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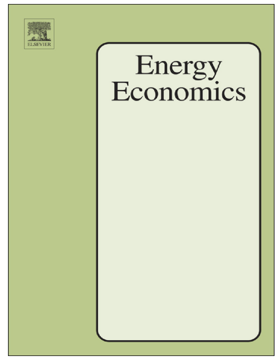

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Oil and Stock Market Momentum

Abstract

This study provides a novel perspective to the oil-stock market nexus by examining the predictive ability of oil return and volatility on stock market momentum in China. We find that oil return volatility serves as a strong predictor of industry momentum, even after controlling for stock market state, volatility and key macroeconomic variables. We argue that the predictive ability of oil over momentum payoffs is driven by time-varying investor sentiment that relates to excess buying pressure on winner stocks during uncertain times, captured by oil return volatility. Our tests also show that an oil-based momentum strategy wherein the investor conditions the trade on the state of oil return volatility yields significant abnormal returns, more than double that could be obtained from the conventional momentum strategy. In short, the findings suggest that oil market dynamics can contribute to stock market inefficiencies in such a way that these inefficiencies create significant abnormal profits for active managers.

JEL Classification Code: G14, G15

Keywords: Industry momentum; Crude oil; Market efficiency; Chinese stock market

1. Introduction

Stock market anomalies reflect inefficiencies in the way information is disseminated in the market place and reflected in asset prices via investors' trades. Anomalies also provide the basis for active investment strategies that aim to generate abnormal profits. One of the widely examined anomalies that has been shown to persist in stock markets is the momentum anomaly which relates to the relationship between a stock's historical and subsequent performance (e.g. Asness, 1994; Carhart, 1997; Moskowitz and Grinblatt, 1999; Jegadeesh and Titman, 1993, 2001). An important implication of this anomaly is an investment strategy called momentum investing that is based on buying past winner stocks and selling past loser stocks. Thus, apart from being a matter of concern from an academic perspective, the presence of this anomaly has significant investment implications as well.

In another popular strand of the literature, numerous studies have explored the effect of oil market dynamics on stock return and volatility. Oil can affect stock market dynamics via a number of different channels. At the firm level, oil price can affect costs and growth expectations, which then affect stock values. At the consumer level, oil price can affect consumer spending via its effect on their disposable income, thus affect the demand for the products that drive firm-level revenues and growth rates. These arguments have in fact been supported in many studies that show a significant oil effect on stock returns and volatility.[1] None of these studies, however, have explored whether oil price dynamics also contribute to stock market anomalies that reflect informational inefficiencies.

[1] The literature on the oil-stock market relationship is quite large. Several noteworthy studies include Jones and Kaul, 1996; Sadorsky, 1999; Park and Ratti, 2008; Kilian and Park, 2009; Issac and Ratti, 2009; Apergis and Miller, 2009; Choi and Hammoudeh, 2010; Gogineni, 2010; Arouri et al., 2011; Basher et al., 2012; Sukcharoen et al., 2014; Sim and Zhou, 2015; Demirer et al., 2015a, Reboredo and Ugolini, 2016, among many others.

From a behavioral perspective, one can argue that oil price fluctuations can affect investor sentiment, which may be particularly significant in high oil-sensitive economies. Such an effect on investor sentiment, in turn, may contribute to mispricing in the stock market in the form of stock market anomalies. In fact, in a recent study, Ding et al. (2017) show that oil price fluctuations significantly affect investor sentiment in the Chinese stock market without relating their findings to stock market anomalies. Therefore, the main contribution of this study is to provide a novel perspective to the oil-stock market nexus by examining the predictive ability of oil price dynamics over a well-studied and yet unresolved stock market anomaly, i.e. the momentum anomaly, that has been shown to persist in financial markets (e.g. Avramov and Chordia, 2006; Liu and Zhang 2008; Liu et al., 2011; Wang and Xu, 2015). Clearly, this is not only a concern from a market efficiency point of view, but can also present considerable abnormal profit opportunities for active managers.

For our empirical study, we focus on China, the second largest oil importer globally (after the U.S.) with an economy that is heavily reliant on oil imports to sustain its economic growth projections.[2] In addition to China's significant role in the world energy markets as a major consumer, several features of the Chinese stock market provide fertile ground to study the oil-stock market nexus from a market anomaly perspective. First, the literature offers robust evidence of an oil price effect on financial markets in China (e.g. Cong et al., 2008; Nguyen and Bhatti, 2012; Wen et al., 2012; Zhu et al., 2016; Broadstock et al., 2016, among others). Second, Demirer et al. (2015b) recently show that the momentum anomaly is present in this emerging stock market and document a significant herding effect on the short-run performance of momentum strategies. Finally, recent evidence by Ding et al. (2017) show that international crude oil price fluctuations significantly Granger cause Chinese stock market investor sentiment such

[2] BP Statistical Review of World Energy (June 2016).

that a one percent fluctuation in the price of crude oil leads to a 3.94 percent negative effect on stock market sentiment. Therefore, given the evidence in the literature, the Chinese stock market offers an interesting setup to examine whether oil market dynamics contribute to the momentum anomaly and allows us to extend the literature in a novel direction.

Our findings show that oil return volatility has robust predictive power over industry momentum payoffs in the Chinese stock market. The predictive power of oil volatility over momentum is irrespective of whether the market is in a positive or negative state and is robust even after controlling for stock market volatility as well as key macroeconomic variables including the short-term rate, default spread and term spread. In fact, our robustness checks suggest that oil return volatility absorbs the predictive ability of stock market volatility, implying that uncertainty surrounding oil price movements contributes to this anomaly more so than the stock market's own volatility does.

Examining possible asymmetries in predictability patterns, we find that predictability comes primarily from winner industries. Consistent with the recent findings by Ding et al. (2017), we argue that oil price fluctuations contribute to time varying investor sentiment, while this effect is channeled on stock prices via investors' over-purchase of high quality stocks in winner industries, thus creating overpricing in those industries, which in turn predicts negative returns in the subsequent periods. Whatever the underlying investor rationale might be, our analysis shows that the predictive power of oil on subsequent momentum payoffs can in fact be used within an active investment strategy. We show that an *oil-based* momentum strategy wherein the investor conditions the trade on the state of oil volatility in month (t) yields significant returns in the following month (t+1), which amounts to a spread of 2.107% per month over the conventional momentum strategy. Overall, our findings suggest that the predictive power of oil volatility is not only a statistical result with implications on the informational efficiency of the Chinese stock market, but also bears quite significant investment implications within an actively managed portfolio strategy.

An outline of the remainder of the paper is as follows. Section 2 provides a brief review of the literature on the effect of oil price on stock market dynamics in China. Section 3 explains the data and methodology. Section 4 presents the empirical results and Section 5 concludes the paper.

2. The literature on oil and the Chinese stock market

As a top player in the world's energy market, China has attracted a fair amount of interest in the academia with numerous studies examining the oil-stock market nexus in this giant emerging economy. In one of the earlier studies, Cong et al. (2008) employ a multivariate VAR model and show that oil price shocks only affect the manufacturing index and some oil companies, while the oil price shocks possess stronger explanatory power over interest rates. Focusing on economic growth measures, Du et al. (2010) document a positive correlation between oil prices and China's GDP, while Tang et al. (2010) show that oil price increases have a negative effect on investment and output with positive effects on inflation and interest rates. However, this finding is later questioned by Kim et al. (2017) who show that the response of Chinese interest rates to oil price shocks is not only time-varying, but also shows different signs over different sub-periods. Supporting the earlier findings, Zhang (2011) and Ou et al. (2012) show that positive oil price shocks lead to negative effects on real output, industrial production and stock prices.

