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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) on 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. In the 2021 Yearbook of World Energy & Climate Statistics, Enerdata (2021) reports that oil accounts for 30% of the total energy consumption in 2020. 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.[1] The inventory of crude oil is a fundamental factor in determining prices and volatility as it affects the elasticity of demand and supply (e.g., Ye et al., 2005; Hamilton, 2009; Ye and Karali, 2016). The US Energy Information Administration (EIA) releases the *Weekly Petroleum Status Report*, typically 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, 2017). Consequently, knowledge of 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).

[1] For instance, the average daily trading volume for the nearby West Texas Intermediate (WTI) futures contract has increased from 288,000 in 2006 to 1.1 million contracts in 2020, while the average daily trading volume for the United States Oil Fund ETF has increased from 150,000 units when it was introduced in 2006 to 9 million units in 2020. Data is obtained from Refinitiv Datastream.

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 in the equity and commodity markets focus on the predictability of the first half-hour on the last half-hour returns of the same day. Gao et al. (2018), for instance, show that the first half-hour return, measured from the previous day's market close, predicts the last half hour-return in the S&P500 SPDR and ten other actively-traded exchange-traded funds (ETFs). A similar finding is documented by Gao et al. (2019), who study intraday momentum across firms in China. Jin et al. (2019) document that the first half-hour return positively predicts the last half-hour return across four Chinese commodity futures contracts, including copper, steel, soybean, and soybean meal. Furthermore, 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. To our knowledge, none of the current energy market studies consider the potential impact of the EIA news release for intraday momentum. We, therefore, complement the above study by examining whether and to what extent the EIA inventory announcements affect the pattern of intraday return predictability. More specifically, we analyze whether the pattern of intraday momentum in the crude oil market varies between days with and without EIA announcements.

It is important to note that the intraday momentum literature focuses on the correlation between the first and the last half-hour return of the day. On a typical trading day, the first and last half-hours of trading are the most important (Bogousslavsky, 2016; Gao et al., 2018, 2019; Jin et al., 2019). 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. This intraday momentum pattern can be explained by the trading behavior of investors who wait until the last half-hour of trading to fully absorb all information released during the day (Gao et al., 2018, 2019; Wen et al., 2020) and/or investors who delay their rebalancing trades to near the market close instead of the market open (Bogousslavsky, 2016; Jin et al., 2019). On days with EIA news announcements, 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.[2] Consequently, we expect a positive correlation between returns following the news release and returns during the last half-hour of trading. Therefore, in this study, we argue that days 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 United States Oil Fund (USO) ETF data, from their introduction on April 10, 2006, to July 31, 2019.[3] 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

[2] 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).

[3] 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).

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 are 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 and periods when active portfolio management is required.

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 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 non-EIA days comes from the overnight component, the return between the price at market open and the previous day's 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 offer theoretical explanations for our findings. We report the robustness tests in Section 4. Finally, we conclude in Section 5.

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 introduced on April 10, 2006, and is traded on the 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.

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 3,240 trading days. For each day t, we calculate intraday half-hour returns during the trading hours, i.e., from 9:30 to 16:00, as follows

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

where i is the half-hour interval, i.e., $i = 1,2, \ldots ,13$, since each trading day has 13 half-hour intervals. As such, $p_{i,t}$ denotes the *i*th half-hour price on day *t*. 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 return, $r_{1,t}$, is calculated as the (log) difference between the price at 10:00 and the closing price at 16:00 the previous trading day. This return has 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.

2.2. Weekly Petroleum Status Report

The EIA, part of the US Department of Energy and a principal government agency for energy statistics, releases the *Weekly Petroleum Status Report* every Wednesday at 10:30 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, but we focus on 591 EIA announcements that fall on Wednesdays at 10:30.[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

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

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 announcements. 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.[7] 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 here]

As further evidence of the importance of the EIA announcements, we plot the intraday trading volume across different days throughout the week. Complimenting the previous figure, we observe that trading volume substantially increases on Wednesday between 10:30 to 11:00. Trading volumes on other times and days are steady and comparable. This finding indicates the absence of confounding sources of information released other than the EIA announcement at 10:30 on Wednesday.

[Insert Figure 2 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 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]

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[7] We observe another trading volume spike at the 10th 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.

[8] Lee and Mykland (2008) show that their stochastic jump estimates are more accurate compared to other nonparametric jump tests such as those

Panel A of Figure 3 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 3 here]

3. EMPIRICAL RESULTS

3.1. Evidence of intraday momentum

We examine the predictive power of the first half-hour returns ($r_{1,t}$) and the forecasting ability of the third half-hour returns ($r_{3,t}$), i.e., when the EIA announcements are made, on the last half-hour returns ($r_{13,t}$) using the following regression model:

$$r_{13,t} = \alpha + \beta_1 r_{1,t} + \beta_3 r_{3,t} + \varepsilon_t. \quad (2)$$

Table 1 reports our main regression results. Turning first to Panel A for the EIA group, the result indicates that on days with EIA news announcements, the third half-hour return is more informative than the first half-hour return. The coefficient for r_3 is 0.038 with an adjusted R^2 of 3.10%. This can be interpreted as a 1% increase in the

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by Barndorff-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 return leads to a 0.038% increase in returns by the end of the trading day. We also control for other potential intraday events, including the floor trading closing time, by using indicator variables for other half-hour intervals. The results remain robust with a regression coefficient of 0.042 and an adjusted R^2 of 8.15%. 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. Compared to the EIA group, however, the non-EIA group shows weaker intraday momentum, demonstrated by the lower coefficient of 0.011 for r_1 and a lower adjusted R^2 of 0.68%. These results suggest that more important market information is released on days with EIA announcements.

