Intraday Return Predictability in the Crude Oil Market: The Role of EIA Inventory Announcements

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Abstract

We study the impact of the announcements released by the US Energy Information Administration (EIA) crude oil storage every Wednesday at 10:30 ET (the beginning of the third half-hour interval) on intraday return predictability, that is, intraday momentum. Our results indicate that returns on the third half-hour on EIA announcement days can significantly and positively predict the returns in the last half-hour, whereas, on non-EIA announcement days, only returns in the first half-hour have significant predictability. The dominant source of prediction in the first half-hour return mainly comes from the overnight component. EIA announcements contribute to intraday momentum because they attract more informed traders and because the period surrounding their release is often associated with a reduction in liquidity. Substantial economic gains can be made by using efficient intraday predictors as trading signals.

Keywords: Crude oil market, EIA announcements, Intraday momentum, Return predictability

JEL Classifications: G14; G17; Q40

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1. Introduction

Crude oil is one of the most important energy commodities and accounts for one-third of the world's energy consumption. Because oil is an essential production factor in many industries and business sectors, including airlines, agriculture, and banking, trading for oil and its derivative products, such as futures and exchange-traded funds (ETFs), is burgeoning. The inventory of crude oil is a fundamental factor in determining prices and volatility in the crude oil market via affecting the elasticity of demand and supply (e.g., Hamilton, 2009; Ye and Karali, 2016; Ye et al., 2005). The US Energy Information Administration (EIA) releases the *Weekly Petroleum Status Report*, typically released every Wednesday at 10:30 Eastern Time (ET). This report provides estimates of the inventory levels of crude oil and petroleum products. A strand of the literature analyzes the impact of these EIA announcements on crude oil prices and their intraday returns (see, e.g., Bu, 2014; Ye and Karali, 2016).

Day trading in the crude oil financial market has become increasingly popular because of the availability of high-speed computers and automated programs. This trading can be highly profitable, with a Sharpe ratio almost ten times higher than that of traditional buy-and-hold strategies (Aldridge, 2010). Consequently, knowledge on intraday return predictability and the profitability of an intraday momentum strategy has recently gained much interest. The existence of intraday momentum has been identified in several markets, including the equity market (Gao et al., 2018; Zhang et al., 2019), foreign exchange market (Elaut et al., 2018), commodity ETF (Wen et al., 2020), and commodity futures (Jin et al., 2020).

The growing strand of literature on intraday return predictability motivates us to analyze the impact of EIA inventory announcements on intraday momentum in the crude oil market. Previous studies mainly investigate the predictability of the first half-hour on the last half-hour returns of the same day (see, e.g., Chang et al., 2009; Gay et al., 2009; Ye and Karali, 2016) without a particular focus on the possible impact of the EIA news release. Wen et al. (2020) show that the first half-hour return in crude oil ETF predicts the last half-hour return on the same day. We complement their study by examining whether and to what extent the EIA inventory announcements affect the pattern of intraday return predictability, a topic that is currently unexplored. More specifically, we analyze whether the pattern of intraday momentum in the crude oil market varies between days with and without EIA announcements.

EIA announcements might affect intraday momentum in the crude oil market. Some studies have shown that on a typical trading day, the first and last half-hours of trading are the most important (see, e.g., Gao et al., 2018, 2019; Jin et al., 2020). This is because most earnings and major economic news are released before the market opens. Hence, prices are typically different at the opening of the market from the previous day at the market closing because they reflect new information. This new information is incorporated in the first half-hour of trading, as is evident from the high volume and volatility, after which the market cools off until the last half-hour when trading starts to pick up again. On days with EIA news announcements, however, we expect to see a buildup period in which participants are anticipating the arrival of new information. This leads to an increase in trading after the news release, which gives an information signal for the remainder of the day.[1] Therefore, in this study, we argue that days

[1] Halova et al. (2014) and Ederington et al. (2019) show that crude oil futures trading volume and volatility on days with EIA crude oil inventory announcements are higher than days without. Similar findings are documented for the natural gas inventory announcements (see, e.g., Fernandez-Perez et al., 2020; Gay et al., 2009; Gu and Kurov, 2018; Prokopczuk et al., 2021).

with EIA news announcements might provide additional information signals, which can lead to an intraday momentum pattern that differs from that on days without these announcements.

In our empirical tests, we employ high-frequency USO ETF data, from their introduction on April 10, 2006, to July 31, 2019.[2] Our analyses provide several key findings. First, we document the evidence of additional information from the EIA announcement for intraday momentum. In particular, the intraday momentum pattern for the days with EIA announcements shows that the third half-hour returns significantly and positively predict the last half-hour returns, whereas, on days without announcements, the first half-hour returns have significant predictability. This difference highlights the unique intraday predictive information in the EIA announcements. Second, we find that on days with EIA announcements, investors pay more attention to the forthcoming inventory news releases than to the information released overnight, and this is reflected in the fact that trades during the third half-hour trading session being more informative than overnight trades. Third, we also find that the importance of the third half-hour returns for the EIA group is more apparent during periods of high volatility, which is consistent with previous studies on the equity and crude oil markets showing that intraday momentum is stronger during periods with more volatility.

We then explore the reasons that the third half-hour returns are informative for the last half-hour returns on days with EIA news announcements. Specifically, we examine the impact of trade size, adverse selection costs, and market illiquidity on intraday momentum. We observe that larger trades and higher adverse selection costs contribute to greater predictive

[2] USO ETF was founded on April 10, 2006, by Victoria Bay Asset Management. It is designed to track the performance of the spot price of West Texas Intermediate light, and is known to be one of the most important and liquid ETFs. The USO ETF is traded on New York Stock Exchange, from 9:30 to 16:00 Eastern Time (ET).

power for the third half-hour returns. This finding suggests that trades by informed market participants contribute to intraday momentum, consistent with the model of informed trading (see, e.g., Cushing and Madhavan, 2000; Gao et al., 2018). Specifically, news announcements create an environment in which some market participants process information more quickly and accurately than others, i.e., trades following news announcements become more informative. This information signals the direction of the market for the remainder of the day. We also find that the more illiquid the crude oil market is, the stronger the predictability of the third half-hour returns, which is consistent with the liquidity provision argument made by Bogousslavsky (2016) and Elaut et al. (2018). Hence, we conclude that EIA announcements contribute to intraday momentum because they attract more informed traders, and the period surrounding these news releases is often associated with a reduction in liquidity.

The economic value of intraday momentum can be demonstrated from the perspective of market-timing strategies, such as taking a long (short) position at the beginning of the last half-hour if the intraday predictor is positive (negative) and then closing the position at the end of each trading day. We construct several intraday momentum strategies based on efficient intraday predictors, which can have substantial payoffs. An intraday momentum strategy using only the first half-hour returns as a trading signal on non-announcement days yields a Sharpe ratio of 9.28, whereas using the overnight component as a trading signal yields a Sharpe ratio of 11.98. Using the third half-hour returns as a trading signal on days with EIA announcements, we obtain a Sharpe ratio of 19.54. All the market-timing strategies have better performance than the passive long-only (Sharpe ratio of 5.15) and buy-and-hold (Sharpe ratio of -10.51) strategies.

