Intraday momentum and return predictability: Evidence from the crude oil market

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Abstract

Our intraday analysis of high-frequency United States Oil Fund (USO) data from 2006 to 2018 shows the existence of intraday momentum, which states that the last half-hour returns can be positively predicted by the first half-hour returns. The results are robust for both in-sample and out-of-sample analysis. Intraday return predictability is stronger during days with higher realized volatility, higher trading volume, higher overnight returns, and jumps. A market timing strategy, which uses the first half-hour return as a trading signal, outperforms two other benchmark strategies.

JEL classification: G1; C5; Q3; Q4

Key words: intraday momentum, return predictability, crude oil market, market timing strategy

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1. Introduction

Subsequent to the findings of Jegadeesh and Titman (1993), momentum has continued to gain interest from researchers and practitioners. Numerous studies show that the use of momentum strategies in equity markets, that is, buying stocks which perform well and selling stocks which perform badly over the past several months, produces significant profits and outperforms other investment strategies (e.g., Grinblatt, Titman and Wermers, 1995; Jagadeesh and Titman, 2001; Griffin et al., 2003). The prevalence of momentum is not limited to equity markets. For a wide range of assets, including currencies, commodities, and bonds, an asset's past performance can predict its future returns (e.g., Asness et al., 2013; Miffre and Rallis, 2007; Moskowitz et al., 2012; Orlov, 2016). However, despite decades of empirical research on momentum, most of the studies are confined to momentum patterns occurring on a weekly or monthly basis, with little attention focused on intraday momentum, namely, momentum patterns during a trading day, until recently. The intraday momentum is first documented by Gao et al. (2018). They find that in the United States equity index market, during any trading day the first and the second-to-last half-hour returns can significantly predict the last half-hour returns. Zhang et al. (2019) report similar findings in relation to the Chinese equity index market.

Although momentum patterns at the intraday level in equity markets is an ongoing topic that attracts increasing interest from academics and practitioners, surprisingly the question of whether and to what extent momentum patterns exist in the crude oil market remains unanswered. We are motivated to investigate the momentum patterns at the intraday level in the crude oil market for two major reasons. First, a considerable volume of studies find strong connections between oil markets and stock markets (e.g., Fenech and Vosgha, 2019; Hou et al., 2019; Nandha and Faff, 2008; Pönkä, 2016; Wang et al., 2019). For example, Nandha and Faff (2008) show that oil price rises, by affecting economic activity, and subsequently lead to negative reactions from stock market. Pönkä (2016) finds that oil prices outperform other commonly used predictors in predicting the direction of stock return in the U.S. and other markets. However, research on such connections are restricted to medium and long horizons, consideration of whether on a trading day momentum patterns exist in the oil markets still has had no exposure in literature. Moreover, explanations to the intraday momentum in equity markets are given from angles of trading behavior, investor sentiment, and degrees of information content at different trading intervals (Gao et al., 2018; Renault, 2017; Zhang et al., 2019), but no extant studies have attempted to examine whether intraday momentum also exists in the oil market.

In this study, we make the first attempt and conduct a pioneering study to test the intraday momentum in the oil market. Understanding the intraday momentum pattern of the oil market also provides insights to future research about connections between equity and oil market at an intraday level. Second, it is commonly known that adding commodities, such as oil and silver, to a portfolio can reduce the overall portfolio risk. Nadha and Faff (2008) state that internationally diversified portfolio could be further diversified by including assets with positive correlations to oil price changes. Exploring price movements of the oil market not only facilitates academics a deeper understanding of the crude oil market's microstructure, particularly its intraday momentum patterns and return characteristics, but also provides practical implications for high-frequency traders and investors who consider adding oil product to their portfolios. In this paper, we examine whether intraday momentum exists in the crude oil market by using United States Oil Fund (USO) data[1].Our study reveals that the first half-hour return of a trading day significantly predicts the last half-hour return of that day, both in-sample (IS) and out-of-sample (OS). For the IS analysis, the predictive R^2 is 0.729%, and our OS analysis further confirms the predictive power of the first half-hour returns, with an R^2_{OS} of 0.659%. Although extant studies (e.g., Gao et al., 2018) show that the second-to-last half-hour returns also have

[1] Three reasons we choose USO ETF to conduct our study. First, USO is an ETF that tracks the price changes in near the month West Texas Intermediate (WTI) light, sweet crude oil futures (www.uscfinvestments.com), where WTI is one of three primary benchmarks in oil pricing (where the other two are Brent Blend and Dubai Crude), and is the only benchmark primarily used in the United States. Second, as USO is specifically designed for short-term investors who closely monitor their positions and pay particular attention to volatility, it fits our intraday momentum research design. Third, our key reference, Gao et al. (2018), implement the study of stock market intraday momentum by using S&P 500 ETF data. Note that the trading hours for ETF products normally start from 9:30 a.m. to 4:00 p.m. Eastern Standard Time (EST). However, for WTI futures, there are mainly three trading venues: the electronic trading markets of Globex and ClearPort open from Sunday to Friday, 6:00 p.m. to 5:15 p.m. EST, and the open outcry market opens from Monday to Friday, 9:00 a.m. to 2:30 p.m. EST. Therefore, regarding the consistent trading period, USO is a good proxy for implementing a similar analysis of Gao et al. (2018) in the crude oil market.

predictive power for the last half-hour returns in equity markets, we find no such intraday momentum pattern in the crude oil market.

We also split our sample into crisis periods and non-crisis periods, with the crisis periods encompassing two crises—the global financial crisis of 1 June 2008 to 31 January 2009 and the oil market crisis of 1 June 2014 to 31 January 2016. We find that predictability is especially strong during the crisis periods, with a predictive R^2 of 1.923%. This level of predictability substantially exceeds the predictive R^2 of 0.335% during the non-crisis periods. We also find that the predictive power of the first half-hour returns is stronger when the first half-hour trading has higher realized volatility, higher trading volume and significant overnight return jumps. Moreover, our further analysis shows that the intraday momentum is stronger on a positive jump day than on a negative one, with the positive (negative) jump usually characterized by the release of good (bad) news overnight.