[Insert Table 1 here]

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

$$r_{13,t} = \alpha + \beta_1 r_{1,t} + \beta_2 EIA_t \cdot r_{1,t} + \beta_3 r_{3,t} + \beta_4 EIA_t \cdot r_{3,t} + \varepsilon_t, \quad (3)$$

where EIA_t is a dummy variable that equals one on days with announcements and zero otherwise. The joint model in the last column shows that the coefficient of the interaction term with r_3 is significant, confirming the earlier results that r_3 is informative, particularly on days with EIA news releases. In addition to the EIA information drops on Wednesdays, there is also the American Petroleum Institute (API) reports released every Tuesday at 16:30pm. While this can potentially affect trading when the market opens on Wednesday morning, our model already accounts for this possibility. Particularly, the coefficient for $(EIA \times r_1)$ in Panel C of Table 1 will have captured the effect of the API announcement when the market opens on Wednesday morning. Nevertheless, we do not find the coefficient for this interaction term to be statistically significant.

Overall, Table 1 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.

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 close 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 ($r_{overnight}$) and the market open component (r_{open}). The overnight component is calculated as the change in logarithmic prices from the previous day's close at 16:00 to the following day's open 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 test the joint predictability of the overnight, market open, and the third half-hour returns using the following equation,

$$r_{13,t} = \alpha + \beta_{overnight} r_{overnight,t} + \beta_{open} r_{open,t} + \beta_3 r_{3,t} + \varepsilon_t. \quad (4)$$

Table 2 reports the results for the two components for the EIA and non-EIA groups. The EIA group in Panel A shows that neither $r_{overnight}$ nor r_{open} is significant in predicting the last half-hour returns, whereas the coefficient for r_3 is. This finding further confirms 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 is positive and significant, whereas the market open component is not. Furthermore, r_3 is not statistically significant, confirming that the third half-hour return is not informative on days without EIA news announcements.

[Insert Table 2 here]

Panel C in Table 2 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. The importance of volatility and active portfolio management for intraday momentum

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

$$RV_t = \sqrt{\sum_s^S m_s^2}, \quad (5)$$

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 Equation (2) and report the results in Table 3.

[Insert Table 3 here]

The EIA group in Table 3 shows that during periods of low volatility, none of the coefficients for r_3 predict r_{13}. The third half-hour returns are significant predictors of the last half-hour returns only during a period with high volatility. The adjusted R^2 for the EIA group is considerably higher in periods of high volatility than those of low volatility (3.89% vs. 0.25%). For the non-EIA group, 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%). 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 last column of each panel further confirms that the pattern of intraday momentum is present only during periods of high volatility.[9]

It is plausible that some weekly reports may be more consequential than others, increasing interest in crude oil markets and market volatility. Thus, our earlier results may simply indicate increased interest in the weekly EIA

[9] We also conduct our analysis by splitting RV into quartiles and find that intraday momentum pattern persists for the quartile with the highest volatility. The findings are reported in Appendix B.

market report rather than being an unrelated feature of the market. To address this concern, we employ several instrumental variables for volatility, all of which are exogenous to the EIA news release. These variables are: (1) crude oil market implied volatility (proxied by the CBOE OVX); (2) stock market implied volatility (the CBOE VIX); (3) geopolitical risk index (Caldara and Iacoviello, 2022); and (4) climate policy uncertainty index (Gavriilidis, 2021). The results in Appendix C show that the pattern of intraday momentum is observed during the period of high uncertainty (high OVX, high VIX, high GPR, and high CPU). These confirm our finding that increased volatility is associated with stronger intraday momentum.

In addition to volatility, active portfolio management may play a role in intraday momentum. To ensure that the return for USO replicates that of the benchmark oil futures contracts, USO's managers need to actively manage their portfolio through monthly rebalancing as futures contract rolls over. This could lead to predictable trades that investors may seek to arbitrage. Consequently, intraday returns for USO may not track those for oil futures even while daily returns remain comparable. To test if this is the case, we split the data into two parts: the first half and the second half of the month. According to the United States Commodity Funds (USCF), the rollover for USO occurs during the first half of the month.[10] Hence, the first group includes days when the portfolio is rebalanced while the other group does not. The results reported in Table 4 show that the intraday momentum pattern is, indeed, observed during the first half of the month when the futures contracts get rolled over. The finding suggests that active management causes predictable trades that investors could seek to arbitrage.[11]

[10] https://www.uscfinvestments.com/filings/commodities/uso

[11] We further test if these results are robust across time. Using the first and second half of the month groups, separately, we estimate rolling regressions of Equation (3) using 5-year daily data (1,250 observations) and obtain time-varying coefficients for the interaction term ($EIA * r_3$). We find that over our sample period, the intraday momentum pattern is stronger if EIA announcements occur during the first half of the month.