Focusing on industry specific effects, Li et al. (2012) utilize panel cointegration and Granger causality tests to examine the relationship between oil prices and the industry sector returns in China. Their empirical results yield a positive effect of real oil price on sector returns in the long-run, while Zhang and Cao (2013) find that only the mining industry has a strong and consistent relationship with international oil price shocks when systematic risk factors are controlled for. Later, focusing on time-varying conditional correlations, Broadstock et al. (2012) and Broadstock and Filis (2014) show that the oil price effect is stronger on energy related stocks and that the impact of oil price got stronger during the global financial crisis period. Likewise, Zhu et al. (2016) show that the oil price effect is present only in recessions or bearish markets with low expected returns.

In more recent studies relating oil prices to the Chinese stock market, Wei and Guo (2017) argue that the effects of oil shocks on monetary and stock market variables depend on the underlying drivers of oil price changes and that monetary policy plays a limited role in the oil-stock market relationship. Luo and Qin (2017) show that shocks in the CBOE crude oil volatility index have negative effects on the Chinese stock market. Similarly, Wang et al. (2017) find that oil price uncertainty exerts a negative effect on corporate investment, while Wei and Guo (2016) argue that oil prices can be utilized in forecasting models for Chinese exports. In a study that is more related to the context of this particular paper, Ding et al. (2017) employ Granger causality tests and document a significant effect of oil price fluctuations on investor sentiment in the Chinese stock market. None of these studies, however, have examined the possible relationship between oil price dynamics and stock market anomalies that reflect inefficiencies in the way information is reflected in investors' trades and thus in stock prices. To that end, this study provides the initial evidence in that regard.

3. Data and Methodology

3.1 Data

We use daily and monthly return data for all A-shares listed on the Shanghai (SH) and Shenzhen (SZ) stock exchanges obtained from the GTA-CSMAR (China Securities Market &

Accounting Research) database. Each month between January 1996 and December 2015, we assign each stock to one of 78 industries using the first two digits of its disclosed industry code based on the China Securities Regulatory Commission's (CSRC) 2012 issue. We exclude industries with fewer than 5 stocks traded on any trading day during the sample period, leaving us with 52 industries and 2,226 stocks in all (1,033 stocks traded on Shanghai and 1,193 traded on Shenzhen exchanges). Table 1 provides the list of industries used in the analysis.

Real Estate and Computer & Electronic Device Manufacturing industries dominate the list with the greatest number of listed firms (105 and 102, respectively), while Financial Services is the largest industry in terms of market capitalization, accounting for 11.27% of total market value. On the performance aspect, technology related industries including Internet & Related Services and Software & IT Services stand out as the best performing industries with average monthly returns of 4.93% and 3.73%, respectively.

--- Insert Table 1 Here ---

In addition to stock return data, our predictive regressions utilize several important business cycle related variables, in monthly frequency, sourced from *Bloomberg* and *Wind Financial Terminal*. Following Wang and Xu (2015) and Demirer et al. (2016), the additional predictors include (i) the dividend yield for the Chinese stock market (DIV)[3]; (ii) the default spread (DEF), i.e. the spread between BBB-rated bonds and AAA-rated bonds; (iii) the term spread (TERM), i.e. the spread between ten-year and three-month government bonds; and (iv) the 3-month deposit rate (YLD). As the focus of the paper is the predictive ability of oil return and volatility on stock market momentum, we use monthly price data on Brent crude oil as this type of oil is considered the global benchmark (Demirer et al., 2015a).

[3] Dividend yield calculation for the aggregate stock market is generally based on large cap stocks, which, in the case of the Chinese stock market, represent about 75% of the total market capitalization.

In order to identify months of high/low oil (stock market) return volatility, we also use daily returns for Brent crude oil (stock market index) and compute the lagged volatility estimates for the stock market and oil returns. However, since there is no single stock market index available for China that includes all A shares traded in both SH and SZ exchanges, we use data on all A shares in our sample covering both exchanges and construct a value-weighted index as a proxy for the aggregate stock market. Daily oil and stock market index return data are then used to identify months of high/low volatility based on the lagged volatility estimates for these two variables. All other estimations are done using monthly data.

3.2 Methodology

The first step in the analysis is to identify winner and loser industries each month. For this purpose, at the beginning of each month (t), we rank each industry based on its return during the formation period from month (t – 12) to month (t – 2). We skip the most recent month (t-1) in order to mitigate issues related to microstructure (e.g. Asness, 1994; Grinblatt and Moskowitz, 2004). An industry is defined as winner (loser) if its formation period return is above (below) the median return across all industries. Table 1 reports, for each industry, the percentage of months when the industry is placed in the winner portfolio. Having identified winner and loser industries at the beginning of each month (t), the industry momentum payoff is computed as the holding month (t) return difference between equal-weighted winner and loser industry portfolios as the conventional industry momentum strategy involves buying past winner industries and selling past loser industries. Repeating this process with monthly rebalancing, we obtain the time series of monthly industry momentum returns (IndMOM_t).

In order to examine the predictive power of oil return and volatility over industry momentum, we follow Wang and Xu (2015) and utilize predictive regressions in the form

$$IndMOM_t = \alpha + \beta \cdot x_{t-1} + \varepsilon_t$$

where $IndMOM_t$ is the industry momentum payoff for month t and x_{t-1} is a vector of predictors measured at the end month *t-1*. The predictive regressions are applied to momentum return series as well as winner and loser industry portfolio returns separately in order to examine whether the predictability of winner and loser industries vary in significant ways across different predictors. Doing so also allows us to examine whether the predictive power of oil emanates from its predictive ability over winner or loser industries.

4. Empirical Findings

4.1 Portfolio sorts based on market state and volatility

Before examining the predictive power of oil return and volatility over momentum in the Chinese stock market, we first establish the baseline evidence for a possible stock market effect on momentum payoffs. Establishing this baseline evidence allows us to compare it with the effect of oil related variables and see whether oil return and volatility is able to absorb the predictive power of stock market return and volatility. For this purpose, we define the stock market state in terms of its lagged return such that a month is in positive (negative) *market state* if the lagged three-year market return is positive (negative). Similarly, we classify a month as in positive (negative) *oil state* if the lagged three-year Brent oil return is positive (negative). Independently, a month is classified as high (low) *market volatility* if the lagged 12-month stock market volatility is larger (smaller) than the lagged three-year market volatility. Finally, a month is of high (low) *oil volatility* if the lagged 12-month Brent oil return volatility is larger (smaller) than the lagged three-year oil return volatility. Having sorted all months in the sample period into four subsets based on the state of the market and level of volatility, we then calculate the average monthly momentum payoff for each of the four categories.

Table 2 reports the average monthly momentum payoff (in percentage) for each of the four categories of positive (negative) market state and high (low) volatility. Panel A (B) presents the momentum payoffs when market state and volatility is defined in terms stock market index (oil) returns, respectively. In both panels, we observe that the market state is a significant driver of momentum payoffs such that industry momentum payoffs are significantly higher (and positive) in positive market states while negative momentum payoffs are observed in negative market states regardless of the level of market volatility. However, comparing the momentum payoffs across the two panels, we observe larger momentum payoffs during positive oil market states compared to positive stock market states. For example, the average momentum payoffs during positive oil states are 3.776% and 4.442% per month for high and low volatility months, respectively, whereas they are 2.204% and 3.344% per month during positive stock market states, a difference of 1.572% (3.776%-2.204%) and 1.098% (4.442%-3.344%) per month, which is economically quite significant. This suggests that the state of the oil market has a greater impact on stock market momentum compared to the state of the stock market in China. Furthermore, although not reported in the table, we find that the average monthly momentum payoff is 2.041% for the full sample period. Therefore, an important investment implication of our findings would be that a momentum strategy conditional on the state of the oil market could generate an abnormal return in the range of 2.401% (4.442%-2.041%) to 1.735% (3.776%-2.041%) depending on the level of oil return volatility.