Our research contributes to the existing literature in several ways. First, we document the importance of EIA announcements for an intraday momentum strategy, an issue that has received little attention to date. Second, we show that the predicting source of the first half-hour returns on EIA days comes from the overnight component, the return between the price at market open and the previous day price at market close. This finding adds to the understanding of the role of overnight returns in intraday momentum, which is the main source of prediction in a normal market state (e.g., Gao et al., 2019) but not in particular contexts, such as during EIA announcements. Third, we explore the theoretical mechanisms in the different predictive sources in third half-hour returns by connecting them to informed trading and liquidity provision, respectively. Therefore, our analysis contributes to an understanding of the theoretical framework explaining different patterns in intraday momentum.

The remainder of our paper is organized as follows. Section 2 presents the data and preliminary analyses on intraday trading volume and jumps. In Section 3, we present our main empirical analyses, and in Section 4, we offer theoretical explanations of our findings. We report the robustness tests in Section 5. Finally, we conclude in Section 6.

2. Data

2.1. United States Oil Fund and intraday returns

The United States Oil Fund (USO) is an ETF that tracks the price of West Texas Intermediate Light Sweet Crude Oil. It was first introduced on April 10, 2006, and is traded on NYSE Arca. Trading hours (in US Eastern Time) are divided into two sessions: the main and extended trading sessions. The main trading session starts with an opening auction at 9:30, then continuous trading occurs between 9:30 and 15:59, and a closing auction takes place at 16:00 when the closing price is settled. The extended trading session consists of a pre-market (4:00–9:30) and after-hours market (16:00–20:00). Because market makers and specialists generally do not participate in these sessions, trading activity is generally limited in volume and liquidity. However, if market updates occur or news is released outside the regular trading period, important market moves could happen in the pre-market or after-hours sessions.

We collect USO ETF data at a one-minute frequency from Refinitv Tick History. The sample period is from April 10, 2006, when the ETF started trading, to July 31, 2019. The data include the trading price, trade volume, number of trades, and the bid and ask prices. Following Gao et al. (2018), trading days with fewer than 500 trades are filtered out. Subsequently, the final sample contains 3,334 trading days.[3] For each day t, we calculate intraday half-hour returns during the trading hours, i.e., from 9:30 to 16:00, as follows

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

where $p_{i,t}$ denotes the ith half-hour price on day t, and each trading day has 13 half-hour intervals. As $p_{0,t}$, we use the previous trading day's closing price, which is at 16:00 for USO. This is consistent with many other intraday momentum studies (see, e.g., Gao et al., 2018, 2019; Wen et al., 2020). As a result, the first half-hour returns, $r_{1,t}$, are calculated as the (log) difference between the price at 10:00 and closing price at 16:00 the previous trading day. These returns have an overnight (i.e., $r_{overnight}$) and a market open component (i.e., r_{open}), in which the former is from the extended trading session, and the latter is from the main trading session.

[3] The total trading days are 3,500, and there are 166 days during which the NO. of trades are fewer than 500, around 4.74% of the total sample size.

2.2. Weekly Petroleum Status Report

The EIA, part of the US Department of Energy and a principal government agency for energy statistics, regularly releases the *Weekly Petroleum Status Report* every Wednesday at 10:30 a.m ET.[4] This report provides an update on changes in the number of barrels of commercial crude oil held by US companies as of the previous Friday. Such information is valuable for oil market analysis and price forecasting because oil inventory can proxy for market demand and is the subject of many studies (see, e.g., Bu, 2014; Ye and Karali, 2016).[5]

During our sample period, 685 weekly EIA crude oil reports were released.[6] To investigate whether EIA announcements have significant impacts on the crude oil market, we first split the sample into two subgroups: days with EIA announcements (EIA group) and days without these announcements (non-EIA group). We then compare the intraday trading patterns between the two groups. Specifically, we plot the average trading volume of every half-hour across the trading days. Figure 1 plots the intraday trading volume for the total, the EIA, and the non-EIA groups. For the EIA group, the largest spike in trading volume occurs at the third half-hour interval between 10:30–11:00, which coincides with the time interval of EIA

[4] When a public holiday falls on a Wednesday, the EIA announcement is made the following day on Thursday at 11:00 am ET.

[5] The American Petroleum Institute (API) also releases information on crude oil inventory levels in the U.S. every Tuesday at 16:30 (ET) called the "Weekly Statistical Bulletin." Nevertheless, we focus on the EIA report for two reasons. First, the EIA report has been documented as the main market mover (Bu, 2014; Ye and Karali, 2016). Second, the EIA report is released during the USO trading hour, whereas the API report is not.

[6] Among the 685 EIA announcements, 591 of them fall on Wednesday, 57 on Thursday, 36 on Friday, and 1 on Monday. Except for the Wednesday announcements which occur at 10:30, all other releases occur at 11:00. For this reason, we only focus on EIA announcements made on Wednesdays.

announcements.[7] In contrast, for the non-EIA group, the pattern of intraday volume takes a U-shape except during the spike at the tenth half-hour interval. In sum, as EIA inventory announcements are normally made at 10:30, market participants tend to adjust their positions with the arrival of new information released at 10:30 on days with EIA announcements. This is reflected in the sharp increase in trading volume during the third half-hour interval.

[Insert Figure 1 about here]

Table 1 reports all the half-hour returns on a trading day with respect to the EIA and non-EIA groups. The mean value of first half-hour returns (i.e., r_1) is positive for the EIA group, whereas it is negative for the non-EIA group. The difference in r_1 between the EIA and non-EIA groups is highly significant. We breakdown r_1 into its overnight (i.e., $r_{overnight}$) and the market open components (i.e., r_{open}) and find a similar pattern, indicating a different trading activity on days with and without EIA announcements. In addition, the standard deviation of the first half-hour returns (i.e., r_1) is higher for the non-EIA group than for the EIA group, whereas the standard deviation of the third half-hour returns (i.e., r_3) for the non-EIA group is lower, suggesting that the patterns of intraday momentum might be very distinctive between the EIA and non-EIA groups.

[Insert Table 1 about here]

News releases cause jumps in various securities, including bonds (Johannes, 2004; Jiang et al., 2011), foreign exchange (Andersen et al., 2007), and energy commodities (Bjursell et al., 2015). To assess the impact of EIA announcements, we compare the jump patterns

[7] We observe another trading volume spike at the 10^{th} half-hour interval between 14:00 – 14:30 for both EIA and non-EIA groups. This is due to the settlement time for the crude oil futures which is between 14:28 and 14:30 ET.

between the EIA and non-EIA groups. More specifically, we employ the intraday jump statistics of Lee and Mykland (2008), which are designed precisely to disentangle jump arrivals using high-frequency observations and, therefore, can minimize the spurious detection of jumps.[8]

Panel A of Figure 2 plots the average intraday five-minute returns for USO on days with EIA announcements, which show two significant intraday jumps, at 9:30 and 10:30, respectively. Specifically, the first jump occurs when the market opens, which is caused mainly by the absorption of overnight market information. The arrival time of the second jump is around 10:30, which coincides with the time that the inventory report is released by the EIA. In contrast, Panel B illustrates the plot on days without EIA announcements, showing only one jump at the time of the market opening. These plots, therefore, highlight additional information in the EIA news release transmitted to oil markets.