[Insert Table 4 here]

Overall, Tables 1 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 and during the period when active portfolio management is involved. 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. 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.[12] Although

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These results are available from the authors upon request.

[12] 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

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.

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 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:

$$PI_i = \frac{q_i(m_{i+k} - m_i)}{m_i}, \quad (6)$$

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 $k = \{15sec, 1min\}$.[13] This price impact is calculated for each trade and then averaged over all trades during

period (McInish and Wood, 1992).

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

the third half-hour interval.[14] The price impact measures the informativeness of trades and is often used to distinguish trades between the informed and uninformed. Subsequently, we split the sample based on the median price impact and formed 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:

$$Illiq = abs[\log(p_{11:00}/p_{10:30})/dollar\_volume_{10:30-11:00}] \quad (7)$$

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 (2) 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

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[14] 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 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.

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 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 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 the 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 here]

It is possible that the anticipated EIA reports attract informed traders and affect market liquidity. Hence, the results earlier may be picking up the heterogeneity in anticipated report features rather than fundamental interactions between market features and EIA report releases. To assess this, we employ instrumental variables to capture informed trading and liquidity. For informed trading, we use the degree of cloud cover surrounding the crude oil storage locations. As documented in Mukherjee et al. (2021), cloudy weather makes it harder for satellite imaging to have a proper inference as to how much oil is kept in the storage facility. In such a case, information made available by energy research firms will not be useful, and informed trading will remain high. In contrast, when the weather is clear, information made available by energy research firms will be utilized by many market participants, and informed trading will be low. We collect hourly sky condition data from the ISD (Integrated Surface Database) via Climate Data Online, provided by NOAA (National Oceanic and Atmospheric Administration). Similar data has been used in Hirshleifer and Shumway (2003) and Mukherjee et al. (2021). More specifically, we take the average cloud cover surrounding the key crude oil storage locations over the daylight period from 7:00 and 18:00.[15]

For liquidity, we use the total open interest for the NYMEX West Texas Intermediate (WTI) Crude Oil Futures collected from Refinitiv Datastream. It reflects the number of outstanding contracts that have not expired, been exercised, or physically delivered. A high open interest indicates that a large amount of money is invested in the crude oil market, i.e., high liquidity. Conversely, a low open interest indicates low liquidity. Unlike trading volume, the total open interest does not aggregate buy and sell transactions and therefore is not affected by the release of EIA reports. Souček (2013) uses open interest as a proxy for trading activity in his study of co-movement between equity, crude oil, and gold futures markets.

The results in Appendix D show that the intraday predictability pattern is observed during the period with high cloud cover (high informed trading) and a period of low open interest (low liquidity). These results support our

[15] The locations are: Cushing, OK; Patoka, IL; Clovelly, LA; Saint James, LA; Houston, TX; Beaumont-Nederland, TX; Corpus Christi, TX; Midland, TX; Wink, TX; and Wichita Falls, TX

main finding that the predictability of the third half-hour returns can be attributed to both informed trading and liquidity provision.

3.5. Market-timing strategy

In this section, we assess the economic value of the efficient intraday predictors, which can be used as a 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

$$\eta^{Non-EIA}(r_1) = \begin{cases} -r_{13}, & r_1 < 0 \\ r_{13}, & r_1 \geq 0. \end{cases} \tag{8}$$

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:

$$\eta^{EIA}(r_3) = \begin{cases} -r_{13}, & r_3 < 0 \\ r_{13}, & r_3 \geq 0. \end{cases} \tag{9}$$

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, D, and E 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 uses 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 on non-announcement days yields -0.36% return. This implies that the third half-hour return is not informative on non-announcement days. Rather, Panel E shows that using r_3 as a trading signal on days with EIA announcements, 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 here]

4. ROBUSTNESS TEST

4.1. Alternative definitions of the third half-hour return

Previously, our predictor r_3 is measured by using prices at 10:30 and 11:00, which is the end of the first 30 minutes following the EIA news release. It is useful to know whether the correlation between the third and the last half-hour returns also extends to other time periods immediately after the EIA release. We conduct a sensitivity analysis by extending the time periods immediately after the news announcement. More specifically, we start r_3 with a five-minute interval (10:30 – 10:35) and keep extending this interval by 5 minutes increment. The dependent variable remains r_{13}. The results in Table 7 show that the intraday pattern of the third-half hour interval starts becoming statistically significant from the 15^{th} minute interval onwards. The results are consistent with Gao et al. (2018), who explain that market takes time to digest new information.

[Insert Table 7 here]

4.2. Intraday momentum over time

For our next robustness test, we examine if our intraday momentum results change over time using rolling window regressions. More specifically, we estimate Equation (3) using 5-year daily data (1,250 observations) and obtain the coefficient for the interaction term ($EIA * r_3$). We do the estimation daily and roll over the regression window to the next day until we reach the end of the sample period. We then plot the time series of the interaction term coefficients along with the 90% confidence interval.

