When Do Short Sellers Trade?

Evidence from Intraday Data and Implications for Informed Trading Models

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July 22, 2025

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ABSTRACT

Using 2015-2019 intraday short sale data from CBOE, we show that shorting flows near the open, middle, and close all negatively predict future returns, but the shorting flows near the open and middle have stronger predictive power than shorting flows near the close. We relate our findings to three informed trading models with different predictions on the timing of the trades. The long term predictive power of shorting flows near the open and midday is consistent with Kyle's (1985) model of steady trading; the intraday variation in shorting flows' predictive power is more consistent with Holden and Subrahmanyam's (1992) aggressive trading model, in the sense that predictive power of shorting flows is stronger when there is greater urgency to trade at open and when the securities lending market is more competitive; and the liquidity timing hypothesis from Collin-Dufresne and Fos (2016) is also supported by the finding that opening shorting flows increase for firms with better liquidity conditions.

Keywords: short selling, intraday trading, information content, off-exchange trading, dynamic informed trading models.
JEL codes: G11, G12, G14, G23.

1. Introduction

Previous literature provides several competing models of informed trading. The dynamic version of the Kyle (1985) predicts steady informed trading, as monopolist informed traders trade steadily over time and gradually benefit from the long-lived information they possess (steady trading hypothesis). Other models, such as Holden and Subrahmanyam (1992), introduce competition and soon-to-become stale information to Kyle model and predict aggressive trading when trading session initially opens and when there is more competition (aggressive trading hypothesis). More recently, Collin-Dufresne and Fos (2016) show that when noise trading is stochastic, informed traders respond to liquidity and noise trading conditions and trade more when there is better liquidity and when there is more noise trading (liquidity-timing hypothesis). While these models provide testable hypotheses for trading dynamics throughout the day, few if any existing studies carefully examine whether any of the existing models describes the actual intraday trading behaviors of informed investors, especially short sellers.

In this study, we use the CBOE time-stamped short sale data to investigate the intraday trading patterns of short-sellers and relate them to the above hypotheses. We first separate intraday shorting into three intervals: near the open (before 11:30 am), midday (between 11:30 am and 2 pm), and near the close (after 2 pm). Next, we use shorting flows to predict one-day ahead returns, and find that shorting from all three intraday intervals has negative and significant coefficients, with the magnitude being the highest for the shorting from the opening hours. When we extend the prediction windows to 12 weeks, shorting near the open and midday hours both negatively and significantly predict returns for the next 12 weeks, but shorting near the close doesn't.

One possible explanation for the negative relations between short selling and future returns is that short sellers are informed. Another possibility is that other informed traders respond to uninformed short selling, and these trading actions are behind the negative return predictability of shorting flows. To study whether shorting flows contain information, we first connect short selling with news releases. Our empirical results show that short sellers near the open quickly respond to news releases from previous overnight, and significantly predict the arrivals of future negative news for the next 12 weeks. Neither midday nor closing shorting flows react to past negative news, but the former predict future arrivals of negative news. These results suggest that opening shorting flows might contain information over both short- and long-run. To further address the alternative mechanism that other informed investors might be behind shorting flows' predictive power for future returns, we focus on one of the most important types of informed traders in the literature: corporate insiders. According to Cohen et al. (2012), insider sales are informed trades and negatively predict future stock returns. We find that insider sales co-move with the open short sales on the same day, and open short sales predict future insider sales, consistent with the notion that some informed traders might respond to short-selling activity. More importantly, when we include both short sales and insider sales to predict returns, they are both significant and negative, implying that they possess distinct information, and short's return predictive power cannot be explained away by the presence of insider sales.[1]

We take the negative relation between returns and short selling as suggestive evidence of informed trading, and differentiate the three types of informed trading models (i.e., steady trading, aggressive trading, and liquidity-timing hypotheses) by examining how well each type describes intraday short selling patterns.

First, the stable long-term return predictive power from both open and midday shorting flows supports the steady trading predictions from Kyle (1985), in the sense that short-sellers

[1] Our empirical investigation also considers Schedule 13D filers as alternative informed traders. Results are quite similar to those using corporate insiders.

gradually incorporate information into prices, and the resulting shorting flows can predict returns over the long run.

Second, the decline in return predictability from open to midday and then to close is consistent with the aggressive informed trading model in Holden and Subrahmanyam (1992). We study the public news release time and find that most of them are released outside of trading hours. As the aggressive trading hypothesis suggests, when information arrives while the market is closed, competing informed investors trade aggressively right after the market reopens for trading, and thus the shorting near the open is the most informative. In addition, we use a borrowing concentration measure to construct a proxy for competition among short sellers, which is lower when there are more short sellers and they might trade more aggressively with greater competition. Our empirical results show that the short-term predictive power of all intraday shorting flows is stronger for stocks with lower borrower concentrations, or firms with more competitions, which further supports the aggressive informed trading model.

Third, the variation in intraday shorting flow's predictive power could reflect an equilibrium response of informed short selling to variations in liquidity and noise trading conditions, as in Collin-Dufresne and Fos (2016). Following their study, we construct multiple intraday liquidity and noise trading measures. There is strong evidence that opening shorts are positively correlated with liquidity and noise trading measures during the opening period, consistent with Collin-Dufresne and Fos (2015) that informed traders time the liquidity and select to trade when liquidity provision and noise trading are greater. We further confirm the liquidity timing hypothesis for opening shorts by using a tick size pilot program that exogenously changes the liquidity level of pilot stocks. These results are much weaker or non-existent for midday and close shorting flows.

Finally, we differentiate the aggressive trading hypothesis and the liquidity timing hypothesis by studying whether and how the urgency around news releases affects short sellers' trading behaviors and their relations to liquidity measures. We find that opening shorts are less likely to time liquidity upon the releases of public news, suggesting that when information is soon to become stale, short sellers are less patient and less capable of timing the liquidity, which supports the aggressive trading hypothesis. While during other times, there is more evidence supporting the liquidity timing hypothesis.[2]

To summarize, when we relate the intraday trading dynamics of short-sellers to informed trading theories, we find supportive evidence for all three models, but under different circumstances. This might not be surprising, because these models carry different assumptions, suggesting that they might work when these assumptions are met, and might not work in other situations. Our empirical results offer many different and useful perspectives in understanding and testing these models.

Our study is related to two strands of literature. The first is the literature of informed trading. We already briefly introduce three types of theoretical models, and their representative models including Kyle (1985), Holden and Subrahmanyam (1992), and Collin-Dufresne and Fos (2016). There are also multiple empirical studies in examining these models. For instance, Koudijs (2015) find strategic informed trading consistent with Kyle (1985) using the information travel delays caused by infrequent (i.e., twice a week) sailboat services between London and Amsterdam in the eighteenth century. Kim, Lin, and Slovin (1997) use the tiered release arrangement of analyst

[2] Our empirical results stay robust for off-exchange intraday shorting flows from FINRA, suggesting that the intraday short sellers' trading patterns are generally consistent across different trading venues. We also consider different intraday intervals and different forecast horizons, and the results remain similar. Besides, we also find intraday shorting flows significantly enhance the information efficiency of prices throughout the day, but the effect is larger near the open than near the closes, suggesting that opening shorts play a more important role in enhancing price efficiency than closing shorts.

recommendations in earlier days and find that almost all of the private information based on pre-released recommendations is impounded in stock prices within 15 minutes of the opening trade, consistent with Holden and Subrahmanyam's (1992) prediction. Collin-Dufresne and Fos (2015) study how activists who are informed of the upcoming proposal trade and find that informed activists trade more when uninformed volume is higher and price impact is lower, supporting Collin-Dufresne and Fos (2016).[3]

The second strand is the literature on intraday trading patterns, including those of short-sellers. Earlier studies, such as Wood et al. (1985), Lee et al. (1993), Ahn, Bae, and Chan (2001), Heston et al. (2010) examine intraday trading patterns of returns, volume (u-shaped), and adverse selection measures such as spread (u-shaped) and quoted depth (inverse u-shaped). More recently, Bogousslavsky (2021) studies the sharp contrast between intraday and overnight returns and finds that overpriced stocks experience less short selling at the end of day; Yueshen, Zamojski, Zhang (2022) propose a structural model and find structure-based trade informativeness declines throughout the day, and Jiang et al. (2024) find short sales migrate toward the close as the recent rise of index-tracking funds enhances liquidity near the close, but their price informativeness deteriorates.[4]

In comparison with previous studies, we make the following three unique contributions to the literature. First, existing empirical studies of informed trading models mostly focus on the

[3] In addition, Boulatov, Hendershott, and Livdan (2013) obtain proprietary daily institutional order flows from NYSE and provide empirical support for a multi-period Kyle model in multiple assets with positively correlated fundamental values. Using a dataset of illegal insider trades based on SEC enforcement actions, Kacperczyk and Pagnotta (2019) also provide support for Collin-Dufresne and Fos (2016) and confirm that adverse selection measures fail to detect the present of informed traders. By contrast, using hacked earnings news, Akey et al. (2022) find that liquidity providers respond to the sudden increases in potential informed order flows by adjusting spreads when the ability of informed traders to time their trades is low and urgency is high.