On the other hand, comparing the momentum payoffs across the high and low volatility states, we see that the level of stock market volatility matters as well, implied by higher momentum profits in low volatility months. For example, in Panel A, low volatility months outperform high volatility months by 1.14% (3.344%-2.204%) within the positive market state, while the spread is 0.826% (-3.456%-(-4.282%)) within the negative market state. A similar observation holds in Panel B when volatility is measured by oil returns so that low volatility months outperform high volatility months within both positive and negative market states. These intuitive comparisons are also supported graphically in Figure 1 where we observe large momentum payoffs following periods of low oil volatility, particularly during 2006-2008 and 2010-2014.[4] Overall, the preliminary analysis suggests that market state and volatility may have predictive ability over momentum payoffs, while this effect is larger when we define market state in terms of oil returns rather than stock market returns.

--- Insert Table 2 Here ---

--- Insert Figure 1 Here ---

4.2 The predictive power of market state and volatility over momentum

Having established the baseline evidence for the effect of market state and volatility on the profitability of momentum, we next perform several predictive regressions in order to formally test the predictive power of these variables over momentum payoffs. In our benchmark model, we regress monthly momentum returns against the lagged three-year market return on annual basis (MKT) and the lagged twelve-month market volatility (VOL). Separately, we define VOL^{+} (VOL^{-}) as equal to VOL if the lagged three-year market return is positive (negative), otherwise equal to 0. This allows us to dissect the possible volatility effect during positive and negative market states. In Table 3, Panels A and C report the results when volatility is measured by stock market volatility and Brent oil return volatility, respectively. The findings in Panel A confirm the findings from the intuitive comparisons presented in Table 2 such that the state of the market has a positive effect on subsequent momentum returns, while stock market volatility negatively

[4] Note that oil volatility is measured by the lagged 12-month Brent oil return volatility. It must also be noted that these findings are robust to alternative definitions of market and volatility states. The robustness checks are available upon request.

affects momentum returns. We also observe that the stock market volatility effect is in fact conditioned on the market state implied by a significant and negative estimate for VOL^{-} in Panel A, implying that stock market volatility predicts momentum during negative market states only. Robustness checks presented in Table B when volatility is calculated over the past six-months further confirm the predictive power of stock market state and volatility on momentum.

Interestingly, however, when oil volatility is used as the predictor, the findings reported in Panel C show that oil volatility has an unconditional effect on stock market momentum regardless of the state of the market. We see that both the value and significance of the estimated coefficients for oil volatility in Panel C are greater than those obtained for stock market volatility in Panel A. The predictive power of oil volatility during both negative and positive market states is also robust when oil volatility is calculated over the past six months (Panel D). Overall, the benchmark predictive regressions in Table 3 suggest that oil volatility has a larger and unconditional effect on stock market momentum in China than stock market volatility, implying that uncertainty surrounding oil price movements contributes to this anomaly more so than the stock market's own volatility does. From an investment perspective, given the findings so far, one can argue that the predictive power of oil presents an opportunity for active managers to generate excess returns this stock market anomaly may offer. In fact, we will later show that the excess returns from an oil-based momentum strategy over the conventional alternative can in fact be quite significant; therefore, the oil effect on momentum offers significant investment opportunities within active investment strategies.

--- Insert Table 3 Here ---

4.3 Asymmetric predictability

Having established the preliminary evidence on the predictive power of oil return volatility over momentum, we next examine whether predictability comes from the winner or the loser industries in China. For this purpose, we regress each return series (winners, losers and momentum) that we obtained using the procedure described in Section 3.2 on a number of predictors in various combinations. In addition to the predictor variables listed in Table 3, we also include the lagged three-year Brent oil return ($\mathbf{OIL}$) as an additional predictor in order to compare the predictive power of oil return to that of oil return volatility. Table 4 presents the findings. Panels A, B and C report the results for industry momentum, winner, and loser industry portfolio returns, respectively.

While the findings for momentum returns in Panel A confirm earlier observations from Tables 2 and 3, the findings in Table 4 suggest that oil volatility absorbs the predictive power of stock market volatility implied by the highly significant VOL_O estimates in alternative model specifications, while VOL_m loses its significance. For example, comparing the results reported in Panel A of Table 3 and 4, we see that while stock market volatility (VOL_m) is significant when used alone in Table 3, it loses its significance in Table 4 when oil return volatility (VOL_O) is included in the model. Furthermore, we see that the significance of the oil volatility term is also robust to the inclusion of oil return in the model and unconditional with respect to the state of the market, implied by highly significant estimates obtained for VOL_m^+ and VOL_m^-. Overall, the evidence from alternative predictive models in Panel A of Table 4 suggests that oil return volatility serves as a robust predictor of momentum returns in the Chinese stock market. This finding is indeed interesting considering the recent evidence in Wang and Xu (2015) for the U.S. stock market wherein stock market volatility is shown to forecast momentum profits, absorbing much of the predictive power of market state and other business cycle variables. To that end, our findings imply that volatility in the oil market dominates stock market volatility in China as an indicator of market uncertainty, thus absorbing the predictive power of stock market volatility over momentum profits.

Examining the findings for winner and loser portfolios in Panels B and C, we observe that predictability comes primarily from winner industries indicated by significant oil volatility estimates in Panel B only, while oil predictors are largely insignificant for losers in Panel C. This finding shows that high level of oil return volatility predicts lower subsequent returns for winner industries in China. A possible explanation for the predictability coming from winner industries is that high volatility in the global oil market makes Chinese investors uncertain regarding economic growth expectations and thus leads them to be more conservative in their investment approach, driving their demand towards the best performing industries, perhaps due to their attractive fundamentals, longer history of earnings, transparency in their operations or government policies towards particular industries, as will be discussed further later. This excess demand for stocks in the best performing industries during such uncertain times then leads to overpricing for these over-bought stocks only to yield negative returns in the subsequent period. On the other hand, as investors largely stay away from loser industries during uncertain times projected by high oil return volatility, we do not observe any pattern of predictability in the case of loser industries, implied by insignificant estimates for oil related predictors reported in Panel C.

--- Insert Table 4 Here ---

When we examine the industries that are most frequently placed in the winner portfolios (Table 1), we see that these industries are not necessarily oil related industries (e.g. alcohol, tea and beverage, automobile manufacturing, internet services, and pharmaceutical manufacturing). This observation suggests that the predictive ability of oil return volatility is not necessarily limited to oil related industries, but instead an artifact of the oil market effect on investors' trading behavior as a whole. To that end, one can argue that oil return volatility as a proxy for market risk serves as a market-wide or systematic risk proxy, which is not specific to oil related firms only.

From a behavioral perspective, the predictive power of oil driven by winner industries may be due to time-varying investor sentiment. As mentioned earlier, in a recent study, Ding et al. (2017) show that oil price fluctuations Granger cause investor sentiment in the Chinese stock market such that a one percent fluctuation in the price of crude oil leads to a 3.94 percent negative effect on stock market sentiment. It can thus be argued that volatility in the oil market affects investor behavior by driving them to high quality stocks from winners industries, thus creating overpricing in those industries, perhaps partially due to herding (Demirer et al., 2015b), which in turn predicts negative returns in the subsequent periods. To that end, our findings add further insight to the effect of oil price fluctuations on the time varying investor sentiment and the channels with which this effect drives stock prices and consequently stock market anomalies.