Figure 4 illustrates the pattern of intraday momentum over time. We observe that the intraday momentum phenomenon is strong and statistically significant over our sample period, albeit with a declining trend. The confidence interval does not cross 0, indicating that the strategy is profitable. It is important to note that during the crude oil price plunge between 2014 and 2016, the intraday return predictability is not observed. This could be due to the combination of factors driving oil prices to historic lows: (1) the strong dollar; (2) the OPEC retaining its production levels; (3) growing global crude oil inventory; (4) the nuclear deal, which allowed Iran to start exporting oil again, and (5) slowing growth in emerging markets, especially China. When oil price is high, inventory information released by the EIA is valuable and will be exploited to make profits. However, when oil price is low, inventory information becomes less relevant, leading to a diminished intraday momentum pattern.

[Insert Figure 4 here]

4.3. Potential information drops on other days of the week

Our results so far show that Wednesdays are particularly different for intraday momentum due to the EIA information drops. There may also be information released on other days of the week that could affect our results. For instance, various economic and geopolitical events are more likely to occur over a weekend than between any two weekdays. In such a case, 'Mondays' could have more information packed into the overnight component of r_1. Consequently, the coefficient for r_1 for these Mondays may be different from the r_1 coefficient for non-Mondays. To assess this possibility, we split the sample into three subgroups: Mondays, EIA days, and non-Monday and non-EIA days.

The results in Panels A to D of Table 8 show that the first half-hour return is predictive of the last half-hour returns on Mondays but not on other days. This confirms our earlier finding that new information is incorporated in the first half-hour of trading, particularly on days without EIA news announcements. Complementing this result, we also estimate Equation (3) using other days of the week as control. Panel E of Table 8 shows that even after controlling for possible information events on other days of the week, the predictive power of r_1 on non-announcement days and r_3 on EIA announcement days remains.

[Insert Table 8 here]

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 provide practical implications to energy market participants. While our findings support the efficient markets hypothesis where prices respond to unexpected news following the EIA reports, we show that the adjustment process is rather slow and is only completed at the end of the trading day. This return correlation can be exploited by crude oil market participants in profitable trading strategies, which yield higher average returns and Sharpe ratios compared to the benchmark strategies. Our findings also have policy implications. We show that on days with EIA announcements, information during the first half-hour following the news release subsumes the information contained in the overnight market news. This knowledge provides a deeper understanding of the price discovery mechanisms of the crude oil market. For energy market regulators, such knowledge may be beneficial in devising a policy to increase liquidity surrounding important public information such that information can be absorbed into the price more quickly.

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

$$L_{t_i} = r_{t_i}\hat{\sigma}_{t_i}^{-1}, \quad \text{(A.1)}$$

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

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

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

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

has a cumulative distribution function $P(\xi \leq x) = \exp(-e^{-x})$, 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 $z_t \geq 4.60$.

APPENDIX B. INTRADAY MOMENTUM FOR VARIOUS VOLATILITY QUARTILES

	Panel A: EIA				Panel B: Non-EIA				Panel C: Full Sample			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Intercept	-0.000	0.000	0.000	0.000	0.000	0.000	-0.000*	0.000***	0.000	0.000	-0.000	0.000**
	[-1.10]	[0.80]	[-0.01]	[0.10]	[0.30]	[0.08]	[-1.71]	[2.59]	[0.08]	[-0.31]	[-1.10]	[2.44]
r_1	0.024	0.015	-0.006	0.021	-0.003	0.013*	0.006	0.014**	-0.006	0.011*	0.007	0.014**
	[1.18]	[0.91]	[-0.48]	[1.65]	[-0.43]	[1.96]	[1.18]	[2.35]	[-0.80]	[1.73]	[1.45]	[2.33]
r_3	0.029	-0.004	-0.012	0.066***	0.012	0.002	0.002	-0.020	0.013	0.010	-0.002	-0.022
	[1.38]	[-0.20]	[-0.60]	[2.67]	[0.80]	[0.17]	[0.12]	[-1.12]	[0.94]	[0.74]	[-0.15]	[-1.24]
$EIA * r_1$									0.016	-0.016	0.003	0.005
									[0.67]	[-0.69]	[0.21]	[0.35]
$EIA * r_3$									0.007	0.001	-0.015	0.082***
									[0.27]	[0.05]	[-0.58]	[3.11]
Obs.	148	148	148	147	662	662	662	663	810	810	810	810
Adj. R^2 (%)	1.09	-0.83	-1.00	7.01	-0.16	0.25	-0.11	1.00	-0.19	-0.06	-0.10	2.01

Notes: This table reports the intraday momentum results based on volatility quartiles. 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 split the sample into quartiles. Q1 represents days with the lowest daily RV, and Q4 represents days with the highest daily 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 one for days with EIA announcements and zero otherwise. Figures in parentheses are the Newey-West (1987) robust t-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

