sensitive to this measure. In each case, approximately 20% of industry-level returns show predictive sensitivity with respect to three and six month net spot price increase. This is comparable to the results from predictive power of spot price changes, reported in Panel A of Table 3.

Industry returns that demonstrate statistically significant predictive sensitivity to WTI spot net price decrease, are reported in Panel B of Table 4. The number of predictable returns using this measure of price changes is slightly lower than those reported in Panel A, ranging between six and eight. The second row, corresponding to the results for six months net price decrease measure, demonstrates predictive power for 12.25% of industry returns. This is slightly larger than cross-sectional variation at 10% level under the null of no predictability and thus should be treated cautiously. Three remaining industries from Panel A of Table 3 are present here. In particular, automotive industry demonstrates predictive sensitivity to lagged WTI net spot price decreases over both three and six month measures.

The two other industries mentioned, telecom and business services, are sensitive to net price decreases over the preceding 12 months, as are tobacco, publishing (books), mining, banking, and finance industries which do not appear in Table 3. Finance, steel, and lab equipment industry returns are sensitive to more than one measure of net spot price decline.

Panels C and D in Table 4 present the results from study of predictive sensitivity of industry-level returns to net future price changes. It is immediately clear that these measures have more predictive power than plain changes in light sweet future prices discussed in Section 3.2. In particular, the null hypothesis of $\hat{\alpha}_i = 0$ is not rejected for many industries in Panel D. We interpret these results as presence of predictive power in net future price changes, especially if there are large deviations from market participants' anticipated returns in future prices formed over longer periods, namely six and twelve months.

Panel C of Table 4 reports industry returns which are sensitive to lagged net price increases for light sweet future prices. First, notice that only net price increase measure in comparison with the preceding 12 months is reported. Also note that the reported eight industries show both positive and negative reaction to this measure. As a side issue, only telecom industry is present both in this panel and in Panel B in Table 3.

In Panel D of Table 4, we see almost all industry returns reported in Panel B of Table 3, along with many others. Twelve months net future price decrease measure seems to have prediction power for 29 industry-level returns, or almost 60% of industry returns in our sample. Again, automotive industry shows evidence of sensitivity to lagged net future price decreases, as do every industry in Panel A of Table 3. We view these results as confirmation of presence of predictive sensitivity in industry returns, using lagged net future price decrease measure.

The following net price change measures have very weak predictive power for industry returns, therefore we do not report their respective results. Net spot price increase over the preceding 12 months could predict three industries. Net oil future price increases for three and six months, could predict just one and three industry returns respectively. These results are weaker than the cross-sectional variation at 5% or 10% confidence level under the null of no prediction, hence we conclude that these three measures can not predict industry returns.

We carried out robustness tests to ensure that predictive results reported here are not due to omitted variables, or net price change measures acting as proxies for other factors. We found that our results are essentially invariant to inclusion of market returns, Fama and French factors, contemporaneous and lagged oil price changes, and contemporaneous net price changes, in different permutations of possible linear relationships. These results are available upon request, but are not reported here.

We believe that based on these findings, the automotive industry is sensitive to unanticipated oil price drops. This industry is sensitive to the majority of net price decrease measures, whether for spot or future prices. In conjunction with the predictability of automotive returns in Section 3.2, we are confident that oil prices can predict automotive industry's returns. Similarly, telecom and business services industry returns show sensitivity to net price decreases. On the other hand, construction, personal services, retail, and meals returns react to net price increase measures, as do aerospace, oil, and gold industries. We consider these results to yield a reasonable categorization of the predictable industry-level returns, based on predictive sensitivity to oil price increase or decrease.

A reasonable question is whether predictability is a results of anticipated component or unanticipated news in oil returns. Pollet (2004) specifically studies anticipated oil price movements and their prediction power. Here we study the predictability content of unanticipated news. We have two measures for unanticipated news. The first measure is "oil shocks", which we construct by using the residuals of fitting the oil returns series using a first order autoregressive ($AR(1)$) process.[7] The intuition is to remove the easily predictable conditional mean component from oil spot or future price changes. We do not want to filter out the potentially present time varying volatility behavior, since we want to test whether these components convey news for the market. Second, we use "oil price volatility" which we construct by squaring oil price shocks. Volatility is a proxy for risk in these markets, and can also proxy for non-linearity in the oil-industry returns relationship.

Under alternative formulations for oil price impact, we substitute $r_t^{oil,\cdot}$ in Eq. (1) with measures for oil shocks or volatility. Oil shocks are denoted as $s_t^{oil,\cdot} = r_t^{oil,\cdot} - \hat{r}_t^{oil,\cdot}$ and $\hat{r}_t^{oil,\cdot}$ is the fitted value for oil price changes from an $AR(1)$ process; oil volatility is denoted as $v_t^{oil,\cdot} = (s_t^{oil,\cdot})^2$. Values are calculated for both spot and future prices.

[7] We fit the oil return series using an $ARMA(1,1)$ formulation too. Using the residuals from an $ARMA(1,1)$ fit does not significantly change our findings.

Estimated values of $\alpha_{i,s}$ parameters are reported in Panel B of Table 3. A cursory look reveals that using the shock measure instead of price changes does not alter estimated values of parameters or their statistical significance. The same industry-level returns show evidence of predictability, and estimated parameters and standard errors are also very close to what is seen in Panel A. On the other hand, the prediction power of oil future price shocks is even less than that of oil future price changes reported in Panel A, hence it is not reported. A single industry returns series, construction, can be predicted and the size of the estimated parameter, -0.081, is different from what is seen in Panel A. This predictively result is lower than what is expected under the null hypothesis of no prediction in the variation of the cross-section of the returns. These findings reinforce our initial conclusion that oil spot price changes have more prediction power than oil future price changes. Moreover, we conclude that first, the prediction model is robust to use of price changes or shocks to oil spot returns, and second, we find evidence suggestive that the predictability stems from the unanticipated "news" contained in the oil price series.

The results from inclusion of the constructed volatility in prediction regression are very weak. Hence, we do not report the results, but briefly discuss the findings. We find that using oil spot volatility as the predictor, the null hypothesis that estimated α_i parameters are equal to zero is rejected at conventional confidence levels for only three industry-level series: agricultural products, wholesale, and real estate. A similar analysis using oil future price volatility similarly yields three predictable industry-level series. They are the aerospace, shipping, and insurance industries. All these estimated parameters have the expected negative sign. Since, using this measure, we can predict less than 10% of industry-level returns series in sample, we conclude that the constructed volatility measure used here does not have much prediction power for industry-level returns. We discuss time-varying risk premia in detail in Section 5.2.

We report the outcome of robustness tests for prediction results with respect to contemporaneous correlation of oil price changes and the duration of the oil effect. To this end, we estimate the following regression model:

$$r_t^i = \mu_i + \alpha_{1,i} r_{t-1}^{oil} + \alpha_{2,i} r_{t-2}^{oil} + \alpha_{3,i} r_t^{oil} + \alpha_{4,i} r_{t-1}^i + \varepsilon_t^i. \tag{4}$$

In this model, inclusion of contemporaneous oil price changes controls for contemporaneous correlation between oil prices and industry-level returns. Similarly, industry-level returns lagged one month control for non-synchronous trading. By considering oil price changes lagged two months in addition to oil price changes lagged one month, we test for how long predictability effects last.[8] The results of regressing industry-level returns on individual variables besides oil price changes are very similar, hence they are not reported.

[8] Lag lengths of three, six, and twelve months where also studied. Since the results are very similar, they are not reported.

Estimated results are reported in Table 5. We only report those industries which have at least one statistically significant estimated parameter. Estimated parameters are the output of OLS regression and all reported standard errors in are Newey-West HAC consistent estimates.

The top panel of Table 5 reports the results using changes in WTI spot prices. Eight industries show statistically significant predictability. Two industries (retail and meals) lose predictability in presence of these additional explanatory variables. On the other hand, the building materials industry becomes predictable once lagged industry returns are included. Length of predictability period is quite short. Only one industry, construction, demonstrates statistically significant predictability using oil price changes at a two-month lag. We conclude that for industry-level returns, predictability does not extend beyond a one-month lag. Four industries, gold, mines, oil, and personal services, show evidence of contemporaneous correlation of oil and industry returns, through statistically significant parameters for contemporaneous oil returns. This is still quite low, just 8.16% of industries show signs of statistically significant contemporaneous correlation between oil and industry returns. This result is within the expected variation in the cross section of returns under the null of no contemporaneous correlation of oil and industry returns at 10% significance. Moreover, such a relationship is not quite surprising for oil and mining industries. We expect information of oil prices to have a significant impact on oil and related industries' returns, but we also expect this information to be quickly absorbed and incorporated in the market prices.

Our findings here differ from Driesprong et al. in one important dimension. They find weak evidence of the importance of lagged index returns in their regression analysis. We, on the other hand, find a significant number of industries where lagged industry-level returns are significant predictors. This is suggestive, but is not conclusive evidence, of the presence of non-synchronous trading. Except for two industries, meals and retail, the inclusion of additional regressors hardly changes the value or significance of estimated one month lagged oil returns parameters. We conclude that predictability is fairly robust to inclusion of other factors.

