High Frequency Trading and Intraday Momentum

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Abstract

This paper links high frequency trading (HFT) to intraday momentum regarding the hedging and information efficiency hypotheses. We document that HFT is negatively associated with intraday momentum, which indicates the impact of HFT on price efficiency improvement is more powerful than HFT's rebalance activity for hedging. Investigating the mechanism behind the negative relation, this paper presents the higher order imbalance of HFT results in a weaker intraday momentum and leads to decreases in profits on intraday momentum strategy. To identify intraday momentum reflects under- or over-reaction, we compare the intraday the predictability of last half-hour return on days with news announcements and in the following day. We find macro-news announcements enlarge intraday momentum and price reversal in the following day, supporting the overreaction hypothesis. Moreover, we display that the intraday momentum becomes stronger on days with a positive return, lower stock liquidity, and higher price volatility. Last, this paper directly shows hedging activity of HFT cannot explain the predictability of the last half-hour return, and our placebo tests suggest that non-HFT drives intraday momentum.

Keywords: high frequency trading; intraday momentum; hedging activity; price efficiency; order flow; macroeconomic news

1. Introduction

High Frequency Trading (HFT) have grown substantially since the mid-1990s, and triggered a great deal of concern about its' impact on the stability risk in financial. Especially, after the flash crash in 2010, HFT trading attracts a lot of debates about its' negative impact on financial stability. Trading volume of HFT now accounts for about 80% of U.S. and European stock market activities. A longstanding discussion in finance thus concerns how HFT affects market quality and existing literature suggests HFT brings salutary effects on market quality. (Hendershott, Jones, and Menkveld, 2011; Hendershott and Riordan, 2013; Menkveld, 2013; Brogaard, Hendershott, and Riordan; 2014; Menkveld and Zoican, 2017; Kirilenko, Kyle, Samadi, and Tuzun, 2017; Brogaard, Carrion, Moyaert, Riordan, Shkilko, and Sokolov, 2018). However, there is barely any study on whether HFT play a role in stock return anomalies as they dominate in trading in developed stock markets and the rise of HFT has obvious direct impacts on price formation process.

It is worth noting that HFT traders usually rebalance their positions around the end of financial markets and associate with market efficiency, which are indicated to be the causes for intraday momentum (Gao, Han, Li, and Zhou, 2018; Elaut, Frömmel, and Lampaert, 2018; Baltussen, Da, Lammers, and Martens, 2021). This paper thus analyzes of the impact of HFT on financial market by putting aside the common question of whether or not HFT improves market quality and focuses on two new questions: Do HFT strengthen or weaken the predictability of the last half-hour asset return based on its' first half-hour return on the day, namely intraday momentum? If so, how do HFT affects the intraday momentum?

The intraday momentum can be caused by unloads of market makers around the closing time. As the market open, market makers supply liquidity for those demanders which go with the wind. For risk management purpose, market makers will off-load their positions at the end of the market, and push the price to go with the wind (Gao et al., 2018; Elaut et al., 2018; Lou, Polk, and Skouras, 2019; Baltussen, et al., 2021). HFT is called as new market makers based on their advantage in information collection ability and trading speed, and thus improve the market liquidity (Hendershott et al., 2011; Menkveld, 2013). But, Carrion (2013) suggests that HFT can shift to become demanding liquidity as HFT investors are necessary to rebalance. Figure 1 presents intraday patterns of HFT' liquidity-demanding and liquidity-supplying trades. We observe that HFT actually contributes to create market liquidity at the opening half-hours, but their demand surges during the same time. We further uncover HFT absorbs liquidity at the last half-hour and their contribution to liquidity significantly decline as well. So, it could reflect high frequency traders actually increase their demand at the time. The possible hedge activity can drive intraday momentum.

Information efficiency theory can explain intraday momentum as well. Lou et al. (2019) suggest that the overnight return contains more information and motivates investors' submissions at the opening. However, it does not imply information will be incorporated immediately. From the perspective of inattention hypothesis (Da, Gurun, and Warachka, 2014), the delay for information incorporation can make the prices in the last half-hour continuously react to the same information set in the morning, and thus generate intraday momentum.

Alternatively, Berkman, Koch, Tuttle, and Zhang (2012) indicate the information in the overnight or at the opening can grab retail investors' attention and makes them overreaction. Gao et al. (2018) suggest that some investors who receive or process information lately, are called as late-informed traders, because of the high liquidity at the last half-hour. Thus, late-informed traders and investor overreaction could push price toward the direction as the return on the first half-hour because of their reactions to the stale information. However, HFT can release the negative impact. Previous literature denotes that active HFT improve price discovery through quickly reacting to new information and revising their quote according to updated information set (Brogaard et al., 2014; Chaboud, Chiquoine, Hjalmarsson, and Vega, 2014; Hoffmann, 2014; Brogaard, Hendershott, and Riordan, 2019). We expect that the HFT could speed up information incorporation process if investor inattention to the news. Similarly, HFT can trade against overreaction and correct the inefficiency. Information efficiency hypothesis would indicate that HFT can dwindle intraday momentum.

Our empirical works frame analyses around the relation between the first half-hour return and the last half-hour return through the lens of a dataset of 120 stocks listed on the NASDAQ and NYSE. We present that those stocks exhibit significant intraday momentum after we control for the time and firm fixed effects. We are the first paper to uncover the intraday momentum anomaly in the individual stock markets rather than stock index. Then, we move to our attention to the research question on the influence of HFT trading on intraday momentum. We include the measure of HFT into the novel model in studies of intraday momentum, and present that stocks exhibit weaker intraday momentum as HFT are more active. Irrespective of whether anomalies represent underreaction or overreaction errors, our main finding support the information efficiency hypothesis that HFT associates intraday momentum anomaly.

To disentangle the impact of HFT trading on the intraday momentum, we conduct a further analysis by replacing the measure of HFT with their order imbalance, which is a well know measurement of trading informativeness. If HFT negatively associates with intraday momentum through improving price efficiency, we would discover that order imbalances of HFT revere the positive relation between the first and last half-hour returns to be negative. Our empirical analysis suggests that trading from HFT contains more information and mitigates the intraday momentum anomaly.

Although we have established the correlation between HFT and intraday momentum through revising price inefficiency, we have not identified the price deviation is more likely to be a consequence of underreaction or overreaction. To disclose the concern, we introduce an analysis to discuss whether price reversal in the following days. If the inefficiency is resulted from overreaction, the price will reverse. By contrast, the price will continuous to move toward the same direction if the intraday momentum reflects underreaction. We find that the last half-hour return is negatively correlated with the daily returns in the following day, which supports the late-informed and overreaction hypotheses that responses to stale information drives intraday momentum.

To directly examine the overreaction hypothesis, this paper looks closer at the impact of new information. First, we expect that noise traders would be more aggressively react to positive shocks because the disposition effect suggests that investors are more likely to hold losers and sell winners. Our empirical work obtains that intraday trend become stronger on days with positive return. Moreover, that noise traders are more likely to overreact to news announcements. Tetlock (2011) indicates that individual investors continuously response to stale information, exerting asset prices overreaction. This paper considers the impact of macro news announcement, and discover news releases drive intraday momentum, indicating that investor overreact to news releases. Furthermore, we note that the active HFT can reduce the predictability of the first half-hour return on days with macro news announcements, which is in line with Brogaard et al. (2014) that HFT contribute to price discovery.

Importantly, HFT changes their trading strategy across market conditions. Hendershott and Riordan (2013) indicate that HFT is more likely to shift to take (supply) liquidity as it is cheap (expensive). Considering another market condition, price volatility, Brogaard et al. (2014) show that HFT are more likely to improve price efficiency on days with high volatility. Moreover, higher trading cost (illiquid market) and uncertainty (high price volatility) is shown to enlarge the predictability of the first half-hour return for the last half return (Gao et al., 2018; Baltussen et al., 2021; Li et al., 2022). Thus, we separately examine intraday momentum and its' interaction with HFT on days with the top and bottom tertiles of market liquidity and price volatility. We obtain similar results that intraday momentum is more likely to exist on days with lower liquidity and higher price volatility. And in line with the literature, we find that HFT contributes to price discovery as market shift to be illiquid and volatile.