4.4 Robustness Checks

Now that we have established the robustness of the explanatory power of oil return volatility via benchmark predictive regressions, we next examine whether this predictive power is robust even after we control for several key macroeconomic variables that relate to business cycles. For this purpose, we extend the set of predictors in our models by including the dividend yield (DIV), the yield spread between BBB and AAA rated bonds (DEF), the yield spread between 10-year and 3-month government bonds (TERM), and the short-term deposit rate (YLD), in addition to the predictors used in the benchmark regressions. Table 5 presents the results. Panels A, B and C report the findings for industry momentum, winner, and loser return series, respectively.

Examining the findings for momentum returns in Panel A, we see that the dividend yield and the short-term deposit rate generally command the strongest predictive power for the time-variation in momentum profits. In the first regression, for example, we see that DIV and YLD stand out as the only significant predictors while market state (MKT) and market volatility variables come out either insignificant or marginally significant. Interestingly, when these results are compared to those from the third regression in Panel A of Table 3 where market state is found to be highly significant, the insignificant estimate for MKT and the volatility terms in Table 5 suggests that macroeconomic variables absorb the predictive power of the stock market state as well as market volatility.

Focusing on the oil volatility term in the second regression of Panel A in Table 5, however, we see that oil volatility retains its predictive power despite the inclusion of macroeconomic variables in the model. We also observe that the predictive power of the short-term deposit rate (YLD) becomes considerably weaker after the inclusion of oil related variables in the model. It is possible that the systematic risk proxy reflected by the state of oil volatility controls for the effect of this liquidity related variable, rendering YLD insignificant following the inclusion of oil related variables in the model. To that end, the effect of oil return volatility on the short-term deposit rate is consistent with Tang et al. (2010) and Kim et al. (2017) who document an oil price effect on Chinese interest rates. Although beyond the scope of this particular paper, it would be interesting to explore whether oil price fluctuations predict liquidity in the stock market as well.

Finally, examining the findings for winner and loser industries reported in Panels B and C, the yield spread between 10-year and 3-month government bonds (TERM) is found to be the dominant predictor for both winner and loser industries. At the same time, we still confirm that the predictive power of oil return volatility comes from winner industries indicated by significant

VOL_O^{+} and VOL_O^{-} estimates for winner industries in Panel B, while oil predictors are insignificant for loser industries in Panel C. In short, the additional robustness checks show that oil return volatility possesses robust predictive power even after controlling for stock market state, volatility and macroeconomic variables.

--- Insert Table 5 Here ---

4.5 An Alternative Momentum Strategy

Given the robust predictive power of oil volatility over subsequent momentum profits, a significant investment implication is whether one can exploit this predictive power in active management strategies. We put this to the test and compare the performance of the conventional momentum strategy to that of an *oil-based* alternative. Note that the conventional momentum strategy buys winner and sells loser industries at the beginning of month (t) based on the industries' formation period returns from month (t – 12) to month (t – 2) as explained in Section 3.2. Given the findings from our predictive regressions, we propose an *oil-based* momentum strategy wherein the investor conditions the trade on the state of oil return volatility in month (t). As explained in Section 4.1, we classify a month as high (low) *oil volatility* if the lagged 12-month Brent oil return volatility is larger (smaller) than the lagged three-year oil return volatility. Having classified each month in the sample as high or low volatility, we then devise a forward-looking strategy in which we take a contrarian position (i.e. buy loser and sell winner industries) at the beginning of month (t), if month (t-1) is of *high oil volatility*; otherwise adopt the conventional momentum strategy if month (t-1) is of *low oil volatility*. This oil-based, active strategy rebalances the portfolio each month, just like is the case with the conventional momentum strategy, however, rebalancing is done conditional on the oil volatility state each month based on the past 12-month oil return volatility. To that end, both momentum strategies will be associated with similar transaction costs as part of their active rebalancing strategies.

Table 6 reports the average monthly out-of-sample payoffs to the conventional and *oil-based* industry momentum strategies along with the corresponding standard deviations. Figure 2 plots the monthly out-of-sample payoffs for the *oil-based* momentum strategy. We see in Table 6 that the *oil-based* strategy indeed yields significant returns (4.149%), more than double that could be obtained from the conventional alternative (2.041%) and yet with lower risk. The return spread is 2.107% per month, both statistically and economically significant. Even if one is to consider the transaction costs associated with rebalancing these portfolios on a monthly basis, it is clear that the *oil-based* momentum strategy yields superior risk-adjusted returns to the conventional strategy. The success of the *oil-based* strategy is further reflected in the time series plots of monthly payoffs to the two strategies presented in Figure 2. Clearly, the *oil-based* strategy is able to avoid some of the major momentum crashes observed in early 2000 and later in 2015 during which the losses from the conventional strategy were as high as 45%. In short, the evidence suggests that the predictive power of oil volatility is not only a statistical result with implications on the informational efficiency of the Chinese stock market, but also bears quite significant investment implications within an actively managed portfolio strategy.

--- Insert Figure 2 Here ---

5. Conclusions

Despite the multitude of studies in the literature suggesting a significant oil price effect on stock market return and volatility, the literature has not yet fully explored whether oil price dynamics also contribute to stock market anomalies that reflect informational inefficiencies. As stock market anomalies form the basis for profitable trading strategies that exploit market inefficiencies, whether or not oil price dynamics have predictive power over these anomalies is not only of interest from an academic point of view, but also can help devise active management strategies in order to generate abnormal profits. This paper examines whether oil price dynamics have predictive power over stock market momentum, one of the most puzzling stock market anomalies with no clear explanation on why this anomaly persists in stock markets.

Given the evidence of a significant oil price effect on financial markets in China (e.g. Cong et al., 2008; Nguyen and Bhatti, 2012; Wen et al., 2012; Zhu et al., 2016; Broadstock et al., 2016) and the recent evidence that oil price fluctuations significantly affect investor sentiment in the Chinese stock market (Ding et al., 2017), we examine whether oil return and volatility can predict momentum in this major emerging economy that is heavily dependent on oil imports to sustain its economic growth. By doing so, we provide a novel perspective to the oil-stock market nexus and propose a new trading strategy based on the predictive power of oil.

Our findings indicate that oil return volatility has robust predictive power over industry momentum payoffs in the Chinese stock market. The predictive power of oil volatility over momentum is irrespective of whether the market is in a positive or negative state and is robust even after controlling for stock market volatility as well as key macroeconomic variables including the short-term rate, default spread and term spread. In fact, our robustness checks suggest that oil return volatility absorbs the predictive ability of stock market volatility and the short-term deposit rate as a measure of market liquidity.

The tests also show that predictability comes primarily from winner industries. Consistent with the recent findings by Ding et al. (2017), our results suggest that oil price fluctuations affect time varying investor sentiment and that the effect of oil market dynamics on investor sentiment is channeled via excess demand for winner industries during uncertain times projected by high oil return volatility, thus predicting negative subsequent returns. Whatever the underlying investor rationale might be, our analysis shows that the predictive power of oil on subsequent momentum payoffs can in fact be used within an active investment strategy. We show that an *oil-based* momentum strategy wherein the investor conditions the trade on the state of oil volatility in month (t) yields significant returns in the following month (t+1), which amounts to a spread of 2.107% per month over the conventional momentum strategy. Overall, our findings suggest that oil price fluctuations can indeed be a driver of stock market inefficiencies, while the predictive power of oil volatility can be utilized to generate abnormal profits.