The bottom panel of Table 5 reports the results using price changes in NYMEX light sweet crude future prices. These results are consistent with the conclusion in Section 3.2 that oil future price changes have weak prediction power for industry-level returns. By introducing new variables in the prediction regression, we find that just two industries, hardware and personal services, show some level of predictability. The length of prediction period is still very short. The coefficient of future price changes lagged two months is statistically significant for a single industry, oil. This result, especially for the oil industry where contemporaneous future price changes and lagged industry returns are also significant, is rather puzzling. We attribute this to cross-sectional variation that can happen under the null hypothesis of no prediction, and view the result as statistically insignificant.

Contemporaneous correlation between future price changes and industry-level returns are significant for six industries: food, drugs, gold, oil, personal services, retail, and meals. Similar to our findings using oil spot price changes, these results provide suggestive but inconclusive evidence of the presence of non-synchronous trading. Since introducing new factors does not change parameter estimates much, we conclude that, while future price changes are not good predictors, the estimation results are reasonably robust to inclusion of other factors. We believe that month to month changes future prices do not posses much prediction power.[9] In other words, expectations of market participants seem to have little ability for predicting industry-level returns in the near future; all their relevant information is already incorporated in the stock prices.

Moreover, we study the model with excess returns, that is industry-level returns minus short term rates. We use the four week (one month) T-Bill rate as the short term risk free rate. We observe that the results are almost identical to using returns instead of excess returns. Based on this evidence, we conclude that the formulation in Eq. (1) is robust to the use of either returns or excess returns.

4 Underreaction to Oil Prices

Oil price information is both publicly available at no cost almost in real time and widely followed by the investors. Hence, it is rather surprising that such widely available information has predictability for a significant portion of US industry-level returns. At first glance, this observation may even be at odds with market efficiency. However, a rationality-consistent explanation is available through the gradual diffusion of information hypothesis of Hong and Stein (1996). We present the evidence supporting this hypothesis in our sample in the subsequent sections.

4.1 Underreaction and Oil Prices

The main assumption driving the Hong and Stein (1996) underreaction hypothesis is decision making by investors who are endowed with bounded rationality in presence of private information. As a result, and based on the additional assumption that private information diffuses gradually across investors who do not extract information from prices,[10] market prices react to information about fundamentals with a delay. The Hong and Stein (1996) framework can be extended to include underreaction in presence of publicly available information.

Hong et al. (2007) consider the scenario where the gradual diffusion of information across asset markets leads to cross-asset return predictability. The basic idea in their study is that some investors, for example those who specialize in trading the broad market index, receive information originating from certain industries, such as commercial real estate or commodities, with a lag.

[9]Introduction of these factors rendered three predictable industries unpredictable. Point and standard errors estimates for the rest, while statistically not significant, do not change much. These results are available upon request, but are not reported.

[10]They call them “newswatchers”.

We may infer that underreaction is possible in at least two cases in the presence of publicly and freely available data. The first case may occur when some investors find it difficult to evaluate the ramifications of existing or new information on equity values. Since market response to public information driven by the sum of private signals, lags in response, or inaction, may result in underreaction. The second case which, according to Hong et al. (2007), may lead to underreaction is when investors react to information at different points in time after it becomes available.

Information needs to have a meaningful impact on economic activity before it is captured by empirical analysis, as pointed out by both Hong et al. and Driesprong et al. Oil prices clearly have an impact on economic activity. It is reasonable to believe that industries such as petroleum or transportation have very accurate assessments of the first order effects of oil price changes. But as Hamilton (2003) shows, the precise second order effects of oil price changes on the economy are not well understood. As a result, the effects of changes in oil prices on stock prices are not quite clear.

There may even be confusion about which source of information should be trusted. As we noted earlier (and as is discussed in Driesprong et al. as an example), many academic articles, including Chen et al. (1986) and more recently Hamilton (2003), are based on the U.S. wholesale oil price. Oil price changes based on wholesale price demonstrate up to three-month lags in movements compared to WTI spot price changes. Hence, if investors use different measures for oil price information, their actions will have very different outcomes which compare favorably with predictions of the underreaction hypothesis.

In our study, we find evidence in favor of the hypothesis that investors may find it hard to analyze the information contained in oil price changes in industries which seem to be less oil-dependent, such as telecom or construction. As discussed earlier, we do have a the puzzling case of the automotive industry in our results. Based on our empirical findings in Sections 3.2 and 3.3, we have compelling evidence that automotive industry returns show oil price change predictability. But intuitively, one expects this industry to closely follow and immediately incorporate information contained in oil price data. As it turns out, this is not the case. We believe that this outcome is due to difficulty of accurate assessment of secondary oil effects on profitability of the automotive industry. Thus, we believe that oil prices satisfy the criteria of Hong and Stein (1996) model, and then proceed to empirically test the underreaction hypothesis, following Driesprong et al. steps.

4.2 Empirical Evidence

In this section, we carry out and report the results of Driesprong et al. "delayed reaction" test. The fundamental idea in this test is the Hong et al. assertion that investors may react to information with a delay, leading to underreaction. The test is developed through the following intuition: if investors "wake up" to new information with a delay, then the predictability effect should become stronger if one introduces small enough lags between monthly stock and lagged oil price changes. We expect the explanatory power of this regression to increase, due to capturing the delayed response up to a certain number of lags, and then to decline.

Since the duration of this delayed reaction to oil price changes is unknown, we try several lag lengths. In the first step, we assume that investors react to oil price changes a week (five trading days) after a price movement.[11] As a result, we expect that introducing a five trading day lag between monthly industry returns and oil price changes should increase the explanatory power of our regressions.

To carry out the testing process empirically, we construct a new monthly oil price series with delays of one and five trading days. WTI data is available on daily frequency from March 1986. Our sample is constructed by dropping the oil price changes of the last trading day (trading week) of the month $(t-1)$ and adding the oil price returns of the last trading day (trading week) of the previous month $(t-2)$. If the delayed reaction hypothesis holds, then the last price changes of the $t-2$ month should have more information content for predicting industry returns than the price changes on the last trading day (trading week) of the $t-1$ month.

The results are reported in Table 6. The top panel reports the regression results with no lags between the monthly industry-level returns and the monthly spot oil price changes of WTI. The middle and bottom panels in the table report the results for 1- and 5-trading day lags. Our findings are mixed, and resemble the results reported for Emerging Markets in the lower panel of Table 7 in Driesprong et al. We find that while the prediction of higher R^2 associated with longer lags holds for the construction industry, it does not hold for any other industry with statistically significant oil price change estimated parameters. However, we note that these drops in R^2 are negligible.

The choice of 1-trading day or one trading week (5-trading days) is arbitrary. We repeat the procedure for up to 11 trading days to avoid overlapping sample problems in estimation. A pattern emerges: after an initial drop, the R^2 rises at around the 7^{th} or 8^{th} trading day lag, and then drops quickly again. With different magnitudes, this pattern is repeated across all industries. We believe that this pattern is supportive of a delayed reaction period of around 7 to 8 days long for a relatively large group of investors.

We also carry out weekly regressions to document the possibility of delayed reaction among investors using a different sampling frequency. The regression model used in this analysis is:

$$r_t^i = \mu_i + \alpha_{i,1} r_{t-1}^{oil} + \alpha_{i,2} r_{t-2}^{oil} + \alpha_{i,3} r_{t-3}^{oil} + \alpha_{i,4} r_{t-4}^{oil} + \alpha_{i,5} r_{t-5}^{oil} + \alpha_{i,6} r_{t-6}^{oil} + \alpha_{i,7} r_{t-7}^{oil} + \alpha_{i,8} r_{t-8}^{oil} + \varepsilon_t^i. \quad (5)$$

In this model, r_t^i represents returns of industry i portfolio, and r_{t-j}^{oil} represents changes in the WTI spot price, lagged j weeks. Naturally, the $\alpha_{i,j}$s represent the coefficient of changes in j-lagged oil prices for industry i. The reported standard errors are the Newey-West HAC consistent estimates. The regression analysis results are reported in Table 7. As is seen in the column Oil$(t-1)$,

[11] The choice of a trading week as the delayed reaction duration is arbitrary. The true duration may be shorter or longer. We test other lag lengths for robustness; see below.

representative of a one-week lag in oil price changes, there is no predictability detectable. On the other hand, the column Oil($t-2$) reports almost universal predictability. This period corresponds to the 7 to 8 trading day delayed reaction in the market. We find this result particularly encouraging. Predictability disappears quickly. For lags of three to seven, evidence of predictability is very weak and it totally vanishes for Oil($t-8$). We take these results to be supportive of delayed reaction hypothesis.

5 Financial and Economic Significance

Our findings are statistically significant. But do they convey any exploitable financial and economic information? Many anomalies documented in the financial literature can not be exploited, since they are "uncovered" through assuming away trading costs. Once trading costs are incorporated in empirical assessment, they dominate any potential gains from active trading strategies based on the alleged anomaly. We carry out a simple exercise to compare the gains from an "oil strategy" and the benchmark "buy and hold" strategy in the presence of reasonable levels of trading costs.

Another issue is whether these predictability results are due to time varying risk premia. The risk premium varies over time. The fact that some economic variables predict stock returns might be related to the predictable variation of the risk premium over the business cycle. Thus, this predictability may not necessarily indicate an anomaly. We address the time-varying risk premium issue in this section. We verify that oil effect is statistically unrelated to time-varying risk premia.