APPENDIX C. INSTRUMENTAL VARIABLES FOR VOLATILITY

	Panel A: OVX		Panel B: VIX		Panel C: GPR		Panel D: CPU	
	Low	High	Low	High	Low	High	Low	High
$Intercept$	0.000	0.000*	0.000*	0.000	0.000	0.000	0.000**	0.000
	[-0.57]	[1.82]	[1.91]	[0.58]	[0.27]	[1.60]	[2.00]	[0.03]
r_1	0.008**	0.012**	-0.004	0.017***	0.011**	0.010	0.005	0.014**
	[2.13]	[2.31]	[-1.10]	[2.94]	[1.97]	[1.52]	[0.97]	[2.41]
r_3	0.000	-0.013	-0.004	-0.015	-0.009	-0.013	0.013	-0.026*
	[0.04]	[-0.91]	[-0.43]	[-1.02]	[-0.56]	[-0.96]	[0.76]	[-1.96]
$EIA * r_1$	-0.012	0.008	0.016	-0.001	-0.010	0.024*	0.002	0.006
	[-1.22]	[0.62]	[1.28]	[-0.05]	[-0.73]	[1.87]	[0.13]	[0.42]
$EIA * r_3$	0.006	0.063***	0.018	0.067***	0.042	0.055***	0.044	0.055**
	[0.34]	[2.83]	[1.18]	[2.71]	[1.42]	[2.70]	[1.61]	[2.54]
Obs.	1,495	1,497	1,622	1,618	1,620	1,620	1,611	1,629
Adj. R^2 (%)	0.09	1.43	0.14	1.7	0.6	1.73	0.92	1.15

Notes: This table reports predictability for periods with high and low volatility. We proxy for volatility using the crude oil implied volatility index, *OVX* (Panel A), stock market implied volatility, *VIX* (Panel B), Geopolitical risk index, *GPR* (Panel C), and Climate policy uncertainty index, *CPU* (Panel D). 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 the Newey-West (1987) robust t-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

APPENDIX D. INSTRUMENTAL VARIABLES FOR INFORMED TRADING AND MARKET LIQUIDITY

	Panel A: Cloud Cover		Panel B: Open Interest	
	High	Low	High	Low
Intercept	0.000	0.000*	0.000*	0.000
	[0.12]	[1.83]	[1.70]	[0.24]
r_1	0.008	0.006	0.009	0.012**
	[1.60]	[1.22]	[1.49]	[2.09]
r_3	-0.025*	0.007	0.010	-0.029*
	[-1.69]	[0.53]	[0.81]	[-1.84]
$EIA * r_1$	0.001	0.006	0.013	-0.005
	[0.06]	[0.49]	[1.09]	[-0.35]
$EIA * r_3$	0.066***	0.028	0.037	0.058**
	[2.60]	[1.53]	[1.64]	[2.23]
Obs.	1,620	1,620	1,618	1,618
Adj. R^2 (%)	0.94	1.31	1.60%	0.94%

Notes: This table reports predictability for high and low cloud cover (Panel A) and high and low open interest (Panel B). 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 the Newey-West (1987) robust t-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