References

Apergis, N. and Miller, S. M., 2009. Do structural oil - market shocks affect stock prices? Energy Economics 31(4), 569-575.

Arouri, M., Jouini, J., and Nguyen, D. K., 2011. Volatility spillovers between oil prices and stock sector returns: Implications for portfolio management. Journal of International Money and Finance 30, 1387-1405.

Asness, C. S., 1994. Variables that explain stock returns. Ph.D. Dissertation, University of Chicago.

Avramov, D. and Chordia, T., 2006. Asset pricing models and financial market anomalies. Review of Financial Studies 19, 1001-1040.

Basher, S. A., Haug, A. A., and Sadorsky, P., 2012. Oil prices, exchange rates and emerging stock markets. Energy Economics 34, 227-240.

Broadstock, D. C. and Filis, G. 2014. Oil price shocks and stock market returns: New evidence from the United States and China. Journal of International Financial Markets, Institutions & Money 33, 417-433.

Broadstock, D. C., Cao, H., and Zhang, D., 2012. Oil shocks and their impact on energy related stocks in China. Energy Economics 34(6), 1888-1895.

Broadstock, D. C., Fan, Y., Ji, Q., and Zhang, D., 2016. Shocks and stocks: a bottom-up assessment of the relationship between oil prices, gasoline prices and the returns of Chinese firms. Energy Journal 37, 1-32.

Carhart, M., 1997. On persistence in mutual fund performance. Journal of Finance 52, 57-82

Choi K., and Hammoudeh S., 2010. Volatility behavior of oil, industrial commodity and stock markets in a regime-switching environment. Energy Policy 38, 4388-4399.

Cong, R., Wei, Y., Jiao, J., and Fan, Y., 2008. Relationships between oil price shocks and stock market: An empirical analysis from China. Energy Policy, 36(9), 3544-3553.

Demirer, R., Pierdzioch, C., and Zhang, H., 2016. On the short-term predictability of stock returns: A quantile boosting approach. Finance Research Letters, forthcoming.

Demirer, R., Jategaonkar, S., and Khalifa, A. 2015a. Oil price risk exposure and the cross-section of stock returns: The case of net exporting countries. Energy Economics 49, 132-140.

Demirer, R., Lien, D., and Zhang, H., 2015b. Industry herding and momentum strategies. Pacific-Basin Finance Journal 32, 95-110.

Ding, Z., Liu, Z., Zhang, Y., and Long, R. 2017. The contagion effect of international crude oil price fluctuations on Chinese stock market investor sentiment. Applied Energy 187, 27-36.

Du, L., He, Y., and Wei, C., 2010. The relationship between oil price shocks and China's macroeconomy: an empirical analysis. Energy Policy 38, 4142-4151.

Gogineni S., 2010. Oil and the stock market: An industry level analysis. Financial Review 45, 995-1010.

Grinblatt, M. and Moskowitz, T., 2004. Predicting stock price movements from past returns: the role of consistency and tax-loss selling. Journal of Financial Economics 71, 541-579.

Issac, M. J., and Ratti, R. A., 2009. Crude Oil and stock markets: Stability, instability, and bubbles. Energy Economics 31, 559-568.

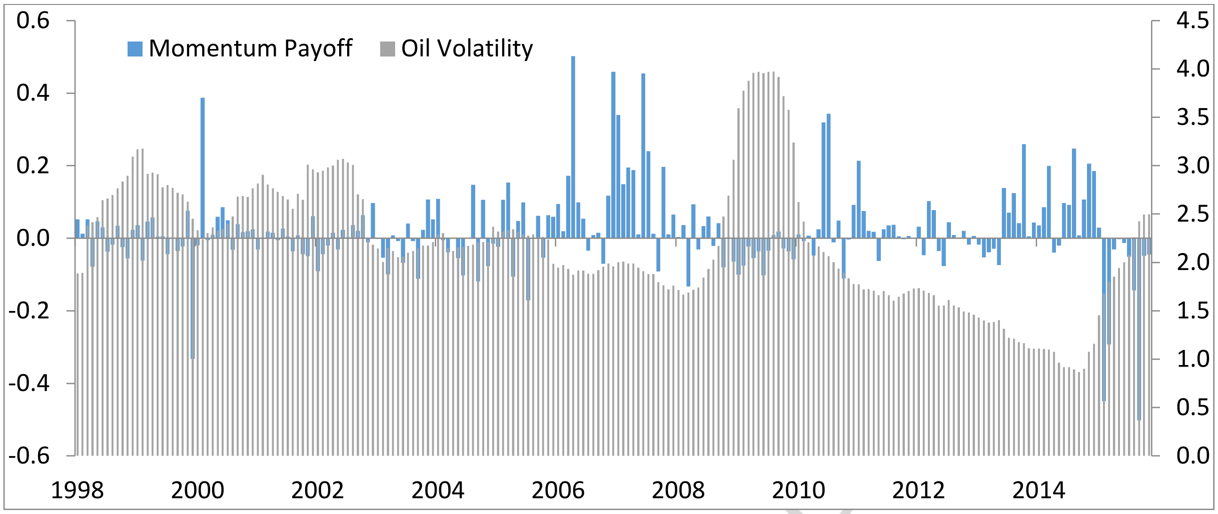
Jegadeesh, N., and Titman, S. 1993. Returns to buying winners and selling losers: Implications for stock market efficiency, Journal of Finance 48, 65-91.

Jegadeesh, N., and Titman, S. 2001. Profitability of momentum strategies: an evaluation of alternative explanations. Journal of Finance 56, 699-720.

Jones, C. M., Kaul, G., 1996. Oil and the Stock Markets. Journal of Finance 51 (2), 463-491.
Kilian, L. and Park, C. 2009. The impact of oil prices shocks and the U.S. stock market. International Economic Review 50, 1267-1287.
Kim, W. J., Hammoudeh, S., Hyun, J. S., and Gupta, R., 2017. Oil price shocks and China's economy: Reactions of the monetary policy to oil price shocks. Energy Economics 62, 61-69.
Li, S., Zhu, H., and Yu, K., 2012. Oil prices and stock market in China: A sector analysis using panel cointegration with multiple breaks. Energy Economics 34(6), 1951-1958.
Liu, L. X., and Zhang, L. 2008. Momentum profits, factor pricing, and macroeconomic risk, Review of Financial Studies 21, 2417-2448.
Liu, M., Liu, Q., and Ma, T. 2011. The 52-week high momentum strategy in international stock markets. Journal of International Money and Finance 30, 180-204.
Luo, X. and Qin, S., 2017. Oil price uncertainty and Chinese stock returns: New evidence from the oil volatility index. Finance Research Letters 20, 29-34.
Moskowitz, T., and Grinblatt, M. 1999. Do industries explain momentum? Journal of Finance 54, 1249-1290.
Nguyen, C. C. and Bhatti, M. I., 2012. Copula model dependency between oil prices and stock markets: Evidence from China and Vietnam. Journal of International Financial Markets, Institutions & Money 22(4), 758-773.
Ou, B., Zhang, X., and Wang, S., 2012. How does China'smacroChina’s macro-economy response to the world crude oil price shock: a structural dynamic factor model approach. Computers & Industrial Engineering 63, 634-640.
Park, J. and, Ratti, R. A., 2008. Oil price shocks and stock markets in the US and 13 European countries. Energy Economics 30, 2587-2608.
Reboredo, J. C. and Ugolini, A., 2016. Quantile dependence of oil price movements and stock returns. Energy Economics 54, 33-49.
Sadorsky, P., 1999. Oil price shocks and stock market activity. Energy Economics 21, 449-469.
Sim, N. and Zhou, H., 2015. Oil prices, US stock return, and the dependence between their quantiles. Journal of Banking and Finance 55, 1-8.
Sukcharoen, K., Zohrabyan, T., and Leatham, D., et al., 2014. Interdependence of oil prices and stock market indices: A copula approach. Energy Economics 44(C), 331-339.
Tang, W., Wu, L., and Zhang, Z., 2010. Oil price shocks and their short- and long-term effects on the Chinese economy. Energy Econ. omics 32, S3-S14.
Wang, K. Q. and Xu, J., 2015. Market volatility and momentum. Journal of Empirical Finance 30, 79-91.
Wang, Y., Xiang, E., Cheung, A., Ruan, W., and Hu, W., 2017. International oil price uncertainty and corporate investment: Evidence from China’s emerging and transition economy. Energy Economics 61, 330-339.
Wei, Y. and Guo, X., 2016. An empirical analysis of the relationship between oil prices and the Chinese macro-economy. Energy Economics 56, 88-100.
Wei, Y. and Guo, X., 2017. Oil price shocks and China’s stock market. Energy 140, 185-197.
Wen, X., Wei, Y., and Huang, D., 2012. Measuring contagion between energy market and stock market during financial crisis: A copula approach. Energy Economics 34(5) , 1435-1446.
Zhang, D. and Cao, H., 2013. Sectoral Rresponses of the Chinese Sstock Mmarket to Iinternational Ooil Sshocks. Emerging Markets Finance & Trade, 49(6), 37-51.
Zhang, Q., 2011. The impact of international oil price fluctuation on China's China’s economy.