[Insert Figure 2 about here]

3. Empirical results

3.1. Evidence of intraday momentum

We examine the impact of EIA news releases on the intraday predictability of oil prices as follows. First, we examine the predictive power of the first half-hour returns ($r_{1,t}$) on the last half-hour returns ($r_{13,t}$) using Equation (2). Second, we assess the forecasting ability of the

[8] Lee and Mykland (2008) show that their stochastic jump estimates are more accurate compared to other nonparametric jump tests such as those by Bandorff-Nielsen and Shephard (2006) and Jiang and Oomen (2005). Similar model has been employed in various recent studies including Piccotti (2018), Kapetanios et al. (2019) and Lee and Wang (2020). The details about this methodology can be found in Appendix A.

third half-hour returns ($r_{3,t}$), i.e., when the EIA announcements are made, using Equation (3). Third, we examine the performance of the joint model using Equation (4).

$$r_{13,t} = \alpha + \beta_1 r_{1,t} + \varepsilon_t, \tag{2}$$

$$r_{13,t} = \alpha + \beta_3 r_{3,t} + \varepsilon_t, \tag{3}$$

$$r_{13,t} = \alpha + \beta_1 r_{1,t} + \beta_3 r_{3,t} + \varepsilon_t. \tag{4}$$

Table 2 reports our main regression results. Turning first to Panel A for the EIA group, we observe that the third half-hour return (model [2]) significantly and positively predicts the last half-hour return. A 1% increase in the third half-hour return leads to a 0.0382% increase in returns by the end of the trading day. In the joint model [3] containing r_1 and r_3, only the latter shows significant forecasting power, with a coefficient of 0.0383 and an adjusted R^2 of 3.10%. These results suggest that on days with EIA news announcements, the third half-hour return is more informative than the first half-hour return. Panel B, on the other hand, shows that for the non-EIA group, it is the first half-hour return that predicts the last half-hour return, with a regression coefficient of 0.0106 and t-statistic of 2.41. This result is further confirmed by the joint model whereby the coefficient for r_1 is positive and statistically significant but not for r_3. Compared to the EIA group, however, the non-EIA group shows weaker intraday momentum, demonstrated by the lower r_1 coefficient of 0.0107 and a lower adjusted R^2 of 0.68%. These results suggest that more important market information is released on days with EIA announcements.

In Panel C, we employ both EIA and non-EIA groups in the same regression using an interaction term as follows

$$r_{13,t} = \alpha + \beta_1 r_{1,t} + \beta_2 EIA_t \cdot r_{1,t} + \beta_3 r_{3,t} + \beta_4 EIA_t \cdot r_{3,t} + \varepsilon_t. \tag{5}$$

where EIA_t is a dummy variable that equals 1 on days with announcements and 0 otherwise. The joint model in the last column shows that the coefficient of the interaction term with r_1 is insignificant, but the coefficient of the interaction term with r_3 is significant, confirming the earlier results.

Overall, Table 2 shows that intraday momentum differs between EIA and non-EIA groups. When the EIA announcements are expected, market participants tend to wait and take action after the news is released, indicating the dominant role of EIA inventory announcements compared to the other general news released overnight.

[Insert Table 2 about here]

3.2. The information content of overnight returns

Previously, r_1 is calculated as the logarithmic difference between prices at 10:00 and the previous day's closing at 16:00. This return covers two distinct trading sessions, after-hour trading (from 16:00 to 20:00 and from 4:00 to 9:30) and regular trading (from 9:30 to 10:00). These trading sessions differ in terms of order types, market participants, and overall liquidity. For instance, in a study of intraday momentum in the S&P 500 ETF, Gao et al. (2018) show that the return measured from the prior day's close to the market open (9:30) contributes more to the predictive power of the first half-hour returns than from the open to 10:00.

In this section, we explore potential differences in the information covered by the two trading sessions by dividing the first half-hour returns into two components: the overnight component ($\mathrm{r}_{overnight}$) and the market open component (r_{open}). The overnight component is calculated as the change in logarithmic prices from the previous day's closing at 16:00 to the following day's opening at 9:30, whereas the market open component is calculated as the change in logarithmic prices from 9:30 to 10:00 during regular trading. We investigate which of the two explains the intraday predictability of the first half-hour returns, using Equations (6) and (7). Additionally, we test the joint predictability of the overnight, market open, and the third half-hour returns using Equation (8).

$$r_{13,t} = \alpha + \beta_{overnight} r_{overnight,t} + \beta_3 r_{3,t} + \varepsilon_t, \tag{6}$$

$$r_{13,t} = \alpha + \beta_{open} r_{open,t} + \beta_3 r_{3,t} + \varepsilon_t, \tag{7}$$

$$r_{13,t} = \alpha + \beta_{overnight} r_{overnight,t} + \beta_{open} r_{open,t} + \beta_3 r_{3,t} + \varepsilon_t. \tag{8}$$

Table 3 reports the results for the two components for the EIA and non-EIA groups. For the EIA group in Panel A, model [1] shows that the coefficient for the overnight component ($\beta_{overnight}$) is insignificant in predicting the last half-hour returns, whereas the coefficient of β_3 is positive and statistically significant in both models. In model [2], the coefficient of the market open component (β_{open}) is also insignificant. Model [3] confirms the previous findings with r_3 being the only significant and efficient predictor. These results further confirm that the third half-hour returns account for the intraday momentum in the EIA group. The results for the non-EIA group in Panel B show that the overnight component is an efficient predictor of intraday momentum in the crude oil market. The overnight coefficient in model [1] is positive and significant, whereas the market open component in model [2] is not. Furthermore, β_3 is not statistically significant in any of the models, confirming that the third half-hour return is not informative on days without EIA news announcements.

[Insert Table 3 about here]

Panel C in Table 3 confirms that the driving factor of the intraday momentum differs between the EIA and non-EIA groups. On non-announcement days, the overnight component of the first half-hour returns contributes to intraday momentum. On days with EIA announcements, however, it is the third half-hour returns that predict the last half-hour returns of the trading day. One plausible explanation is that on announcement days, investors pay more attention to forthcoming news releases than to information released overnight. This results in greater informativeness of trades during the third half-hour trading session and highlights the potentially different economic mechanisms driving the intraday return predictability between the EIA and non-EIA groups.

3.3. Intraday momentum during periods of high and low volatility

Previous studies have shown that intraday momentum can be affected by the degree of market volatility and that momentum is generally stronger on days with high volatility (see, e.g., Gao et al., 2018; Zhang et al., 2019). These studies also document that a momentum strategy based on low-frequency data often performs well when the market has extreme fluctuations. For this reason, we investigate how intraday momentum performs during periods with low and high volatility and whether it differs between the EIA and non-EIA groups.

We calculate the realized volatility (RV) on day t using midpoint quotes at a five-minute frequency using the following equation

$$RV_t = \sqrt{\sum_s^S m_s^2}, \tag{9}$$

where S is the total number of five-minute intervals in the trading session. We then split our sample into two groups based on the median of the RVs. The first group is for days with low RV, and the second group is for days with high RV. For each group, we re-estimate Equations (2) to (4) and report the results in Table 4.