Our next step is to assess the economic implications by using the predictor r_1, the first half-hour returns, as a trading signal in the market timing strategy. Specifically, if r_1 is positive (negative), we take a long position at the beginning of the first half hour, and close the position at the end of the last half hour. Our results show that the market timing strategy significantly outperforms two other benchmark strategies, the 'always-long' and the 'buy-and-hold' strategies, as it generates a higher average return along with a lower standard deviation and a higher Sharpe ratio.

Our study contributes to existing literature on intraday momentum patterns of asset prices (e.g., Heston, 2010; Murphy and Thirumalai, 2017). To the best of our knowledge, it also represents the first effort to examine, by using United States Oil (USO) exchange-traded funds (ETFs), intraday momentum in the crude oil market; USO is one of the most liquid and largest crude oil ETFs in the world. The different intraday momentum patterns we find between the crude oil and equity market suggest that high-frequency traders should apply trading strategies in the crude oil market that differ from those used in equity markets.

The structure of the rest of our paper is as follows. In Section 2 we describe our data and methodology. Our empirical findings are in Section 3. Section 4 examines the economic outcomes of the first half-hour return, afforded by adoption of the market timing strategy, Finally, Section 5 concludes.

2. Data and Methodology

We use the 1-min intraday prices of USO ETF to calculate half-hour returns for the crude oil market. Our transaction data, obtained from Thomson Reuters Datascope Select, includes the close bid and ask prices, number of trades, and trading volume from 10 April 2006 to 4 December 2018. After excluding, through reference to Gao et al. (2018), trading days with under 500 trades, our final sample includes 3,171 trading days.

For each day, t, we compute the first half-hour return, $r_{1,t}$, by subtracting the previous trading day's close price from the price at 10:00 a.m.. Here $r_{1,t}$ contains information released after the previous day's trading.[2] We compute all half-hour returns from 9:30 a.m. to 4:00 p.m. by using equation (1) below, which leads to us obtaining 13 half-hour returns per trading day.

$$r_{i,t} = \log\left(p_{i,t}\right) - \log\left(p_{i-1,t}\right),\ \text{i=1,2,…,13}, \tag{1}$$

here, $p_{i,t}$ denotes the price at the *i*th half hour on day t. Note that $p_{0,t}$ is the close price of previous trading day at 4:00 p.m.

Table 1 shows the descriptive statistics of all the half-hour returns across the day. Compared with the other half hour returns of the day (i.e., $r_2, r_3, \dots, r_{12}$), the first half hour returns (r_1) exhibit lowest minimum value, highest maximum value, highest standard deviation and lowest kurtosis. In contrast, the last half hour returns (r_{13}) reveal highest minimum value, lowest maximum value, highest positive skewness and low standard deviation, compared to the other half hour returns.

[Insert Table 1 about here]

3. Empirical Findings

3.1 Predictive analysis

We first test the intraday momentum by checking whether the market's first half-hour return predicts the last half-hour return on the same day. The regression (2) we use for this purpose is

[2] We use the natural logarithm of the USO ETF prices to calculate returns to control for non-normality.

$$r_{13,t} = \alpha + \beta r_{1,t} + \varepsilon_t \text{ , } t=1, 2,\ldots,T, \tag{2}$$

where $r_{1,t}$ and $r_{13,t}$ denote the first and last half-hour returns on day t, respectively. T is the total number of trading days. We focus on the first and last half hours because they are the most active trading times on a typical trading day (see Figure 3 later in this paper). Price-sensitive news released before the market opens increases the likelihood of large price moves during the first half hour of trading. News such as this is also likely to create a gap between the opening price and the last closing price, thereby creating a significant overnight return. The trading activities become less active after the first half hour (Gao et al. 2018).

To realize portfolio returns and avoid after-hours risks, institutional traders and professionals actively exit their positions in the last half hour, an action that again prompts high volume and high volatility in the market. As reported by *the Wall Street Journal*, "… more than 25 per cent of all trading at the NYSE happens after 3.30pm, the final half-hour trading" (www.wsj.com).Our results, tabulated in Panel A of Table 2, show that the first half-hour return (i.e., r_1) has positive predictive power for the last half-hour return (i.e., r_{13}) at the 1% significance level, with the R^2 of 0.729% indicating the existence of a strong intraday momentum in the crude oil market. If the first half-hour return (i.e., r_1), constructed from the previous trading day's market close, is positive, then the last half-hour return also tends to be positive, which suggests that the good market news released previous night remains positive impacts on today's last half trading hour.

[Insert Table 2 about here]

Prior research, most notably the work by Gao et al. (2018), also documents the significant predictability by the second-to-last half-hour return (i.e., r_{12}) for the last half-hour return (i.e., r_{13}) in equity markets. We use the same approach that Gao et al. (2018) use to assess the predictive power of r_{12} in the crude oil market; specifically, we take the USO ETF sample and then regress the last half-hour return on the twelfth half-hour return:

$$r_{13,t} = \alpha + \beta r_{12,t} + \varepsilon_t \text{ , } t=1,2,\ldots,T. \tag{3}$$

The second column of Panel A in Table 2 shows that the coefficient of r_{12} is not statistically significant, meaning that the second-to-last half-hour return does not predict the last half-hour return. This finding is inconsistent with that of prior studies based on equity markets, and implies that the trading strategies high-frequency traders apply in the crude oil market should differ from the strategies used in equity markets. Because we find that r_{12} is not an efficient predictor in the crude oil market, we thereafter consider only the predictor r_1 in our analyses.[3]

3.2 Out-of-sample analysis

Although our in-sample analysis in the previous section reveals the existence of intraday momentum in the crude oil market, we recognize that in-sample predictability could be attributed to over-fitting issues and might not, therefore, imply out-of-sample predictability (Welch and Goyal, 2008). However, the out-of-sample predictability is most valuable to practitioners because it can help them predict returns and make trading decisions. With this point in mind, we perform an out-of-sample (OS) analysis by running monthly-frequency regressions based on a recursive estimation window to assess the robustness of intraday momentum in the crude oil market (e.g., Henkel et al., 2011; Lettau and Nieuwerburgh, 2008; Rapach et al., 2010; Zhang et al., 2019a; Zhang et al., 2019b).