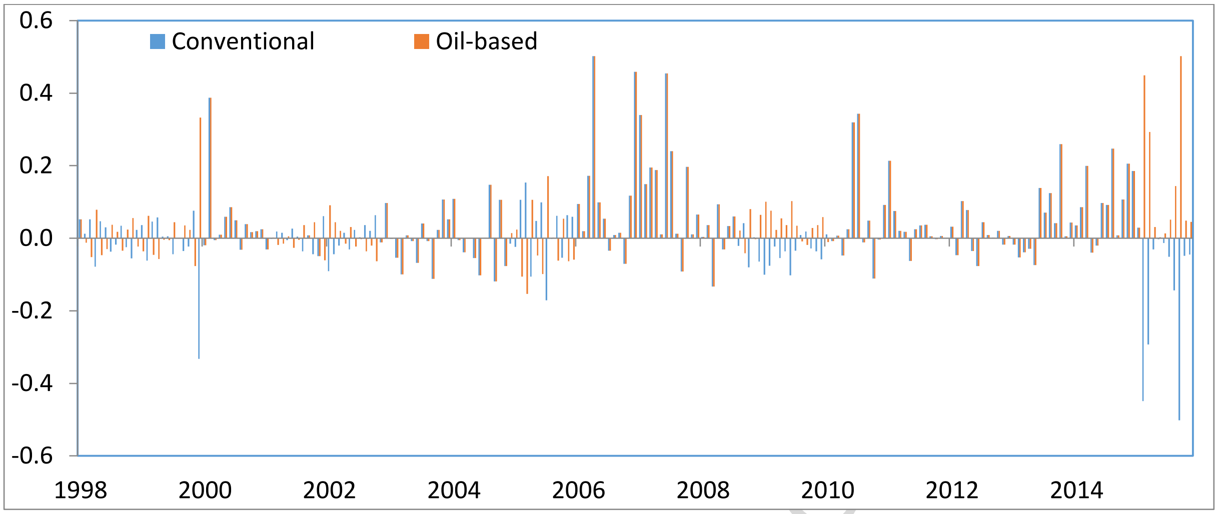
Energy Procedia 5, 1360-1364.
Zhu, H., Guo, Y., You, W., and Xu, Y., 2016. The heterogeneity dependence between crude oil price changes and industry stock market returns in China: Evidence from a quantile regression approach. Energy Economics 55, 30-41.

Figure 1. Oil return volatility and industry momentum returns



Note: At the beginning of each month (t), industries are ranked based on their returns during the formation period from month (t – 12) to month (t – 2). The most recent month (t-1) is skipped in order to mitigate issues related to microstructure. An industry is defined as winner (loser) if its formation period return is above (below) the median return across industries. Industry momentum payoff (IndMOM_t) is the out-of-sample return, calculated as the holding month (t) return difference between equal-weighted winner and loser industry portfolios. Oil volatility (Vol_o) is the lagged twelve-month Brent oil return volatility.

Figure 2. Payoffs to the conventional and *oil-based* momentum strategies



Note: The figure plots the monthly out-of-sample payoffs to the conventional and the *oil-based* industry momentum strategies. The conventional momentum strategy buys winner and sells loser industries at the beginning of month (t) based on the industries' formation period returns from month (t – 12) to month (t – 2). The oil-based strategy adopts a contrarian strategy (i.e. buy loser and sell winner industries) at the beginning of month (t), if month (t-1) is of *high oil volatility*; otherwise adopt the conventional momentum strategy if month (t-1) is of *low oil volatility*.

Table 1. Summary statistics

Industry	# of Firms	Market Share	Return	Months in Winner Portfolio
Agriculture	9	0.47%	1.63%	37.50%
Air Transportation	8	1.47%	1.69%	44.49%
Alcohol, tea and beverage	27	2.87%	1.83%	63.75%
Apparel	11	0.35%	2.37%	45.87%
Architectural Decoration & Other Construction	7	0.29%	2.21%	50.83%
Automobile Manufacturing	46	3.18%	2.26%	61.25%
Broadcast, TV and Film/TV Recording	6	0.25%	3.58%	40.61%
Business Services	13	0.82%	2.65%	55.83%
Capital market services	13	2.11%	2.93%	44.17%
Chemical Fiber Manufacturing	15	0.66%	1.84%	45.00%
Civil Engineering	27	1.87%	1.98%	44.58%
Coal Mining & Processing	17	2.85%	1.59%	45.83%
Computer and Electronic Device Manufacturing	102	5.86%	2.56%	57.08%
Conglomerates	26	1.57%	1.98%	46.67%
Culture, Education & Entertainment Products	6	0.12%	3.40%	42.59%
Electric & Thermal Power Production/Supply	51	5.07%	1.75%	51.67%
Electrical Machine Manufacturing	73	3.48%	2.49%	64.58%
Farm Products Processing	20	1.06%	2.09%	54.58%
Ferrous Metal Mining	6	0.37%	1.79%	34.58%
Financial services	8	11.27%	1.28%	54.17%
Fishery	5	0.16%	1.67%	37.50%
Food Manufacturing	14	0.74%	2.04%	57.92%
General Equipment Manufacturing	44	1.85%	2.25%	60.83%
Highway Transportation	21	1.94%	1.52%	50.00%
Hotels	7	0.32%	1.93%	45.83%
Instrument and Meter manufacturing	7	0.12%	3.94%	50.45%
Internet & Related Services	6	0.32%	4.93%	63.33%
Metal Products	18	0.74%	2.18%	50.42%
News & publishing	11	0.56%	2.25%	47.08%
Nonferrous Metal Mining & Dressing	16	1.11%	2.14%	46.25%
Non-metallic Mineral Products	44	2.05%	2.15%	51.67%
Other Manufacturing	7	0.23%	2.53%	42.92%
Papermaking & Paper Products	15	0.53%	1.56%	42.92%
Petroleum and Nuclear Fuel Processing	15	1.66%	1.43%	41.25%
Pharmaceutical Manufacturing	84	4.20%	2.36%	65.83%
Production/Supply of Gas	8	0.98%	1.99%	43.33%
Production/Supply of Water	10	0.69%	1.82%	45.00%
Public Facilities Management	12	0.80%	1.89%	46.25%
Railway, Shipbuilding & Airplane	22	1.54%	2.46%	59.58%
Raw Chemical Materials	96	4.43%	2.10%	57.50%