[4] More papers using intraday short sale data include Jain et al. (2012) and Florindo et al. (2023), which use intraday short data to evaluate the impact of the SEC Rule 201; and Comerton-Forde, Jones, and Putnins (2016), which use intraday short data to classify short sales into liquidity-demanding and liquidity-supplying ones.

variations of informed trading across different days, while we examine how well different informed trading models describe the *intraday* patterns of informed traders, especially short sellers, which is not done in previous studies.[5] Second, existing literature on intraday trading patterns has mainly relied on adverse selection measures to infer about intraday informed trading patterns, while direct evidence on how informed traders trade at the intraday level is rare. Our large-scale high-frequency shorting data offers a unique opportunity to more directly investigate the intraday trading patterns of informed traders and observe how they respond to news, competitions, liquidity conditions at the intraday level. Finally, our paper contributes to the understanding of how short sellers time their trades throughout the day rather than at a particular time of the day, such as the closing hours. One novel insight we generate is that shorting flow near the open is the most informative for next day return, and its behavior can be consistent with the aggressive trading hypothesis or the liquidity timing hypothesis, depending on time urgency of trading and informed traders' ability to time liquidity. In contrast, shorting near the close does not have much predictive power for future returns beyond one day, and it responds positively to increases in illiquidity measures, suggesting that shorting near the close may be driven by liquidity provision reasons.

The rest of the paper is structured as follows. Section 2 discusses the existing dynamic informed trading models and develops hypotheses for empirical study. We introduce the intraday shorting data and empirical methodology in Section 3. The main empirical results are provided in Section 4. Section 5 provides additional analyses and Section 6 concludes.

2. Hypothesis Development

[5] Hu et al. (2017), Rogers et al. (2017) and Bolandnazar et al. (2020) use high-frequency intraday data to examine trading patterns around information releases, where subsets of investors enjoy early peak advantage and gain access to material information a few seconds earlier than other market participants. They mainly focus on a very short period around each information release and do not study intraday variations of informed trading.

Many papers show that shorts negatively predict future stock returns (e.g., Asquith et al. 2005; Boehmer et al. 2008). One explanation for the negative relation is that short sellers are informed, by processing public information or possessing private information. An alternative explanation is that other informed traders respond to short selling, and the return predictability is a result of the actions from other informed traders.[6] For example, they may provide liquidity to other informed traders and receive a liquidity premium. Before assuming short sellers are informed and testing the different theoretical informed trading models, we examine whether short sellers are indeed informed. Therefore, we formalize our first hypothesis as the following:

H1. (hypothesis of informed short selling): The negative relation between short selling and future returns might be related to short-sellers' ability of processing and predicting public news, or it can be explained by other informed traders trading responding to uninformed short selling.

If we find supportive evidence for Hypothesis 1 that short sellers are informed, we then go ahead and examine whether the trading patterns of intraday short sellers are consistent with existing informed trading models. The first informed trading model dates back to Kyle (1985). There are three key assumptions: (1) the informed traders possess long-lived information; (2) they have monopolistic power over the information they possess; and (3) noise trading is constant. Under these assumptions, this dynamic model with sequential equilibria implies steady trading by the informed trader over time, until the long-lived information is released at a known time T. Following Kyle (1985), we have our second hypothesis:

H2. (hypothesis of steady trading): The trading of short-sellers and the informativeness of these trades are stable throughout time till the expiration of the long-lived information.

[6] We thank our referee for pointing out this mechanism.

Compared to the patient informed trading based on Kyle (1985), the second type of models predicts more aggressive informed trading, either by introducing short-spanned or time-decayed information rather than long-lived information, and/or by introducing competition among informed traders. In Holden and Subrahmanyam (1992), the timing, nature, and duration of private information are the same as in Kyle (1985), but they relax assumption (2) to introduce competition among informed traders who receive the same private signal of value. As a result, the informed traders trade aggressively in the first few rounds of trading, leaving little remaining information for later rounds before the information is publicly released. Similarly, in Foster and Viswanathan (1990), an informative public signal is released at intermediate times when the market is closed, and this leads informed traders to trade more aggressively early on, carrying less private information forward to future trading sessions. Bernhardt and Miao (2004) examine the related case where private information gradually becomes stale, either because it is publicly released over time or because other traders get correlated signals. They generally find that this leads to more rapid trading on private information initially, with more subdued informed trading later on.[7] Therefore, we have our third hypothesis:

H3. (hypothesis of aggressive trading): The informativeness of shorting flows is higher when there is more urgency in trading the news, and when competition among short-sellers is higher.

[7] Slezak (1994) introduces a noisy rational expectations model with periodic exchange closures and examines informed trading before and after the closure. He finds that informed trading is always lower pre-closure and greater after the market reopens, mainly because the informed traders receive more information during the closure, and risk-averse uninformed traders who provide liquidity are less willing to do so before the closure. Recently, Coles, Heath and Ringgenberg (2022) and Haddad, Huebner and Loualiche (2021) provide additional theoretical and empirical evidence on the equilibrium behaviors of competitive informed investors, when information environment changes. For instance, with more index investing, competitive informed traders endogenously choose level of information production, and the overall price informativeness stays the same.

The third type of models are liquidity timing models, including Back and Pedersen (1998) and Collin-Dufresne and Fos (2016).[8] They keep the monopolistic and long-lived nature of information in Kyle (1985) and relax assumption (3) by allowing variation in noise trading. Collin-Dufresne and Fos (2016) state that informed traders trade more aggressively when uninformed volume is higher and when price impact, a form of illiquidity, is lower. The intuition is that if informed traders have monopolistic power over long-lived information, they may be able to trade patiently and time their trades according to the liquidity conditions. In other words, variations in the trading of short-sellers may reflect an equilibrium response to variations in noise trading.[9] This leads to our fourth hypothesis:

H4. (hypothesis of liquidity timing): The trading of short-sellers is more active when there is more noise trading and when liquidity is higher.

As far as we know, none of the previous empirical studies in short selling directly examine these hypotheses. We next carry these four hypotheses to the data and examine which dynamic models of informed trading are supported. Notice that all the models have specific assumptions, and it is likely that we find supportive evidence for different models under different circumstances.

3. Data and Empirical Methodology

3.1 Data on Short Selling

We focus on a recent sample period from January 2, 2015 to December 31, 2019, and obtain publicly available short-selling intraday data from exchange and off-exchange venues.

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[8] We thank our referee for suggesting liquidity timing models.

[9] In particular, Collin-Dufresne and Fos (2016) introduce stochastic noise trading into the model and obtain better model features (especially regarding the patterns of price impacts) than Back and Pedersen (1998) that allow noise trading to only change deterministically. Admati and Pfleiderer (1988) also predict that informed trading varies with noise trading, but under a very different setup of short-lived information. Because information acquired will expire at the end of each trading session, the information acquired will be used in the same session. Since information is of higher valuable when noise trading is high, insiders optimally acquire and use more information (i.e., trade more) in times of high noise trading volatility.

Since exchange data from NYSE and NASDAQ are proprietary and not available to public, we collect on-exchange, time-stamped shorting data from the 3rd largest exchange group, CBOE, which releases shorting data for all four of its exchanges (BYX, BZX, EDGA, and EDGX), every night on its website, https://markets.cboe.com/us/equities/market_statistics/short_sale. The CBOE short sale dataset is similar to the consolidated tape of all U.S. equity transactions, and includes the ticker symbol, trade price, size, and other sale conditions, along with a time stamp to the nearest second. We obtain similar data items from FINRA, which provides the time-stamped *off-exchange* shorting data to the public.[10]

If we combine all on-exchange and off-exchange trading venues, short sales on CBOE and FINRA account for about 9.69% and 13.63% of total trading volumes, respectively, which represents ample coverage of overall shorting for our study's purpose. In terms of the choice between exchange and off-exchange venues, existing studies such as Reed, Samadi, and Sokobin (2020) find that informed shorts with short-lived information trade urgently on exchanges to ensure execution, while Menkveld, Yueshen, and Zhu (2017) argue that informed institutional traders, who try to execute relatively large parent orders, tend to disproportionately use dark pools and crossing networks (at least at first) as venues for child orders in order to pay less for immediacy and also perhaps to reveal as little as possible about their underlying trading intentions. In our case, we consider the on-exchange results as the main results, and examine off-exchange trading dynamics in the robustness section to obtain additional insights.