We begin our analysis by splitting our sample observations into an in-sample subset that contains m observations up until 31 December 2009, and an OS subset that contains the rest of the q observations. We then take the parameters α_m and β_m, generated by applying regression (2) to the m in-sample observations, and use the following equation to calculate the first predicted OS $\hat{r}_{13,m+1}$:

$$\hat{r}_{13,m+1} = \alpha_m + \beta_{1,m} r_{1,m+1} . \tag{4}$$

Here $r_{1,m+1}$ is the actual first half-hour return of the number m+1 observation. We then calculate the next OS forecast, $\hat{r}_{13,m+2}$, via

[3] The predictive analysis of the other half-hour returns is also ~~are~~ conducted and no significant predictive power has been found.

$$\hat{r}_{13,m+2} = \alpha_{m+1} + \beta_{1,m+1} r_{1,m+2}\,, \tag{5}$$

where α_{m+1} and $\beta_{1,m+1}$ are the parameters generated by applying regression (2) to the m+1 observations, and $r_{1,m+2}$ is the actual first half-hour return of the number m+2 observations. Continuing in this manner, we obtain q OS forecast $\hat{r}_{13}$. We then use the OS R^2_{OS} statistic to evaluate the performance of predictive model, defined as follows:

$$R^2_{OS} = 1 - \frac{\sum_{t=1}^{T}\left(r_{13,t} - \hat{r}_{13,t}\right)^2}{\sum_{t=1}^{T}\left(r_{13,t} - \overline{r}_{13,t}\right)^2}\,, \tag{6}$$

here, $\hat{r}_{13,t}$ denotes the forecasted last half-hour return predicted by the sample up to t-1, and $\overline{r}_{13,t}$ is the historical average return for the corresponding period. If R^2_{OS} is positive, the OS predictability surpasses the predictability of the historical average (Campbell and Thompson, 2008). Panel B of Table 2 presents the OS results. As evident, the out-of-sample R-square, R^2_{OS}, is at the 1% significance level with a positive value of 0.659%, indicating that OS offers better predictability than the historical average. This result, in turn, confirms the persistence of intraday momentum in the OS analysis.

3.3 Crisis periods

Because various studies document that the standard monthly momentum performs weakly during financial crises in equity markets (e.g., Li and Tsiakas, 2017; Lin et al., 2017; Rapach et al., 2010; Wang et al., 2018), we are interested in investigating if the intraday momentum persists in the oil market during crises. We consider two oil-market crisis periods identified by Singh et al. (2018), namely, 1 June 2014 to 31 January 2016 and 1 June 2008 to 31 January 2009. For comparative purposes, we conduct the predictability analysis for the crisis and non-crisis periods. Table 3 reports the results.

[Insert Table 3 about here]

β_1 is at the 5% significance level for both the crisis (i.e., 1 June 2008 to 31 January 2009 and 1 June 2014 to 31 January 2016) and the non-crisis periods, indicating that the predictability of r_1 remains strong throughout the entire sample period despite the market fluctuations during the two oil-market crises. Note, in particular, from Table 3 that although the sample size of the crisis period is less than 25% of the non-crisis periods, magnitude of β_1 for the crisis period (0.0223) was nearly three times as much as its counterpart for the non-crisis periods (0.0079). Note also that the R^2 for the crisis periods (1.923%) substantially exceeds the R^2 for the non-crisis periods (0.335%). These results jointly suggest that the predictability of r_1 remain significant for both crisis and non-crisis periods, but it is much stronger during crises. It is natural to infer that the intraday momentum effect is stronger when market fluctuations are high. In the latter part of the work, we will further analyze intraday momentum in crude oil market under various volatility regimes.

The next step in our investigation is to look at the stability of the predictability by r_1, that is, slope of r_1. The graph in Figure 1 presents the time-varying slopes of r_1 estimated recursively over time. After minor initial volatility, the slope of r_1 stays relatively stable until it is disturbed by the crude oil crisis, starting from mid-2014. Then, after a continuous decrease throughout the crisis period, it sharply climbs and rises to a higher level compared to its pre-crude oil crisis counterpart, and remains stable after that. The information in Figure 1 suggests that, overall, the slope of r_1 is stable, which indicates that the intraday momentum pattern is stable. Equally interesting is the fact that when the slopes of r_1 are destabilized by the fluctuating crude oil crisis, the predictability of r_1 becomes much stronger for the post-crisis period.

[Insert Figure 1 about here]

3.4 Trading patterns across the day

In this section, we present a series of graphs that summarize oil-market trading patterns measured in terms of realized volatility, trading volume, number of (undecomposed) jumps and number of positive (or negative) jumps of USO ETFs for the period 10 April 2006 to 4 December 2018. Since trading hours are from 9:30 a.m. to 4 p.m., each trading day includes thirteen 30-minute subintervals, labelled from 1 to 13 in Figures 2 to 5.

Figure 2 plots the 30-minute average realized volatility, which is calculated using Equation (8) in the appendix to this paper. Note that the highest realized volatility in Figure 2 occurs in the first half hour, which is driven by the overnight information as discussed previously. The realized volatility drops by more than 60%, from the first half hour to the second half hour of trading, and exhibits a decreasing trend afterwards, showing that the market's response to the overnight information was strongest in the first half hour and quickly stabilized thereafter.

[Insert Figure 2 about here]

Figure 3 plots the 30-minute average trading volume. Like the pattern of realized volatility, the pattern for trading volume is at its highest point during the first half hour of a trading day. However, unlike the pattern in Figure 2, there is no sharp decrease in trading volume in the second half hour. Except for a spike in the tenth half hour, the trading activities generally cool down from the second half hour. Of greater importance, however, is the substantial jump in trading volume during the last half hour, a pattern which captures the fact that institutional traders and professionals actively exit positions in order to realize portfolio returns and avoid after-hours risks.