5.1 Economic Significance

We compare the performance of buy and hold and oil-based trading strategies returns in the presence of reasonable trading costs. Unless the oil-based trading strategy delivers a better performance than buy and hold strategy outcomes, after subtraction of trading costs, it has no practical value. Based on our results in Section 3.2, particularly the Wald test for presence of statistically significant negative oil effects in the cross-section of the industry-level returns, we find that a negative oil effect can not be ruled out. Hence, we can construct oil based strategies for all industries in our sample, although just 20% of these returns are oil-predictable at the conventional 5% or 10% confidence levels. We find that the oil strategy indeed delivers superior performance for almost all industries in the sample.

We take the following steps to construct the returns of the oil trading strategy. First, we take sixty observations from January 1979 to December 1983 for each industry. Thus, the sample period of comparison is January 1984 to December 2008. We estimate Eq. (1) using the initial 60 observations, then use the estimated parameters and the last observed oil price change to form a prediction for industry returns in the coming month.

We re-estimate the model every month using a sliding window of length sixty, and form one month ahead forecasts of industry returns as described above. We compare these forecast values with four week (one month) US T-Bill rates. If the expected return is higher than the T-Bill rate, we invest fully in the industry, otherwise we invest fully in T-Bills. We repeat this investment rule for every month. We assume switching costs equal to 0.10%. In this respect, we follow Solnik (1993) and Driesprong et al.

We thus construct oil strategy trading outcomes for each industry. These results are reported in Table 8. It is immediately obvious that the oil strategy delivers higher Sharpe ratios than the buy and hold strategy. Across all industries, the buy and hold strategy generates a return average of 10.67%.[12] These returns on average have standard deviation equal to 22.26%, with a maximum return obtained for smoke (tobacco industry) equal to 17.83%, and a minimum return of -0.583 for real estate in this sample period. The average Sharpe ratio for this strategy is 0.478, with a maximum value of 0.845 for food and minimum value of -0.047 for real estate.

In contrast, the oil strategy delivers average returns of 12.92%. This translates to an improvement in returns equal to 2.25% compared with the buy and hold across all industries in our sample. The best return of the oil strategy is the software industry with 19.26% annual returns. The worst performance belongs to the real estate with 5.53% in annual returns. Notice that using the oil strategy, we could improve real estate's returns by 6.12%. The average standard deviation of returns of this strategy is 18.89% or an average risk reduction equal to 3.37%. In particular, the risk associated with the gold industry is reduced by 9.85% which we consider quite impressive. Even the smallest risk reduction, utilities, is still a respectable 1.05%. Average Sharpe ratio for oil strategy is 0.67 which translates to an average 0.19 improvement over buy and hold. As it is evident, this result is achieved through combined risk reduction and improved returns performance.

For the nine industries with strong evidence of oil-predictability in Table 3, average returns performance increases by 2.85%, average risk is reduced by 2.87%, and the average Sharpe ratio as a result increases from 0.487 to 0.721.

Our results are somewhat different from what Driesprong et al. report for the US. In their study, for a shorter sample and for MSCI index returns, the oil strategy outperforms buy and hold by 1.2% in average returns, reduces risk by 5.3%, and improves the Sharpe ratio from 0.39 to 0.72. In our exercise, the oil strategy delivers better average performance, but does not reduce risk as much. Still, it is clear that the oil strategy returns are superior to those of the buy and hold strategy.

An important issue which deserves attention is whether the risk free rate and market portfolio span the results of the oil strategy. Formally, we calculate Jensen's alpha from estimating the following model:

$$r_t^{os,i} - r_t^f = \alpha_i + \beta_i (r_t^m - r_t^f) + \varepsilon_t^i. \tag{6}$$

Here, $r_t^{os,i}$ are the returns from the oil strategy for industry i, r_t^m are market returns, and r_t^f is the

[12] This value is almost identical to the reported value in Driesprong et al.

risk-free rate. We use the four-week (one month) Treasury Bill rate as the risk-free rate and S&P 500 returns as the market returns proxies. Columns 8, 9, 17, and 18 in Table 8 report parameter estimates and t-statistics, in square brackets, based on Newey-West HAC consistent standard error estimates. As it is clearly seen in the table, the null hypothesis that Jensen's α ($\hat{\alpha_i}$) is equal to zero is frequently rejected. Since $\hat{\beta}_i$s are almost universally significant and reasonable, we can say that mean-variance efficiency is rejected across industry returns.[13] These results suffer from a slight look ahead bias: an oil effect exists and persists in the 1984 to 2008 period.

Again, our findings here differ from Driesprong et al. (2008) in one important dimension. We find that on average, a switch occurs every three to four months. Estimated Jensen's α for the US in Driesprong et al. (2008) is equal to 4.58% per year. Our estimated α's are much smaller; they range between 0.299% to 1.103%. Hence, while this strategy is profitable at transaction costs equal to 0.10%, profitability vanishes as transaction costs increase. This is contrary to what Driesprong et al. claim. Their results are said to be robust to transaction costs up to 0.5%.

In conclusion, we can say that first, the evidence for index market returns and risk-free rates spanning of oil-strategy returns is weak, and second, oil strategy appears to be a reasonable trading rule for practitioners.

5.2 Time Varying Risk Premia

We have already shown that oil price change related predictability is short-lived. As seen in Tables 5, 6, and 7, and contrary to Fama and French (1989), the oil effect does not last more than a month. This results is in line with findings of Driesprong et al. Fama and French (1989) argue that dividend yields, the term spread, and the default spread are reasonable variables for forecasting stock returns since they contain information about expected business conditions. Similarly, Chen et al. (1986) argue in favor of default spread as a good indicator for future business conditions. More recent examples include Ang and Bekaert (2007) who favor interest rates as predictors for equity returns, and Campbell and Thompson (2008) who favor a wide range of pricing ratios, among them interest rates, as well as term and default spreads.

As it is seen in Table 9, sample correlations between changes in WTI spot or future prices and US interest rates, term structure, or dividend yields are very close to zero. Correlation between changes in spot prices and the default spread is not negligible, but it is within the same order of magnitude as in Driesprong et al. (2008). These two sets of results are thus comparable and consistent. One may comfortably conclude that oil prices are linearly independent from accepted predicting variables for time-varying risk premia.

[13] Hardware, software, chip making, and finance industries have statistically significant estimated βs greater than unity. But these parameter values are close enough to one to suggest almost perfect cyclicality, an empirically acceptable regularity in these industries.

Also, as Hamilton (2003) documents, oil price shocks increase systemic risk in the economy. Such an event should be followed by increased expected (or average) returns across the industries. Our results demonstrate a negative relationship between oil prices and industry-level returns across the board, regardless of statistical significance. It can be argued that with time-varying risk premia, the contemporaneous effect of an increase in oil prices can be negative, due to uncertainty about short term profitability. But eventually, returns must rise if oil price changes are proxies for this phenomenon. Our econometric evidence rejects this assertion. We believe that the oil effect documented by Driesprong et al. (2008) and explored in our research does not proxy for time-varying risk premia and is a salient feature of the market.

In a seminal paper, Merton (1980) argues that (excess) market returns should be directly and proportionally related to the market's systemic risk. Empirical study of this prediction underlies the extensive application of (G)ARCH-in-Mean models, starting with Engle et al. (1987), in the literature. We explore the issue of volatility further and formally study the consequences of the inclusion of one month lagged oil price changes in risk-return trade-off at industry-level. Formally, we fitted a GARCH(1,1)-in-Mean model with oil prices lagged one month as an exogenous variable in the volatility process. In this respect, we follow French et al. (1987). This formulation allows us to explicitly check whether a lagged oil price change increases future industry-level volatility. We find out that the inclusion of oil price changes does not significantly alter the estimated parameters of the GARCH process or the value of the GARCH-in-Mean coefficient. The real estate industry has statistically significant estimated coefficients for both the GARCH-in-Mean term and the oil returns. But the sign of the GARCH-in-Mean coefficient is negative (-0.0791), which is counter intuitive, and only significant at the 10% significance level. This result implies that there is a negative relationship between risk and return, while financial theory expects a positive relationship. All other results are both statistically insignificant and have negative GARCH-in-Mean parameters, hence we do not report them. We conclude that oil price changes do not alter the risk-return trade-off in the sample. Based on these results, it is possible to claim that predictability is not related to the time-varying risk premium. If predictability from oil price changes is indeed related to time-varying risk premia, then we expect that inclusion of lagged oil price changes should improve the performance of GARCH-in-Mean regressions. Notice that our industry-level returns are portfolio returns, most of them consist of many companies. Hence application of Merton's approach is, in our opinion, valid.[14]

We find that first, there is no statistical evidence of improvement of fit. And second, the esti-

[14]Industry portfolio returns are the weighted average of returns from a large number of companies in the relevant sector. Since the number of company returns is large enough, running a regression on measures of (industry) systemic risk is reasonable. If the number of companies in a typical industry portfolio is not sufficiently large, then portfolio returns must be priced through their conditional correlation with some aggregate market return measure which realistically reflects systemic, rather than idiosyncratic, risk.

mated coefficients do not have economically meaningful interpretations. Our estimated parameters for oil-in-volatility (exogenous parameter in GARCH process) are generally positive and indicative of increased volatility due to oil price changes. But bar very few instances, they are not statistically significant. We could not justify the assertion that inclusion of oil price changes improves the performance of the GARCH-in-Mean model based on econometric evidence. As a result, we believe that the main issue is independence of oil related predictability from time varying-risk premia.