We obtain stock prices and characteristics data from CRSP. There are three filters for an observation to be included in our sample: 1) we retain only common stocks (those with a CRSP share code of 10 or 11) and exclude securities such as warrants, preferred shares, American

[10] Details of FINRA data are discussed in Internet Appendix A to save space.

Depositary Receipts, closed-end funds, and REITs; 2) we require a minimum share price of $1 for the stock;[11] and 3) we exclude from the sample a small number of trading days just before major holidays, which have an early 1:00 pm stock market close. Finally, we cross-match the trade-by-trade short sale data to CRSP using CUSIPs and ticker symbols.

3.2 Intraday Shorting Measures

Following previous studies on shorting flows (Boehmer, Jones, and Zhang, 2008, and Wang, Yan, and Zheng, 2020), we compute daily proportional shorting flow over total volume for stock *i* on day *t* as,

$$SS_{it} = \frac{Shares\ Shorted_{it}}{Total\ Daily\ Share\ Volume_{it}}. \tag{1}$$

To be more specific, for CBOE shorting flows, the numerators are the total shares shorted at CBOE exchanges, and the denominators are share volumes on CBOE exchanges.

To examine intraday trading patterns, we partition each trading day into three relatively even time buckets: the opening hours between 9:30 and 11:30 (*open*), the last two hours of continuous trading between 14:00 and 16:00 (*close*) and the interval from 11:30 to 14:00 (*middle*).[12] The intraday shorting flow measures are defined for each stock *i* and day *t* as:

$$SSOPEN_{it} = \frac{Shares\ Shorted\ over\ [9{:}30,11{:}30)_{it}}{Total\ Daily\ Share\ Volume_{it}},$$

$$SSMIDDLE_{it} = \frac{Shares\ Shorted\ over\ [11{:}30,14{:}00)_{it}}{Total\ Daily\ Share\ Volume_{it}},$$

$$SSCLOSE_{it} = \frac{Shares\ Shorted\ over\ [14{:}00,16{:}00)_{it}}{Total\ Daily\ Share\ Volume_{it}}. \tag{2}$$

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[11] We also consider an alternative filter of $5 minimum price, and the results are qualitatively similar. Since many shorting flows are on stocks with prices between $1 and $5, we lose around 20% of our observations if we adopt the $5 filter. Therefore, our main results use the $1 minimum price filter to maximize sample size.

[12] We split the day into three relatively even 2-hour periods to make the duration of intraday shorting flows more comparable. We consider two alternatives to the above three buckets of partition. First, we define the opening bucket to cover only the first 30 minutes, closing bucket to cover the last 30 minutes, and middle bucket to cover the rest 5.5 hours. Second, we consider thirteen 30-minute trading buckets. The results using these two alternatives are quite similar to the main results reported in the text, and are reported in the Internet Appendix Table 1 Panel A and B.

Here we keep the denominator the same for all intraday shorting measures to ensure that we capture only the intraday variation in short-selling activities.

Empirically speaking, the opening hour is the first opportunity to trade overnight news, and thus may capture short sales that are driven by information that will soon become stale (Foster and Viswanathan 1990). Other than trading on information, there are also liquidity-related short sells, which are short sale positions taken to provide liquidity to the market; hedging-related short sells, which are short sale positions carried to hedge against the future payoffs of existing positions; and inventory-related short sells, which are short sale positions due to market makers' needs to manage inventory and to fulfill their market making responsibility. As pointed out by Hua et al. (2024), Jegadeesh and Wu (2021), Jiang et al. (2024), and Chen and Wang (2025), the closing hour features higher index trading, and thus ample liquidity and lower transaction costs (also illustrated in the Internet Appendix Figure 1). It is possible that the better liquidity conditions might attract various short-sellers to trade near the close.

[Insert Table 1 about here]

Table 1 provides summary statistics on CBOE shorting flows during different parts of the trading day. All the statistics are computed over a pooled sample across days and stocks, and overall there are 3,570,989 observations for the CBOE sample. From Panel A, shorts during the open, middle and close account for 15.86%, 14.94% and 26.03% of CBOE trading volume, respectively. Panel B reports autocorrelations and correlations among the shorting variables. Two interesting patterns emerge. First, the intraday shorting measures have positive autocorrelation AR(1) coefficients, ranging between 0.03 and 0.18, indicating persistence to some extent. Second, all three shorting flow measures are negatively correlated with each other. For example, opening shorting flow is negatively correlated with midday shorting flow (coefficient -0.09) and closing shorting flow (coefficient -0.22). These statistics indicate that the information contained in the three measures is mostly not overlapping, and there is a slight reversal in shorting flows over the day.

[Insert Figure 1 about here]

We also present the intraday shorting patterns for each 30-minute interval in Figure 1 Panel A. The on-exchange shorting follows a J-shape over the course of the trading day, with the opening half hour accounting for about 4% of the daily trading volume, the closing half hour accounting for about 15%, while the middle part is below 4% on average. In Panel B, we plot the time series of average short selling of daily total, opening, middle, and closing buckets over our sample period. The daily total CBOE short-sale market share is around 55% of CBOE trading volume. Consistent with the summary statistics in Table 1, both open and middle buckets account for around 15% of daily total volume, while the close bucket accounts for around 25%. There are no strong time trends in our sample period.

3.3 Baseline Empirical Method

To examine the informativeness of shorting flow during our 2015-2019 sample period for future returns, we begin with a simple Fama-MacBeth regression similar to the one in Boehmer, Jones and Zhang (2008). That is, for each day *t*, we estimate the following cross-sectional specification:

$$Ret_{i,t+1} = b_{0t} + b_{1t}Shorting_{it} + b_{2t}{}'Control_{it} + \epsilon_{i,t+1}. \tag{3}$$

Here the dependent variable $Ret_{i,t+1}$ is the future return for stock *i* on day *t*+1 (close to close), computed using corresponding bid-ask average prices to avoid bid-ask bounce.[13] In the original

[13] Here "close-to-close" means from the close of the market today at 16:00 pm to the close of the next trading day at 16:00 pm. For our main result, we examine and compare open, middle, close short sales' predictive powers for close-to-close returns, in order to keep the return prediction task constant and allows us to directly compare the predictive power of short sales from different times of the day. Alternatively, we also consider returns over next 24-hours

Boehmer, Jones and Zhang (2008) specification, the shorting measure $Shorting_{it}$ is the daily SS variable defined in equation (1). To mitigate potential effects of any time trend in shorting prevalence and to reduce the effects of outliers in the cross section, we adopt a rank transformation for the original shorting measures, as in Cao and Narayanamoorthy (2012) and Livnat and Mendenhall (2006). Take *SSOPEN* as an example. For day *t*, we first rank the intraday shorting variable, $SSOPEN_{it}$, cross-sectionally into 100 groups, from the lowest to the highest. Then we use the rank variable divided by 100 as a new shorting flow variable, $RSSOPEN_{it}$ for firm *i* on day *t*. The regression coefficient on this rank variable can be intuitively interpreted as the effect of changing the shorting variable from the 1st percentile to the 100th percentile, and it is comparable for different shorting flow variables we examine.[14] For our main results, the independent variables are *RSSOPEN, RSSMIDDLE and RSSCLOSE* on day *t*. From Table 1 Panel B, the rank variables all have correlations above 80% with the raw shorting measures, indicating that the rank variables capture most of the information in the raw shorting variables.[15]

After we obtain the time-series of daily coefficients $\{b_{0t}, b_{1t}, b_{2t}\}$, we calculate the time-series average coefficients $\{b_0, b_1, b_2\}$, and conduct inference using Newey-West (1987) standard errors with eight lags.[16] A significant and negative coefficient of b_1 indicates that the shorting flows at t predict future returns $Ret_{i,t+1}$ negatively, or high shorting flows mean lower future returns.

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immediately following the end of each intraday shorting flow interval. The results using the alternatives are quite similar to the main results reported in the text, and are reported in the Internet Appendix Table 1 Panel C.

[14] Similarly, 0.5* the regression coefficient of the rank variable captures the effect of moving the shorting variable from the 25th percentile to the 75th percentile.

[15] Our main empirical results are similar when we use original shorting flow variables. For future sections, we use the rank variables for return predictions, in order to easily compare the economic magnitudes over time and in cross section; and we use original shorting variables to relate to all other non-return variables, to capture the direct relation between short-selling and other variables of interest.

[16] Following Andrews (1991), we use $0.75*T^{1/3}$ to calculate the optimal lag. With number of days in our sample *T*=1247, our optimal lag is 8.07. Our results are robust if we use one lag in daily and intraday regressions, and five lags in weekly regressions. The results are also robust if we use four lags throughout the paper.