[Insert Table 4 about here]

In Panel A of Table 4, we show that for the EIA group, the third half-hour returns are significant predictors of the last half-hour returns only during a period with high volatility. During periods of low volatility, none of the coefficients for r_3 predict r_{13}. The adjusted R^2 is considerably higher in periods of high volatility than those of low volatility (3.89% vs. 0.25%) for the joint model [3]. Panel B reports the results for the non-EIA group. Similar to the EIA group shown previously, the first half-hour returns contribute to intraday momentum only during a period of high volatility. The adjusted R^2 is also higher in periods of high volatility than those of low volatility (0.97% vs. 0.20%) for the joint model. These results are consistent with Zhang et al. (2019) and Gao et al. (2018), who find that the predictability of the first half-hour returns generally rises with volatility, i.e., as uncertainty increases, the intraday momentum trend becomes more persistent. The results in Panel C lend further support to the above findings. Hence, we conclude that for both the EIA and non-EIA groups, the pattern of intraday momentum is present only during periods of high volatility.

Overall, Tables 2 to 4 show that EIA and non-EIA groups show very distinctive patterns of intraday momentum. In particular, the predictability for the former group comes mainly from the EIA news releases during the third half-hour trading session, around 10:30 ET. The predictability for the latter group, on the other hand, is mostly driven by information released overnight. Moreover, the intraday momentum is more apparent during periods of high volatility. In the next section, we investigate the channels for this intraday momentum pattern.

3.4 Explaining intraday momentum on days with the EIA announcements

The existing literature provides several explanations for the role of the first half-hour of trading in an intraday momentum strategy. First, the model of late-informed trading suggests that investors are heterogeneous in their ability to collect and interpret information (e.g., Baker and Wurgler, 2006; Cohen and Frazzini, 2008). Those who have better skills at processing overnight information can act early in the morning trading session. However, those with less capacity to process the overnight information tend to wait until the last half-hour of trading to fully absorb the information precisely. Hence, trading in the same direction as the first half-hour can yield a positive return in the last half-hour (Gao et al., 2018). Second, the model of liquidity provision suggests that, at the beginning of a trading session, temporary order imbalances may arise as market participants react to news released overnight (Bogousslavsky, 2016). Hence, during the first half-hour of trading, liquidity providers supply liquidity to earn the bid-ask spread.[9] Although these liquidity providers might close out winning positions throughout the day, their reluctance to close losing positions can lead them to offload undesired inventory at the end of the day to avoid overnight risk. This results in a positive correlation between the first and last half-hour returns. Thus, the pattern of intraday momentum can, to an extent, be attributed to the illiquidity of the market at the beginning of the trading session.

[9] It is well-documented that the bid-ask spread is J-shaped, i.e., spreads are higher at the beginning and end of the day relative to the interior period (McInish and Wood, 1992).

In this section, we examine the role of informed trading and liquidity on the predictability of the third half-hour sessions for an intraday momentum strategy. To test the importance of informed trading, we perform two types of analysis. First, we split our sample into two groups based on the median of the average trade size (total volume divided by the total number of trades) during the third-half-hour interval (between 10:30 and 11:00): the first group for trade size above the median (the large trade group), and the second group based on trade size below the median (the small trade group). The idea is to investigate whether the contributions made by individual and institutional investors to intraday momentum. Because information about institutional and individual trades is not available, we use the average trade size to proxy for the two groups, as in Gao et al. (2018).

Second, we measure the price impact (i.e., PI) of trades during the third half-hour interval as follows:

$$PI_i = \frac{q_i(m_{i+k} - m_i)}{m_i}, \tag{10}$$

where q_i is the trade indicator (+1 for buys, -1 for sells), m_i is the prevailing midquote at the time of the i^{th} trade, and m_{i+k} is the midpoint quote k periods after the i^{th} interval. We use $k = 30sec$ and also conduct robustness using $k = \{15sec, 1min\}$.[10] This price impact is calculated for each trade and then averaged over all trades during the third half-hour interval.[11] The price impact measures the informativeness of trades and is often used to

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[10] These robustness results are not reported, but available upon request.

[11] We obtain transaction-level data for USO from Refinitiv Tick History to compute the price impact of each trade. This data contains all activity observed at the best bid and offer, which includes recorded transactions and revisions in the bid and ask prices and depths, all time-stamped to the nearest millisecond. We treat multiple trades that are executed with the same timestamp as one trade, as they typically reflect a trade initiated by one market participant but executed against the limit orders of multiple market participants. In such cases, we use the value-weighted average price and aggregate the volume traded. Trades are divided into buyer- and seller-initiated trades

distinguish trades by the informed and uninformed. Subsequently, we split the sample based on the median price impact and form two groups: low- and high-price impact.

Finally, we examine the role of liquidity on intraday momentum. To proxy for liquidity, we employ the Amihud (2002) illiquidity ratio as follows:

$$Illiq = abs[\ln(p_{11:00}/p_{10:30})/dollar\_volume_{10:30-11:00}] \tag{11}$$

where p is the transaction price, and $dollar\_volume$ is the total trading volume (in dollars) during the third half-hour interval. This ratio measures illiquidity in the market. Hence, a large number represents a less liquid market, whereas a low number represents a more liquid market.

For each of the groups above, we perform regression Equation (4) on days with EIA announcements. If the predictability of the third half-hour is due to informed market participants, then we expect the regression coefficient for r_3 to be more positive and statistically significant for the groups with large trades and high price impact. Subsequently, we expect the coefficients for r_3 to be less positive and statistically significant for the groups with small trades and low price impact. If intraday momentum is driven by the liquidity of the market, then we expect the coefficient for r_3 to be more (less) positive and statistically significant for the groups with a high (low) Amihud illiquidity ratio.

Panel A of Table 5 reports the results for the small and large trade groups. We observe that intraday momentum on EIA days is observed only in the large trade group, which represents trades by the more informed participants. The coefficients for the third half-hour returns are positive and statistically significant, suggesting that only large trade returns have

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based on the prevailing quotes prior to the trade. A trade is classified as buyer- (seller-) initiated if it is above (below) the midquote. For trades that occur at the midquote, we employ the tick rule and compare the current price with the previous price.

predictive power over the last half-hour returns. Panel B provides further evidence on the importance of informed trading for the predictability of the third half-hour returns. In particular, returns from trades with a higher price impact contribute to intraday momentum, but not trades with a low price impact. These results suggest that EIA announcements contribute to the predictability of third half-hour returns due to the presence of market participants with better information processing skills. In Panel C of Table 5, we also observe the importance of market liquidity for the predictability of the third half-hour returns. Specifically, a positive relationship with the end-of-day returns is observed when illiquidity of third half-hour returns is high, i.e., liquidity is an important driver of the predictability of the third half-hour returns, consistent with the model of liquidity provision (Bogousslavsky, 2016; Cohen and Frazzini, 2008, Elaut et al., 2018). Therefore, the predictability of third half-hour returns can be attributed to both informed trading and liquidity provision.

[Insert Table 5 about here]

3.5. Market-timing strategy

In this section, we assess the economic value of the efficient intraday predictors, which can be used as a timing signal for day trading. Specifically, we take the long (short) position at the beginning of the last half-hour of the regular trading session if the intraday predictor is positive (negative) and then close the position at the end of each trading day.