[Insert Figure 3 about here]

Recognizing, at this point, that realized volatility consists of continuous and jump (discontinuous) variation, we adopt the model-free methodology proposed by Barndorff-Nielsen and Shephard (2004, 2006) to extract the jump component of realized volatility. The equations we use for this exercise are Equations (8) to (14) in the appendix to this paper. Figure 4, which presents the average size of each 30-minute (undecomposed) jump during the sample period, shows that the jump size in the first half hour of trading is substantially larger than the sizes of the remaining 30-minute intervals, indicating that most jump variation is caused by news that is released overnight.

[Insert Figure 4 about here]

A large body of literature demonstrates that financial markets react asymmetrically to positive and negative news (e.g., Guo and Wang, 2014; Kilic and Shaliastovich, 2019; Patton and Sheppard, 2015; Segal et al., 2015; Xiao et al., 2018; Amendola et al., 2019). Figure 5 presents the average 30-minute positive (and negative) jump sizes, measured by Equation (10) in the appendix. In contrast to Figure 4, Figure 5 details the direction of market movement (or the direction of market risk). The important feature of Figure 5 is that the average sizes of the 30-minute positive and negative jumps are quite similar.

[Insert Figure 5 about here]

3.5 Volatility, trading volume, overnight return and jump

Our previous results reveal that the intraday momentum shows stronger predictability during crises, the periods characterized by higher volatility. This pattern raises for us the question of what role volatility plays in intraday momentum in the crude oil market. For high-frequency traders, volatility is the primary ingredient for making a profit; understanding volatility therefore offers opportunities to capitalize on intraday momentum. We endeavor to answer this question by ordering our sample of 3,171 trading days according to realized volatility of the first half hour by referring to Gao et al. (2018). We split the ordered sample into three subgroups—low, medium, and high volatility. Each subsample consists of 1,057 trading days.

Panel A of Table 4 presents the extent to which the crude oil market's first half-hour return, r_1, predicts the last half-hour return, r_{13}. We generate r_1 and r_{13} by applying each subsample of different levels of volatility to regression (2). The results, summarized in the panel, show that the only β_1 that is statistically significant at the 1% level is the one generated by the high-volatility subsample, a finding which indicates that in a highly volatile crude oil market the first half-hour returns strongly predict the last half-hour returns. Note also that the significance of β_1 and R^2 increases markedly with volatility, suggesting that stronger intraday momentum corresponds to higher volatility.

[Insert Table 4 about here]

In keeping with recent studies exploring momentum in equity markets (e.g., Gao et al. 2018; Zhang et al. 2018), we also analyze the impact of trading volume on the first half-hour returns in the crude oil market. After sorting all sample trading days by their first half-hour trading volumes, we split the whole sample into three subgroups of equal size: low-, medium- and high-volume. We then calculate the OS R^2 for each group. Panel B of Table 4 presents the results. These results show that the estimated coefficient β_1 is statistically significant at the 5% level for both the medium- and the high-volume subsamples. Also, like the results in Panel A, the values of β_1 and OS R^2 increase substantially as trading volume increases. These results suggest that the correlation between intraday momentum and trading volume is highly positive.[4]

As we discussed previously, price-sensitive news released after trading hours increases the likelihood of pre-market moves and overnight returns. We therefore explore how the intraday momentum performs on days that differ from one another in terms of level of overnight returns. We calculate the overnight returns by using Equation (1), where i =1, and then order the whole sample of trading days according to the absolute values of overnight returns. This step allows us to divide the sample into three subsamples that are of equal size but are differentiated according to low-, medium- and high-overnight returns. Panel C presents the predictive power of the crude oil market's first half-hour return, r_1, generated by applying each subsample to regression (2). The high-level overnight return subsample produces a highly significant β_1 and an impressive R^2 of 1.508%, whereas the other two subsamples produce insignificant β_1 along with much lower R^2 values. These results indicate that intraday momentum is most likely to occur on trading days with high overnight returns.

Although we find that the predictability of the first half-hour return on the last half-hour return is significantly influenced by the realized volatility, we are uncertain if the predictability is driven by the jump variation, that is, the discontinuous component of the realized volatility.[5] To answer this question, we analyze the impact of jump variation occurring during the first half hour of trading on intraday momentum. We divide all observations into the 'jump' or 'no-jump' subsample. We then divide the jump subsample into two groups, one containing observations with positive jumps, and the other containing observations with negative jumps - characterized by good news and bad news releases, respectively.

We apply the subsamples to regression (2); the results of that analysis are presented in Table 5.

[4] We also ordered our sample according to the total trading volume on each trading day and found no significant differences between the analysis based on the total trading volume and the analysis based on the first half-hour's trading volume.

[5] Jumps are defined as sudden and large infrequent movements in stock prices (e.g., Barndorff-Nielsen and Shephard 2004, 2006). For a description of the details of the jump measure construction, see the appendix to this paper.

Panel A demonstrates that the first half-hour returns strongly and significantly predict the last half-hour returns for the observations with jumps, whereas no such predictability is found for the observations without jumps. The predictability, as measured by R^2, for the days with return-jumps is 1.033%, notably greater than that (0.012) for the no-jump subsample. The results therefore indicate the existence of strong intraday momentum on trading days with jumps in the first half hour.

[Insert Table 5 about here]

Panel B presents the results for days with positive and negative return jumps, respectively. Although the coefficients generated by the positive and negative jump subsamples are both at the 5% significance level, the predictability for the positive jump subsample is 70% stronger than that for the negative jump subsample. These results imply that while intraday momentum is strong on days with either positive or negative jumps, it is much stronger on days with positive jumps. The positive (negative) jumps might relate with good (bad) news.

4. Economic implications: Market timing trading strategy

This section presents our assessment of the economic outcomes of using the first half-hour return, r_1, as a predictor, which is named market timing strategy. Specifically, we take a long (short) position of the asset at the beginning of the first half hour if r_1 is positive (negative), and then close the position at the end of the last half hour. In the following equation, the return realized at the end of the trading day is $\omega(r_1)$:

$$\omega(r_1) = \begin{cases} r_{13}, & \text{if } r_1 \geq 0 \\ -r_{13}, & \text{if } r_1 < 0 \end{cases} . \tag{7}$$

We then compare the returns generated by the timing strategy with two other benchmark trading strategies. The first one is the 'always-long' strategy, which indicates taking a long position at the beginning of trading day and closing the position at the end of trading day, regardless of r_1. With the second strategy, the 'buy-and-hold' strategy, we take a long position at the beginning of the sample period and then close it at the end of the period.