To understand whether shorts can predict returns over longer horizons, we also examine the predictive patterns for the next 12 weeks. In the format of equation (3), the independent variables are still *RSSOPEN, RSSMIDDLE* and *RSSCLOSE* on day *t*, while the dependent variables are changed to the average daily returns for week 1 (day *t*+1 to *t*+5), week 2 (day *t*+6 to *t*+10), and up through week 12 (day *t*+56 to *t*+60).

Following previous literature, our $Control_{it}$ variables include the following variables measured for stock *i* on day *t*: previous day's return, *Ret [-1]*; the return over the past six months *Ret [-120,-21]*; the return over the past month *Ret [-20,-2]*; the log market capitalization at the most recent quarter end, *Lsize*; log book-to-market ratio at the most recent quarter end, *Lbm*; the previous month's daily return volatility following Ang et al. (2006), *Volatility*; and last month's consolidated trading volume as a fraction of outstanding shares, *Turnover*. The summary statistics of the control variables are presented in Panel A of Table 1, and the numbers are mostly consistent with previous findings.

4. Main Empirical Results

4.1 Intraday Shorting Flows and Future Returns in the Cross Section

In this subsection, we examine the predictive patterns of intraday shorting flows for future stock returns. We start with short-term predictions using daily returns, and we move on to long-term predictions using weekly returns. All results are presented in Table 2.

[Insert Table 2 about here]

We report the estimation results using CBOE intraday shorting flow variables to predict next day returns in Panel A. For the first three regressions, we include only one intraday shorting measure at a time, and in the last regression, we include all three of them together. In regression I, the b_1 coefficient for *RSSOPEN* is -8.20 basis points, with a significant *t*-statistic of -7.91.

Economically speaking, this coefficient means that moving through the cross-sectional shorting distribution near the open from the 25th percentile to the 75th percentile increases the normalized shorting variable by 0.5 and reduces next-day return by -8.20 * 0.5 = 4.1 basis points (about 10% annualized). That is, shorting flow near the open negatively and significantly predicts next day returns. The *RSSMIDDLE* and *RSSCLOSE* also significantly predict next-day returns, with coefficients of -0.0584 (*t*-stat = -5.75), and -0.0397 (*t*-stat = -3.88), respectively. In the last regression, when included together, all three shorting variables maintain their negative signs and statistical significance, and the coefficient of *RSSOPEN* is still the largest. It seems that all CBOE intraday shorting flows can predict next-day returns, with the strongest results for short sales near the open. To make sure the results are not driven by outliers in the time-series, we present the time-series of Fama-MacBeth regression coefficients in Figure 2, which presents no obvious outliers or clear trends over time.

[Insert Figure 2 about here]

For the control variables, the coefficients in Panel A on previous-day and previous-month returns are both negative and strongly significant. For example, in regression I, the coefficient on the previous-day return is -0.3438, indicating an estimated reversal of around half of the previous day's return. This is even more notable, given that we use closing bid-ask average prices throughout the paper to calculate returns, which should limit or eliminate reversals from microstructure sources such as bid-ask bounce. The coefficient on the previous-month return is a smaller -0.1448, indicating a smaller reversal magnitude, but the coefficient has a significant *t*-stat of -2.53. Most of the other control variables are insignificant, except for lagged turnover, which is negative and sometimes borderline significant. In later tables, we omit the estimates for the control variables to save space.

The evidence for next-day returns indicates that all three intraday shorting flow variables can predict returns for the next day, but the predictive power is strongest for shorting near the open,[17] consistent with the aggressive trading hypothesis from the Foster and Viswanathan (1990), Holden and Subrahmanyam (1992), and Bernhardt and Miao (2004) models. The greater predictability of opening shorts versus the weaker predictability of shorts near the close also provides support for Slezak (1994).

To understand whether the predictive power of shorting continues or reverses over longer horizons, we also examine shorts' predictive power over longer horizons up to 12 weeks. The results are reported in Panel B of Table 2. Two patterns emerge from the long-term prediction results. First, both *RSSOPEN and RSSMIDDLE* remain negative and mostly significant for long-term future returns up to 12 weeks, with *RSSOPEN* significant for 9 weeks and *RSSMIDDLE* significant for 8 of them, out of 12 weeks. The magnitude of coefficients on *RSSOPEN* is relatively stable within a range between -0.0063 and -0.0308, while the *RSSMIDDLE* coefficients have slightly smaller magnitudes. Second, none of the coefficients of *RSSCLOSE* is significant over any of the 12 weeks, indicating that the shorting flow around the market close does not have predictive power for future long-term returns. The long-term predictive power of the shorting near the open and in the middle of the day is consistent with the Kyle (1985) model, in the sense that the informed investors gradually trade on long-lived information, which leads to long-term predictive power. These findings can also be consistent with Collin-Dufresne and Fos (2016), which reflects an equilibrium response of informed short selling to variations in noise trading and liquidity

[17] When we test the differences in coefficients, the coefficient differences between *RSSOPEN* and *RSSCLOSE* and between *RSSOPEN* and *RSSMIDDLE* are both statistically significant at 1% (*t*-stat=2.92 and *t*-stat=2.31, respectively).

conditions, in the sense that the informed short selling chooses to trade more when liquidity is higher, and it may gradually trade and have long-term predictive power.[18]

4.2 Short Sellers and Informed Trading

In the previous subsection, we establish that short selling throughout the day, especially short sales near the open, negatively predict future intraday returns and returns in the next 12 weeks. One explanation for the negative relation is that short sellers are informed about short- and long-term firm level information. An alternative explanation is that other informed traders respond to or move together with shorting flows, and the other informed traders' return predictability is behind the negative return predictive power of short sellers. In this subsection, we first investigate how short-seller's intraday trading behavior is related to firm-level news events in subsection 4.2.1, and then examine whether other informed traders are behind the negative return predictive power of short sellers in subsection 4.2.2.

4.2.1 Short-Sellers' information advantage and news events

We obtain data on all public news events over year 2015-2019 from RavenPack Equity Module database. Three filters are applied to the data. First, to include the most relevant news events related to a stock, we require the relevance score to be 100, which means that the stock is prominent in the news story. Second, to filter out news related to public price and return data, which doesn't contain much new information, we restrict the subject or theme of events to be "business", and exclude three groups of events "stock-prices", "order-imbalances", and "technical-analysis", which are usually press releases summarizing recent price movements and past returns. Third, given that our aim is novel information and not stale news, we require the Event Similarity

[18] As mentioned earlier, in Internet Appendix Table 1, we consider alternative specifications of short-flows and returns over different intraday intervals. There are two patterns. First, the predictive power of intraday shorts stays strong and significant for future returns. Second, the shorting flows' predictive power decreases gradually throughout the day. These patterns are consistent with the main results in the text.

Days (*SIM*) to be more than 90 days, meaning that the news is a novel and has no proceeding similar reporting in the previous 90 days. In total, we have 3,704,510 intraday firm news releases. Since short-sellers are sensitive towards negative news, we focus on the public negative news releases. To be specific, we define a news to be negative news if the *ESS* (event sentiment score) is negative, where *ESS* is a stock-event sentiment score between -1 and +1, computed by Ravenpack using its proprietary algorithm. Similarly, *ESS* is 0 for neutral news, and *ESS* is positive for positive news.

[Insert Figure 3 about here]

We first present the distribution of company public news arrival times over the 24 hours of the day in Figure 3. In Panel A, we present the arrival times of all public news from the Raven Pack Equity Module. The highest hourly arrival intensity occurs between 4 pm and 5 pm ET (right after the stock market closes), accounting for 18% of all news over the day; and the second highest arrival intensity occurs between 7 am and 8 am (right before the U.S. stock market opens), accounting for 9% of total news arrivals. About 22% of news is released during trading hours, while 78% is released outside of trading hours. Among all firm-level news, the most important information events for stock returns are earnings announcements and analyst recommendation changes. Therefore, we also obtain data from I/B/E/S and Compustat and present the distribution of these news arrival times in Panel B. Similar to Panel A, most of the news arrives between 4 pm and 5 pm, accounting for 44% and 11% of total earnings news and analyst news; while the morning period between 6 am and 9 am is another information intensive period, accounting for over 30% of total earnings and analyst news.[19] Overall, Figure 3 shows that most of the public news arrives

[19] Our statistics are consistent with prior literature that documents a gradual shift in earnings announcement timing from regular trading hours to outside of regular trading hours. Patell and Wolfson (1984) find 67% of their sample in 1976/1977 announce during regular hours, while Lyle, Rigsby, Stephan, and Yohn (2018) document more than 95% of firms announce outside of regular trading hours from 2006 to 2015.

either in the morning before the market opens or in the afternoon after the market closes. In other words, firm-specific news mostly arrives when the stock market is closed.