With regarding to the economic significance, we follow Gao et al. (2018) to compare the performances of intraday momentum strategy in high and low HFT activity, and find that active HFT can alleviate the value of the strategy. Furthermore, the momentum strategy obtains a better performance as lower information content in HFT's order flow is lower. This section further evidences the HFT can remove the arbitrage opportunity from overreaction bias.

Last, we start our robustness test by implementing an examination of hedge hypothesis. Although our primary model has ruled out the possibility that hedging activity drives intraday momentum, we directly track the impact of HFT' liquidity supply and demand in the first half-hour and last half-hour, respectively. Although the coefficients on those variables proxy for hedging activity, we obtain weak evidence that the net liquidity-supplying of HFT is more likely to go with the wind at the first half-hour. Likely, we display that the coefficient on net liquidity-demanding of HFT is insignificantly negative. These findings provide us further evidence for that behavior bias drives intraday momentum, and HFT is against the noise trading.

Then we have a placebo test by replacing our key independent variable with the frequency of non-HFT and total trading volume in the day. Interestingly, we find that the non-HFT is positively associate the predict power of the first half-hour return, indicating the non-HFT drives intraday momentum. Alternatively, the analysis evidences that there is no significant relation between intraday momentum and total trading volume. Additionally, we exploit a new proxy for the HFT, measured by the total trading volume. We still obtain the same findings with our primary model.

Our study contributes primarily to three areas. First, we connect intraday momentum with new market maker, HFT. Although recent literature notes that the intraday momentum can be driven by some specific purposes, e.g., hedge demand, institutional traders' risk management, late-informed trading, infrequent trading, market conditions (Gao et al., 2018; Lou et al., 2019; Baltussen et al., 2021; Li et al., 2022), they never disclosure who could take those actions to cause price moves in the same direction or trade against it.

Second, previous literature indicates that price momentum reflects investor overreaction to information because of behavior bias (Daniel, Hirshleifer, and Subrahmanyam, 1998; Cooper, 1999; Hong and Stein, 1999). This paper echo to their theory and empirical works from the perspective of intraday momentum. We show that the overreaction on the intraday basis can only last for one day; price reversals on the following day. Besides, different from previous literature, this paper uncovers HFT can correct the over-price and therefore reduce the level of price reversal.

Third, there is a vast literature discussing how HFT trading affects financial market quality from the perspectives of liquidity (Hendershott et al., 2011; Hendershott and Riordan, 2013; Brogaard et al., 2018), price discovery (Brogaard et al., 2014; Chaboud et al., 2014), and price volatility (Brogaard et al., 2014; Kirilenko et al., 2017). As our best knowledge, this is the first paper to establish the causal impact of HFT on asset pricing anomaly. The intraday momentum can be a better target for the issue since HFT are believed to build up trading strategy based on daily basis information set and clear their position every day.

In what follows, Section 2 describes our sample and variables and Section 3 documents our preliminary analyses. Section 4 examines possible explanations and implications, and Section 5 conducts robustness checks. Section 6 concludes this study.

2. Sample, and variable definitions

Data on the defining HFT trading and stock price is obtained from NASDAQ, which compromises of 120 randomly selected firms listed on NASDAQ and the NYSE from 2008 to 2009. For each transaction, the data contains the symbol of a firm, date, time in milliseconds, deal price, trading volume, buy-sell indicator, and an identification of liquidity demand or supply from a HFT or non-HFT. The database creates HH, HN, NH, and NN to identify liquidity-supplier and liquidity-taker is HFT or non-HFT for each trade, which provides us the unique advantage to study the impact of HFT in the intraday momentum.

According to the variable definitions of the database, as a trade is denoted as HH, it indicates the liquidity supplier is HFT and the liquidity taker is the same as well. HN indicates the liquidity supplier is non-HFT and the liquidity taker is HFT. In the contrast, as HFT supplies liquidity to non-HFT, it is denoted as NH. NN represents that non-HFT trades with each other. The details give an advantage for discussing the hedging hypothesis that has suggested to be one important determinant for intraday momentum.

For macro news announcements, we collect the historical announcement dates of the Consumer Price Index (CPI), Retail Sales (RETAIL), Purchasing Managers Index (PMI), and Producer Price Index (PPI) from Bureau of Labor Statistics, Bureau of Census, Institute for Supply Management, and Bureau of Labor Statistics, respectively.

3. Main analysis

3.1. Intraday momentum

We start our empirical work by testing whether the intraday momentum exists in the individual stocks in the U.S. This paper follows Gao et al. (2018) to regress the last half-hour return against the first half-hour return

$$r_{i,t}^{LH} = \alpha + \beta r_{i,t}^{FH} + \delta Year + firmFE + \varepsilon_{i,t}\ , \tag{1}$$

where $r_{i,t}^{FH}$ represents the first half-hour return, which is calculated by the different between the close price at 4:00 pm on day *t*-1 and the price at 10:00 am on day *t* eastern time; $r_{i,t}^{LH}$ represents the last half-hour return, which is calculated by the different between the price at 3:30 am and the price at 4:00 am on day *t*. $Year$ and $firmFE$ present the year and firm fixed effect, respectively.

Column (1) of Table 1 reports that the coefficient on $r_{i,t}^{FH}$ is 3.22, indicating that the first half-hour return positively predicts the last half-hour return. On the basis of intraday momentum that the price can persist over the day, we estimate the predictability of the last second half-hour ($r_{i,t}^{SLH}$) for the last half-hour return to examine whether price continuously move toward the same direction in the day. With the re-estimation of the Model (1) by replacing $r_{i,t}^{FH}$ with $r_{i,t}^{SLH}$, Column (2) presents that coefficient on $r_{i,t}^{SLH}$ is significantly positive at 1% level. The both significantly positive numbers imply the intraday momentum patterns. The evidence extends the studies of Gao et al. (2018) and Baltussen et al. (2021) to individual stock level and confirms that intraday momentum exists in U.S. stock markets.

As the coefficients on $r_{i,t}^{FH}$ and $r_{i,t}^{SLH}$ are separately positively significant, a question would emerge that does $r_{i,t}^{SLH}$ just proxy for $r_{i,t}^{FH}$ or have its' own impact on the closed return. We combine $r_{i,t}^{FH}$ and $r_{i,t}^{SLH}$ into a model, and the both coefficients are still economically and statistically significant, shown in the third column. Thus, we know that the prices during the first half-hour and last second half-hour have predictability ability for the price return in the last half-hour individually. Moreover, the joint adjusted R^2 is roughly 1.5%, which is almost the same as the sum of the individual R^2s in Columns (1) and (2). The evidence in last model would demonstrate the predictabilities of $r_{i,t}^{FH}$ and $r_{i,t}^{SLH}$ are independent and complementary.

3.2. The impact of HFT on intraday momentum

Intraday momentum is driven by hedging activity or price inefficiency is an open question (Gao et al., 2018; Baltussen et al., 2021). HFT is critical resource of liquidity supply in past decay. The trading strategy of HFT can make it is required to rebalance they position at the end of the market, which could lead to intraday momentum. Alternatively, HFT can update their quotes with the new information immediately, and reduce the predictability of the first half-hour return for the last half-hour return.

This section examines the correlation between HFT and intraday momentum by including the HFT trading on the day into model (1)

$$r_{i,t}^{LH} = \alpha + \beta r_{i,t}^{FH} + \gamma HFT_{i,t} + \phi r_{i,t}^{FH} \times HFT_{i,t} + \delta Year + firmFE + \varepsilon_{i,t} \quad (2)$$

where $HFT_{i,t}$ presents the frequency of HFT of firm *i* on day *t*, calculated by dividing the sum of total trading volume of HFT by the overall volume of firm *i* on day *t*. The definitions of the other variables are the same as in Equation (1). In this analysis, we pay attention to the sign of ϕ. If ϕ is positive, it implies that HFT is the driver for intraday momentum, or it can lead to a weaker intraday momentum.