Table 6 provides summary statistics of the returns obtained from each trading strategy. In Panel

A, we can see that the timing strategy generates an average return, $\omega(r_1)$, of 1.85% per annum at the 5% level of statistical significance. The always-long strategy (Panel B) achieves an annualized average return of 0.76%, which is not statistically significant. The average return obtained from the buy-and-hold strategy of -17.89% is statistically significant at the 1% level. The timing strategy return therefore substantially outperforms the other two benchmark strategies.[6]

[Insert Table 6 about here]

When we compare the risk imbedded in each investment strategy, we record a standard deviation of 0.21% and a Sharpe ratio of 8.99 for the timing strategy return, $\omega(r_1)$. Although the standard deviation for the always-long strategy equals that of the timing strategy, it results in a lower Sharpe ratio of 3.7. The buy-and-hold strategy generates the worst outcome, with a much higher standard deviation (1.45%) and a negative Sharpe ratio (-12.34). The timing strategy therefore again significantly outperforms the other two benchmark strategies. The success rates, calculated as the percentage of the trading days with non-negative returns, are 57.38% and 57.31% respectively for the timing strategy and the always-long strategy, indicating that the probability of attaining non-negative last half-hour returns is likely to be above 50%.

5. Economic explanation

To this end, both the in-sample and out-of-sample analysis ~~estimations~~ confirms the intraday predictability in the crude oil market. What is the economic driving force behind this interesting phenomenon? ~~This section presents~~ There are two possible explanations ~~as~~ documented by Gao et al. (2018) and Zhang et al.(2018).

One explanation is based on the model of infrequent portfolio rebalancing ~~model~~ proposed by Bogousslavsky (2016). ~~In the light of the theoretical model, the infrequent portfolio rebalancing of some traders can induce the intraday momentum pattern.~~ Due to slow moving capital (e.g., Duffie

[6] Given that all the strategies are traded on daily basis, all returns are annualized by multiplying 252, and are expressed in percentages.

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(2010)). ~~The~~ some investors may delay their rebalancing orders to near the market close, ~~rather than the market open probably due to the slow-moving capital~~. ~~If investors trade in the first half hour the same direction as in the last half hour, it~~ which consequently leads to the same trading direction ~~the positive correlation~~ between the first and last ~~two~~ half-hour returns, i.e., the intraday momentum.

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The other explanation focuses on the existence of ~~the~~ late-informed investors. Even though overnight news is released in the first half hour and some investors can immediately take actions, there are still some investors learn the news later (e.g., Baker and Wurgler, 2006), or need take longer time to process the new market information (e.g., Huang et al., 2015; Cohen and Frazzini, 2008). Therefore, the late informed investors will trade in the last half hour when is one of the most liquid periods in the same direction as the market open, resulting in a positive correlation between the first and last half hour returns.

Apart from the above explanations, it is worthwhile to compare the intraday trading volume pattern between crude oil and equity markets.

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~~5~~6. Conclusion

We investigate whether intraday momentum exists in the crude oil market by using 1-min high-frequency USO ETF data. We find that the first half-hour return significantly and positively predicts the last half-hour return both in-sample and out-of-sample. The coefficient of the first half-hour return remains stable most of the time, indicating good predictability. Although the oil crisis period disturbs the stability of the coefficient, we find predictability is even stronger during crises. We also find predictability to be stronger on days characterized by higher volatility, higher trading volume, higher overnight returns and jumps. When we use the market-timing strategy to test the economic outcomes of the predictability of the first half-hour return, we find it substantially outperforms the other trading strategies, namely, the always-long strategy and the buy-and-hold strategy.

In addition, we also examine the extent to which the predictability of the second-to-last half-hour return holds in the crude oil market, as its predictive power has been confirmed in equity markets. We find evidence of this intraday momentum pattern in the crude oil market. Although we have yet to identify the economic significance of this difference, our findings provide practical implications for high-frequency traders and investors of USO ETFs, and should also be of interest to academics.

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Appendix

To assess the possible impact of jumps on the intraday predictability, we construct the measure of the positive and negative jump risks by using high-frequency intraday data. First, we draw on work by Barndorff-Nielsen and Shephard (2004) to define the realized variance (RV). This leads to the following equation:

$$RV_t = \sum_{i=1}^{m} r_{t,i}^2 , \tag{8}$$

where m is the total number of observations, and $r_{t,i}$ is the i-th1-min return during the subsample period t. We then, again with reference to Barndorff-Nielsen and Shephard (2004) as well as to Huang and Tauchen (2005), compute the bipower variation (BV) as follows:

$$BV_t = \frac{\pi}{2}\frac{m}{m-1}\sum_{i=2}^{m}|r_{t,i}||r_{t,i-1}|. \tag{9}$$

The statistic that we consequently use to detect the presence of a positive (or negative) jump during the sample period t is

$$\hat{J} = sign(r_t) \times \sqrt{(RV_t - BV_t) \times I\left(ZJ_t \geq \Phi_{\tilde{\alpha}}^{-1}\right)}, \tag{10}$$

where ZJ_t is specifically defined as

$$\mu_k = 2^{k/2}\frac{\Gamma\left[(k+1)/2\right]}{\Gamma[1/2]}, k > 0, \tag{11}$$