Consider the intraday momentum pattern in the non-EIA group, in which the first half-hour return (i.e., r_1) is considered the efficient intraday predictor, as demonstrated by Wen et al. (2020). Subsequently, the payoff of the market-timing strategy based on a trading signal r_1 on day t is

$$\eta^{Non-EIA}(r_1) = \begin{cases} -r_{13}, & r_1 < 0 \\ r_{13}, & r_1 \geq 0. \end{cases} \tag{12}$$

The previous analysis demonstrates that the third half-hour return (i.e., r_3) shows significant predictability for the EIA group. Therefore, on EIA days, we construct a trading strategy using r_3 as a trading signal:

$$\eta^{EIA}(r_3) = \begin{cases} -r_{13}, & r_3 < 0 \\ r_{13}, & r_3 \geq 0. \end{cases} \tag{13}$$

We compare the performance of the intraday momentum strategy with two benchmark strategies: long-only and buy and hold. Specifically, the long-only strategy takes a long position at the beginning of the last half-hour regardless of the sign of the intraday predictors and closes the position when the market closes. The buy-and-hold strategy takes a long position at the beginning of the sample period and holds it until the end of the sample period.

Table 6 presents the payoff generated by the various trading strategies, including the mean, Sharpe ratio, and success rate. As in Gao et al. (2018), the success rate is defined as the percentage of trading days with a zero or positive payoff. Panel A shows the average payoff of the two benchmark strategies. The long-only strategy generates a statistically insignificant annualized return of 1.04%, whereas the buy-and-hold strategy yields a -15.26% annual return. Both returns indicate poor performance. To account for risk, we calculate the Sharpe ratio by scaling the average returns with their standard deviation. The long-only and buy-and-hold strategies yield a Sharpe ratio of 5.15 and -10.51, respectively.

Panels B, C, and D report the average returns generated by intraday momentum strategies. Panel B shows substantially higher mean returns of intraday momentum strategy using the first half-hour returns as intraday predictors on non-announcement days. The average return is 1.88% per annum, statistically significant at the 5% level. The Sharpe ratio is 9.28, which is higher than the Sharpe ratio of the benchmark strategies. Panel C also focuses on non-announcement days but using the overnight component of the first half-hour return as a trading signal. The average return is 2.39% per annum (t-statistic of 2.45) and the Sharpe ratio is 11.98. Panel D shows that using the third half-hour return as an intraday predictor for the EIA group, we can generate an even higher average return of 4.14% per annum and a Sharpe ratio of 19.54. This performance is much better than any of the previous strategies.

[Insert Table 6 about here]

4. Robustness test

4.1. The out-of-sample (OS) analysis

The previous analyses show that EIA news releases play an important role in intraday predictability. However, good in-sample (IS) predictability does not necessarily infer good out-of-sample (OS) predictive performance. In this section, we analyze the OS performance of our predictive models, which is of great importance for practitioners.

We first examine the OS forecasting power of the first and third half-hour returns. Our sample is divided into two subperiods: from April 10, 2006, to December 31, 2009, for the IS analysis, and from January 1, 2010, to July 31, 2019, for the OS analysis. We follow the approach of Campbell and Thompson (2008) and apply the following steps. First, we estimate Equation (4) using the in-sample subset containing m observations and obtain the parameters

$\hat{\alpha}_m$, $\hat{\beta}_{1,m}$, and $\hat{\beta}_{3,m}$. Using these coefficients, we forecast the last half-hour returns at any time m+1, using data only up to time m as follows:

$$\hat{r}_{13,m+1} = \hat{\alpha}_m + \hat{\beta}_{1,m} r_{1,m+1} + \hat{\beta}_{3,m} r_{3,m+1} \tag{14}$$

where $r_{1,m+1}$ and $r_{3,m+1}$ are the actual first and third half-hour returns, and $\hat{r}_{13,m+1}$ is the predicted last half-hour returns of the $m+1$ observation. Second, we extend the regression window by incorporating one additional observation and reapply it to Equation (4) and obtain the parameters $\hat{\alpha}_{m+1}$, $\hat{\beta}_{1,m+1}$, and $\hat{\beta}_{3,m+1}$. The next OS predicted last half-hour returns are calculated as

$$\hat{r}_{13,m+2} = \hat{\alpha}_{m+1} + \hat{\beta}_{1,m+1} r_{1,m+2} + \hat{\beta}_{3,m+1} r_{3,m+2}, \tag{15}$$

where $r_{1,m+2}$ and $r_{3,m+2}$ are the actual first and third half-hour returns of the $m+2$ observations, respectively, and $\hat{r}_{13,m+2}$ is the predicted last half-hour returns. Recursively repeating these procedures, we obtain the OS predicted last half-hour returns (i.e., $\hat{r}_{13}$), which contain q observations. Third, the performance of OS prediction is calculated using the R^2 statistic (i.e., R^2_{OS}):

$$R^2_{OS} = 1 - \frac{\sum_{t=1}^{T}\left(r_{13,t} - \hat{r}_{13,t}\right)^2}{\sum_{t=1}^{T}\left(r_{13,t} - \bar{r}_{13,t}\right)^2}, \tag{16}$$

where $\hat{r}_{13,t}$ is the predicted last half-hour returns using the data subset containing observations m to $(m+q-1)$, and $\bar{r}_{13,t}$ denotes the historical average return in the same period. A positive R^2_{OS} indicates that our model has higher out-of-sample predictability than its average historical counterpart (Campbell and Thompson, 2008).

Table 7 shows the results for the OS prediction of first and third half-hour returns on days with and without EIA news releases. Turning first to Panel A, we observe that the OS predictability of the third half-hour returns for the EIA group (model [2]) is confirmed by the positive R^2_{OS}, with a value of 3.26%. In model [3] where we combine both the first and third half-hour returns, we obtain a R^2_{OS} of 4.37%. These results confirm that the predictive model for the EIA group has a better OS performance than the historical average benchmark.

[Insert Table 7 about here]

In the final three columns in Table 7, we consider R^2_{OS} in the model with overnight and market open components. The approach is similar to the recursive regressions presented earlier, except that the first half-hour returns $\hat{\beta}_1$ are now split into the overnight $\hat{\beta}_{overnight}$ and market open components $\hat{\beta}_{open}$. We observe that for the model [4] with the overnight component, R^2_{OS} is 3.91%, whereas for the model [5] with the market open component, R^2_{OS} is 3.60%. Combining these components with the third half-hour returns (model [6]), we obtain an R^2_{OS} of 4.18%.

Panel B reports the OS results for the non-EIA group. In general, the predictive model for the non-EIA group has an inferior OS performance than the historical average benchmark, as shown by the negative R^2_{OS} across the different models. However, when combined with the EIA group, many of the R^2_{OS} become positive as shown in Panel C. Overall, these findings suggest that the out-of-sample results are consistent with the IS results, i.e., the third half-hour returns induced by EIA announcements contribute to intraday momentum in the crude oil market.

5. Conclusion

In this study, we examine the importance of EIA announcements for the intraday momentum pattern in the crude oil market. Our findings highlight the unique intraday predictive information contained in the EIA inventory announcements. Specifically, the third half-hour returns provide market participants with additional information, which can significantly and positively predict the returns during the last half-hour of daily trading. On days with EIA announcements, investors pay more attention to the forthcoming releases than to the information released overnight or during the market open.

Further analysis shows that the pattern of intraday momentum is influenced by trades among more informed market participants. News announcements create an environment in which some market participants can process information more quickly and accurately than others, i.e., trades following news announcements become more informative. This information signals the market direction for the remainder of the day. In addition, the intraday momentum pattern is also affected by the liquidity in the market. The more illiquid the crude oil market is, the stronger the pattern of intraday momentum. Our results also show that the efficient intraday predictors for the EIA and non-EIA groups can be used in profitable trading strategies, as demonstrated by higher average returns and Sharpe ratios compared to the benchmark strategies.