Next we establish the relation between the intraday shorting flows and firm-level news, either in the sense of processing public news releases from the previous day or predicting future news releases. In particular, we follow Engelberg et al. (2012) and Reed et al. (2020) and use the following specification to examine how shorting flows *respond to recently released negative public news*:

$$Shorting_{it} = b_{0t} + b_{1t}PreviousNegNews_{it} + b'_{2t}Controls_{it} + \epsilon_{it}. \qquad (4)$$

The independent variable, $PreviousNegNews_{it}$ equals 1, if and only if there is a negative news release for firm *i* after the market closes on day *t*-1, but before the market opens on day *t*. If short-sellers can effectively process the negative news released before market opens on day *t* and trade on it, we expect the coefficient b_1 (average of time-series of b_{1t}) to be positive, because negative news should lead to more short-selling as short-sellers process and respond to the negative news. Among open, middle and close intervals, following predictions from Foster and Viswanathan (1990), the open is the closest in time to the previous day after-hour news releases, and would be the most related intraday shorting flow measure.

In parallel, to examine whether short selling *predicts arrivals of future negative news*, we estimate the following specification:

$$FutureNegNews_{i,t+1} = b_{0t} + b_{1t}Shorting_{it} + b_{2t}{}'Controls_{it} + \epsilon_{i,t+1}. \qquad (5)$$

The independent variable, $FutureNegNews_{i,t+1}$, equals 1, if and only if there is a negative news release for firm *i* between market closes on day *t* and day *t*+1.[20] If short sellers can predict the

[20] Our results are robust if we use shorting flows as the dependent variable and future news as the independent variable as in Engelberg et al. (2012) and Reed et al. (2020).

forthcoming negative news, we expect the coefficient b_1 (average of time-series of b_{1t}) to be positive. Given our prior findings that the open and middle intraday shorting flows predict long-term returns up to future 12 weeks, we also investigate whether the opening and midday shorting flows predict the arrival of future negative news up to 12 weeks using equation (5), while the dependent variable becomes $FutureNegNews_{i,w+k}$, which equals 1, if and only if there is a negative news release within the *k*th-week after market close on day *t.* We estimate equation (4) and (5) using Fama-MacBeth regressions and adjust standard errors using Newey-West (1987) with eight lags.

[Insert Table 3 about here]

The estimation results are presented in Table 3. Panel A presents the estimation results for past news ($PreviousNegNews_{it}$). The results show that opening shorting flows are positively and significantly related to previous overnight negative news releases, while the coefficients on shorting flows at the midday and close are both negative and significant, possibly indicating a short-term reversal after opening. These patterns suggest that the opening flows react to the previous negative news, which is consistent with the aggressive trading hypothesis that informed investors trade early during the day in response to previous released news. Panel B reports the results for predicting future negative news releases ($FutureNegNews_{it}$). The open shorting flows have positive and significant coefficients for the next 12 weeks in predicting future negative news arrivals. The coefficients for midday shorting are mostly positively significant over long run, but with smaller magnitudes than open shorting, and the coefficients for the closing shorts are mostly insignificant. These findings on open and midday shorts are consistent with Kyle (1985)'s model, in the sense that informed traders who have monopoly over private information trade gradually and steadily release information every day.

To examine whether arrivals of negative news actually boost short sellers' predictive power for future returns, we interact intraday components of shorting flows with news events indicators in our return prediction regressions. Table 3 Panel C shows that the predictive power for next-day returns of all three intraday shorting flow variables is stronger when there are arrivals of negative news before the open. Short sellers' significant long-term return predictive power is however not affected by the interaction terms, suggesting that short sellers' interaction with negative public news released previous overnight cannot explain their long-term return predictive power.

To summarize, we find open shorting flows react strongly to public information from previous night, and predict future short-term and long-term negative news releases, suggesting that open shorting flows might contain relevant short-term and long-term information. Midday shorts positively predict long-term negative news with smaller magnitude, and the coefficients for the closing shorts are mostly insignificant, indicating they are less informed than open shorting flows. Given that some short-sellers trade prior to public news releases, they might have private information. Meanwhile, some short-sellers trade right after public news releases, suggesting that they might be capable of processing news quickly.

4.2.2 Short sellers and other informed traders

Many previous papers interpret shorting's negative predictive power for future returns as that short sellers are informed traders. Alternatively, the negative return relation between short selling and returns could be driven by other informed traders reacting to the actions of short sellers. To better understand this alternative mechanism, we focus on one of the most important types of informed traders in the literature: the insiders. A few studies, such as Cohen et al. (2012) and Bogousslavsky et al. (2024), point out that insiders are informed investors and insider sales negatively predict future stock returns.

According to the SEC definition, insiders consist of directors and officers of the company, as well as any shareholders, owning 10% or more of the company's outstanding stocks. We obtain the insider sales data from Thomson Reuters Insider Form 4, which is a document that is required to be filed to SEC and becomes public whenever there is a material change in the holdings of company insiders. In fact, Form 4 is required to be filed within two business days from the end of the day the material transaction occurs. To align with short sales, here we follow Massa et al. (2015) and focus on insiders' open market sales, excluding the open market purchases and private transactions. Since the filing happens at the end of the day, the insider sales data are daily. There are 136,022 insider sales events, which account for 3.81% of our total sample.

We first examine the dynamic relation between insider sale and short selling, by estimating the contemporaneous relation between them as follows:

$$Shorting_{it} = b_{0t} + b_{1t}DInsiderSale_{it} + b_{2t}'Controls_{it} + \epsilon_{it}. \quad (6)$$

The dependent shorting variables $Shorting_{it}$ is the intraday showing flows defined in equation (2).[21] Following Bogousslavsky et al. (2024) and Collin-Dufresne and Fos (2015), the independent variable, $DInsiderSale_{it}$, equals to one if insiders sell on firm *i* on day *t*, and zero otherwise. Besides the control variables in the baseline specification (3), we also include the previous day's intraday shorting flows to control for the persistence of shorting flows. If insiders sell contemporaneously as shorting happens, coefficient of b_1 should be positive. For the question as whether insiders respond to today's short selling in their future selling activity, we investigate whether the intraday shorting flows predict insider sales for future:

$$DInsiderSale_{i,t+1} = b_0 + b_{1t}Shorting_{it} + b_{2t}'Controls_{it} + \epsilon_{i,t+1}. \quad (7)$$

[21] We use the raw shorting data instead of cross-sectionally rank transformation, because the insider events are unevenly distributed across different day, and using raw shorting data better captures the trading dynamics between insider sales and short selling. The results are robust to using rank transformation shorting flow variables and are available upon request.

Here $DInsiderSale_{i,t+1}$ is set to 1, if and only if there is an insider sales event on day t+1. We later replace $DInsiderSale_{i,t+1}$ with $DInsiderSale_{i,w+k}$, which is set to 1, if and only if there is an insider sales event within the next k-th week. If insiders respond to current short sales in their future sales, we expect the coefficient b_1 to be positive.

[Insert Table 4 about here]

The results are reported in Table 4. Panel A presents the estimation results for the relation of contemporaneous insider sales and intraday shorting flows. Only the shorting flows near the open are positively related to contemporaneous insider sales with a coefficient of 0.0018 (t-stat = 5.38), while the coefficients on short flows at the midday and close are both negative and significant, indicating that insider sales only trade in the same direction of shorting near the open. Panel B reports the results for predicting future insider sales. The opening short sales exhibit steady positive relation with future insider sales up to next three weeks, indicating that insider sales likely respond to opening short sales, which is consistent with Massa et al. (2015) that insider sells respond to short sales with monthly short sale data. The coefficients for midday and close shorting have mixed signs and are mostly insignificant. Overall, our empirical evidence suggests that future insider sales might respond to current short sales at the opening hours.

Next, we investigate whether intraday shorting flows' return predictive power is driven or related to insider sales. That is, we include $DInsiderSale_{it}$ together with open, middle, and close short sales on day t to predict future returns:

$$Ret_{i,t+k} = b_{0t} + b_{1t}RSSOPEN_{it} + b_{2t}RSSMIDDLE_{it} + b_{3t}RSSCLOSE_{it} + b_{4t}DInsiderSale_{it} + b_{5t}{}'Controls_{it} + \epsilon_{i,t+k}. \quad (8)$$

If shorting flows' predictive power is driven by or affected by contemporaneous insider sales, coefficient b_4 should be negative and significant, while coefficients b_1, b_2 and b_3 should cease to be negative and significant.