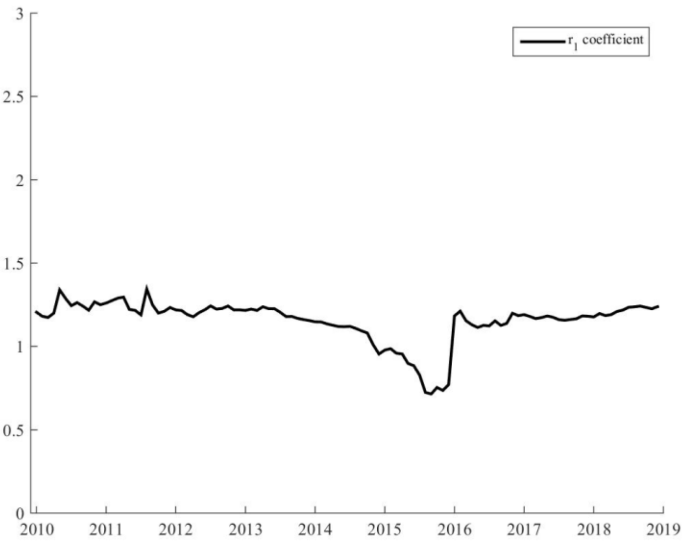
$$TP_t = m\mu_{4/3}^{-3}\frac{m}{m-2}\sum_{i=3}^{m}|r_{t,i-2}|^{4/3}|r_{t,i-1}|^{4/3}|r_{t,i}|^{4/3}, \tag{12}$$

$$RJ_t = \frac{RV_t - BV_t}{RV_t}, \tag{13}$$

$$ZJ_t = \frac{RJ_t}{\sqrt{\left\{(\pi/2)^2 + \pi - 5\right\}/m \times \max\left(1, TP_t/BV_t^2\right)}}, \tag{14}$$

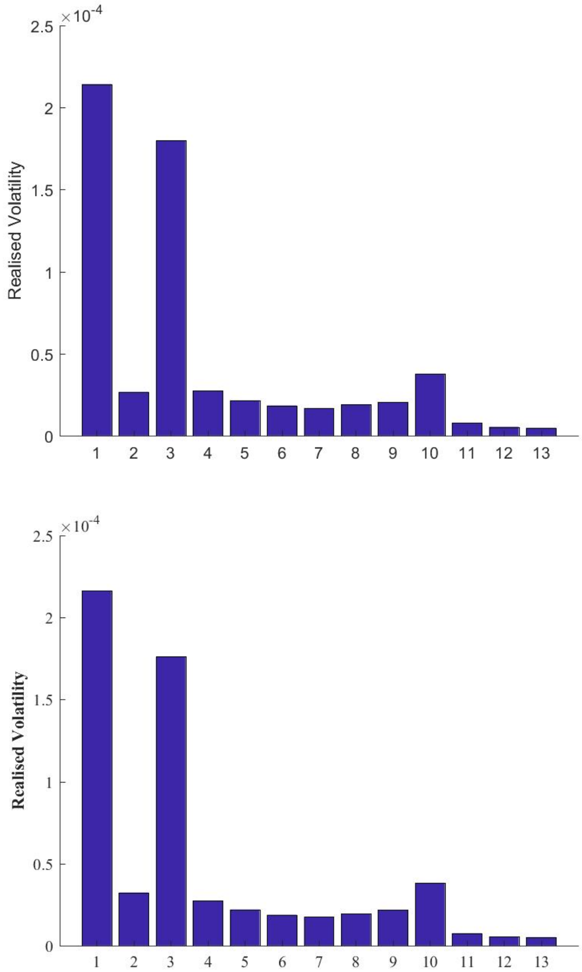
and $\Phi_{\tilde{\alpha}}^{-1}$ denotes the inverse cumulative distribution function (CDF) of the standard normal distribution, I denotes an indicative function (i.e., it takes the value of 1 if the criterion is met, and 0 otherwise), $sign()$ function takes the same sign as the input variable, and Γ denotes the gamma function. If the probability exceeds 99.9%, as defined in Equation (10), then we can assume the existence of a jump.

Figure 1. Time series of the r_1 coefficient



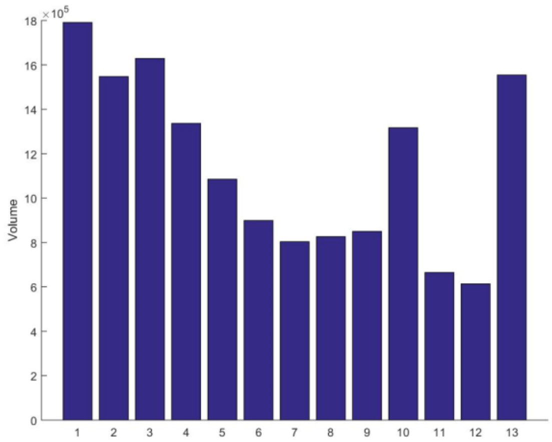
Notes: This figure plots the time-varying coefficient (scaled by 100) of r_1 in the predictive regression (2). We initially use the sample up to 31 December 2009 to estimate the coefficient, after which we recursively estimate it over time. r_1 denotes the first half-hour return.

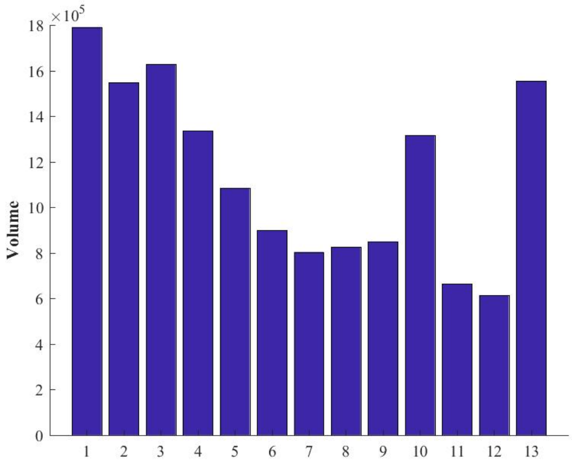
Figure 2. Average 30-minute average realized volatility



Notes: This figure plots the 30-minute average realized volatility, defined as Equation (8), in the USO data from 10 April 2006 to 4 December 2018. The daily trading period encompasses 9:30 a.m. to 4:00 p.m. and thus includes thirteen 30-minute subintervals in total, labelled from 1 to 13.