Column (1) of Table 2 displays that HFT weaken the predictability of the first half-hour return. After we control for firm fixed effect, Column (2) still shows that the HFT significantly reverse the positive predictability at 1% level. To retrieve the possible effect of time trend, we use difference-in-difference regression to replicated the analysis in the first two columns. Columns (3) and (4) report that higher HFT trading companies with weaker price adjustment toward the same direction no matter we control for time and firm fixed effect or not. Those negative coefficients indicate HFT are more likely to make intraday momentum weaker. Thus, it seems that the finding is more likely to support HFT can increase the price discovery process and speed up the price converge to fundamental values.

4. Mechanism discussion

4.1. Order imbalance of HFT

Section 3 has shown that information efficiency improvement can be more likely to establish causality between HFT and intraday momentum. We directly test the possibility by substituting HFT trading in Equation (2) with order imbalance, which is a measure of the informativeness of HFT. We calculate the order imbalance by the absolute value of dividing the difference in numbers of buy and sell orders by the sum of numbers of buy and sell. If the reduced predictability of the first half-hour return is attributed to the increased price efficiency, we will find that the coefficient on the interaction term of order imbalance of HFT and the first half-hour return is negative.

Column (1) of Table 4 reports that order imbalance of HFT reduces the predictability of the first half-hour return, and Column (2) retains the same conclusion after we include the time and firm fixed effects into our model. To remove the impact of time trend, we run a difference-in-difference regression and report results in Columns (3) and (4). Our empirical results confirm the finding that informativeness of HFT order flows contributes to price efficiency and so as reduce the predictability of the first half-hour turn on the last half-hour return.

Moreover, comparing the Adjusted R^2 of Columns (2) and (4) in Table 4 with the numbers in Table 2, we find the predictive power proxy for HFT becomes stronger, supporting the informativeness of HFT trading can be important for bridging HFT and intraday momentum.

4.2. Underreaction or overreaction

Despite the negative relation between HFT and intraday momentum is obtained in previous sections, it does not necessarily imply the HFT can completely resolve the inefficiency. Especially, until now, we do not understand the inefficiency is resulted from underreaction or overreaction. If the intraday momentum is caused by underreaction, we will find the returns continue in next day. Conversely, the price will reversal in the following day if the intraday momentum represents for overreaction.

In this section, we examine whether price will continue to move toward the same direction or reversal in the following day by regressing the following day return on the last half-hour return today. Additionally, we include the HFT trading into the model to examine its' impact on the following day return. This paper substitutes last half-hour return with the daily return ($r^{W}_{i,t+1}$) in the following day in the Models (1) and (2) to investigate the under- and over-reaction arguments.

Columns (1) and (2) of Table 4 display a negative relation between $r^{LH}_{i,t}$ and $r^{W}_{i,t+1}$, implying that stock return reversals in the following day no matter we control for the year and firm fixed effects or not. Alternatively, we substitute the daily order imbalance with the first half-hour order imbalance in day *t*, and show results in Columns (3) and (4). The coefficients on $r^{LH}_{i,t+1}$ are still significantly negative. Thus, we know that intraday momentum is more likely to results from overreaction.

Based on the information improvement hypothesis, we expect that the HFT trading can reduce the level of price reversal in the following day, that is the coefficient on the interaction of $r^{LH}_{i,t}$ and HFT must be positive. Table 4 reports that the coefficients of our target variable are significantly positive, implying that HFT can reduce the level of price reversal. This finding further supports that HFT can speed up the price converts to the fundamental value. Importantly, this section confirms that the overreaction leads to intraday momentum and HFT arbitrages the deviation to correct the inefficiency.

4.3. Asymmetry between positive and negative shocks

Considering that investor can differently react to good and bad news (Soroka, 2006; Eil and Rao, 2011; Willian, 2015), this paper examines whether investors heterogeneously react to positive and negative surprises and affect the existence of intraday momentum. Especially, we have shown that the intraday momentum is resulted from overreaction; disposition effect suggests that investors aggressively response to good news, but passively response to bad news (Barberis, Huang, and Santos, 2002; Frazzini, 2006). Accordingly, we conjecture that the predictability of the first half-hour return is more powerful on days with positive return.

This paper classifies our samples into days with positive and negative returns and re-estimate our models (1) and (2). Columns (1) and (2) in Table 5 show that the positive correlation between $r_{i,t}^{FH}$ and $r_{i,t}^{LH}$ is economically and statistically stronger on days with positive return than days with negative return. Our empirical consequence indicates the intraday momentum is more pronounced as good news is released.

The difference between good and bad news in affecting investors' trading behavior can also change HFT' strategy. The disposition effect can reduce the arbitrage opportunity, and thus reduce the function of HFT in making the last half-hour return less predictable. Column (3) of Table 5 presents that the HFT can reverse the positive relation between $r_{i,t}^{FH}$ and $r_{i,t}^{LH}$, but it does not work in Column (4). The overreaction hypothesis and disposition effect play important role in understanding the intraday momentum.

4.4. Macro news announcement

This section directly studies the intraday momentum and the function of HFT trading in price movement on the basis of macroeconomic news announcements. Although previously, we have known that the investors' aggressive reaction to news can lead to intraday momentum, we have not tested the arguments around the windows of news releases. We follow previous literature (Andersen, Bollerslev, Diebold, and Vega, 2003) to focus on four major announcements, including CPI, Retail, ISM, and PPI, and look into how intraday momentum varies around those windows.

This section estimates the model (1) on days with and without the four types of macro news, respectively, to compare the predictability of the first half-hour return. Then, we estimate model (2) around those four announcements as well. Column (1) of Panel A, Table 6 reports that the coefficient on $r_{i,t}^{FH}$ is 9.05 and significant at 1% level on days with CPI announcements. But, the coefficient decreases to 2.99 on days without CPI announcements. Even, the R^2 decreases from 5.2% to 0.4%. The studies of intraday momentum based on the windows around the next three macro news announcements provide identical patterns. Panel A concludes that on the profitability of intraday momentum is higher on days with news releases, supporting the overreaction hypothesis rather than underreaction.

Next, we pay our attention to the interaction term of $r_{i,t}^{FH}$ and HFT. The Column (1) of Panel B, Table 6 reports that coefficients on $r_{i,t}^{FH} \times HFT$ drop from -22.4 to -4.66 comparing days with and without news announcements. The R^2 also drops from 6.5% to 0.4%. This indicates that much of the alleviating power of HFT for the positive relation between $r_{i,t}^{FH}$ and $r_{i,t}^{LH}$ is due to news announcements attract investors' attention and lead to overreaction, which is shown in Panel A.

4.5. Market conditions

Market illiquidity and high volatility could make price inefficiency (Admati and Pfleiderer, 1988; Chakravarty, Gulen, and Mayhew, 2004; Da, Engelberg, and Gao, 2015), and this section thus exploits the subsample analysis to assess how well the intraday momentum carries out as the market is less liquid and volatile. If the price inefficiency is the key driver for intraday momentum, we will find that intraday momentum becomes greater as market illiquidity and price volatility expand. Moreover, market microstructure has shown that the HFT is responsible for market making in this new era, and they can immediately update their quotes as they detect new information (Hendershott et al., 2011; Hendershott and Riordan, 2013; Hoffmann, 2014; Brogaard et al., 2019). Likely, literature responses to the highly concerned issue that whether active HFT bring in high volatility. Broggard et al. (2018) indicate HFT does not induce abnormal price volatility. To reconcile those studies on intraday momentum and HFT trading, we conjecture that the connection between the two issues can be tighten on days with high illiquidity and price volatility.

Following Gao et al. (2018), this paper sorts all trading days of a firm in our sample by the first half-hour liquidity, and divide them into three groups: high, medium, and low liquidity days. Then, we separately estimate models (1) and (2) for the three terciles. We also have the same analysis considering price volatility.