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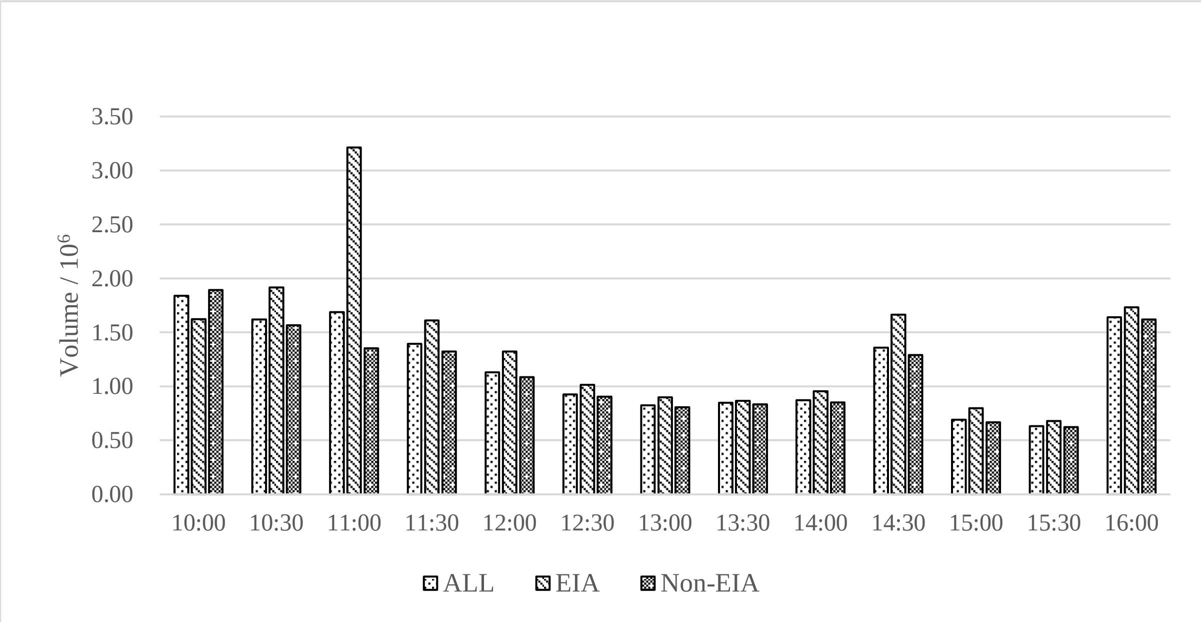
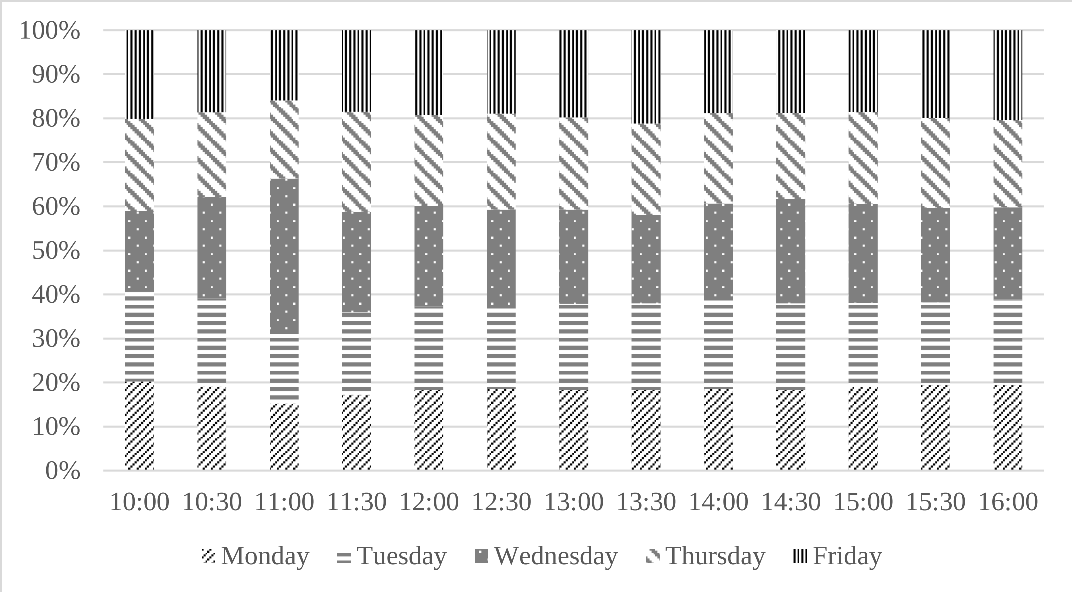
Figure 1: Intraday USO trading volume: EIA and Non-EIA groups



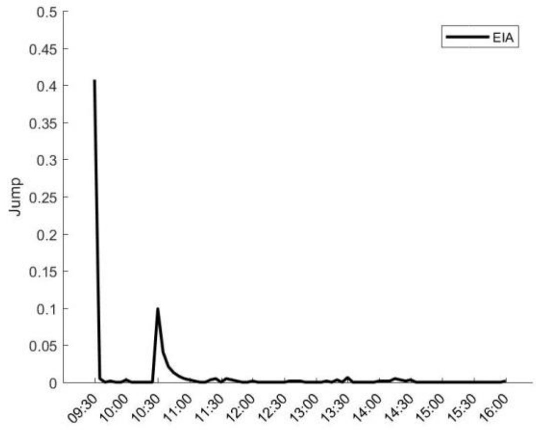
Notes: This figure plots the intraday patterns of the average half-hour trading volume of USO ETF for the total, the EIA, and the Non-EIA groups. The sample period is from April 10, 2006, to July 31, 2019.

Figure 2: Intraday USO trading volume on different days

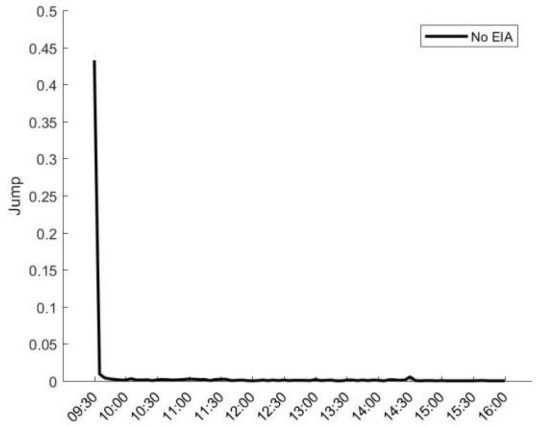


Notes: This figure plots the intraday trading volume across different days throughout the week: Monday, Tuesday, Wednesday, Thursday, and Friday. The sample period is from April 10, 2006, to July 31, 2019.