6 Conclusions

We use disaggregated data to take a closer look at the oil effect documented by Driesprong et al. (2008). We use forty nine US industry-level return series and West Texas Intermediate spot and NYMEX light sweet crude future prices to verify the existence of predictability of stock returns, using oil price changes as predictors. Moreover, we study the predictive sensitivity of industry-level returns to measures of net oil price increase or decrease. Our findings provide several important refinements to the original results of Driesprong et al., both for the oil effect and the underreaction hypothesis.

We find that industry-level returns in slightly less than twenty percent of the forty nine US industries studied in this paper can be predicted using logarithmic differences in West Texas Intermediate spot prices as predictor. Moreover, we find that this predictability almost disappears when we use logarithmic differences of NYMEX light sweet crude future prices. Using net oil price change measures, we can provide a categorization of predictable industry returns based on their sensitivity to measures of net oil price increase or decrease. We find that net oil price changes in futures market have significantly more predictive power than simple percentage changes in future prices.

Based on various robustness checks, we conclude that predictability is rather short lived, it is lost beyond a one-month lag. Less than 10% of industry-level returns demonstrate signs of contemporaneous correlation with oil returns. We find suggestive, but inconclusive, evidence of the presence of non-synchronous trading in a significant number of industry returns. Our results are robust to the use of excess returns, instead of raw returns, in the regression analysis. We find that the inclusion of oil price shock measures does not alter our findings, and that our measure of oil price volatility does not have much prediction power. In addition, we find that the oil effect seems to be independent of time-varying risk premia. Our findings differ in an important dimension from Driesprong et al. We show that gains from trading based on an "oil strategy" are sensitive to the size of trading costs. Existence of the oil effect seems to be a feature of US financial markets.

We find that our results are consistent with the delayed reaction hypothesis among investors. In particular, by carrying out regression analysis between industry-level returns and lagged changes in monthly oil prices, we find an increase in explanatory power of these regressions, after an initial drop, at around seven to eight trading day lags. We interpret this results as a seven to eight trading day delay by a significant number of investors. The delayed reaction is negative. This is consistent with the assertion that investors wake up to information at different points in time, as proposed by Hong and Stein (1996) and refined by Hong et al. (2007). Based on our findings, we believe that investors underestimate the indirect economic effects of oil price changes and take action with a non-negligible delay. We find that our results are more pronounced in non-oil related sectors such as construction and business services.

Comparison of predictability performance of oil price and valuation ratio based models is beyond the scope of the present paper. We will address this issue in future research.

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7 Tables

Table 1: Basic Characteristics of Oil Price Changes.

	Date	No. of Obs.	Mean (%)	Std. Dev. (%)	Skewness	Kurtosis
WTI Spot Price	1979-01 : 2009-01	360	0.23	10.28	-0.70	4.77
NYMEX Future Price	1986-02 : 2009-01	275	0.10	10.27	-1.06	6.56

We report summary statistics for changes in West Texas Intermediate spot and NYMEX contract number 1 on Cushing, Oklahoma light sweet crude future oil prices. Oil price changes are defined as $r_t^{oil} = 100 \times [\ln(P_t^{oil} - \ln(P_{t-1}^{oil})]$. Average returns and standard deviations are reported as percentages. Excess Kurtosis values are reported. Source: Thomson Datastream and Energy Information Administration, US Department of Energy.

Table 2: Sample Statistics for Industry-Level Returns

Industry	Mean (%)	Std. Dev. (%)	Skewness	Kurtosis	Industry	Mean (%)	Std. Dev. (%)	Skewness	Kurtosis
Agric	1.22	5.98	-0.21	2.90	Guns	1.24	6.66	-0.32	3.25
Food	1.28	4.64	0.02	1.84	Gold	1.09	11.55	0.90	5.44
Soda	1.10	6.98	0.07	3.41	Mines	1.02	7.46	-0.64	2.69
Beer	1.45	5.42	-0.14	1.77	Coal	1.30	10.40	0.15	1.97
Smoke	1.56	6.87	-0.17	2.47	Oil	1.24	5.68	0.02	1.54
Toys	0.90	6.94	-0.44	1.83	Util	1.00	4.03	-0.34	0.63
Fun	1.11	7.11	-0.88	3.30	Telcm	0.90	5.09	-0.28	1.46
Books	0.87	5.47	-0.43	2.36	PerSv	0.97	6.02	-0.22	1.98
Hshld	1.05	4.61	-0.43	2.46	BusSv	0.99	5.60	-0.69	2.71
Clths	1.07	6.32	-0.54	2.76	Hardw	0.91	7.93	-0.28	1.72
Hlth	1.10	7.14	-0.24	1.52	Softw	1.53	9.09	0.25	0.67
MedEq	1.11	5.30	-0.51	1.71	Chips	1.08	8.14	-0.47	1.65
Drugs	1.21	4.94	-0.09	0.82	LabEq	0.97	7.47	-0.15	1.35
Chems	0.98	5.51	-0.54	3.13	Paper	0.93	5.49	-0.05	3.15
Rubbr	1.01	5.67	-0.72	3.14	Boxes	1.09	5.93	-0.63	2.74
Txtls	0.92	6.51	-0.97	3.97	Trans	1.03	5.66	-0.49	2.05
BldMt	1.00	5.83	-0.86	4.62	Whlsl	0.98	5.32	-0.59	3.54
Cnstr	1.12	7.29	-0.21	1.64	Rtail	1.20	5.62	-0.40	2.10
Steel	0.86	7.84	-0.42	2.76	Meals	1.10	5.43	-0.47	1.21
FabPr	0.48	7.13	-0.72	2.56	Banks	1.10	5.88	-0.55	1.93
Mach	0.88	6.41	-0.89	3.24	Insur	1.08	5.32	-0.49	2.96
ElcEq	1.31	6.29	-0.53	2.61	RlEst	0.39	6.35	-1.11	5.16
Autos	0.71	6.90	-0.68	3.14	Fin	1.25	6.45	-0.63	1.76
Aero	1.14	6.54	-0.60	3.08	Other	0.74	6.50	-0.40	1.49
Ships	0.94	7.03	-0.34	1.82					

Data spans January 1979 to January 2009 with 360 observations for each series. Industries are defined based on Compustat SIC codes when available, and CRSP SIC codes otherwise. Reported values are based on value-weighted industry portfolio returns, formed on July of each year, and revised at the end of the month of June of the subsequent year. Average returns and standard deviations are reported as percentages. Excess Kurtosis values are reported.
Source: Kenneth French's website.

Table 3: US Industry-Level Returns and Lagged Oil Price Changes

Panel A

	Cnstr	Rtail	Meals	Rubbr	Autos	Telcm	PerSv	BusSv	Boxes
Oil Spot Price $\hat{\alpha}$	$-0.079^{\dagger}$	$-0.074^{\dagger}$	$-0.081^{\ddagger}$	$-0.070^{\dagger}$	$-0.088^{\dagger}$	$-0.050^{\dagger}$	$-0.063^{\dagger}$	$-0.064^{\dagger}$	$-0.066^{\dagger}$
	(0.046)	(0.040)	(0.035)	(0.039)	(0.046)	(0.030)	(0.035)	(0.037)	(0.033)
Oil Future Price $\hat{\alpha}$	$-0.095^{\dagger}$	$-0.080^{\ddagger}$	$-0.075^{\dagger}$						
	(0.053)	(0.040)	(0:045)						

Panel B

	Cnstr	Rtail	Meals	Rubbr	Autos	Telcm	PerSv	BusSv	Boxes
Oil Spot Price Shock $\hat{\alpha}$	$-0.075^{\dagger}$	$-0.073^{\dagger}$	$-0.079^{\dagger}$	$-0.070^{\dagger}$	$-0.087^{\dagger}$	$-0.051^{\dagger}$	$-0.063^{\dagger}$	$-0.063^{\dagger}$	$-0.065^{\dagger}$
	(0.045)	(0.040)	(0.035)	(0.039)	(0.046)	(0.030)	(0.034)	(0.037)	(0.034)

Notes: Newey-West HAC consistent standard errors appear in parentheses. ‡, and † denote rejection of the null hypothesis that the parameter equals zero at the 5%, and 10% significance levels, respectively. The estimated parameters were obtained by applying OLS to $r_t^i = \mu_i + \alpha_i r_{t-1}^{oil,\cdot} + \varepsilon_t^i$. Sample length for spot oil price covers January 1979 to December 2008 period. Our sample for future oil prices covers January 1986 to December 2008 period. Panel A reports the estimated parameters when percentage changes in spot or oil future prices are used as predictor. Panel B reports parameter estimates when residuals from fitting a first order autoregressive to percentage spot price changes ("news" shocks) are used as predictor.