The first three columns in Panel A of Table 7 demonstrates the predictability of the last half-hour return is a decreasing function of liquidity. As the first half-hour liquidity is low, predictability is maximal, with an R^2 of 2% and a significantly coefficient for the first half-hour return. At the intermediate liquidity level, the R^2 decreases to 0.7% and the coefficient of the first half-hour return becomes smaller. Finally, when the first half-hour liquidity is high, both the R^2 and the coefficient are almost the same as sample with intermediate liquidity level. In sum, Panel A indicates intraday momentum is larger on days with higher illiquidity. Thus, we show that higher illiquidity companies with larger intraday momentum, which is in line with Gao et al. (2018).

To further investigate the potential causal role of HFT in intraday momentum, we track how changes in HFT trading affect the intraday momentum during days with different liquidity levels. The last three columns support our conjecture that the impact of HFT trading appears stronger according to the corresponding coefficients, t-values, and R^2.

Next, we employ the same empirical strategy to identify the role of price volatility in intraday momentum. Panel B of Table 7 displays the estimates of models (1) and (2) under disparate levels of price volatility. The first three columns show the predictive ability of the first half-hour return is stronger on the high volatility days, echoing the uncertainty hypothesis. Zhang (2006) and Gao et al. (2018) indicates that high volatility reflect high uncertainty and price trend will persist over time.

Wu et al. (2022) indicate that high uncertainty can make price less efficiency as the arbitrage cost increase. In this situation, we expect HFT are more important in facilitating information digestion and therefore reducing intraday momentum. Column (4) of Table 7 reports the predictability power of the first half-hour return is barely affected. However, the impact of HFT on the predictive ability of the first half-hour return rise as the price volatility increases, which seems intuitive that HFT contribute more to price efficiency as price deviation is more difficult to exploit away with high uncertaity.

5. Robustness checks

5.1. Market timing

This section echoes what we obtained in previous section from the performances of intraday momentum strategy. First, if the intraday momentum actually exists in the market, we would find the strategy works. Second, considering the impact of HFT, if HFT reduces the predictability of the first half-hour return for the further price movements, the profits on the intraday momentum strategy can decrease on days with active HFT.

We follow Gao et al. (2018) to calculate the arbitrage return based on the sign of first half-hour return. If the first half-hour return of a stock is positive, we purchase the stock at the beginning of the last half-hour or short the stock otherwise. Thus, the corresponding return on our strategy will be $r_{i,t}^{LH}$ as the first half-hour return reveal a positive signal, otherwise, the return will be $-r_{i,t}^{LH}$. The performance on the intraday momentum mathematically can be represented as

$$\eta(\mathrm{r}^{\mathrm{FH}}) = \begin{cases} \mathrm{r}^{\mathrm{LH}}, & \text{if } \mathrm{r}^{\mathrm{FH}} > 0 \\ -\mathrm{r}^{\mathrm{LH}}, & \text{if } \mathrm{r}^{\mathrm{FH}} <= 0 \end{cases}$$

For robustness purpose, Gao et al. (2018) employ sharp ratio and the success rate to measure performances of different strategy. The defined of success rate is calculated as the ratio of number of zero or positive returns in the day.

Panel A of Table 8 presents summary statistics on intraday momentum returns. We find that the intraday momentum strategy can yield 11.09% on an annual basis, which lead to a sharp ratio of 4.41. Also, the success rate is 51.63, which is higher than 50%. Those numbers indicate intraday momentum strategy can work in the U.S. stock market.

Then, we move to study how HFT interrupt the performance of intraday momentum strategy comparing the benchmark in Panel A. This paper categories our samples into three groups: high, medium, and low HFT trading days based on trading volume. We separately compute the means of market timing performances for the days with high and low HFT. Panel B of Table 8 presents the average return on days with low HFT trading volume outperforms that on days with high HFT trading volume. The sharp ratio and success rate on days with low HFT trading volume perform better than days with active HFT. Those results evidence intraday momentum strategy is better on days with less active HFT, supporting that the active HFT can remove the profitability of the first half-hour return.

Section 4 indicates that HFT can release the intraday momentum effect by improving price efficiency. We further category our samples into three groups based on order imbalance. If the informativeness contained in HFT' order flow determines the intraday momentum, we would find that the performances of intraday momentum can be better on days with less informed HFT. Panel C presents that the average return on intraday momentum is 5.27%, which is higher than 4.40% and 4.31% in Panels A and B. Similarly, based on the Sharp ratio and success rate, we find that the performance of intraday momentum reaches the peak on days with lower HFT order imbalance. So, this section not only supports that the intraday momentum strategy is profitable, but also indicates informativeness of the HFT trading is critical for the strategy.

5.2. Test for hedging hypothesis

The previous section has provided evidence to show that HFT is more likely to influence the intraday momentum by improving price efficiency, but we cannot rule out the mechanism of hedging activity that HFT supply liquidity at the first half-hour and rebalance their position by taking liquidity at the last half-hour. This section builds up a model to access the connection between HFT' hedging activity and intraday momentum.

First, we create the hedging variables by calculating the HFT' net supply and demand in the direction of the first half-hour return, which is similarly used in Broggard et al. (2018). For example, if the first half-hour return is positive, the HFT liquidity supply ($HFT^{\mathrm{FS}+}$) in the same direction is the difference between NH buy and NH sell and the HFT liquidity demand (HFT^{FD+}) in the same direction is the difference between

NH buy and NH sell in the first half-hour. Then, the net liquidity supply of HFT (HFT^{FNS+}) in the first half-hour is computed by subtracting HFT^{FD+} from HFT^{FS+}. We calculate similar a metric for net liquidity demand of HFT in the last half-hour (HFT^{LND+}). We define the hedge activity ($Hedging$) equals one if the both numbers of HFT^{FNS+} and HFT^{LND+} are larger than zero. Likely, we build up two dummy variables, including $DHFT^{FNS+}$ or $DHFT^{LND+}$, to capture the HFT' hedging activity, which equals one if HFT^{FNS+} or HFT^{LND+} is larger than 0, respectively. Then, we follow Baltussen et al. (2021) to build up the model

$$r_{i,t}^{LH} = \alpha + \beta r_{i,t}^{FH} + \phi r_{i,t}^{FH} \times Hedging_{i,t} * + \delta Year + firmFE + \varepsilon_{i,t}$$

Based on the model, we expect that ϕ is positive if HFT' hedging activity drive the intraday momentum. Moreover, to shed more lights on the impact of HFT on intraday momentum, we further separately estimate models with replacing $Hedging$ with $DHFT^{FNS+}$ and $DHFT^{LND+}$. Regarding the hedging hypothesis, HFT supply liquidity in the first half-hour and the coefficient on $DHFT^{FNS+}$ is therefore positive. Correspondingly, the coefficient on $DHFT^{LND+}$ is positive as HFT shift to take liquidity at the last half-hour for the purpose of rebalancing.

Column (1) of Table 9 displays that the coefficient on $r_{i,t}^{FH} \times Hedging_{i,t}$ is insignificantly, which is not identical to the expectation of the hedge hypothesis. To further understand HFT' hedging activity, we re-estimate the Equation (4) with including $DHFT^{FNS+}$ and $DHFT^{LND+}$. Column (2) of Table 9 reports insignificantly positive coefficient on $r_{i,t}^{FH} \times DHFT^{FNS+}$ and indicates that HFT liquidity supply in the first half-hour actually drives intraday momentum.

Yet, although the coefficient on $r^{FH} \times DHFT^{LND+}$ is insignificant, we obtain a contrary result that HFT' liquidity demanding reduces the predictability of the first half-hour return rather than being a driver of intraday momentum. The result reveals that the HFT trade at the opposite side of the last half-hour return after we control for fixed effects. In sum, this section confirms that HFT do not drive intraday momentum by hedging activity.