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Appendix A. Intraday jump statistics

We employ the intraday jump statistics developed by Lee and Mykland (2008) to identify information such as jump arrival time, jump size, direction, and the number of jumps that occurred within a trading day. More specifically, the jump detection statistic is based on the relative size of the intraday return to its instantaneous volatility at time t_i, which is

$$\mathrm{L}_{t_i} = \mathrm{r}_{t_i}\hat{\sigma}_{t_i}^{-1}, \tag{A.1}$$

where the instantaneous volatility (i.e., $\hat{\sigma}_{t_i}$) is estimated by using the bi-power variation defined as

$$\hat{\sigma}_{t_i}^2 = (k-2)^{-1}\sum_{j=i-k+2}^{i-1}\left|r_{t_j}\right|\left|r_{t_{j-1}}\right|. \tag{A.2}$$

As recommended by Lee and Mykland (2008), the value of K can be set to 270 if five-minute intraday data are used. They further demonstrate that under the null hypothesis of no jump, the statistic

$$z_t = \frac{(|L_t| - C_n)}{s_n}, \tag{A.3}$$

has a cumulative distribution function $P(\xi \le x) = \exp(-e^{-x})$, where $C_n = \sqrt{\pi}(\log n)^{\frac{1}{2}} - \frac{\sqrt{\pi}}{4}(\log n)^{-\frac{1}{2}}(\log \pi + \log(\log n))$, and $S_n = \frac{\sqrt{\pi}}{2}(\log n)^{-\frac{1}{2}}$. If the significance level is 1%, the null hypothesis of no intraday jump would be rejected if $z_t \ge 4.60$.

Table 1. Descriptive statistics

This table reports the descriptive statistics for the intraday returns on days with EIA announcements (Panel A) and days without announcements (Panel B). Panel C reports the mean difference as well as its statistical test. In all, there are 687 days with EIA announcements and 2,647 days without EIA announcements over our sample period from April 10, 2006, to July 31, 2019. The mean values are scaled up by 10^4.

	Panel A: EIA		Panel B: Non-EIA		Panel C: Difference	
	Mean	Std.dev.	Mean	Std.dev.	Mean difference	t-stat
r_1	5.95	1.28	-9.24	1.45	15.19***	[2.58]
r_2	-2.20	0.66	-0.12	0.53	-2.08	[-0.73]
r_3	-4.07	0.84	-2.72	0.51	-1.34	[-0.38]
r_4	-2.04	0.59	-2.48	0.48	0.45	[0.18]
r_5	5.21	0.54	2.11	0.44	3.10	[1.29]
r_6	-0.24	0.41	-0.73	0.39	0.49	[0.27]
r_7	1.50	0.43	1.95	0.37	-0.45	[-0.23]
r_8	0.03	0.47	0.42	0.41	-0.38	[-0.19]
r_9	2.36	0.47	0.80	0.42	1.55	[0.71]
r_{10}	0.08	0.64	2.07	0.57	-1.98	[-0.72]
r_{11}	0.64	0.27	-0.96	0.23	1.59	[1.34]
r_{12}	-0.39	0.20	0.10	0.20	-0.48	[-0.54]
r_{13}	0.10	0.21	0.48	0.20	-0.39	[-0.40]
$r_{overnight}$	4.62	1.21	-6.59	1.40	11.20**	[2.01]
r_{open}	1.33	0.40	-2.65	0.53	3.98**	[2.02]

Table 2. Intraday momentum: EIA and non-EIA groups

This table reports the results for the intraday momentum pattern of Equations (2) to (3). The dependent variable is the last half-hour returns on the trading day, r_{13}. r_1 and r_3 are the first and third half-hour returns, respectively. EIA is an indicator variable that equals 1 on days with EIA announcements and 0 otherwise. Figures in parentheses are Newey-West (1987) robust t-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
Panel A: EIA			
Intercept	0	0	0
	[0.01]	[0.31]	[0.21]
r_1	0.0149		0.015
	[1.58]		[1.61]
r_3		0.0382**	0.0383**
		[2.03]	[2.12]
Obs.	591	591	591
Adj. R^2 (%)	0.81	2.28	3.10
Panel B: Non-EIA			
Intercept	0	0	0
	[1.48]	[1.16]	[1.42]
r_1	0.0106**		0.0107**
	[2.41]		[2.44]
r_3		0	0
		[-0.92]	[-1.02]
Obs.	2,649	2,649	2,649
Adj. R^2 (%)	0.59	0.07	0.68
Panel C: Full Sample			
Intercept	0	0	0
	[1.338]	[1.176]	[1.360]
r_1	0.0106**		0.0107**
	[2.41]		[2.44]
$EIA * r_1$	0.0042		0.0042
	[0.413]		[0.417]
r_3		-0.0104	-0.0114
		[-0.94]	[-1.05]
$EIA * r_3$		0.0487***	0.0499***
		[2.74]	[2.89]
Obs.	3,240	3,240	3,240
Adj. R^2 (%)	0.63	0.52	1.16

Table 3. Predicting source of the first half-hour returns

This table reports the results for the intraday momentum pattern of Equations (6) to (8). The dependent variable is the last half-hour returns on the trading day, r_{13}. $r_{overnight}$, r_{open}, and r_3 are the overnight, market open, and third half-hour returns, respectively. EIA is an indicator variable that equals 1 for days with EIA announcement and 0 otherwise. Figures in parentheses are Newey-West (1987) robust t-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	[1]	[2]	[3]
Panel A: EIA			
Intercept	0	0	0
	[0.24]	[0.25]	[0.19]
$r_{overnight}$	0.0131		0.0129
	[1.28]		[1.23]
r_{open}		0.0349	0.034
		[1.58]	[1.57]
r_3	0.0384**	0.0377**	0.0380**
	[2.13]	[1.97]	[2.07]
Obs.	591	591	591
Adj. R^2 (%)	2.84	2.70	3.24
Panel B: Non-EIA			
Intercept	0.0001	0	0.0001
	[1.38]	[1.11]	[1.35]
$r_{overnight}$	0.0127***		0.0125***
	[2.64]		[2.61]
r_{open}		-0.0089	-0.0056
		[-0.80]	[-0.52]
r_3	-0.0111	-0.0101	-0.0109
	[-1.01]	[-0.89]	[-0.99]
Obs.	2,649	2,649	2,649
Adj. R^2 (%)	0.87	0.13	0.89
Panel C: Full Sample			
Intercept	0	0	0
	[1.34]	[1.10]	[1.28]
$r_{overnight}$	0.0127***		0.0125***
	[2.64]		[2.62]
$EIA * r_{overnight}$	0.0004		0.0003
	[0.03]		[0.02]
r_{open}		-0.0089	-0.0057
		[-0.81]	[-0.53]
$EIA * r_{open}$		0.0437	0.0394
		[1.36]	[1.24]
r_3	-0.0111	-0.0101	-0.0109
	[-1.03]	[-0.91]	[-1.01]
$EIA * r_3$	0.0497***	0.0479***	0.0491***
	[2.89]	[2.63]	[2.78]
Obs.	3,240	3,240	3,240