Table 4 Panel C presents the estimation results. The coefficients b_4 on insider sales are significantly negative for future one day and one week returns, indicating that insider sales can predict future returns for the next one week. More interestingly, after controlling for the insider sales, the coefficients b_1, b_2 and b_3 are still negative and significant for the next day and next one week returns, and the economic magnitudes of shorting flows' predictive power for future returns remain largely unchanged. For instance, the coefficient of *RSSOPEN* is -0.0860 in Table 2 Panel A regression IV, indicating that moving through the shorting near the open from the 25th percentile to the 75th percentile reduces the next-day returns by 4.3 basis points, without including insider sales trading. When we include insider sales trading, the coefficient becomes -0.0862 in Table 4 Panel C, which is comparable to the coefficient without insider sales trading. This finding suggests that controlling for insider sales trading minimally affects the predictive power of short selling, and insider sales may have different information for future returns than shorting flows. The negative predictive power of open shorts and midday shorts also stays intact for the next 12 weeks returns, in the presence of insider sales.

As an alternative to corporate insiders as informed traders, we also look into Schedule 13D filers, as discussed in Collin-Dufresne and Fos (2015). To be specific, Rule 13D-1(a) of the 1934 Securities Exchange Act requires investors to file with the SEC within 10 days of acquiring more than 5% of the stock, if they have an interest in influencing the management of the company. Collin-Dufresne and Fos (2015) show that Schedule 13D filers' actions and ownership contain positive private information, and Schedule 13D filers are likely informed traders. A recent study by Bogousslavsky et al. (2024) directly provides a stock-day informed trading intensity measure, ITI, for Schedule 13D trades, based on machine-learning techniques. The ITI measure is a strong detector of Schedule 13D trading and has a high signal-to-noise ratio. We include both the ITI measure and our intraday short measures, to separate the predictive power of short-selling and the ITI measure. Our empirical results, reported in Table 4 Panel D, show that they both have significant predictive power for future returns, while the economic magnitudes of the coefficients of short selling are almost the same as before. These results suggest the ITI measure and intraday short-selling have distinct information for future returns.

Overall, while we cannot exhaust all informed trades given that they are generally unobservable, our results using insider sales and Schedule 13D trades suggest that these informed trades co-move and respond to the shorting flows at open, but it is unlikely that short's predictive power for future returns are due to these informed traders' responding to uninformed short sellers. Therefore, results in this subsection support Hypothesis 1 that the negative relation between short selling and future returns is related to short-sellers' ability of processing and predicting public news, and cannot be explained by trading of other informed traders, such as insiders and Schedule 13D investors.

4.3 The Steady Trading Hypothesis

The steady trading hypothesis is based on Kyle (1985) model. By assuming the informed traders being monopolistic and holding long-lived information, the model implies that the trading and informativeness of short-sellers to be steady and long-lasting till the expiration of the long-lived information. As discussed earlier, Panel B of Table 2 provides strong evidence for this hypothesis, in the sense that the shorting-flows close to open and midday have strong and negative predictive power for future returns for at least up to 12 weeks. Meanwhile, Panel B of Table 3 provides further evidence that open and midday shorting flows can predict arrivals of future negative news for the next 12 weeks, which echoes the finding in Table 2 Panel B.

To reconcile the various trading patterns from same intraday intervals but over different days, and from different intraday intervals over same days, we study whether particular short sellers tend to trade at certain times of a trading day, or they participate indifferently across all hours of a trading day. Following Heston et al. (2010), we project changes in shorting volumes for each 30-minute interval on its lags over past 5 days using Fama-MacBeth regression, as follows:

$$\log\left(\frac{shorting_{i,j}}{shorting_{i,j-1}}\right) = b_{0,t} + b_{k,j}\log\left(\frac{shorting_{i,j-k}}{shorting_{i,j-k-1}}\right) + \varepsilon_{i,t}. \qquad (9)$$

Here $\frac{shorting_{i,j}}{shorting_{i,j-1}}$ represents the changes in shorting volumes of firm i over the j-th 30-minute interval, and k = 1, 2, 3, …, 65 (65 intervals for 5 days, 13 intervals each day). If there are seasonal patterns of shorting flows in the same time interval of consecutive days, then coefficient $b_{13}, b_{26}, b_{39}, b_{52}, b_{65}$ would share similar patterns, while the other coefficients would not.

[Insert Figure 4 about here]

Figure 4 provides clear evidence of large and positive relations between changes in half-hour shorting flow with its 13th lag (same interval from previous trading day), 26th lag (same interval from two trading days ago), 39th lag (same interval from three trading days ago), 52nd lag (same interval from four trading days ago), and 65th lag (same interval from five trading days ago). In other words, there are strong seasonal patterns in shorting flows at half-hour intervals that are exact multiples of trading days, similar to the 13-hour seasonality patterns in returns and volumes documented in prior literature (Heston et al. 2010; Bogousslavsky 2016). This evidence suggests that some short sellers might prefer to trade at particular time of the trading day rather than participate in all hours of a trading day. In the light of Kyle (1985) steady trading hypothesis, this pattern might suggest that the short-sellers with long-lived information prefer to trade at particular times, which might be related to the long-term predictive power of shorting flows at open and midday.

Given ample evidence in support of the steady trading hypothesis using shorting flow at open and middle, here we don't provide further empirical evidence for Hypothesis 2.

4.4 The Aggressive Trading Hypothesis

Other than long term predictions of shorting-flows for future returns and future negative news, we also find in Table 2 that the intraday short flows' predictive power for next day returns decays from open to middle and then to close, supporting the aggressive trading hypothesis, which is based on time urgency and competition. That is, given that most public news is released overnight outside of the trading hours, the stronger predictive of shorting flows at the open than middle and close might be a result of the time urgency of trading on public news after the release. With multiple pieces of supportive evidence on time urgency in previous sections, in this subsection we focus on the competition aspect among short-sellers.

To better understand how short-sellers trade in the presence of competition, we obtain a firm level borrower concentration variable from Markit. This is an Herfindahl index based on the market shares of different borrowers' demands and reflects the level of concentration of borrower demands on the securities lending market. To be precise, assume there are *N* borrowers for stock *i* on day *t*, with borrower *n*'s borrower share being $s(i,t,n)$, then the total borrower shares are $S(i,t) = \sum_{n=1}^{N} s(i,t,n)$. Markit's borrower concentration variable is calculated as,

$$BC_{it} = \sum_{n=1}^{N} \left[\frac{s(i,t,n)}{S(i,t)}\right]^2. \qquad (10)$$

Variable BC_{it} takes a value between 0 and 1. If there is only 1 borrower in the market and no competition, $BC_{it} = 1$. If there is a large number of borrowers and presumably more competitions, BC_{it} decreases and approaches zero. Table 5 Panel A presents the summary statistics of borrower concentrations. The median borrower concentration is 0.3028 in our sample. If we assume that each borrower borrows similar shares, a value of 0.3028 would indicate around 3 borrowers for the stock.[22] We find borrower concentration is lower for firms with lower shorting fees, suggesting that short sellers face lower fees when the securities lending market is more competitive.

[Insert Table 5 about here]

We investigate how the competition is related to shorting flows and its informativeness in two steps. In the first step, we examine whether competition status is related to shorting flows by estimating the following Fama-MacBeth regression:

$$Shorting_{it} = b_{0t} + b_{1t}BC_{it} + b_{2t}'Controls_{it} + \epsilon_{it}. \qquad (11)$$

If short-sellers prefer the lower fees in the more competitive securities lending market, then there should be more shorting flows when there are more competitions (less borrower concentration), and we expect coefficient b_1 to be negative. From results presented in Table 5 Panel B, the coefficient for *SSOPEN* is -0.0390 (*t*-stat = -50.79), indicating that there are more open shorting flows for stocks with lower borrower concentration. Similar patterns also hold for shorting flows at midday and close, suggesting more shorting flows for stocks with more competitions.

For the second step, we interact intraday shorting flows with borrower concentration dummies and examine how they affect shorts' predictive power for future returns, as follows:

$$Ret_{i,t+\text{k}} = b_{0t} + b_{1t}RSS_{it} + b_{2t}RSS_{it} \times DHighBC_{it} + b_{3t}'Controls_{it} + \epsilon_{i,t+\text{k}}. \quad (12)$$

The dummy variable, $DHighBC_{it}$, takes a value of 1 if the firm's *BC* is higher than the cross-sectional median of *BC*, and zero otherwise. Coefficient b_1 captures short's predictive power for future returns for firms with lower borrower concentration, while coefficient b_2 captures the

[22] We consider the cases where *BC* = 1, indicating monopoly, to examine Kyle's model with monopolistic informed trader. However, there are only less than 1% of firms with *BC* = 1, which is not enough for a reliable cross-sectional estimation.

additional predictive power of shorting flows for firms with higher borrower concentration. If the aggressive trading hypothesis is true, then short's predictive power is stronger for firms with more competitions (lower borrower concentration), and is weaker for firms with less competitions (higher borrower concentration). That is, coefficient b_1 should be negative, while coefficient b_2 should be positive.