5.3. Placebo test

The results in the previous section cannot rule out the possibility that the frequency of HFT trading volume proxies for market liquidity, which improves market efficiency. To distinguish the alternative scheme from the effect of HFT trading, we conduct placebo tests using two alternative measurement of trading activity: (i) daily trading volume (*Volume*) and (ii) the frequency of non-HFT trading volume (*non-HFT*).

First, we replicate Table 2 by regressing the last half-hour return on $r_{i,t}^{FH}$, *Volume,* and the interaction term of $r_{i,t}^{FH}$ and *Volume* and reports results in Table 10. Colum (1) displays that coefficient on the interaction term of $r_{i,t}^{FH}$ and *Volume* is 2.25 (*t*-value =2.29), indicating total trading volume on the day cannot depict the intraday momentum effect.

Next, we replace *HFT* with *non-HFT* to have our second placebo test. Surprisingly, Panel B of Table 10 presents that the coefficient on $r_{i,t}^{FH}$ shifts to be negative and insignificant. However, the interaction term of $r_{i,t}^{FH}$ and *non-HFT* is significantly positive, implying the *non-HFT* is the main driver of intraday momentum. It implies that non-HFT would drive asset price away from the fundamental and make price inefficiency.

So, our placebo tests not only confirm that the HFT actually captures the HFT activities, but also confirm that there are some noise trading delays price discovery process and lead to intraday momentum.

5.4. Alternative variables

We conclude this paper by having an alternative measurement of our key independent variable, HFT, to confirm our empirical finding is robust. This section directly exploits the total trading volume of HFT to predict the impact of HFT. This paper replaces the HFT in model (2) with the natural logarithm of the total trading volume of HFT on the day. Columns (1) and (2) of Table 11 presents that the coefficients on the interaction term of the $r_{i,t}^{FH}$ and *HFT* are significantly negative no matter we consider the year and firm fixed effects or not. Also, the adjusted R^2s in Columns (1) and (2) are almost the same as we obtained in Table 2.

We implement the difference-in-difference analysis to remove the time trend effect. In both cases in Columns (3) and (4), the results are similar in coefficient, statistical significance, and the goodness of fit in regression models. The results are consistent with what we obtained in Table 2. Thus, this analysis collaborates our main findings in previous sections.

6. Conclusions

This paper contributes to the central debate in finance on the notion of intraday momentum by proposing a test based on high-frequency individual stock trading data. We present that the intraday momentum existing in the U.S. stock market. Additionally, this paper considers whether the most important market makers, HFT investors, impact the intraday momentum, and show a negative association between the intraday momentum and HFT. The finding is more likely to support that price inefficiency is one of the drivers of intraday momentum, and HFT can weaken the momentum by improving price efficiency.

To shed light on our main findings, we examine whether the information content in HFT order flow can reduce the predictability of the first half-hour return for the last half-hour return and evidence that the predictability decreases as the order imbalance of HFT increases. This provides direct evidence that price deviations from the fundamental prices lead to the momentum. But, is it a result of overreaction or underreaction? To answer the question, we regress the next day return on the first half-hour return, and show price reversals in the following days. We further study the intraday momentums around windows of the direction of price movement, macro news announcements, and divergent market conditions. We discover the predictability of the first half-hour return become stronger on days with positive return, news releases, low stock liquidity and high price volatility. Moreover, we demonstrate that HFT is negatively associated with intraday momentum under those heterogenous conditions. Alternatively, the non-HFT enhance the predictability of the first half-hour return, supporting the behavioral bias again.

Reference

Andersen, T. G., Bollerslev, T., Diebold, F. X., Vega, C., 2003. Micro effects of macro announcements: Real-time price discovery in foreign exchange. *American Economic Review* 93, 38-62.

Barberis, N., Huang, M., Santos, T., 2002. Prospect theory and asset prices. *Quarterly Journal of Economics* 116, 1-54.

Baltussen, G., Da, Z., Lammers, S., Martens, M., 2021. Hedging demand and market intraday momentum. *Journal of Financial Economics* 142, 377-403.

Berkman, H., Koch, P., Tuttle, L., Zhang, Y., 2012. Paying attention: overnight returns and the hidden cost of buying at the open. Journal of Financial Quantative Analysis 47, 715-741.

Brogaard, J., Hendershott, T., Riordan, R., 2014. High-frequency trading and price discovery. *Review of Financial Studies* 27, 2267-2306.

Brogaard, J., Carrion, A, Moyaert, T., Riordan, R., Shkilko, A., Sokolov, K., 2018. High frequency trading and extreme price movements. *Journal of Financial Economics* 128, 253-265.

Brogaard, J., Hendershott, T., Riordan, R., 2019. Price discovery without trading: Evidence from limit orders. *Journal of Finance* 74, 1621-1658.

Carrion, A., 2013. Very fast money: High-frequency trading on the NASDAQ. *Journal of Financial Markets* 16, 680-711.

Chaboud, A. P., Chiquoine, B., Hjalmarsson, E., Vega, C., 2014. Rise of the machines: Algorithmic trading in the foreign exchange market. *Journal of Finance* 69, 1540-6261.

Chakravarty, S., Gulen, H., Mayhew, S., 2004. Informed trading in stock and option markets. *Journal of Finance* 59, 1235-1257.

Cooper, M., 1999. Filter rules based on price and volume in individual security overreaction. *Review of Financial Studies* 12, 901-935.

Da, Z., Engelberg, J., Gao, P., 2015. The sum of all fears investor sentiment and asset prices. *Review of Financial Studies* 28, 1-32.

Da, Z., Gurun, U. G., Warachka, M., 2014. Frog in the pan: Continuous information and momentum. *Review of Financial Studies* 27, 2171-2218.

Daniel, K., Hirshleifer, D., Subrahmanyam, A., 1998. Investor psychology and investor security market under-and overreactions. *Journal of Finance* 53, 1839-1886.

Eil, D., Rao, J. M., 2011. The good news-bad news effect: Asymmetric processing of objective information about yourself. *American Economic Journal: Microeconomics 3*, 114-38.

Elaut, G., Frömmel, M., Lampaert, K., 2018. Intraday momentum in FX markets: Disentangling informed trading from liquidity provision. *Journal of Financial Market* 37, 35-51.

Frazzin, A., 2006. The disposition effect and uderreaction to news. *Journal of Finance* 61, 2017-2046.

Gao, L., Han, Y., Li, S. Z., Zhou, G., 2018. Market intraday momentum. *Journal of Financial Economics* 129, 394-414.

Hendershott, T., Riordan, R., 2013. Algorithmic trading and the market for liquidity. *Journal of Financial Quantitative Analysis* 48, 1001-1024.

Hendershott, T., Jones, C. M., Menkveld, A. J., 2011. Does algorithmic trading improve liquidity? *Journal of Finance* 66, 1-33.

Hoffmann, P., 2014. A dynamic limit order market with fast and slow traders. *Journal of Financial Economics* 113, 156-169.

Hong, H., Stein, J., 1999. A unified theory of underreaction, momentum trading, and overreaction in asset markets. *Journal of Finance* 54, 2143-2184.

Kirilenko, A., Kyle, A. S., Samadi, M., Tuzun, T., 2017. The flash crash: High frequency trading in an electronic market. *Journal of Finance* 72, 967-998.

Li, Z., Sakkas, A., Urquhart, A., 2022. Intraday time series momentum: Global evidence and links to market characteristics. *Journal of Financial Markets* 57, 100619

Lou, D., Polk, C., Skouras, S., 2019. A tug of war: Overnight versus intraday expected returns. *Journal of Financial Economics* 134, 192-213.

Menkveld, A.J., 2013. High frequency trading and the new-market makers. *Journal of Financial Markets* 16, 712-740.

Menkveld, A. J., Zoican, M. A., 2017. Need for speed? Exchange latency and liquidity. *Review of Financial Studies* 30, 1188-1228.

Murphy, D., Thirumalai, R. S., 2013. Short-term return predictability and repetitive institutional net order activity. *Journal of Financial Research* 40, 455-477.