Adj. R^2 (%)	1.26	0.65	1.36

Table 4. Intraday momentum during periods of low and high volatility

This table reports the predictability during periods of low and high volatility. We construct the daily realized volatility (RV) using five-minute data over the full sample period from April 10, 2006, to July 31, 2019. We then use the median of the RV to group days with low and high RV. The dependent variable is the last half-hour returns on the trading day, r_{13}. r_1 and r_3 are the first and third half-hour returns, respectively. EIA is an indicator variable that equals 1 for days with EIA announcements and 0 otherwise. Figures in parentheses are Newey-West (1987) robust t-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Low-volatility period			High-volatility period		
	[1]	[2]	[3]	[1]	[2]	[3]
Panel A: EIA						
Intercept	0	0	0	0	0.0001	0.0001
	[-0.54]	[-0.51]	[-0.53]	[0.30]	[0.58]	[0.54]
r_1	0.0018		0.0008	0.016		0.0165
	[0.13]		[0.05]	[1.57]		[1.61]
r_3		0.0132	0.0131		0.0422**	0.0426**
		[0.72]	[0.71]		[2.02]	[2.14]
Obs.	244	244	244	347	347	347
Adj. R^2 (%)	0.01	0.25	0.25	1.01	2.82	3.89
Panel B: Non-EIA						
Intercept	0	0	0	0.0001*	0.0001	0.0001
	[-0.03]	[-0.01]	[-0.03]	[1.69]	[1.23]	[1.57]
r_1	0.0049		0.0048	0.0117**		0.0119**
	[0.98]		[0.97]	[2.43]		[2.47]
r_3		0.0121	0.012		-0.0167	-0.0177
		[1.24]	[1.23]		[-1.18]	[-1.28]
Obs.	1,382	1,382	1,382	1,267	1,267	1,267
Adj. R^2 (%)	0.08	0.12	0.20	0.78	0.17	0.97
Panel C: Full Sample						
Intercept	0	0	0	0.0001*	0.0001	0.0001*
	[-0.24]	[-0.21]	[-0.24]	[1.68]	[1.38]	[1.66]
r_1	0.005		0.0049	0.0116**		0.0118**
	[0.99]		[0.97]	[2.45]		[2.50]
$EIA * r_1$	-0.0041		-0.005	0.0043		0.0046
	[-0.24]		[-0.30]	[0.40]		[0.42]
r_3		0.0121	0.012		-0.0167	-0.0179
		[1.26]	[1.25]		[-1.20]	[-1.32]
$EIA * r_3$		0.0011	0.0013		0.0590***	0.0607***
		[0.06]	[0.06]		[2.78]	[2.95]
Obs.	1,626	1,626	1,626	1,614	1,614	1,614
Adj. R^2 (%)	0.07	0.14	0.21	0.82	0.73	1.59

Table 5. The impact of trade size, adverse selection, and market illiquidity

This table reports predictability for small and large trades (Panel A), low and high price impacts (Panel B), and low and high Amihud illiquidity ratios (Panel C). Each metric is calculated daily using trades during the third half-hour interval. We use the median of each metric to identify the two groups. The dependent variable is the last half-hour returns on the trading day, r_{13}. r_1 and r_3 are the first and third half-hour returns, respectively. Figures in parentheses are Newey-West (1987) robust t-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Individual vs. institutional	Small trades			Large trades		
	[1]	[2]	[3]	[1]	[2]	[3]
Intercept	-0.0001	-0.0001	-0.0001	0.0001	0.0002	0.0002
	[-1.06]	[-0.96]	[-1.01]	[1.18]	[1.48]	[1.37]
r_1	0.0071		0.0086	0.0217		0.0203
	[0.57]		[0.66]	[1.61]		[1.64]
r_3		0.0338	0.0347		0.0422*	0.0406*
		[1.23]	[1.30]		[1.75]	[1.80]
Obs.	295	295	295	296	296	296
Adj. R^2 (%)	0.15	1.49	1.72	2.09	3.40	5.22

Panel B: Informed vs. uninformed	Low price impact			High price impact		
Intercept	-0.0001	-0.0001	-0.0001	0.0001	0.0002	0.0001
	[-1.19]	[-1.08]	[-1.08]	[1.06]	[1.34]	[1.14]
r_1	0.0032		0.0035	0.0238*		0.0236**
	[0.33]		[0.36]	[1.93]		[2.06]
r_3		0.021	0.0211		0.0484**	0.0481**
		[1.29]	[1.29]		[2.05]	[2.17]
Obs.	296	296	296	295	295	295
Adj. R^2 (%)	0.05	0.74	0.80	1.79	3.51	5.26

Panel C: Liquid vs. illiquid market	Low Amihud ratio			High Amihud ratio		
Intercept	0.0001	0.0001	0.0001	-0.0001	-0.0001	-0.0001
	[1.18]	[1.32]	[1.25]	[-0.99]	[-0.68]	[-0.72]
r_1	0.0346**		0.0338**	0.0007		0.0034
	[2.54]		[2.54]	[0.06]		[0.28]
r_3		0.023	0.0212		0.0776***	0.0782**
		[1.15]	[1.23]		[2.60]	[2.59]
Obs.	296	296	296	295	295	295
Adj. R^2 (%)	3.84	1.23	4.88	0.00	5.12	5.17

Table 6. Market-timing strategy

Panel A reports the performance of the benchmark strategies. The long-only strategy opens a position at the beginning of the last half-hour interval, regardless of the sign of the predictive half-hour return, and closes the position at the market close. The buy-and-hold strategy takes a long position at the beginning of the sample period and holds it until the end of the sample period. Panels B, C, D, E, and F report the performance of the intraday momentum strategy, i.e., taking a long (short) position at the beginning of the last half-hour interval if the predictive return is positive (negative) and close the position at the end of each trading day. The success rate is the ratio of the number of days when the strategy has zero or positive returns to the total number of trading days.

	Mean (%)	t-stats	Std. dev.	Sharpe ratio	Skewness	Kurtosis	Success (%)
Panel A: Benchmark strategy							
Long-only	1.04	(1.16)	0.20	5.15	0.82	14.49	58
Buy-and-hold	-15.26**	(-2.37)	1.45	-10.51	-0.32	5.52	50
Panel B: using r_1 as a trading signal on non-EIA days							
$\eta^{Non-EIA}(r_1)$	1.88**	(2.10)	0.20	9.28	0.14	14.56	57
Panel C: using $r_{overnight}$ as a trading signal on non-EIA days							
$\eta^{Non-EIA}(r_{overnight})$	2.39**	(2.45)	0.20	11.98	0.08	15.79	58
Panel D: using r_3 as a trading signal on EIA days							
$\eta^{EIA}(r_3)$	4.14*	(1.88)	0.21	19.54	0.66	10.09	58

Table 7. Out-of-sample analysis

This table reports the out-of-sample R^2 statistic (R^2_{OS}) for the following models:

$$r_{13,t} = \alpha + \beta_1 r_{1,t} + \varepsilon_t, \quad [1]$$

$$r_{13,t} = \alpha + \beta_3 r_{3,t} + \varepsilon_t, \quad [2]$$

$$r_{13,t} = \alpha + \beta_1 r_{1,t} + \beta_3 r_{3,t} + \varepsilon_t. \quad [3]$$

$$r_{13,t} = \alpha + \beta_{overnight} r_{overnight,t} + \beta_3 r_{3,t} + \varepsilon_t, \quad [4]$$

$$r_{13,t} = \alpha + \beta_{open} r_{open,t} + \beta_3 r_{3,t} + \varepsilon_t, \quad [5]$$

$$r_{13,t} = \alpha + \beta_{overnight} r_{overnight,t} + \beta_{open} r_{open,t} + \beta_3 r_{3,t} + \varepsilon_t. \quad [6]$$

Panel A reports the results only for EIA days. Panel B reports the results only for non-EIA days. Panel C reports the full sample results.