Estimation results are reported in Table 5 Panel C. If we take *RSSOPEN* as an example, the coefficient b_1 is negative for both next day and next 12 weeks, while coefficient b_2 is positive for next day and next 12 weeks. These results are consistent with the aggressive trading hypothesis, in the sense that *RSSOPEN* negatively predicts future short-term and long-term returns, with the predictive power weaker for firms with lower competitions (higher borrow concentrations). Similar patterns are observed for *RSSMIDDLE* and *RSSCLOSE*, both supporting the aggressive trading hypothesis.

To summarize, we construct a proxy for competition using a borrower concentration measure, which is lower when there are more competitions in the securities lending market, and vice versa. We find that there are more intraday shorting flows for stocks with more competitive securities lending market, and the short- and long-term predictive power of all intraday shorting flows are stronger in stocks with lower borrower concentrations, or firms with more competitions, which supports the aggressive informed trading hypothesis.

4.5 The Liquidity Timing Hypothesis

4.5.1 The Liquidity Timing Hypothesis in the Cross Section

In this subsection, we investigate whether informed short sellers vary their trading decisions according to liquidity and noise trading conditions, as proposed by Collin-Dufresne and

Fos (2016). We first construct multiple proxies for the intraday liquidity and noise trading conditions.

For intraday liquidity, we use two commonly-used stock liquidity measures: the effective spread (*ES*), and the lambda (LA). For a given stock *i* and day *t*, the effective spread for trade *m* is measured as $ES_{itm} = \frac{2 \times BuySell_m (P_{itm} - M_{itm})}{M_{itm}}$, where P_{itm} is the price of the m-th trade of stock *i* on day *t*, M_{itm} is the midpoint of the consolidated BBO (best bid and offer) prevailing at the time of the *m*-th trade of stock *i* on day *t*, and $BuySell_m$ is the buy-sell indicator (+1 for buys, -1 for sells). We then compute the intraday effective spreads ($ESOPEN_{it}$, $ESMIDDLE_{it}$ and $ESCLOSE_{it}$) as the share-weighted average of the ES_{itm} of all trades for the stock over respective time intervals. Higher effective spreads indicate lower liquidity.

The lambda is designed to capture the adverse selection costs, which is the cost of demanding a certain amount of liquidity over a given time period. We follow Hasbrouck (2009) and Goyenko, Holden, Trzcinka (2009) and calculate the slope coefficient λ_{it} in the regression $ret_{ith} = \delta_{ith} + \lambda_{it} S_{ith} + \epsilon_{ith}$, where ret_{ith} is the *h*-th five-minute period on day *t* and stock *i*, and S_{ith} is the sum of the signed square-root dollar volume, $BuySell_{itm}\sqrt{DollarVol_{itm}}$, over all transactions in that five minute interval. The intraday lambdas ($LAOPEN_{it}$, $LAMIDDLE_{it}$ and $LACLOSE_{it}$) are the slope estimates for corresponding time intervals. The lambda captures illiquidity from the perspective of return-volume relation, and a higher lambda indicates lower liquidity.

Many prior studies, such as Collin-Dufresne and Fos (2015) and Kacperczyk and Pagnotta (2019), argue that retail investors are less informed than institutional investors and short sellers, and are natural candidates for noise traders. We first identify retail order flows and compute the retail proxy for intraday noise trading using Boehmer et al. (2021) algorithm and the Barber et al.

(2024) modification. To be specific, for stock i on day t, the intraday retail measures ($NoiseOPEN_{it}$, $NoiseMIDDLE_{it}$ and $NoiseCLOSE_{it}$) are defined as retail buys volume plus sells volume scaled by total trading volume for each corresponding intraday intervals. Previous literature argues that higher retail order flows suggest higher level of noise trading.[23]

[Insert Table 6 about here]

We present the summary statistics of the liquidity and noise trading measures in Panel A of Table 6. For intraday effective spread, its sample average for the open, middle and close buckets are 70 bps, 33 bps and 31 bps, respectively, indicating that the liquidity conditions are the worst during the open. We observe similar patterns for intraday lambda measures. As for the intraday noise trading, the open, middle and close retail trading account for 3.33%, 2.83%, and 3.06% of stock daily trading volume, respectively, suggesting that noise traders trade more during the open period than the rest of the day.

We take two steps to examine the liquidity timing hypothesis. First, we study whether the intraday shorting flows are correlated with the contemporaneous liquidity and noise trading conditions, by estimating the following Fama-MacBeth regression:

$$Shorting_{it} = b_{0t} + b_{1t}LIQ_{it}/Noise_{it} + b'_{2t}Controls_{it} + \epsilon_{it}. \tag{13}$$

Here the dependent shorting variables $Shorting_{it}$ is the intraday shorting flows defined in equation (2). The independent variables are liquidity and noise measures ES_{it}, LA_{it}, and $Noise_{it}$, in the same time interval of the shorting variables. Besides the control variables in the baseline specification as in equation (3), we also include the previous day's $Shorting_{i,t-1}$ to control for the persistence of short selling. If the liquidity timing hypothesis is true, short sellers should trade

[23] Boehmer et al. (2021) actually find that retail order flows positively and significantly predict future short- and long-run returns, which suggests that retail investors might not all be noise traders. The separation of retail investors between informed and noise traders is beyond the scope of this study. Here we follow the logic from Collin-Dufresne and Fos (2015), and Kacperczyk and Pagnotta (2019) to be comparable.

more for stocks with better liquidity conditions and stocks with more noise trading, which indicates a negative coefficient for illiquidity measures, and a positive coefficient for noise trading.

We present the estimation results in Table 6. For the effective spreads in Panel B, the coefficient for $SSOPEN$ is -0.4481, with a significant t-statistic of -22.37. The finding suggests that there are more opening shorting flows for stocks with better liquidity, which is consistent with the liquidity timing hypothesis. However, the coefficient for *SSMIDDLE* is positive and significant, suggesting that there are more shorting flows in the midday for illiquid stocks, which is at odds with liquidity timing hypothesis. The coefficient for *SSCLOSE* is insignificant. From Panel C using lambdas, the coefficients on *SSOPEN* and *SSCLOSE* are both negative and significant, supporting the liquidity timing hypothesis, while the coefficient on *SSMIDDLE* is positive and significant. For the noise trading results in Panel D, all coefficients are positive and significant, implying there are more shorting flows for stocks with more noise trading, despite of trading time, which supports the liquidity timing hypothesis.

For the second step, we study how the informativeness of intraday shorting flows varies with retail trading and liquidity conditions by interacting the liquidity and noise trading measures with the intraday short sales as follows:

$$Ret_{i,t+k} = b_{0t} + b_{1t}RSS_{it} + b_{2t}RSS_{it} \times (LIQ_{it}/Noise_{it}) + b_{3t}Controls'_{it} + \epsilon_{i,t+k}. \quad (14)$$

If informed short sellers time the liquidity, then the coefficient b_2 for firm illiquidity measures interact with shorting flows' predictive power should be positive, and the coefficient b_2 for firm noise trading measures interact with shorting flows' predictive power should be negative.

[Insert Table 7 about here]

The estimation results are provided in Table 7. Panel A provides results on interaction of shorting flows and effective spread. Take *RSSOPEN* as an example, the coefficient b_2 is positive and significant for predicting the next day return. The positive coefficient on the interaction term indicates that open shorting flows' predictive power for next day return is stronger for stocks with lower effective spreads (higher liquidity). Relating to the liquidity timing hypothesis, the informed short-sellers might prefer to trade in stocks with better liquidity conditions, and their shorts contain more information about future returns. Similar patterns are observed for *RSSMIDDLE* and *RSSCLOSE*, supporting the liquidity timing hypothesis. For long-term predictions, the coefficients on the interactive terms are all positive but mostly insignificant. Results are similar but weaker when interacting with lambda in Panel B, and when interacting with noise trading in Panel C.

To summarize, we find strong evidence that shorts near the open are negatively correlated with illiquidity measures and positively correlated with noise trading measures, supporting the liquidity timing hypothesis in Collin-Dufresne and Fos (2016). The high liquidity and high noise trading conditions strengthen the opening shorting flows' predictive power for future returns, but the effects are weaker for midday and close shorting flows.