Hendershott, T., Riordan, R., 2013. Algorithmic trading and the market for liquidity. *Journal of Financial and Quantitative Analysis* 48, 1001-1024.

Menkveld, A. J., 2013, High frequency trading and the new market makers. *Journal of Financial Markets* 16, 712-740.

Soroka, S. N., 2006. Good news and bad news: Asymmetric responses to economic information. *The Journal of Politics 68*, 372-385.

Tetlock, P. C. (2011). All the news that's fit to reprint: Do investors react to stale information? *The Review of Financial Studies 24*, 1481-1512.

Williams, C. D., 2015. Asymmetric responses to earnings news: A case for ambiguity. *The Accounting Review 90*, 785-817.

Zhang, X. F., 2006. Information uncertainty and stock returns. *Journal of Finance* 61, 105-137.

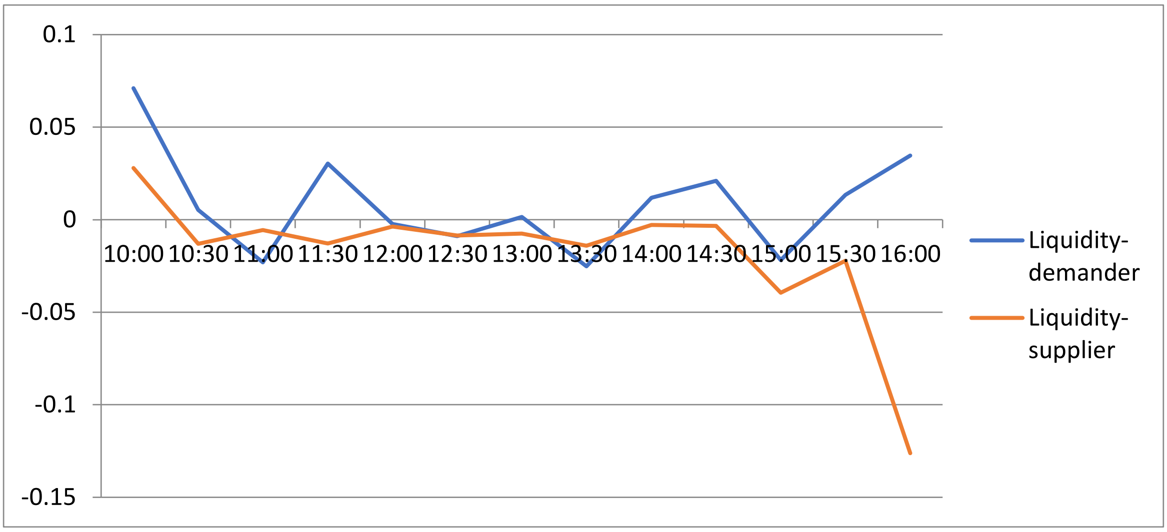

Figure 1. Intraday pattern of HFT

This figure presents the fraction of net HFT liquidity-demanding and liquidity-supplying volume in the direction of the price return from 9:30 to 16:00. According to the identification of each transaction, we classify each HFT into liquidity-demander and liquidity-supplier, and sum the trading volume by its liquidity motivation by every 30 minutes.

Table1. The intraday momentum regressions

This table presents results of the predictability of the first half-hour return on the last half-hour return by the fixed effect regression, which is as follows:

$$r_{i,t}^{LH} = \alpha + \beta r_{i,t}^{FH} + \delta Year + firmFE + \varepsilon_{i,t}$$

where $r_{i,t}^{FH}$ represents the first half-hour return, which is calculated by the different between the close price at 4:00 pm on day *t*-1 and the price at 10:00 am on day *t* eastern time; $r_{i,t}^{LH}$ represents the last half-hour return, which is calculated by the different between the price at 3:30 am and the price at 4:00 am on day *t*. To further understand the intraday momentum, this paper replaces the first half-hour return with the last second half-hour return ($r_{i,t}^{SLH}$) in the regression model. Firm and year fixed effect is included in this table. The *t*-statistics are provided in parentheses and calculated with heteroskedasticity-robust standard errors clustered by firm. ***, **, or * indicate significance at the 1%, 5%, and 10% level, respectively. To make numbers in the table readable, coefficients and Adjusted R^2 are multiplied by 100.

	r^{LH}		
	(1)	(2)	(3)
r^{FH}	3.22***		3.02***
	(8.11)		(7.78)
r^{SLH}		13.0***	12.7***
		(13.94)	(13.91)
Intercept	0.86**	0.93**	0.83**
	(2.09)	(2.27)	(2.00)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	58,429	58,546	58,429
Adjusted R^2	0.5	1.1	1.5

Table2. The intraday momentum and high frequency trading (HFT)

This table presents results of the impact of HFT trading on the predictability of the first half-hour return on the last half-hour return by the following model:

$$r_{i,t}^{LH} = \alpha + \beta r_{i,t}^{FH} + \gamma HFT_{i,t} + \phi r_{i,t}^{FH} \times HFT_{i,t} + \delta Year + firmFE + \varepsilon_{i,t}$$

where $r_{i,t}^{FH}$ represents the first half-hour return, which is calculated by the different between the close price at 4:00 pm on day *t*-1 and the price at 10:00 am on day *t* eastern time; $r_{i,t}^{LH}$ represents the last half-hour return, which is calculated by the different between the price at 3:30 am and the price at 4:00 am on day *t*. $HFT_{i,t}$ presents the frequency of HFT trading of firm *i* on day *t*, calculated by dividing the sum of total trading volume of HFT by the overall volume of firm *i* on day *t*. Firm and year fixed effect is included in our model. The *t*-statistics are provided in parentheses and calculated with heteroskedasticity-robust standard errors clustered by firm. ***, **, or * indicate significance at the 1%, 5%, and 10% level, respectively. To make numbers in the table readable, coefficients and Adjusted R^2 are multiplied by 100.

	r^{LH}		Δr^{LH}	
	(1)	(2)	(3)	(4)
r^{FH}	5.47***	5.30***		
	(7.30)	(7.43)		
HFT	-5.99**	-1.62		
	(-2.33)	(-0.38)		
r^{FH}×HFT	-5.95***	-5.29***		
	(-3.92)	(-3.68)		
Δr^{FH}			8.15***	7.91***
			(8.96)	(8.61)
ΔHFT			2.74	2.81
			(0.37)	(0.38)
Δr^{FH}×HFT			-7.41***	-6.74***
			(-3.78)	(-3.40)
Intercept	4.31***	2.15	2.16***	2.20***
	(2.85)	(1.00)	(4.74)	(8.13)
Firm FE	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	58,429	58,429	57,507	57,507
Adjusted R^2	0.5	0.6	1.4	1.3

Table 3 Intraday momentum and HFT order imbalance

This table presents results of the impact of HFT' order imbalance on the predictability of the first half-hour return on the last half-hour return by the following model:

$$r_{i,t}^{LH} = \alpha + \beta r_{i,t}^{FH} + \gamma HFT_{i,t}^{OF} + \phi r_{i,t}^{FH} \times HFT_{i,t}^{OF} + \delta Year + firmFE + \varepsilon_{i,t}$$

where $r_{i,t}^{FH}$ represents the first half-hour return, which is calculated by the different between the close price at 4:00 pm on day *t*-1 and the price at 10:00 am on day *t* eastern time; $r_{i,t}^{LH}$ represents the last half-hour return, which is calculated by the different between the price at 3:30 am and the price at 4:00 am on day *t*. $HFT_{i,t}^{OF}$ presents the order flows of HFT trading of firm *i* on day *t*, calculated by the absolute value of dividing the difference in numbers of buy and sell orders by the sum of numbers of buy and sell of firm *i* on day *t*. Firm and year fixed effect is included in our model. The *t*-statistics are provided in parentheses and calculated with heteroskedasticity-robust standard errors clustered by firm. ***, **, or * indicate significance at the 1%, 5%, and 10% level, respectively. To make numbers in the table readable, coefficients and Adjusted R^2 are multiplied by 100.