Panel A: EIA	[1]	[2]	[3]	[4]	[5]	[6]
R^2_{OS} (%)	1.11	3.26	4.37	3.91	3.6	4.18
Panel B: Non-EIA						
R^2_{OS} (%)	0.15	-0.91	-0.85	-1.06	-1.3	-1.33
Panel C: Full Sample						
R^2_{OS} (%)	0.51	-0.19	0.3	0.15	-0.44	0.1

Figure 1. Intraday USO trading volume: EIA and Non-EIA groups

This figure plots the intraday patterns of the average half-hour trading volume of USO ETF for the total (dark blue), the EIA (light blue), and the non-EIA (yellow) groups. The sample period is from April 10, 2006, to July 31, 2019.

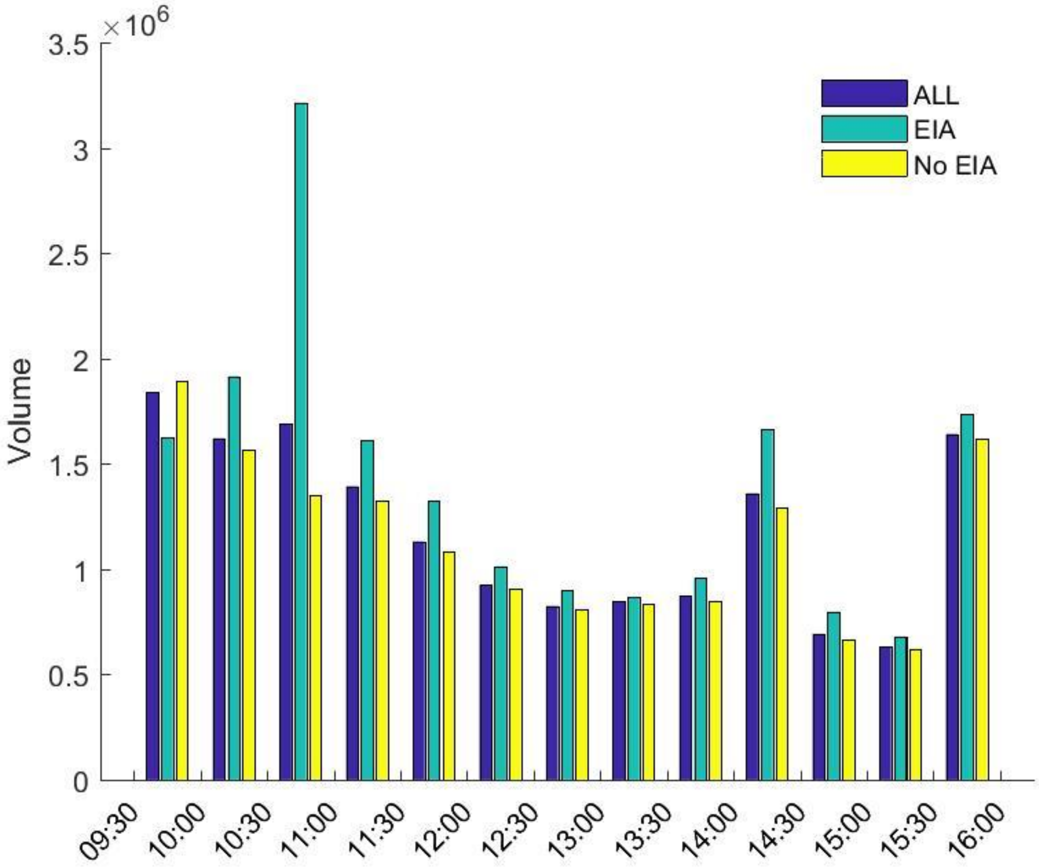
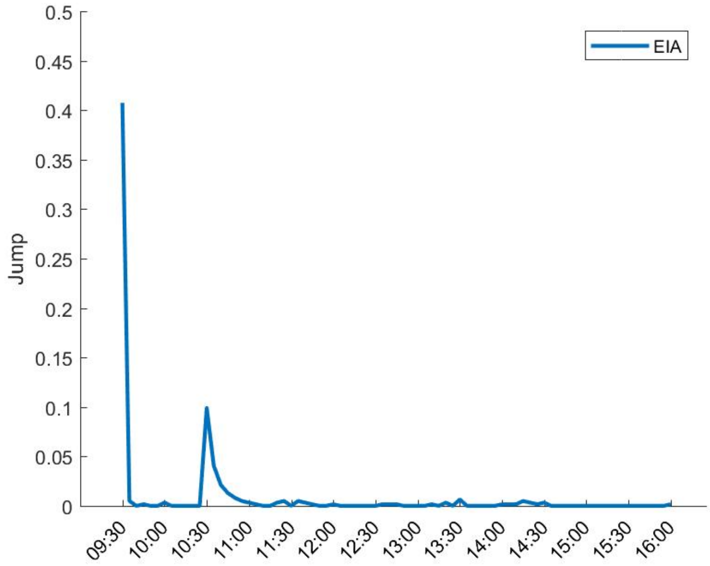
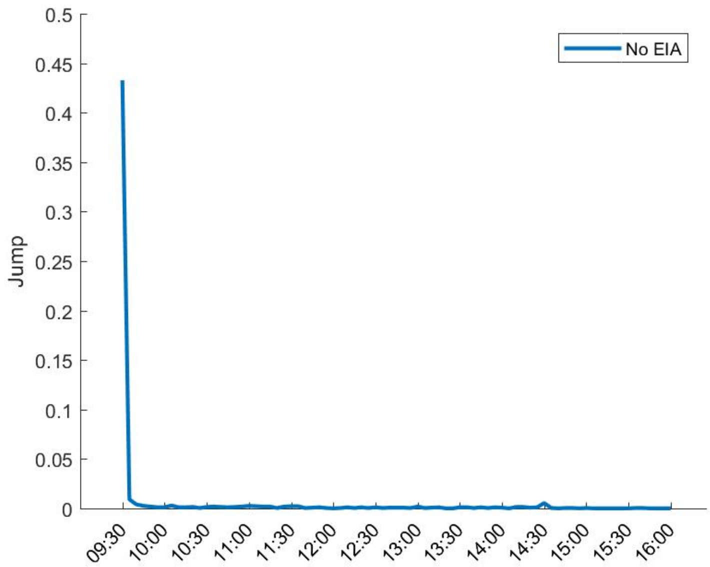


Figure 2. Intraday jump pattern of USO: EIA and non-EIA groups

This figure plots the time-varying intraday jump pattern of USO ETF on days with EIA announcements (Panel A) and without announcements (Panel B). The intraday jump statistic is calculated using the five-minute high-frequency returns of USO ETF following the nonparametric methodology proposed by Lee and Mykland (2008). The sample period is from April 10, 2006, to July 31, 2019.



Panel A: EIA group



Panel B: Non-EIA group