Real Estate	115	7.81%	2.18%	52.50%
Retail Trade	66	3.66%	1.85%	44.58%
Rubber & Plastic Products	20	0.70%	2.28%	58.75%
Smelting and Pressing of Ferrous Metals	26	4.06%	1.44%	46.67%
Smelting and Pressing of Nonferrous Metals	33	2.27%	1.93%	46.25%
Software and IT services	43	1.61%	3.73%	57.50%
Special Equipment Manufacturing	54	2.22%	2.79%	61.67%
Telecommunications, Broadcast, Satellite Services	7	1.33%	2.52%	52.08%
Textile	23	0.71%	2.00%	42.50%
Timber Processing	7	0.22%	2.84%	37.50%
Water Transportation	20	1.99%	1.68%	47.50%
Wholesale	50	2.58%	2.12%	58.33%

Note: Each month between January 1996 and December 2015, all A shares listed in Shanghai and Shenzhen exchanges are assigned to an industry based on the first two-digits of industry codes following the China Securities Regulatory Commission's (CSRC) 2012 issue. We exclude industries with fewer than 5 stocks traded on any trading day during the sample period, leaving us with 52 industries and 2,226 stocks in all (1,033 stocks traded on Shanghai and 1,193 traded on Shenzhen exchanges). **Market share** and **# of firms** refer to the time-series average of industry market cap as a percentage of the whole market and time-series average of the number of firms in each industry, respectively. **Return** is the time series average of monthly industry returns. **Months in the winner portfolio** is the percentage of months an industry is placed in the winner industry portfolio.

TABLE 2. Market states, volatility, and industry momentum payoffs.

POSITIVE market state		**NEGATIVE** market state	
High volatility	Low volatility	High volatility	Low volatility
Panel A: Market state and volatility measured by *stock market return*			
2.204	3.344	-4.282	-3.456
(9.822)	(8.625)	(-5.842)	(-4.273)
Panel B: Market state and volatility measured by *oil return*			
3.776	4.442	-5.077	-4.640
(9.188)	(4.750)	(-8.087)	(-4.682)

Note: At the beginning of each month (t), industries are ranked based on their returns during the formation period from month (t – 12) to month (t – 2). The most recent month (t-1) is skipped in order to mitigate issues related to microstructure. An industry is defined as winner (loser) if its formation period return is above (below) the median return across industries. Industry momentum return (IndMOM_t) is the out-of-sample return, calculated as the holding month (t) return difference between equal-weighted winner and loser industry portfolios. A month is in positive (negative) market state if the lagged three-year stock market return (or oil return in Panel B) is positive (negative). A month is of high (low) *volatility* if the lagged 12-month stock market (or oil) return volatility is larger (smaller) than the lagged three-year stock market (or oil) return volatility. The average monthly momentum payoff (in percentage) for each of the four categories of positive (negative) market state and high (low) volatility is reported. Panels A and B report the payoffs conditioned on market and volatility states based on stock market and Brent oil return, respectively. In parenthesis are robust t-statistics.

TABLE 3. Predictive power of market state and volatility on industry momentum.

	MKT	VOL	VOL^{+}	VOL^{-}	Adj. R^2
Panel A. Volatility measured by stock market volatility					
	1.744				0.045
	(2.837)				
		-1.192			0.005
		(-2.241)			
	1.934	-0.529			0.042
	(2.663)	(-1.678)			
	2.255		-0.464	-0.722	0.040
	(2.473)		(-0.412)	(-3.077)	
Panel B. Stock market volatility calculated over the past six months					
	1.628	-1.292			0.041
	(2.380)	(-2.313)			
	1.851		0.326	-0.751	0.038
	(2.036)		(0.346)	(-2.043)	
Panel C. Volatility measured by oil return volatility					
		-2.377			0.069
		(-3.161)			
	2.271	-2.895			0.146
	(3.685)	(-3.690)			
	2.240		-3.154	-3.580	0.146
	(3.602)		(-3.480)	(-2.937)	
Panel D. Oil return volatility calculated over the past six months					
	2.258	-2.176			0.115
	(3.633)	(-3.086)			
	2.134		-2.513	-3.226	0.121
	(3.322)		(-3.259)	(-3.029)	

Note: At the beginning of each month (t), industries are ranked based on their returns during the formation period from month (t – 12) to month (t – 2). The most recent month (t-1) is skipped in order to mitigate issues related to microstructure. An industry is defined as winner (loser) if its formation period return is above (below) the median return across industries. Industry momentum return (IndMOM_t) is the out-of-sample return, calculated as the holding month (t) return difference between equal-weighted winner and loser industry portfolios. Monthly momentum returns are regressed on the lagged three-year, i.e. month (t-1) to month (t-36), market return on annual basis (**MKT**) and the lagged twelve-month, i.e. month (t-1) to month (t-12), market volatility (**VOL**). VOL^{+} (VOL^{-}) is equal to Vol if the lagged three-year market return is positive (negative), otherwise equal to 0. Panels A and C report the regression results when volatility is measured by stock market volatility and Brent oil return volatility, respectively. Panels B and D report robustness checks when volatility is calculated over the past six-months. In parenthesis are robust t-statistics.

Table 4. Asymmetric predictability.

MKT	VOL_m	VOL_m^+	VOL_m^-	OIL	VOL_O	VOL_O^+	VOL_O^-	Adj. R^2
				Panel A: Industry momentum				
2.052	-0.738			-0.654				0.041
(2.722)	(-1.659)			(-1.826)				
1.682	-1.880				-3.377			0.155
(2.546)	(-1.970)				(-4.669)			
1.834	1.640			-0.864	-3.427			0.158
(2.722)	(1.580)			(-1.170)	(-4.409)			
0.979		-1.752	-1.749			-3.064	-3.633	0.159
(1.620)		(1.697)	(-2.610)			(-4.191)	(-4.519)	
1.181		1.878	0.691	-0.830		-3.706	-3.778	0.159
(1.338)		(1.955)	(0.562)	(-1.032)		(-4.248)	(-4.420)	
				Panel B: Winner industries				
0.462	0.838			-1.687				-0.002
(0.348)	(0.384)			(-1.174)				
-0.008	-2.965				-2.228			0.014
(-0.006)	(-1.275)				(-1.645)			
0.314	2.457			-1.830	-2.333			0.010
(0.241)	(1.032)			(-1.299)	(-1.782)			
-2.424		0.320	-0.643			-4.187	-3.202	0.034
(-1.367)		(1.516)	(-2.216)			(-2.970)	(-2.123)	
-2.339		3.262	-0.665	-0.346		-4.121	-3.262	0.030
(-1.294)		(1.454)	(-0.279)	(-0.207)		(-2.906)	(-2.125)	
				Panel C: Loser industries				
-1.590	1.575			-1.032				0.003
(-1.301)	(0.867)			(-1.883)				
-1.690	-1.085				1.150			0.005
(-1.405)	(-0.549)				(1.009)			
-1.520	0.816			-0.965	1.094			0.003
(-1.262)	(0.407)			(-0.837)	(0.956)			
-3.402		1.303	-1.387			-0.323	0.431	0.021
(-2.069)		(0.708)	(-1.721)			(-0.289)	(0.330)	
-3.520		1.384	-1.356	0.484		-0.415	0.515	0.017
(-2.077)		(0.729)	(-0.698)	(0.328)		(-0.364)	(0.385)	