	r^{LH}		Δr^{LH}	
	(1)	(2)	(3)	(4)
r^{FH}	4.31***	4.27***		
	(8.19)	(7.92)		
HFT^{OF}	3.06	-4.50		
	(1.06)	(-1.44)		
$r^{FH}\times HFT^{OF}$	-8.87***	-7.86***		
	(-3.48)	(-3.02)		
Δr^{FH}			7.11***	6.94***
			(7.48)	(7.54)
ΔHFT^{OF}			2.31	2.36
			(0.35)	(0.37)
$\Delta r^{FH}\times HFT^{OF}$			-5.67***	-5.58***
			(-2.71)	(-2.75)
Intercept	2.62***	3.89***	5.83***	7.63***
	(4.16)	(6.73)	(8.95)	(29.45)
Firm FE	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	58,427	58,427	57,507	57,507
Adjusted R^2	0.4	0.7	1.2	1.4

Table 4 Intraday momentum, HFT trading, and the next day return

This table presents results of the predictability of the daily return on day *t*+1 ($r^{W}_{i,t+1}$) on the first half-hour return ($r^{LH}_{i,t}$) on day *t*, and the impact of HFT order imbalance on the connection between $r^{W}_{i,t+1}$ and $r^{LH}_{i,t}$. Besides the first half-hour return on day *t*+1, definitions of the other variables in this table are consistent with that of Table 3. Firm and year fixed effect is included in our model. The *t*-statistics are provided in parentheses and calculated with heteroskedasticity-robust standard errors clustered by firm. *** , ** , or * indicate significance at the 1%, 5%, and 10% level, respectively.

	r^{W}			
	Daily order imbalance		First half-hour order imbalance	
	(1)	(2)	(3)	(4)
r^{LH}	-36.3***	-36.3***	-37.6***	-37.6***
	(-15.52)	(-15.48)	(-13.60)	(-13.54)
HFT^{OF}	-3.85	-1.21	-2.53	-7.91
	(-0.48)	(-1.14)	(-0.48)	(-1.26)
$r^{LH}\times HFT^{OF}$	46.5***	45.6***	34.4***	33.8***
	(2.89)	(2.85)	(2.94)	(2.89)
Intercept	16.0***	17.3***	16.0***	17.4***
	(8.81)	(8.34)	(8.72)	(8.35)
Firm FE	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	57,622	57,622	57,416	57,416
Adjusted R^2	1.0	0.8	1.0	0.9

Table5 Conditional intraday momentum

This table presents results of the impact of HFT trading on the predictability of the first half-hour return on the last half-hour return, using the model in Table 2, on days with positive and negative returns based on the price change in the first half-hour, respectively. The *t*-statistics are provided in parentheses and calculated with heteroskedasticity-robust standard errors clustered by firm. ***, **, or * indicate significance at the 1%, 5%, and 10% level, respectively. To make numbers in the table readable, coefficients and Adjusted R^2 are multiplied by 100.

	r^{LH}			
	(1) $r^{FH}>0$	(2) $r^{FH}<0$	(3) $r^{FH}>0$	(4) $r^{FH}<0$
r^{FH}	5.94***	1.90**	8.23***	3.77**
	(9.35)	(2.56)	(7.19)	(2.28)
HFT			17.7**	-13.2**
			(2.44)	(-2.00)
$r^{FH}\times$HFT			-9.68***	-5.76
			(-2.84)	(-1.45)
Intercept	-6.37***	4.11***	-13.3***	10.0***
	(-5.60)	(3.57)	(-3.52)	(2.92)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	27,856	29,692	27,856	29,692
Adjusted R^2	1.5	0.2	1.5	0.2

Table 6. The impact of news announcements on intraday momentum

This table presents results of the predictability of the first half-hour return on the last half-hour return, using the model in Table 1, on days with (*Release*) and without (*Nonrelease*) macro news announcements, respectively, in Panel A. Then, considering the impact of HFT, Panel B present presents results of the impact of HFT on the predictability of the first half-hour return on the last half-hour return, using the model in Table 1, on days with (*Release*) and without (*Nonrelease*) macro news announcements, respectively, by the model in Table 2. This analysis considers four common macroeconomics indicators, including Consumer Price Index (CPI), Retail Sales (RETAIL), Purchasing Managers Index (PMI), and Producer Price Index (PPI). The *t*-statistics are provided in parentheses and calculated with heteroskedasticity-robust standard errors clustered by firm. *** , ** , or * indicate significance at the 1%, 5%, and 10% level, respectively. To make numbers in the table readable, coefficients and Adjusted R^2 are multiplied by 100.

Panel A								
	Release	*Nonrelease*	*Release*	*Nonrelease*	*Release*	*Nonrelease*	*Release*	*Nonrelease*
	CPI		RETAIL		ISM		PPI	
r^{FH}	9.05***	2.99***	8.78***	2.82***	5.31***	3.11***	13.5***	2.83***
	(7.30)	(7.41)	(6.76)	(7.24)	(5.17)	(7.53)	(9.25)	(7.25)
Intercept	39.7***	-1.07**	9.21***	0.59	3.94***	0.70	-6.68***	1.34***
	(27.87)	(-2.58)	(6.62)	(1.40)	(3.12)	(1.62)	(-4.33)	(3.31)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,826	55,603	2,813	55,616	2,711	55,718	2,818	55,611
Adjusted R^2	5.2	0.4	5.6	0.4	1.7	0.4	3.2	0.4
Panel B								
	Release	Nonrelease	Release	Nonrelease	Release	Nonrelease	Release	Nonrelease

	CPI		RETAIL		ISM		PPI	
r^{FH}	18.3***	4.80***	18.1***	4.92***	15.1***	5.17***	27.0***	4.97***
	(6.31)	(6.29)	(4.61)	(5.58)	(4.24)	(6.51)	(5.73)	(6.55)
HFT	85.7***	-7.09	-21.7	-1.79	-1.94	-2.96	7.85	-3.78
	(4.53)	(-1.57)	(-0.98)	(-0.38)	(-0.10)	(-0.61)	(0.37)	(-0.86)
$r^{FH}\times$HFT	-22.4***	-4.66***	-25.1***	-5.38***	-21.6***	-5.05***	-28.1***	-5.40***
	(-2.93)	(-2.70)	(-2.65)	(-2.66)	(-2.71)	(-3.13)	(-2.72)	(-3.46)
Intercept	-5.83	1.81	19.1*	1.35	7.53	1.88	-8.37	2.92
	(-0.63)	(0.78)	(1.71)	(0.58)	(0.76)	(0.77)	(-0.76)	(1.32)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,826	55,603	2,813	55,616	2,711	55,718	2,818	55,611
Adjusted R^2	6.5	0.4	5.5	0.4	2.5	0.4	4.2	0.4

Table 7 The impact of market conditions on intraday momentum

This table presents results of the predictability of the first half-hour return on the last half-hour return, using the model in Table 1, on days with different market conditions. Panel A presents result of the predictive regression on days with high and low stock liquidity, based on Amihud illiquidity measure, which is computed as the average daily ratio of the absolute stock return to the dollar trading volume over the previous five-day window. Panel B presents result of the predictive regression on days with high and low price volatility, which is measured by the standard deviation of 5-minute prices in the day. The *t*-statistics are provided in parentheses and calculated with heteroskedasticity-robust standard errors clustered by firm. *** , ** , or * indicate significance at the 1%, 5%, and 10% level, respectively. To make numbers in the table readable, coefficients and Adjusted R^2 are multiplied by 100.