Table 4: Impact of Net Oil Price Increase and Decrease

Panel A									
Net Oil Spot Price Increase (Q) $\hat{\alpha}$	Food	Clths	Cnstr	Aero	Gold	Oil	PerSv	Rtail	Meals
	$0.114^{\dagger}$ (0.067)	$0.152^{\dagger}$ (0.079)	$0.143^{\ddagger}$ (0.072)	$0.114^{\dagger}$ (0.068)	$-0.313^{\ddagger}$ (0.123)	$-0.121^{\ddagger}$ (0.050)	$0.120^{\dagger}$ (0.071)	$0.176^{\ddagger}$ (0.059)	$0.142^{\ddagger}$ (0.062)
Net Oil Spot Price Increase (SA) $\hat{\alpha}$	Soda	Smoke	Hshld	Aero	Gold	Oil	BldMt	Hardw	Other
	$0.187^{\dagger}$ (0.105)	$0.176^{\dagger}$ (0.092)	$0.130^{\ddagger}$ (0.054)	$0.156^{\ddagger}$ (0.071)	$-0.324^{\ddagger}$ (0.093)	$-0.153^{\dagger}$ (0.082)	$0.166^{\ddagger}$ (0.064)	$0.210^{\dagger}$ (0.120)	$0.216^{\ddagger}$ (0.077)
Panel B									
Net Oil Spot Price Decrease (Q) $\hat{\alpha}$	Steel	FabPr	ElcEq	Autos	Mines	LabEq	Fin	Other	
	$0.161^{\ddagger}$ (0.050)	$0.159^{\ddagger}$ (0.049)	$0.128^{\ddagger}$ (0.063)	$0.118^{\dagger}$ (0.069)	$0.093^{\ddagger}$ (0.047)	$0.135^{\ddagger}$ (0.062)	$0.136^{\ddagger}$ (0.054)	$0.135^{\ddagger}$ (0.057)	
Net Oil Spot Price Decrease (A) $\hat{\alpha}$	Smoke	Books	Telcm	BusSv	Mines	Banks	Fin		
	$-0.087^{\dagger}$ (0.053)	$0.157^{\ddagger}$ (0.076)	$0.168^{\ddagger}$ (0.077)	$0.169^{\dagger}$ (0.091)	$0.205^{\dagger}$ (0.117)	$0.149^{\ddagger}$ (0.063)	$0.217^{\ddagger}$ (0.072)		
Panel C									
Net Oil Futures Price Increase (A) $\hat{\alpha}$	Agric	Food	Beer	Fun	Hshld	FabPr	Telcm	Other	
	$-0.134^{\ddagger}$ (0.065)	$-0.125^{\dagger}$ (0.071)	$-0.249^{\dagger}$ (0.110)	$0.370^{\dagger}$ (0.210)	$-0.123^{\ddagger}$ (0.061)	$-0.127^{\ddagger}$ (0.065)	$0.207^{\ddagger}$ (0.076)	$0.367^{\ddagger}$ (0.186)	
Panel D									
Net Oil Futures Price Decrease (Q) $\hat{\alpha}$	Rubbr	Steel	FabPr	Mach	ElcEq	Autos	Gold	Mines	Softw
	$0.190^{\dagger}$ (0.104)	$0.209^{\ddagger}$ (0.061)	$0.176^{\ddagger}$ (0.059)	$0.135^{\dagger}$ (0.079)	$0.179^{\ddagger}$ (0.079)	$0.150^{\dagger}$ (0.081)	$0.200^{\ddagger}$ (0.099)	$0.102^{\dagger}$ (0.058)	$0.148^{\dagger}$ (0.084)
	Chips	LabEq	Banks	Fin	Other				
	$0.149^{\dagger}$ (0.082)	$0.164^{\ddagger}$ (0.073)	$0.138^{\ddagger}$ (0.057)	$0.162^{\ddagger}$ (0.057)	$0.193^{\ddagger}$ (0.064)				
Net Oil Futures Price Decrease (SA) $\hat{\alpha}$	Steel	Mach	ElcEq	Coal	Hardw	Chips	Whlsl		
	$-0.182^{\dagger}$ (0.095)	$-0.173^{\ddagger}$ (0.081)	$-0.169^{\dagger}$ (0.088)	$-0.443^{\ddagger}$ (0.127)	$-0.272^{\ddagger}$ (0.121)	$-0.232^{\dagger}$ (0.129)	$-0.145^{\dagger}$ (0.063)		
Net Oil Futures Price Decrease (A) $\hat{\alpha}$	Toys	Books	Clths	Chems	Rubbr	BldMt	Cnstr	Steel	FabPr
	$0.337^{\ddagger}$ (0.110)	$0.269^{\ddagger}$ (0.054)	$0.295^{\ddagger}$ (0.091)	$0.167^{\ddagger}$ (0.074)	$0.228^{\ddagger}$ (0.063)	$0.233^{\ddagger}$ (0.081)	$0.276^{\ddagger}$ (0.108)	$0.139^{\ddagger}$ (0.064)	$0.160^{\ddagger}$ (0.048)
	Autos	Aero	Ships	Mines	Oil	Telcm	PerSv	BusSv	Hardw
	$0.241^{\ddagger}$ (0.095)	$0.221^{\ddagger}$ (0.084)	$0.242^{\ddagger}$ (0.088)	$0.261^{\dagger}$ (0.094)	$0.157^{\ddagger}$ (0.069)	$0.272^{\ddagger}$ (0.087)	$0.245^{\ddagger}$ (0.065)	$0.305^{\ddagger}$ (0.088)	$0.330^{\ddagger}$ (0.054)
	Softw	Chips	Paper	Boxes	Trans	Rtail	Meals	Banks	RlEst
	$0.357^{\ddagger}$ (0.118)	$0.247^{\ddagger}$ (0.073)	$0.148^{\ddagger}$ (0.068)	$0.183^{\dagger}$ (0.100)	$0.213^{\ddagger}$ (0.079)	$0.209^{\dagger}$ (0.116)	$0.171^{\ddagger}$ (0.062)	$0.218^{\ddagger}$ (0.044)	$0.208^{\ddagger}$ (0.070)
	Fin	Other							
	$0.313^{\ddagger}$ (0.075)	$0.165^{\dagger}$ (0.097)							

Notes: Newey-West HAC consistent standard errors appear in parentheses. ‡, and † denote rejection of the null hypothesis that the parameter equals zero at the 5%, and 10% significance levels, respectively. The estimated parameters were obtained by applying OLS to $r_t^i = \mu_{i,m} + \alpha_{i,m} nopi_{t-1}^j + \varepsilon_t^{i,m}$ or $r_t^i = \mu_{i,n} + \alpha_{i,n} nopd_{t-1}^j + \varepsilon_t^{i,n}$. Sample length for spot oil price covers January 1979 to December 2008 period. Our sample for future oil prices covers January 1986 to December 2008 period. Variables $nopi_t^j$ and $nopd_t^j$ are constructed following Eq. (2) and Eq. (3). $j = \{3, 6, 12\}$, corresponding to Q, SA, and A in the table, which represent quarterly, semi-annual, and annual length in calculation of the net oil price increase or decrease, respectively.

Table 5: Robustness Checks

Spot Oil Price					Spot Oil Price				
Industry	Oil(t-1)	Oil(t-2)	Oil(t)	r(t-1)	Industry	Oil(t-1)	Oil(t-2)	Oil(t)	r(t-1)
Fun	−0.028 (0.052)	0.006 (0.037)	−0.026 (0.058)	$0.166^{\ddagger}$ (0.066)	Gold	−0.007 (0.061)	−0.093 (0.071)	$0.177^{\ddagger}$ (0.065)	−0.027 (0.062)
Books	−0.018 (0.036)	−0.009 (0.027)	−0.016 (0.049)	$0.191^{\ddagger}$ (0.077)	Mines	−0.044 (0.036)	−0.053 (0.037)	$0.106^{\ddagger}$ (0.053)	0.046 (0.075)
Clths	−0.062 (0.044)	0.015 (0.030)	−0.063 (0.055)	$0.205^{\ddagger}$ (0.062)	Oil	0.001 (0.027)	−0.038 (0.025)	$0.162^{\ddagger}$ (0.035)	−0.063 (0.059)
Hlth	0.026 (0.047)	0.018 (0.036)	−0.025 (0.041)	$0.132^{\ddagger}$ (0.049)	Telcm	$-0.050^{\dagger}$ (0.030)	0.008 (0.025)	−0.002 (0.036)	0.066 (0.048)
Rubbr	$-0.068^{\dagger}$ (0.037)	0.002 (0.029)	−0.009 (0.047)	0.068 (0.061)	PerSv	−0.049 (0.031)	0.009 (0.029)	$-0.066^{\dagger}$ (0.036)	$0.114^{\ddagger}$ (0.046)
Txtls	−0.051 (0.055)	−0.017 (0.028)	−0.063 (0.051)	$0.228^{\ddagger}$ (0.050)	BusSv	$-0.065^{\ddagger}$ (0.033)	−0.018 (0.027)	0.015 (0.041)	$0.130^{\ddagger}$ (0.052)
BldMt	$-0.057^{\dagger}$ (0.034)	−0.025 (0.027)	−0.003 (0.061)	$0.100^{\dagger}$ (0.051)	Boxes	$-0.061^{\dagger}$ (0.034)	0.004 (0.027)	−0.039 (0.043)	0.064 (0.062)
Cnstr	$-0.081^{\ddagger}$ (0.040)	$-0.054^{\dagger}$ (0.033)	0.015 (0.051)	$0.165^{\ddagger}$ (0.051)	Whlsl	−0.009 (0.030)	−0.005 (0.024)	−0.014 (0.041)	$0.127^{\ddagger}$ (0.059)
FabPr	−0.026 (0.057)	0.049 (0.037)	0.050 (0.056)	$0.171^{\ddagger}$ (0.068)	Rtail	−0.059 (0.038)	0.011 (0.029)	−0.064 (0.043)	$0.141^{\ddagger}$ (0.065)
Mach	$-0.071^{\dagger}$ (0.043)	0.010 (0.030)	0.050 (0.053)	$0.133^{\ddagger}$ (0.066)	Meals	−0.069 (0.033)	−0.024 (0.026)	−0.056 (0.038)	0.129 (0.050)
Autos	$-0.084^{\ddagger}$ (0.040)	−0.001 (0.036)	−0.015 (0.070)	$0.132^{\ddagger}$ (0.056)	RlEst	−0.050 (0.042)	0.002 (0.032)	−0.021 (0.055)	$0.330^{\ddagger}$ (0.058)
Aero	−0.039 (0.041)	−0.007 (0.029)	−0.020 (0.047)	$0.107^{\ddagger}$ (0.050)	Fin	−0.057 (0.048)	0.013 (0.030)	−0.022 (0.051)	$0.165^{\ddagger}$ (0.067)
Ships	−0.033 (0.051)	−0.026 (0.037)	−0.016 (0.042)	$0.093^{\dagger}$ (0.054)					