Figure 3: Intraday jump pattern of USO: EIA and non-EIA groups



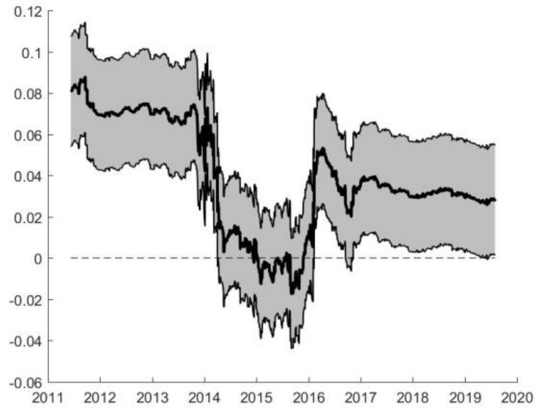
Panel A: EIA group



Panel B: Non-EIA group

Notes: 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.

Figure 4: Intraday momentum over time



Notes: This figure plots the coefficient for the interaction term $EIA * r_3$ from Equation (3) based on rolling window regressions using 5-year daily data (1,250 observations). The estimation is conducted daily, and the period window is rolled over to the following day until the end of the sample period. The figure also plots the 90% confidence interval. The sample period is from April 10, 2006, to July 31, 2019.

Table 1: Intraday momentum: EIA and non-EIA groups

	Panel A: EIA		Panel B: Non-EIA		Panel C: Full Sample	
	[1]	[2]	[1]	[2]	[1]	[2]
Intercept	0.000	0.000	0.000	0.0001	0.000	0.000
	[0.21]	[0.24]	[1.42]	[1.40]	[1.360]	[1.15]
r_1	0.015	0.013	0.011**	0.011**	0.011**	0.010**
	[1.61]	[1.32]	[2.44]	[2.47]	[2.44]	[2.47]
r_3	0.038**	0.042***	0.000	-0.011	-0.011	-0.012
	[2.12]	[2.85]	[-1.02]	[-1.08]	[-1.05]	[-1.11]
$EIA * r_1$					0.004	0.006
					[0.417]	[0.60]
$EIA * r_3$					0.050***	0.043**
					[2.89]	[2.27]
Other intervals	No	Yes	No	Yes	No	Yes
Obs.	591	591	2,649	2,649	3,240	3,240
Adj. R2(%)	3.10	8.15	0.68	1.97	1.16	1.79

Notes: This table reports the results for the intraday momentum pattern. 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 one on days with EIA announcements and zero otherwise. Figures in parentheses are the Newey-West (1987) robust t-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 2: Predicting the source of the first half-hour returns

	Panel A: EIA		Panel B: Non-EIA		Panel C: Full Sample	
	[1]	[2]	[1]	[2]	[1]	[2]
Intercept	0.000	0.000	0.000	0.000	0.000	0.000
	[0.19]	[0.23]	[1.35]	[1.32]	[1.28]	[1.17]
$r_{overnight}$	0.013	0.011	0.013***	0.013***	0.013***	0.012***
	[1.23]	[1.00]	[2.61]	[2.75]	[2.62]	[2.79]
r_{open}	0.034	0.033	-0.006	-0.008	-0.006	-0.007
	[1.57]	[1.42]	[-0.52]	[-0.75]	[-0.53]	[-0.65]
r_3	0.038**	0.042***	-0.011	-0.011	-0.011	-0.012
	[2.07]	[2.79]	[-0.99]	[-1.04]	[-1.01]	[-1.01]
$EIA * r_{overnight}$					0.000	0.001
					[0.02]	[0.07]
$EIA * r_{open}$					0.039	0.041
					[1.24]	[1.38]
$EIA * r_3$					0.049***	0.053***
					[2.78]	[2.73]
Other intervals	No	Yes	No	Yes	No	Yes
Obs.	591	591	2,649	2,649	3,240	3,240
Adj. R^2 (%)	3.24	8.30	0.89	2.25	1.36	2.27

Notes: This table reports the results for the intraday momentum pattern. 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 one for days with EIA announcement and zero otherwise. Figures in parentheses are the Newey-West (1987) robust t-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3: Intraday momentum during periods of low and high volatility

	Panel A: Low-volatility period			Panel B: High-volatility period		
	EIA	Non-EIA	Full Sample	EIA	Non-EIA	Full Sample
Intercept	0.000	0.000	0.000	0.000	0.000	0.000*
	[-0.53]	[-0.03]	[-0.24]	[0.54]	[1.57]	[1.66]
r_1	0.001	0.005	0.005	0.017	0.012**	0.012**
	[0.05]	[0.97]	[0.97]	[1.61]	[2.47]	[2.50]
r_3	0.013	0.012	0.012	0.043**	-0.018	-0.018
	[0.71]	[1.23]	[1.25]	[2.14]	[-1.28]	[-1.32]
$EIA * r_1$			-0.005			0.005
			[-0.30]			[0.42]
$EIA * r_3$			0.0013			0.061***
			[0.06]			[2.95]
Obs.	244	1,382	1,626	347	1,267	1,614
Adj. R^2 (%)	0.25	0.20	0.21	3.89	0.97	1.59

Notes: 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 one for days with EIA announcements and zero otherwise. Figures in parentheses are the Newey-West (1987) robust t-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4: Active portfolio management and intraday momentum