Note: At the beginning of each month (t), industries are ranked based on their returns during the formation period from month (t – 12) to month (t – 2). The most recent month (t-1) is skipped in order to mitigate issues related to microstructure. An industry is defined as winner (loser) if its formation period return is above (below) the median return across industries. Industry momentum return (IndMOM_t) is the out-of-sample return, calculated as the holding month (t) return difference between equal-weighted winner and loser industry portfolios. We regress each return series (winners, losers and momentum) on a number of predictors in various combinations. **MKT** is the lagged three-year market return on annual basis, **OIL** is the lagged three-year Brent oil return, $\mathbf{VOL}_{\boldsymbol{m}}$ ($\mathbf{VOL}_{\boldsymbol{O}}$) is the lagged twelve-month stock market (Brent oil) return volatility, respectively. VOL_i^+ (VOL_i^-), i=m,o, is equal to VOL_i if the lagged three-year market return is positive (negative), otherwise equal to 0. Panels A, B and C report the results for industry momentum, winner, and loser return series, respectively. In parenthesis are robust t-statistics.

Table 5. Robustness checks using business cycle variables.

MKT	VOL_m^+	VOL_m^-	OIL	VOL_o^+	VOL_o^-	DIV	DEF	TERM	YLD	Adj. R^2
Panel A: Industry momentum										
1.078	-5.937	-6.123				-1.927	2.822	1.191	5.333	0.122
(0.254)	(-1.539)	(-1.967)				(-2.486)	(1.443)	(1.892)	(2.470)	
0.990				-2.756	-3.969	-2.543	5.032	1.599	3.016	0.138
(0.367)				(-4.074)	(-4.067)	(-3.029)	(2.130)	(2.036)	(1.800)	
0.247			-3.507	-2.915	-3.952	-2.537	6.496	1.721	3.313	0.097
(0.095)			(-2.337)	(-3.916)	(-3.651)	(-3.152)	(2.500)	(2.288)	(0.163)	
-1.791	-12.308	-11.303		-3.083	-4.270	-1.383	3.889	1.757	6.168	0.132
(-0.454)	(-2.205)	(-2.539)		(-3.790)	(-3.853)	(-2.131)	(1.543)	(2.135)	(2.709)	
-1.972	-11.708	-10.558	-2.920	-3.362	-4.156	-1.458	5.245	1.873	3.928	0.141
(-0.518)	(-2.164)	(-2.427)	(-2.105)	(-3.808)	(-3.093)	(-2.282)	(1.862)	(2.270)	(1.650)	
Panel B: Winner industries										
-14.686	7.590	-0.277				-0.592	3.351	3.847	5.781	0.162
(-2.056)	(1.292)	(-0.054)				(-0.359)	(0.734)	(3.277)	(1.689)	
-13.153				-4.347	-3.221	-0.668	11.199	6.299	4.277	0.198
(-2.565)				(-2.918)	(-2.106)	(-0.425)	(2.265)	(4.706)	(1.462)	
-14.420			-5.976	-4.433	-3.187	-0.658	13.694	6.507	4.331	0.218
(-2.926)			(-1.833)	(-2.781)	(-2.019)	(-0.456)	(2.863)	(5.236)	(0.099)	
-23.441	-12.291	-16.099		-4.355	-3.534	1.085	8.038	5.895	8.289	0.250
(-4.042)	(-1.537)	(-2.451)		(-2.710)	(-2.142)	(0.641)	(1.538)	(4.877)	(2.643)	
-23.740	-11.302	-14.872	-4.810	-4.409	-3.417	0.961	10.272	6.087	4.269	0.260
(-4.285)	(-1.467)	(-2.316)	(-1.557)	(-2.809)	(-2.274)	(0.610)	(1.967)	(5.303)	(1.191)	
Panel C: Loser industries										
-15.765	13.526	5.847				1.336	0.529	2.659	0.448	0.205
(-3.127)	(3.796)	(1.543)				(0.988)	(0.137)	(2.993)	(0.181)	
-14.143				-1.591	0.748	1.875	6.167	4.701	1.260	0.238
(-3.858)				(-0.714)	(0.701)	(1.398)	(1.420)	(5.501)	(0.595)	
-14.667			-2.469	-1.518	0.765	1.879	7.198	4.787	1.018	0.236
(-4.110)			(-0.957)	(-0.693)	(0.690)	(1.452)	(1.704)	(5.457)	(0.263)	
-21.650	0.017	-4.796		-1.272	0.736	2.468)	4.149	4.138	2.121	0.264
(-5.517)	(0.003)	(-1.019)		(-0.845)	(0.719)	(1.694)	(0.951)	(4.497)	(0.965)	
-21.767	0.405	-4.314	-1.891	-1.047	0.739	2.419	5.027	4.214	0.541	0.259
(-5.663)	(0.071)	(-0.914)	(-0.765)	(-0.809)	(0.778)	(1.713)	(1.162)	(4.661)	(0.203)	

Note: At the beginning of each month (t), industries are ranked based on their returns during the formation period from month (t – 12) to month (t – 2). The most recent month (t-1) is skipped in order to mitigate issues related to microstructure. An industry is defined as winner (loser) if its formation period return is above (below) the median return across industries. Industry momentum return ($IndMOM_t$) is the out-of-sample return, calculated as the holding month (t) return difference between equal-weighted winner and loser industry portfolios. We regress each return series (winners, losers and momentum) on a number of predictors in various combinations. **MKT** is the lagged three-year market return on annual basis, **OIL** is the lagged three-year Brent oil return, $\mathbf{VOL_m}$ ($\mathbf{VOL_O}$) is the lagged twelve-month stock market (Brent oil) return volatility, respectively. VOL_i^+ (VOL_i^-), i=m,o, is equal to VOL_i if the lagged three-year market return is positive (negative), otherwise equal to 0. Additional predictors include the dividend yield (**DIV**), the yield spread between BBB and AAA rated bonds (**DEF**), the yield spread between 10-year and 3-month government bonds (**TERM**), and the short-term deposit rate (**YLD**). Panels A, B and C report the results for industry momentum, winner, and loser return series, respectively. In parenthesis are robust t-statistics.

TABLE 6. The out-of-sample performance of the oil-based momentum strategy.

	Mean	Std. Deviation
Conventional momentum strategy	2.041%	11.614%
Oil-based momentum strategy	4.149%	11.036%
Return spread (oil minus conventional)	2.107%	
	(2.418)	

Note: The table reports the average monthly out-of-sample payoffs to the conventional and oil-based industry momentum strategies. The conventional momentum strategy buys winner and sells loser industries at the beginning of month (t) based on the industries' formation period returns from month (t – 12) to month (t – 2). The oil-based strategy adopts a contrarian strategy (i.e. buy loser and sell winner industries) at the beginning of month (t), if month (t-1) is of *high oil volatility*; otherwise adopt the conventional momentum strategy if month (t-1) is of *low oil volatility*. Return spread is average difference between the monthly payoffs to the two strategies.

Highlights

- Oil return volatility predicts momentum payoffs in the Chinese stock market.
- Oil absorbs the predictive power of stock market volatility and state.
- Oil's predictive power is robust to the inclusion of key macroeconomic variables.
- Predictability comes from winner industries.
- Oil-based momentum strategy generates significant abnormal profits.