Future Oil Price					Future Oil Price				
Industry	Oil(t-1)	Oil(t-2)	Oil(t)	r(t-1)	Industry	Oil(t-1)	Oil(t-2)	Oil(t)	r(t-1)
Food	0.042 (0.032)	−0.028 (0.026)	$-0.080^{\ddagger}$ (0.038)	0.045 (0.069)	Ships	−0.010 (0.064)	−0.041 (0.036)	−0.008 (0.043)	$0.145^{\ddagger}$ (0.059)
Fun	−0.032 (0.063)	0.011 (0.043)	−0.028 (0.063)	$0.211^{\ddagger}$ (0.072)	Gold	−0.031 (0.063)	−0.100 (0.074)	$0.235^{\ddagger}$ (0.074)	−0.102 (0.066)
Books	0.001 (0.041)	−0.028 (0.035)	−0.015 (0.056)	$0.167^{\dagger}$ (0.092)	Oil	0.005 (0.031)	$-0.050^{\dagger}$ (0.029)	$0.172^{\ddagger}$ (0.043)	−0.107 (0.081)
Clths	−0.030 (0.058)	−0.010 (0.041)	−0.076 (0.059)	$0.205^{\ddagger}$ (0.067)	PerSv	$-0.060^{\dagger}$ (0.036)	0.022 (0.031)	$-0.074^{\dagger}$ (0.039)	$0.113^{\ddagger}$ (0.053)
Hlth	0.064 (0.053)	−0.015 (0.035)	−0.048 (0.046)	$0.121^{\ddagger}$ (0.061)	BusSv	−0.062 (0.041)	−0.007 (0.031)	−0.005 (0.048)	$0.116^{\dagger}$ (0.062)
Drugs	0.025 (0.037)	−0.024 (0.029)	$-0.091^{\ddagger}$ (0.037)	0.031 (0.074)	Hardw	$-0.102^{\dagger}$ (0.060)	0.074 (0.052)	0.019 (0.054)	0.058 (0.059)
Txtls	−0.030 (0.068)	0.004 (0.039)	−0.084 (0.057)	$0.247^{\ddagger}$ (0.052)	Whlsl	0.012 (0.035)	−0.018 (0.026)	−0.026 (0.047)	$0.139^{\dagger}$ (0.070)
Cnstr	−0.080 (0.050)	−0.054 (0.036)	−0.003 (0.060)	$0.126^{\dagger}$ (0.067)	Rtail	−0.036 (0.050)	−0.004 (0.041)	$-0.088^{\dagger}$ (0.046)	0.111 (0.079)
FabPr	−0.040 (0.065)	0.066 (0.042)	0.056 (0.066)	$0.184^{\ddagger}$ (0.080)	Meals	−0.048 (0.041)	−0.034 (0.026)	$-0.072^{\dagger}$ (0.039)	$0.127^{\ddagger}$ (0.060)
Mach	−0.071 (0.053)	0.033 (0.035)	0.051 (0.061)	$0.144^{\dagger}$ (0.076)	RlEst	−0.039 (0.055)	−0.029 (0.032)	−0.027 (0.064)	$0.352^{\ddagger}$ (0.061)
Autos	−0.051 (0.058)	0.010 (0.042)	−0.034 (0.078)	$0.134^{\ddagger}$ (0.058)	Fin	−0.039 (0.058)	0.007 (0.036)	−0.044 (0.058)	$0.161^{\ddagger}$ (0.074)
Aero	−0.004 (0.046)	−0.010 (0.029)	−0.028 (0.049)	$0.117^{\dagger}$ (0.061)					

Notes: Newey-West HAC consistent standard errors appear in parentheses. ‡, and † denote rejection of the null hypothesis that the parameter equals zero at the 5%, and 10% significance levels, respectively. The estimated parameters were obtained by applying OLS to $r_t^i = \mu_i + \alpha_{i,1} r_{t-1}^{oil} + \alpha_{i,2} r_{t-2}^{oil} + \alpha_{i,3} r_t^{oil} + \alpha_{i,4} r_{t-1} + \varepsilon_t^i$. Our measure for oil price changes is returns to West Texas Intermediate spot and NYMEX light sweet crude future prices. Sample length for spot oil price covers January 1979 to December 2008 period. Our sample for future oil prices covers January 1986 to December 2008 period.

Table 6: Regression results with different lags between stock returns and lagged oil price changes.

No Lag				No Lag			
Industry	Coeff.	Std. Err.	R^2 (%)	Industry	Coeff.	Std. Err.	R^2 (%)
Cnstr	$-2.546^{\ddagger}$	1.179	2.85	Hardw	$-2.223^{\dagger}$	1.263	1.45
Autos	$-2.122^{\dagger}$	1.277	1.85	Softw	$-2.939^{\ddagger}$	1.414	2.54
Telcm	$-1.593^{\ddagger}$	0.788	1.88	Chips	$-2.662^{\dagger}$	1.421	2.01
PerSv	$-2.099^{\ddagger}$	0.835	2.64	Rtail	$-1.829^{\dagger}$	0.958	2.23
BusSv	$-1.882^{\ddagger}$	0.863	2.58	Meals	$-2.528^{\ddagger}$	0.853	4.75
One Day Lag				One Day Lag			
Industry	Coeff.	Std. Err.	R^2 (%)	Industry	Coeff.	Std. Err.	R^2 (%)
Cnstr	$-2.713^{\ddagger}$	1.225	3.29	Softw	$-2.659^{\dagger}$	1.542	2.12
Telcm	$-1.505^{\dagger}$	0.888	1.71	Rtail	$-1.782^{\dagger}$	0.972	2.16
PerSv	$-1.923^{\ddagger}$	0.813	2.26	Meals	$-2.187^{\ddagger}$	0.832	3.62
BusSv	$-1.711^{\dagger}$	0.944	2.17				
Five Day Lag				Five Day Lag			
Industry	Coeff.	Std. Err.	R^2 (%)	Industry	Coeff.	Std. Err.	R^2 (%)
Autos	$-1.896^{\dagger}$	1.095	1.70	BusSv	$-1.520^{\dagger}$	0.874	1.94
Coal	$2.907^{\dagger}$	1.701	1.69	Rtail	$-1.608^{\dagger}$	0.970	1.99
Telcm	$-1.339^{\dagger}$	0.752	1.53	Meals	$-1.824^{\ddagger}$	0.847	2.85
PerSv	$-1.533^{\dagger}$	0.789	1.62				

Notes: Estimation results of regression equation $r_t^i = \mu_i + \alpha_i r_{t-1}^{oil} + \varepsilon_t^i$ with lags of a different number of trading days between monthly stock market returns and lagged monthly oil price changes. We report results for West Texas Intermediate spot oil price changes over the period March 1986-December 2008, with lags of 0,1,and 5 trading days. Newey-West HAC consistent standard errors appear in parentheses. ‡, and † denote rejection of the null hypothesis that the β_i parameter equals zero at the 5%, and 10% significance levels, respectively.