Panel A Liquidity						
	(1)High	(2) Medium	(3) Low	(4)High	(5)Medium	(6)Low
r^{FH}	1.02***	1.29***	4.72***	1.43*	2.89***	8.18***
	(2.62)	(2.98)	(9.32)	(1.73)	(3.24)	(8.26)
HFT				-3.09	-6.28	-1.65
				(-0.65)	(-1.28)	(-0.21)
r^{FH}×HFT				-1.15	-4.75**	-10.7***
				(-0.61)	(-2.21)	(-4.19)
Intercept	2.80***	6.55***	10.9***	4.27*	9.17***	9.84**
	(6.55)	(13.03)	(11.25)	(1.74)	(3.62)	(2.43)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,023	18,013	18,006	18,023	18,013	18,006
Adjusted R^2	0.7	0.6	2.0	0.7	0.7	2.1

Panel B Volatility						
	(1)Low	(2)Medium	(3)High	(4)Low	(5)Medium	(6)High
r^{FH}	0.87**	1.07**	4.77***	1.02*	3.06***	7.30***
	(2.21)	(2.18)	(9.20)	(1.72)	(2.80)	(6.84)
HFT				1.40	-7.97	8.21
				(0.28)	(-1.38)	(0.88)
r^{FH}×HFT				-0.22	-4.71**	-6.0***
				(-0.11)	(-2.28)	(-2.78)
Intercept	3.04***	7.25***	9.99***	-2.45	10.9***	4.80
	(6.83)	(15.64)	(11.30)	(-0.95)	(3.83)	(1.01)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Observations	19,512	19,459	19,417	19,512	19,459	19,417
Adjusted R^2	0.7	1.0	2.1	0.2	1.0	2.1

Table 8 The economic value intraday momentum strategy

This table presents results of the average performance of the timing strategy based on the sign of the first half-hour stock return. As the sign of the first half-hour return for a stock is positive, this strategy takes a long position in the stock, but takes a short position as the return is negative. Panel A presents the average performance of the timing strategy by whole sample. Panels B and C present the average performances of the timing strategy according to the high and low trading volume and order imbalance of HFT, respectively. The *t*-statistics are provided in parentheses and calculated with heteroskedasticity-robust standard errors clustered by firm. *** , ** , or * indicate significance at the 1%, 5%, and 10% level, respectively.

Timing	Avg ret(%)	Std dev(%)	SRatio	Skewness	Kurtosis	Success(%)
Panel A. Whole sample						
r^{FH}	11.09***	1.00	4.41	0.22	5.89	51.63
	(10.68)					
Panel B: HFT trading volume						
low HFT	10.85***	0.98	4.40	0.20	6.19	51.97
	(6.15)					
High HFT	9.65***	1.00	3.84	0.24	5.75	50.83
	(5.35)					
Panel C. Order Imbalance of HFT						
low HFT Imbalance	13.27***	1.04	5.08	0.25	5.61	51.77
	(7.10)					
High HFT Imbalance	6.72***	0.94	2.83	0.19	6.34	50.74
	(3.95)					

Table9 Intraday momentum and hedging activity of HFT

This table presents results of the impacts of HFT hedging activity, liquidity demand, and liquidity supply on the predictability of the first half-hour return on the last half-hour return. To build up the proxy for the hedging activity (*Hedging*), this paper identifies whether HFT is net liquidity supply in the first half-hour (HFT^{FNS+}) and net liquidity demand in the last half-hour (HFT^{LND+}) in the same direction of the first half-hour return in the same day. *Hedging* equals 1 if the both values of HFT^{FNS+} and HFT^{LND+} are positive on the day, otherwise equals 0. The *t*-statistics are provided in parentheses and calculated with heteroskedasticity-robust standard errors clustered by firm. ***, **, or * indicate significance at the 1%, 5%, and 10% level, respectively. To make numbers in the table readable, coefficients and Adjusted R^2 are multiplied by 100.

	r^{LH}		
	(1)	(2)	(3)
r^{FH}	2.77***	3.26***	3.18***
	(5.98)	(7.22)	(7.66)
Hedging	3.63***		
	(3.01)		
r^{FH}×Hedging	0.255		
	(0.32)		
$DHFT^{FNS+}$		-0.482	
		(-0.56)	
r^{FH}×$DHFT^{FNS+}$		0.930	
		(1.63)	
$DHFT^{LND+}$			5.11***
			(4.21)
r^{FH}×$DHFT^{LND+}$			-0.0463
			(-0.07)
Intercept	-0.05	-1.74**	1.11**
	(-0.09)	(-2.24)	(2.08)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	58,429	58,429	58,429
Adjusted R^2	0.5	0.6	0.5

Table 10 Placebo test

This table presents results of the impact of total trading volume (*Volume*) and the frequency non-HFT trading (*non-HFT*) on intraday momentum analysis. We replace the measurement of HFT trading in Table 2 with the *Volume* and *non-HFT*. The definitions of the other variables are the same as that in Table 2 as well. Firm and year fixed effect is included in this table. The *t*-statistics are provided in parentheses and calculated with heteroskedasticity-robust standard errors clustered by firm. *** , ** , or * indicate significance at the 1%, 5%, and 10% level, respectively. To make numbers in the table readable, coefficients and Adjusted R^2 are multiplied by 100.

Panel A.				
	r^{LH}		Δr^{LH}	
	(1)	(2)	(3)	(4)
r^{FH}	2.25**	2.29**		
	(2.29)	(2.29)		
Volume	0.02	10.6		
	(0.00)	(1.27)		
r^{FH}×Volume	0.30	0.31		
	(0.25)	(0.26)		
Δr^{FH}			3.62***	3.62***
			(3.08)	(3.07)
ΔVolume			18.2	18.2
			(0.90)	(0.90)
Δr^{FH}×Volume			1.46	1.46
			(0.99)	(0.99)
Intercept	-1.04	-10.7	-0.49***	-0.49***
	(-0.23)	(-1.42)	(-3.37)	(-3.25)
Firm FE	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	58,429	58,429	57,507	57,507
Adjusted R^2	0.4	0.5	1.0	0.8

Panel B. Non-HFT				
	r^{LH}		Δr^{LH}	
	(1)	(2)	(3)	(4)
r^{FH}	-4.86	-4.93		
	(-1.48)	(-1.49)		
non-HFT	6.14	4.08		
	(1.31)	(0.57)		
r^{FH} ×non-HFT	7.66**	7.78**		
	(2.15)	(2.17)		
Δr^{FH}			-7.81	-7.81
			(-1.52)	(-1.52)
Δnon-HFT			20.4	20.4
			(0.92)	(0.92)
Δr^{FH} ×non-HFT			14.3**	14.3**
			(2.53)	(2.53)
Intercept	-4.83	-2.96	-0.44***	-0.44***
	(-1.17)	(-0.46)	(-4.64)	(-4.85)
Firm FE	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	58,429	58,429	57,507	57,507
Adjusted R^2	0.4	0.4	1.2	1.0

Table11 Intraday momentum and alternative measurement of HFT trading

This table presents the impact of HFT trading on the intraday momentum. Different from the analysis of Table 2, this table display the results based on an alternative measurement of HFT trading ($HFT_{i,t}$), the natural logarithm of the total trading volume of HFT of firm *i* on day *t*. Firm and year fixed effect is included in this table. The *t*-statistics are provided in parentheses and calculated with heteroskedasticity-robust standard errors clustered by firm. *** , ** , or * indicate significance at the 1%, 5%, and 10% level, respectively. To make numbers in the table readable, coefficients and Adjusted R^2 are multiplied by 100.

	r^{LH}		Δr^{LH}	
	(1)	(2)	(3)	(4)
r^{FH}	6.57***	6.55***		
	(5.49)	(5.48)		
HFT	-0.40**	-0.84		
	(-2.22)	(-1.03)		
r^{FH}×HFT	-0.35***	-0.34***		
	(-3.25)	(-3.17)		
Δr^{FH}			10.00***	10.00***
			(5.53)	(5.53)
ΔHFT			12.0***	12.0***
			(7.31)	(7.30)
Δr^{FH}×HFT			-0.42***	-0.42***
			(-2.83)	(-2.83)
Intercept	5.56**	10.6	-0.41***	-0.41***
	(2.30)	(1.12)	(-4.87)	(-5.08)
Firm FE	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	58,427	58,427	57,503	57,503
Adjusted R^2	0.5	0.5	1.4	1.2