	Panel A: First half of the month		Panel B: Second half of the month	
Intercept	0.000*	0.000	0.000	0.000
	[1.89]	[1.33]	[-0.08]	[-0.47]
r_1	0.009*	0.009*	0.012*	0.012**
	[1.81]	[1.86]	[1.96]	[2.01]
r_3	-0.022	-0.021	0.001	-0.002
	[-1.43]	[-1.40]	[0.05]	[-0.12]
$EIA * r_1$	0.009	0.009	-0.003	-0.002
	[0.84]	[0.86]	[-0.20]	[-0.14]
$EIA * r_3$	0.078***	0.079***	0.014	0.022
	[3.29]	[3.17]	[0.52]	[0.79]
Other Intervals	No	Yes	No	Yes
Obs.	1,604	1,604	1,636	1,636
Adj. R^2 (%)	1.77%	3.21%	0.54%	2.43%

Notes: This table reports the predictability during the first and second half of the month. The sample period is from April 10, 2006, to July 31, 2019. 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 one for days with EIA announcements and zero otherwise. Figures in parentheses are the Newey-West (1987) robust t-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

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

	Panel A: Trade size		Panel B: Price impact		Panel C: Amihud Ratio	
	Small	Large	Low	High	Low	High
Intercept	-0.000	0.000	-0.000	0.000	0.000	-0.000
	[-1.01]	[1.37]	[-1.08]	[1.14]	[1.25]	[-0.72]
r_1	0.009	0.020	0.004	0.024**	0.034**	0.003
	[0.66]	[1.64]	[0.36]	[2.06]	[2.54]	[0.28]
r_3	0.035	0.041*	0.021	0.048**	0.021	0.078**
	[1.30]	[1.80]	[1.29]	[2.17]	[1.23]	[2.59]
Obs.	295	296	296	295	296	295
Adj. R^2 (%)	1.72	5.22	0.80	5.26	4.88	5.17

Notes: 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 the Newey-West (1987) robust t-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6: Market-timing strategy

	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 non-EIA days							
$\eta^{Non-EIA}(r_3)$	-0.36	[-0.37]	0.20	-1.80	-0.86	15.72	57
Panel E: 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

Notes: 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, and E 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 closing 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.

Table 7: Alternative definitions of the third half-hour return

	$r_{10:30-10:35}$	$r_{10:30-10:40}$	$r_{10:30-10:45}$	$r_{10:30-10:50}$	$r_{10:30-10:55}$	$r_{10:30-11:00}$
Intercept	0.000	0.000	0.000	0.000	0.000	0.000
	[1.35]	[1.42]	[1.46]	[1.45]	[1.40]	[1.36]
r_1	0.011**	0.011**	0.011**	0.011**	0.011**	0.011**
	[2.41]	[2.40]	[2.41]	[2.40]	[2.41]	[2.44]
r_3	0.013	0.004	0.000	-0.018	-0.013	-0.011
	[0.45]	[0.18]	[-0.87]	[-1.29]	[-1.09]	[-1.05]
$EIA * r_1$	0.004	0.005	0.005	0.006	0.005	0.004
	[0.42]	[0.49]	[0.48]	[0.56]	[0.53]	[0.42]
$EIA * r_3$	-0.006	0.022	0.052**	0.056**	0.053**	0.050***
	[-0.13]	[0.64]	[1.97]	[2.46]	[2.54]	[2.89]
Obs.	3240	3240	3240	3,240	3,240	3,240
Adj. R^2 (%)	0.65	0.74	0.98	1.07	1.09	1.16

Notes: This table reports the results for the intraday momentum using alternative definitions for the third half-hour returns. The top row shows the various intervals considered for the sensitivity analysis. 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 one on days with EIA announcements and zero otherwise. Figures in parentheses are the Newey-West (1987) robust t-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 8: Intraday momentum: Mondays and other days of the week

	Panel A: Mondays	Panel B: EIA Days	Panel C: Non-Monday non-EIA	Panel D: Full Sample	Panel E: Full Sample
Intercept	0.000	0.000	0.000	0.000	0.000
	[1.37]	[0.21]	[1.12]	[1.48]	[0.17]
r_1	0.025***	0.015	0.006	0.006	0.011**
	[3.17]	[1.61]	[1.00]	[1.05]	[2.45]
r_3	0.016	0.038**	-0.017	-0.017	-0.011
	[0.63]	[2.12]	[-1.40]	[-1.42]	[-1.04]
$Monday * r_1$				0.019**	
				[1.97]	
$Monday * r_3$				0.032	
				[1.23]	
$EIA * r_1$				0.009	0.004
				[0.83]	[0.44]
$EIA * r_3$				0.055***	0.050***
				[2.92]	[2.87]
Day-of-the-week	No	No	No	No	Yes
Obs.	625	591	2,024	3,240	3,240
Adj. R^2 (%)	3.88	2.77	0.23	1.35	1.07

Notes: This table reports the results for the intraday momentum pattern. 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. $Monday$ is an indicator variable that equals one on Mondays and zero otherwise. EIA is an indicator variable that equals one on days with EIA announcements and zero otherwise. Figures in parentheses are the Newey-West (1987) robust t-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.