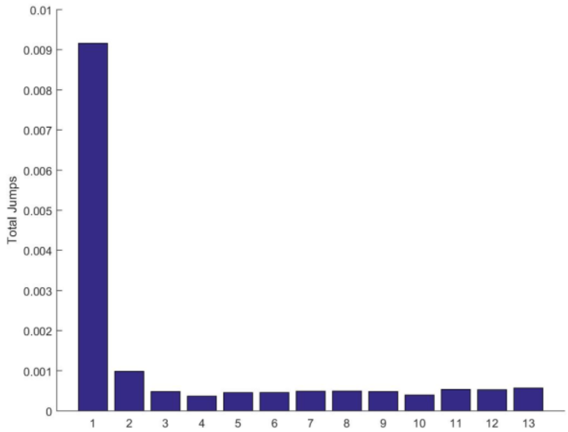
Figure 3. Average 30-minute trading volume

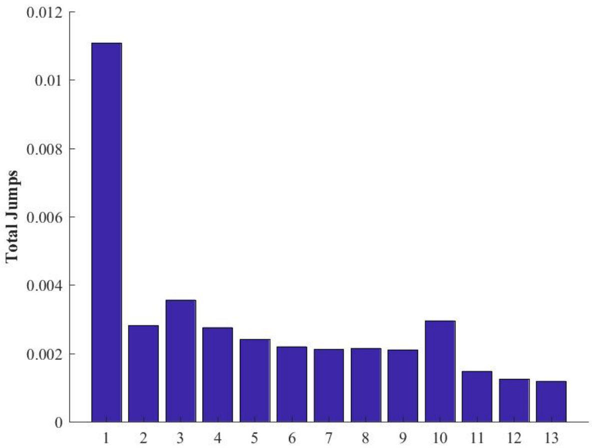




Notes: This figure plots the 30-minute average trading volume of the USO data from 10 April 2006 to 4 December 2018. The daily trading period encompasses 9:30 a.m. to 4:00 p.m. and thus includes thirteen 30-minute subintervals in total, labelled from 1 to 13.

Figure 4. Average 30-minute jump size





Notes: This figure plots the 30-minute (e.g., the first half-hour subinterval starts from 9:30 a.m. to 9:59 a.m.) average number of (undecomposed) jumps, defined as Equation (10), of the USO data from 10 April 2006 to 4 December 2018. The daily trading period encompasses 9:30 a.m. to 4:00 p.m. and thus includes thirteen 30-minute subintervals in total, labelled from 1 to 13. ~~For each half-hour interval, 1-minute returns between the lower bound (included) of the interval and its upper bound (not included) are used to calculate the relevant jumps. For example, when calculating the jump in the second half-hour interval, 1-minute returns starting from 10:00 am. to 10:29 am. are used, and the return at 10:00 am. is computed by the log difference between 9:59 am. and 10:00 am.~~

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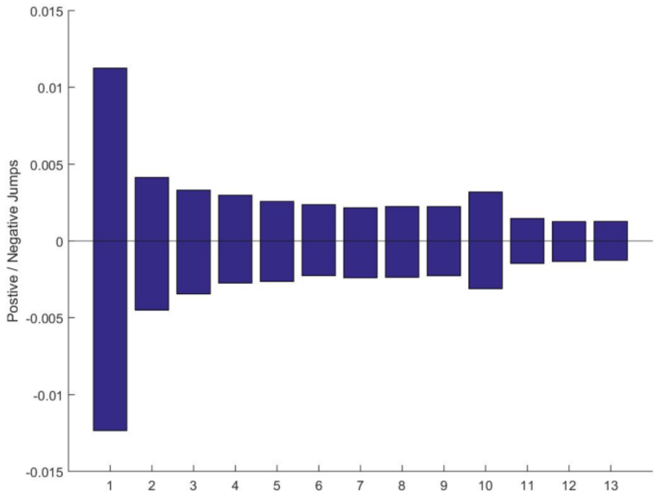
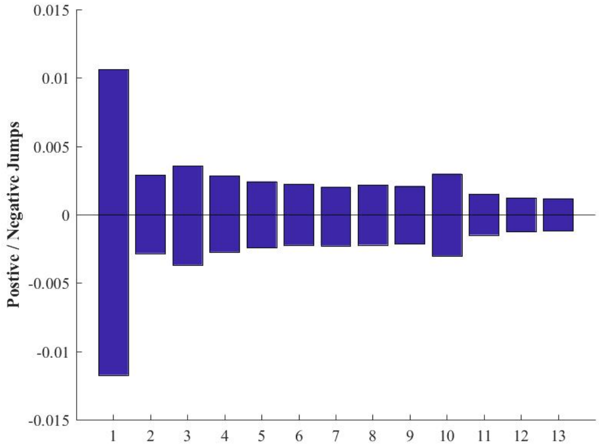
Figure 5. Average 30-minute positive (or negative) jump size





Notes: The figure plots the 30-minute average number of positive or negative jumps, defined as Equation (10), of the USO data from 10 April 2006 to 4 December 2018. The daily trading period encompasses 9:30 a.m. to 4:00 p.m. and thus includes thirteen 30-minute subintervals in total, labelled from 1 to 13. ~~For each half-hour interval, 1-minute returns between the lower bound (included) of the interval and its upper bound (not included) are used to calculate the relevant jumps. For example, when calculating the jump in the second half-hour interval, 1-minute returns starting from 10:00 am. to 10:29 am. are used, and the return at 10:00 am. is computed by the log difference between 9:59 am. and 10:00 am.~~