Table 7: Weekly Predictability Results

Ind.	Oil(-1)	Oil(-2)	Oil(-3)	Oil(-4)	Oil(-5)	Oil(-6)	Oil(-7)	Oil(-8)
Agric	−0.005 (0.005)	−0.012‡ (0.004)	0.003 (0.005)	−0.004 (0.005)	0.002 (0.006)	0.007† (0.004)	−0.001 (0.005)	−0.002 (0.005)
Food	0.001 (0.004)	−0.007† (0.004)	−0.001 (0.004)	−0.004 (0.004)	−0.002 (0.004)	0.002 (0.003)	0.003 (0.003)	0.004 (0.003)
Beer	0.003 (0.005)	−0.012‡ (0.005)	−0.001 (0.005)	−0.005 (0.004)	0.000 (0.005)	0.003 (0.004)	0.000 (0.004)	0.008‡ (0.004)
Smoke	0.006 (0.005)	−0.009 (0.007)	−0.004 (0.006)	0.005 (0.006)	−0.013‡ (0.007)	0.000 (0.005)	0.003 (0.006)	0.004 (0.005)
Toys	−0.004 (0.005)	−0.013‡ (0.005)	0.003 (0.006)	0.004 (0.005)	−0.002 (0.006)	0.005 (0.004)	−0.010‡ (0.005)	−0.006 (0.006)
Fun	−0.004 (0.006)	−0.013‡ (0.006)	0.006 (0.007)	−0.006 (0.007)	−0.001 (0.012)	−0.005 (0.006)	0.002 (0.005)	−0.003 (0.008)
Books	0.000 (0.005)	−0.013‡ (0.004)	0.004 (0.005)	−0.005 (0.004)	0.002 (0.007)	0.001 (0.004)	0.000 (0.004)	−0.003 (0.006)
Hshld	0.001 (0.004)	−0.011‡ (0.004)	−0.001 (0.004)	0.001 (0.004)	−0.003 (0.005)	0.005 (0.003)	−0.001 (0.004)	0.002 (0.003)
Clths	−0.004 (0.005)	−0.011‡ (0.005)	−0.001 (0.006)	−0.004 (0.005)	0.001 (0.007)	−0.004 (0.005)	−0.001 (0.004)	−0.008† (0.005)
MedEq	0.003 (0.004)	−0.008† (0.005)	−0.004 (0.005)	−0.002 (0.004)	−0.005 (0.006)	0.006† (0.004)	0.003 (0.004)	0.001 (0.004)
Chems	0.000 (0.004)	−0.011‡ (0.005)	0.006 (0.005)	0.000 (0.004)	0.000 (0.006)	0.001 (0.004)	0.002 (0.004)	0.003 (0.005)
Rubbr	−0.001 (0.004)	−0.012‡ (0.004)	−0.001 (0.004)	0.001 (0.004)	−0.002 (0.005)	−0.004 (0.004)	0.000 (0.004)	−0.004 (0.005)
Txtls	−0.004 (0.005)	−0.017‡ (0.006)	0.002 (0.006)	−0.007 (0.005)	0.002 (0.008)	−0.005 (0.005)	0.000 (0.005)	−0.005 (0.007)
BldMt	−0.001 (0.005)	−0.013‡ (0.004)	0.002 (0.005)	0.001 (0.004)	−0.003 (0.005)	−0.002 (0.004)	−0.004 (0.004)	−0.004 (0.005)
Cnstr	−0.003 (0.006)	−0.023‡ (0.006)	0.004 (0.006)	−0.002 (0.006)	−0.005 (0.008)	−0.006 (0.006)	−0.004 (0.005)	−0.010 (0.009)
Steel	−0.002 (0.008)	−0.013‡ (0.006)	0.005 (0.007)	0.001 (0.006)	−0.005 (0.008)	−0.001 (0.006)	−0.002 (0.006)	−0.006 (0.008)
FabPr	−0.002 (0.005)	−0.011‡ (0.005)	0.003 (0.007)	−0.003 (0.006)	−0.002 (0.007)	0.008 (0.005)	0.004 (0.006)	−0.002 (0.006)
Mach	−0.001 (0.005)	−0.016‡ (0.004)	0.006 (0.006)	−0.006 (0.005)	−0.001 (0.007)	0.001 (0.004)	−0.003 (0.004)	0.000 (0.005)
ElcEq	−0.001 (0.005)	−0.014‡ (0.005)	0.004 (0.006)	−0.007 (0.005)	−0.005 (0.006)	0.001 (0.005)	−0.002 (0.004)	0.004 (0.005)
Autos	0.001 (0.006)	−0.020‡ (0.005)	0.004 (0.007)	−0.009 (0.005)	−0.001 (0.007)	−0.005 (0.005)	−0.002 (0.005)	−0.002 (0.006)
Ships	0.003 (0.005)	−0.014‡ (0.005)	−0.003 (0.005)	−0.003 (0.005)	−0.001 (0.005)	−0.001 (0.004)	0.004 (0.004)	−0.004 (0.004)
Guns	0.003 (0.006)	−0.008†) (0.005)	−0.001 (0.006)	0.001 (0.005)	0.002 (0.006)	0.003) (0.005)	0.000 (0.005)	−0.003 (0.004)

Ind.	Oil(-1)	Oil(-2)	Oil(-3)	Oil(-4)	Oil(-5)	Oil(-6)	Oil(-7)	Oil(-8)
Mines	−0.005 (0.007)	−0.010‡ (0.005)	0.005 (0.006)	−0.006 (0.005)	−0.003 (0.007)	−0.011‡ (0.005)	0.006 (0.005)	−0.007 (0.008)
Coal	−0.010 (0.009)	−0.015‡ (0.007)	0.013 (0.011)	−0.009 (0.008)	0.011 (0.010)	0.000 (0.007)	0.008 (0.007)	−0.012 (0.010)
Oil	−0.004 (0.005)	−0.014‡ (0.007)	0.005 (0.005)	0.005 (0.004)	−0.001 (0.005)	−0.001 (0.004)	−0.001 (0.004)	−0.003 (0.004)
Util	0.002 (0.003)	−0.011‡ (0.005)	0.001 (0.004)	0.001 (0.004)	0.001 (0.004)	−0.001 (0.003)	0.000 (0.003)	0.000 (0.003)
Telcm	0.002 (0.004)	−0.010† (0.005)	0.005 (0.005)	−0.007 (0.004)	−0.007 (0.005)	0.000 (0.004)	0.002 (0.004)	−0.002 (0.005)
PerSv	−0.007 (0.005)	−0.011‡ (0.005)	−0.003 (0.005)	−0.004 (0.004)	−0.003 (0.007)	0.000 (0.004)	0.001 (0.004)	−0.003 (0.005)
BusSv	0.001 (0.004)	−0.011‡ (0.004)	0.006 (0.005)	−0.007† (0.004)	−0.007 (0.006)	−0.001 (0.004)	−0.004 (0.004)	−0.002 (0.004)
Hardw	0.001 (0.007)	−0.011† (0.006)	0.010 (0.006)	−0.006 (0.006)	−0.005 (0.007)	0.002 (0.006)	−0.010† (0.006)	0.007 (0.006)
Softw	0.002 (0.006)	−0.010† (0.006)	0.010 (0.006)	−0.008 (0.005)	−0.012† (0.006)	0.000 (0.006)	−0.007 (0.005)	0.005 (0.006)
Chips	0.003 (0.006)	−0.014‡ (0.006)	−0.011† (0.006)	−0.014‡ (0.006)	−0.007 (0.007)	0.004 (0.006)	−0.012‡ (0.006)	0.005 (0.006)
LabEq	0.003 (0.005)	−0.09 (0.006)	0.009 (0.006)	−0.006 (0.005)	−0.006 (0.006)	0.007 (0.006)	−0.009† (0.005)	−0.001 (0.005)
Paper	−0.001 (0.004)	−0.011‡ (0.004)	0.003 (0.004)	0.001 (0.004)	0.000 (0.005)	0.001 (0.004)	0.003 (0.004)	0.000 (0.004)
Boxes	−0.006 (0.005)	−0.013‡ (0.004)	0.002 (0.005)	−0.005 (0.004)	−0.001 (0.006)	−0.001 (0.005)	−0.004 (0.004)	0.001 (0.005)
Trans	−0.003 (0.004)	−0.012‡ (0.004)	0.002 (0.004)	−0.005 (0.004)	−0.002 (0.005)	0.002 (0.004)	−0.002 (0.004)	0.001 (0.004)
Whlsl	−0.002 (0.004)	−0.010‡ (0.004)	0.004 (0.005)	0.001 (0.004)	−0.002 (0.005)	0.001 (0.003)	−0.002 (0.003)	0.000 (0.004)
Rtail	0.000 (0.005)	−0.014‡ (0.004)	0.004 (0.005)	−0.005 (0.004)	−0.006 (0.006)	0.003 (0.004)	−0.006 (0.004)	0.002 (0.005)
Meals	−0.002 (0.004)	−0.015‡ (0.004)	0.000 (0.004)	−0.009‡ (0.004)	−0.005 (0.005)	−0.001 (0.004)	−0.001 (0.004)	0.001 (0.004)
Banks	−0.002 (0.005)	−0.014‡ (0.006)	0.004 (0.006)	−0.005 (0.005)	−0.001 (0.007)	−0.004 (0.005)	0.000 (0.005)	−0.009 (0.008)
Insur	−0.003 (0.004)	−0.015‡ (0.006)	0.002 (0.006)	−0.002 (0.004)	−0.004 (0.005)	0.001 (0.004)	0.003 (0.004)	−0.004 (0.006)
RlEst	−0.004 (0.005)	−0.010‡ (0.005)	0.001 (0.005)	−0.004 (0.005)	−0.001 (0.009)	−0.007† (0.004)	−0.007 (0.004)	−0.006 (0.007)
Fin	0.001 (0.006)	−0.018‡ (0.006)	0.014† (0.008)	−0.011† (0.006)	−0.006 (0.008)	−0.003 (0.006)	−0.004 (0.005)	−0.004 (0.007)
Other	−0.002 (0.005)	−0.007† (0.004)	0.004 (0.005)	−0.007 (0.005)	−0.005 (0.006)	−0.001 (0.004)	0.000 (0.004)	0.001 (0.005)

Notes: Estimation results of regression Eq. (5): $r_t^i = \mu_i + \alpha_{i,1} r_{t-1}^{oil} + \alpha_{i,2} r_{t-2}^{oil} + \alpha_{i,3} r_{t-3}^{oil} + \alpha_{i,4} r_{t-4}^{oil} + \alpha_{i,5} r_{t-5}^{oil} + \alpha_{i,6} r_{t-6}^{oil} + \alpha_{i,7} r_{t-7}^{oil} + \alpha_{i,8} r_{t-8}^{oil} + \varepsilon_t^i$ using weekly data. We report results for West Texas Intermediate spot oil price changes over the period March 1986-December 2008, with lags of 1, 2, 3, 4, 5, 6, 7, and 8 trading weeks. Newey-West HAC consistent standard errors appear in parentheses. ‡, and † denote rejection of the null hypothesis that the $\beta_{i,j}$ parameter equals zero at the 5%, and 10% significance levels, respectively.