Table 1. Descriptive summary

Variables	Mean	Median	Min	Max	Sd. Dev.	Skewness	Kurtosis
r_1	-0.0007	-0.0001	-0.0772	0.0746	0.0142	-0.3090	5.4960
r_2	-0.0001	0	-0.0336	0.0460	0.0055	0.1440	8.0370
r_3	-0.0003	0	-0.0505	0.0509	0.0059	-0.2720	10.4700
r_4	-0.0003	0	-0.0314	0.0345	0.0051	-0.1310	8.3040
r_5	0.0003	0	-0.0242	0.0372	0.0046	0.5250	8.6430
r_6	0	0	-0.0283	0.0251	0.0040	-0.0880	7.9080
r_7	0.0002	0	-0.0257	0.0337	0.0039	0.3550	11.7200
r_8	0	0	-0.0641	0.0445	0.0042	-0.4060	28.5300
r_9	0.0001	0	-0.0304	0.0478	0.0043	0.6590	13.6700
r_{10}	0.0002	0.0003	-0.0350	0.0584	0.0058	0.2330	11.3400
r_{11}	-0.0001	0	-0.0255	0.0282	0.0023	0.4620	25.6100
r_{12}	0	0	-0.0151	0.0189	0.0020	0.7720	16.3300
r_{13}	0	0	-0.0132	0.0176	0.0021	0.8570	14.6500

Notes: The table reports descriptive statistics such as the sample size (N), mean (Mean), median (Median), minimum (Min), standard deviation (Sd. Dev.), skewness (Skewness), and kurtosis (Kurtosis) for the intraday half-hour returns: r_1, r_2, …, r_{13}.

Table 2. In-sample and out-of-sample predictability

	Panel A: In sample		*Panel B: Out of sample*
Predictor	r_1	r_{12}	r_1
Intercept	0 [1.08]	0 [0.82]	2.53E-5*** [8.09]
β_1	0.0124*** [2.93]		0.006*** [2.602]
β_{12}		-0.0099 [-0.20]	
R^2 (%)	0.729	0.009	0.659

Notes: The table reports the results of regressing r_{13} on r_1 and r_{12}. Panel A displays the in-sample estimation; Panel B shows the OS results. The OS predictability is measured by R_{OS}^2:

$$R_{OS}^2 = 1 - \frac{\sum_{t=1}^{T}\left(r_{13,t} - \hat{r}_{13,t}\right)^2}{\sum_{t=1}^{T}\left(r_{13,t} - \overline{r}_{13,t}\right)^2}.$$

The numbers in brackets are Newey West (1987) robust t-statistics with significance set at the 1%, 5%, and 10% levels, denoted respectively by ***, **, and *.

Table 3. Impact of oil crisis periods on predictability

	Crisis	Non-crisis
Intercept	0.0002**	0
	[1.98]	[-0.03]
β_1	0.0223**	0.0079**
	[2.54]	[2.21]
Observations	590	2581
R^2 (%)	1.923	0.335

Notes: The table reports the predictive results for two periods: oil crises and non-oil crises (i.e., crisis excluded). The entire sample covers the period from 10 April 2006 to 4 December 2018, with the crisis subsample encompassing two periods of time: 1 June 2008 to 31 January 2009 and 1 June 2014 to 31 January 2016. Data from the crisis periods consist of the 'crisis' subsample, while data from the days outside the crisis periods consist of the 'non-crisis' subsample. The numbers in brackets are Newey West (1987) robust t-statistics, significant at the 1%, 5%, and 10% levels, denoted respectively by ***, **, and *.

Table 4. Impact of volatility, trading volume and overnight return

	Panel A: Volatility			*Panel B: Trading volume*			*Panel C: Overnight return*		
	Low	Medium	High	Low	Medium	High	Low	Medium	High
Intercept	0	0	0.0002**	0	0	0.0002**	0	0	0.0001
	[-0.93]	[-0.29]	[2.13]	[0.53]	[-0.75]	[2.04]	[-0.56]	[0.48]	[1.47]
β_1	-0.0011	0.0037	0.0151***	-0.0011	0.0121**	0.0154**	-0.0041	0.0019	0.0153***
	[-0.13]	[0.52]	[3.08]	[-0.20]	[2.15]	[2.54]	[-0.47]	[0.31]	[4.02]
R^2 (%)	0.002	0.036	1.401	0.005	0.567	1.314	0.021	0.009	1.508

Notes: The table reports the estimation results of the predictive power of the first half-hour returns under various levels of volatility and trading volume during the first half hour of trading, and overnight return. The volatility calculation is based on the one-minute returns in the first half hour; the trading volume is the total volume in the first half hour; and the overnight return is calculated by using Equation (1), where $i = 1$. Volatility, trading volume and overnight return percentiles are then used to sort data into low, medium and high levels. The numbers in brackets are Newey West (1987) robust t-statistics, significant at the 1%, 5%, and 10% levels, denoted respectively by ***, **, and *.

Table 5. Impact of return jumps

	Panel A		*Panel B*	
	Jump	No jump	Jump>0	Jump<0
Intercept	0.0001*	-0.0001	-0.0002	0.0003**
	[1.91]	[-1.15]	[-1.61]	[2.12]
β_1	0.0133***	0.0029	0.0276**	0.0198**
	[3.07]	[0.23]	[2.56]	[1.98]
Observations	2,184	977	1,096	1,087
R^2 (%)	1.033	0.012	1.629	0.961

Note: The table shows the impact of the first half-hour return jumps on the intraday predictability. The samples are grouped by 'jump', 'no jump', 'positive jump', and 'negative jump'. The numbers in brackets are Newey West (1987) robust t-statistics significant at 1%, 5%, and 10% levels, denoted by ***, **, and *, respectively.

Table 6. Market timing strategy

Timing	Ave ret (%)	Std dev	Sharpe Ratio	Skewness	Kurtosis	Success (%)
Panel A: Market timing						
$\omega(r_1)$	1.85**	0.21	8.99	0.06	14.71	57.38
	[2.01]					
Panel B: Benchmarks						
Always-long	0.76	0.21	3.70	0.86	14.65	57.31
	[0.83]					
Buy-and-hold	-17.89***	1.45	-12.34	-0.30	5.70	
	[-2.76]					

Notes: The table reports the economic outcomes of the market timing strategy, compared with the benchmark 'always-long' strategy and 'buy-and-hold' strategy. The table reports summary statistics on the returns obtained from each strategy. Each return is annualized by multiplying 252, and is expressed in percentage. The numbers in brackets are Newey West (1987) robust t-statistics, significant at the 1%, 5%, and 10% levels, denoted respectively by ***, **, and *.