Table 8: Economic significance of the oil strategy

Industry	Buy and Hold Strategy			Oil Strategy				
	Mean	Std. Dev.	S.R.	Mean	Std. Dev.	S.R.	$\hat{\alpha}$	$\hat{\beta}$
Agric	13.03	20.53	0.615	15.34	18.78	0.796	1.073‡ [3.747]	0.581‡ [5.551]
Food	14.35	16.50	0.845	13.03	15.75	0.802	0.856‡ [3.132]	0.512‡ [5.764]
Soda	12.82	25.41	0.489	12.30	22.83	0.522	0.752‡ [2.197]	0.610‡ [4.464]
Beer	15.52	18.88	0.801	14.67	17.27	0.826	0.977‡ [3.607]	0.547‡ [5.377]
Smoke	17.83	25.04	0.696	13.82	21.77	0.617	0.915‡ [2.428]	0.527‡ [4.903]
Toys	7.541	23.72	0.301	13.35	17.35	0.747	0.866‡ [3.118]	0.550‡ [5.818]
Fun	12.22	24.85	0.476	14.29	21.13	0.658	0.764‡ [2.409]	0.952‡ [8.694]
Books	7.214	18.78	0.363	12.27	16.11	0.737	0.684‡ [3.389]	0.755‡ [8.253]
Hshld	11.89	16.05	0.716	11.67	14.70	0.767	0.708‡ [3.112]	0.588‡ [6.668]
Clths	9.819	22.37	0.421	10.96	18.72	0.564	0.566‡ [1.808]	0.774‡ [6.592]
Hlth	8.590	23.59	0.347	10.64	17.88	0.573	0.660‡ [2.239]	0.503‡ [4.873]
MedEq	12.41	18.40	0.652	12.94	16.77	0.748	0.754‡ [3.215]	0.723‡ [8.069]
Drugs	14.15	17.63	0.780	12.72	16.50	0.747	0.769‡ [3.170]	0.649‡ [7.574]
Chems	10.48	19.12	0.527	12.66	15.83	0.774	0.764‡ [3.347]	0.639‡ [5.984]
Rubbr	10.66	19.75	0.520	11.55	17.61	0.633	0.619‡ [2.249]	0.766‡ [7.587]
Txtls	7.518	23.18	0.307	13.59	17.46	0.756	0.860‡ [3.101]	0.608‡ [4.871]
BldMt	10.40	20.10	0.498	10.67	17.03	0.603	0.564‡ [2.172]	0.764‡ [7.555]
Cnstr	11.47	24.03	0.461	13.17	20.28	0.630	0.753‡ [2.437]	0.768‡ [6.498]
Steel	9.013	27.69	0.311	14.37	22.55	0.620	0.770‡ [2.759]	0.955‡ [8.073]
FabPr	3.672	24.65	0.133	12.66	16.96	0.723	0.839‡ [2.932]	0.482‡ [5.357]
Mach	10.22	22.59	0.435	12.29	18.57	0.641	0.651‡ [2.457]	0.834‡ [8.169]
ElcEq	14.05	21.99	0.621	14.97	19.89	0.737	0.811‡ [3.552]	0.972‡ [8.801]
Autos	6.627	24.47	0.255	12.83	19.45	0.640	0.731‡ [3.251]	0.755‡ [7.020]
Aero	12.11	21.72	0.539	12.37	19.74	0.606	0.670‡ [2.347]	0.804‡ [7.485]
Ships	8.367	23.60	0.338	11.04	19.67	0.541	0.637‡ [2.027]	0.633‡ [4.936]

Industry	Buy and Hold Strategy			Oil Strategy				
	Mean	Std. Dev.	S.R.	Mean	Std. Dev.	S.R.	$\hat{\alpha}$	$\hat{\beta}$
Guns	12.74	22.14	0.557	12.32	18.52	0.644	0.813‡ [2.747]	0.475‡ [4.429]
Gold	8.269	38.02	0.207	15.03	28.17	0.519	1.103‡ [3.087]	0.334‡ [2.607]
Mines	11.42	25.28	0.290	13.68	21.53	0.617	0.832‡ [2.751]	0.686‡ [6.983]
Coal	16.10	37.13	0.423	19.20	30.17	0.623	1.402‡ [2.644]	0.440‡ [3.336]
Oil	13.77	18.17	0.736	13.80	17.06	0.786	0.899‡ [3.860]	0.559‡ [7.759]
Util	11.07	14.13	0.755	11.26	13.08	0.831	0.796‡ [3.799]	0.316‡ [4.762]
Telcm	10.03	18.38	0.524	13.54	15.80	0.832	0.825‡ [3.214]	0.675‡ [9.143]
PerSv	9.002	20.72	0.415	12.32	18.13	0.658	0.703‡ [2.528]	0.722‡ [6.101]
BusSv	8.723	18.80	0.443	11.14	16.25	0.661	0.558‡ [2.705]	0.825‡ [8.541]
Hardw	10.14	28.73	0.339	13.95	25.10	0.540	0.691‡ [1.722]	1.049‡ [7.578]
Softw	13.71	29.77	0.447	19.26	26.37	0.715	1.101‡ [2.688]	1.124‡ [7.298]
Chips	10.86	29.30	0.357	15.83	25.00	0.617	0.851‡ [2.244]	1.044‡ [6.568]
LabEq	8.599	25.37	0.323	13.81	20.49	0.655	0.780‡ [2.481]	0.826‡ [6.526]
Paper	9.539	18.67	0.490	8.671	16.92	0.489	0.417‡ [1.681]	0.682‡ [6.689]
Boxes	12.54	21.43	0.567	15.96	18.00	0.864	1.025‡ [3.876]	0.680‡ [6.702]
Trans	9.925	18.72	0.509	11.92	16.88	0.683	0.676‡ [2.732]	0.708‡ [6.922]
Whlsl	8.753	17.64	0.474	9.961	15.86	0.603	0.495‡ [2.276]	0.746‡ [7.764]
Rtail	12.12	19.57	0.599	14.65	17.90	0.797	0.841‡ [3.484]	0.847‡ [8.290]
Meals	11.42	18.41	0.598	13.09	16.33	0.777	0.774‡ [3.573]	0.706‡ [8.359]
Banks	11.87	20.54	0.559	13.62	17.57	0.753	0.801‡ [3.133]	0.744‡ [7.685]
Insur	11.62	18.63	0.603	11.54	16.16	0.689	0.666‡ [2.702]	0.658‡ [7.643]
RlEst	-0.583	20.84	-0.047	5.535	14.40	0.357	0.299 [1.201]	0.362‡ [4.751]
Fin	13.45	23.13	0.564	13.47	20.88	0.626	0.648‡ [2.647]	1.059‡ [9.192]
Other	5.757	22.67	0.236	9.468	18.61	0.488	0.474† [1.636]	0.703‡ [5.874]

Notes: Economic significance results are reported for all industries over January 1979-December 2008 period. Means and standard deviations are reported as annualized percentages. "S.R." denotes Sharpe ratio in this table. Results for the oil strategy are based on updated parameter estimates of the rolling regression in equation (1): $r_t^i = \mu_i + \alpha_i r_{t-1}^{oil,spot} + \varepsilon_t^i$, starting from January 1979. Sample size is 60 observations, and we roll the sample window forward, one month at a time, while keeping the window's length fixed. $\hat{\alpha}$ and $\hat{\beta}$ are estimated using regression equation (6): $r_t^{os} - r_t^f = \alpha_i + \beta_i(r_t^m - r_t^f) + \varepsilon_t$. Here, r_t^{os} represents returns to oil strategy, r_t^m represents market returns, and r_t^f is the risk free rate. We use S&P500 returns as market returns proxy and 1-month T-Bill rate series as risk free rate proxy. Reported $\hat{\alpha}$ values are in annual percentages. Reported t-statistics are based on Newey-West HAC consistent standard errors for West Texas Intermediate oil spot price series and appear in square brackets. ‡, and † denote rejection of the null hypothesis that the parameter equals zero at the 5%, and 10% significance levels, respectively.

Table 9: Correlations between West Texas Intermediate spot oil price changes and some U.S. economic variables.

U.S. Economic Variables	Spot Oil Price	Oil Future Price
Default Spread	0.18	0.00
Term Structure	-0.02	0.05
Dividend Yield	-0.09	-0.07
Interest Rate	0.00	-0.07

The sample period is January 1983 to January 2009. The sampling frequency is monthly. Default spread is defined as the difference between Aaa and Baa corporate bond interest rates, rated by Moody's. The term structure is defined as the difference between the 10-year US Treasury bond and the 3-month US Treasury Bill rates. The interest rate is the 3-month US Treasury Bill rate. Dividend yields are from Thomson Datastream US market index series. Source: St. Louis Fed and Thomson Datastream.