4.5.2 Exogenous Liquidity Shocks: The Tick Size Pilot Program

In the previous subsection, we estimate the contemporaneous relation between liquidity conditions and shorting flows to test the liquidity timing hypothesis. One concern for this approach is that the liquidity measures and the shorting flows happen at the same time, and their relation can be endogenous. Therefore, in this subsection, we leverage on the tick size pilot program (TSP) to further examine how intraday shorting flows respond to exogenous changes in the liquidity level of pilot stocks.

The SEC launched the TSP program on October 3, 2016, and terminated it on September 30, 2018. The regulation change provides a natural experiment for investigating the effects of tick sizes on liquidity, intraday shorting flows and their predictive power for future returns. We obtain the list of the TSP pilot stocks from the FINRA website. The TSP program divided stocks into three test groups and one control group. All stocks in the three test groups are subject to the Quote (Q) rule (quoted in $0.05 increments) and the stocks in the control group are quoted and traded in $0.01 increments or smaller. We adopt the filters in Chung, Lee, and Rosch (2020), and obtain the names of 986 pilot stocks and 987 control stocks.

We first examine whether the TSP brings significant changes in the intraday liquidity and noise trading for the pilot stocks, as in the following diff-in-diff regression:

$$LIQ_{it} = b_0 + b_1 Pilot_i \times TSP_t + b_2 Pilot_i + b_3 TSP_t + b_4' Controls_{it} + \epsilon_{it}. \tag{15}$$

Here the LIQ_{it} represents the intraday effective spreads and lambda, and we later replace it with $Noise_{it}$ or shorting flows $Shorting_{it}$. Firm variable $Pilot_i$ is equal to one for the test stocks, and zero otherwise. Time variable TSP_t is equal to one between October 3 of 2016 and September 30 of 2018, and zero otherwise. The control variables are the same as in Table 2. We also control for previous day liquidity, noise trading, and shorting variables to control for potential persistence in these measures. Standard errors are clustered by both firm and day. Given that the tick size becomes larger for pilot firms during the TSP period, if larger tick size hurts the liquidity of the pilot firms, the coefficient of b_1 should be positive for illiquidity measures. If the retail investors reduce their trading because of higher tick size, the coefficient of b_1 should be negative for noise trading measures. If the liquidity timing hypothesis is true that short-sellers prefer to trade when liquidity is high and when there is more noise trading, and if liquidity worsens and noise trading drops during TSP, then the coefficient of b_1 should be negative for shorting flows.

[Insert Table 8 about here]

Table 8 presents the estimation results for the diff-in-diff analysis. For brevity, we only report the b_1 coefficient on the interaction terms. In Panel A, the b_1 coefficient is 0.0009 (*t*-stat =

5.63) for the effective spread measure, suggesting that the effective spread near the open increases by 0.0009 for the pilot stocks. The b_1 coefficients for midday and close effective spreads are also positive and highly significant. We observe similar results for lambda measures. All the above empirical results suggest that the liquidity conditions are significantly worse during the TSP period for the pilot stocks. Regarding the results for noise trading in Table 8 Panel B, the b_1 coefficient for open, middle and close periods are all negative and significant, suggesting that the noise trading significantly decreases throughout the day for pilot stocks over the TSP period.

Table 8 Panel C presents the results for intraday shorting. The b_1 coefficient for *SSOPEN* is -0.0061 (*t*-stat = -6.07), the midday shorting flows is -0.0022 (*t*-stat = -2.54), and for close is 0.0212 (*t*-stat =15.32). These results imply that short sales near the open and midday significantly decrease for pilot stocks over the TSP period, which supports the liquidity timing hypothesis in the sense that shorting flows likely decrease for pilot stocks over TSP because the liquidity and noise trading conditions significantly deteriorate for these stocks over this period. In contrast, closing short selling significantly increases when liquidity conditions become worse for pilot stocks over TSP period. This result, combined with the fact that closing shorts are not predictive of future returns beyond one day, is consistent with shorting near the close is less likely to be driven by information and maybe related to liquidity provisions. Thus, the higher the spread is, the greater the closing short selling is.

We then examine whether and how the return predictive power of intraday shorting flows varies between the TSP and non-TSP periods. For each day *t,* we estimate the cross-sectional regression of equation (3), and obtain the time series of coefficients b_{1t}. We then compare the average of b_{1t} over the TSP period and the non-TSP period, with the standard errors estimated using Newey-West (1987) standard errors with eight lags. If the liquidity timing hypothesis is true, then the predictive power of shorting flows should be higher during non-TSP period than the TSP period.

Our results in Table 8 Panel D show that during the TSP period when liquidity condition is worse, the next day return predictive power of opening short flow decreases and the difference in the coefficients of *RSSOPEN* between the TSP period and non-TSP period is statistically significant at 1% (t-stat = -5.31), supporting the liquidity timing hypothesis. However, the predictive power of midday and closing shorting flows actually increases, but not statistically significant.

To summarize, we find supportive evidence for the liquidity timing hypothesis in the sense that opening shorting flows are higher when liquidity is better and where this is more noise trading. We also study the TSP program, which exogenously deteriorates liquidity conditions for pilot stocks, and find that open shorting flows are significantly lower for pilot stocks during TSP period, and its predictive power becomes weaker during TSP period, both supporting the liquidity timing hypothesis from Collin-Dufresne and Fos (2016).

4.6 Further Evidence on Aggressive Trading Hypothesis and Liquidity Timing Hypothesis

So far, our evidence suggests that the aggressive trading hypothesis and liquidity timing hypothesis can both be consistent with varying (rather than steady) return predictive power of shorting over different intraday intervals. We seek to further differentiate between these two hypotheses in this section. In the previous sections, we mainly test the two hypotheses using the cross-sectional analysis, which may not capture the short sellers' aggressive trading and liquidity timing behavior across different days around a firm news event. In this section, we further study these two hypotheses using Ravenpack's negative news events, which provide an ideal situation to examine how short sellers trade before and after public news releases.

Following Collin-Dufresne and Fos (2015), for each negative news released on day 0, we include the 60 days before and 60 days after day 0 as the event period, and examine the dynamics of shorting flows in the event window using the following specification:

$$Shorting_{itk} = b_0 + b_1 D_{itk}^{-60,-21} + b_2 D_{itk}^{-20,-6} + b_3 D_{itk}^{-5,-1} + b_4 D_{itk}^{0} + b_5 D_{itk}^{1,5} + b_6{}' Controls_{itk} + \eta_k + \epsilon_{itk}. \tag{16}$$

Here $D_{itk}^{-60,-21}$ equals to one if firm *i* on day *t* is within the [-60, -21] window before the negative news event *k*, and zero otherwise. Variables $D_{itk}^{-20,-6}$, $D_{itk}^{-5,-1}$, D_{itk}^{0}, and $D_{itk}^{1,5}$ are all defined similarly. The control variables are the same as in Table 2. Variable η_k is the event fixed effect. The standard errors are clustered at the event level. If the aggressive trading hypothesis is true, we expect to see the coefficient of D_{itk}^{0} to be positive because shorting flows would react to the overnight news release, and it should also be larger in magnitude and more significant than other coefficients, because day 0 is when the time-urgency is the highest.

[Insert Table 9 about here]

Table 9 Panel A presents the results. For the open short selling, the coefficients for $D_{itk}^{-60,-21}$, $D_{itk}^{-20,-6}$, $D_{itk}^{-5,-1}$ and $D_{itk}^{1,5}$ are 0.0001, 0.0006, 0.0011, 0.0011 respectively, indicating that shorting flows increase when time is closer to the negative news release. The coefficient for D_{itk}^{0} at 0.0069 is the largest and highly significant. The patterns of the five coefficients are consistent with the aggressive trading hypothesis, in the sense that short sellers trade more aggressively when there is more time urgency in trading the news, which is right after the news release on day 0. The five coefficients for *SSMIDDLE* and *SSCLOSE* are negative, which means less midday and close shorting during the event period compared to normal period.

We then examine the dynamics relation between intraday shorting flows and liquidity measures over different horizons, as follows:

$$Shorting_{itk} = b_0 + \left[b_1 + b_2 D_{itk}^{-60,-21} + b_3 D_{itk}^{-20,-6} + b_4 D_{itk}^{-5,-1} + b_5 D_{itk}^{0} + b_6 D_{itk}^{1,5}\right] \times LIQ_{itk} + b_7{}'Controls_{itk} + \eta_k + \epsilon_{itk}, \quad (17)$$

The coefficient b_1 reflects the relation between intraday shorting flows and liquidity conditions during regular time outside the event window. If the liquidity timing hypothesis is true that short sellers trade more when illiquidity measures are lower, b_1 should be negative. The coefficients on $D_{itk}^{-60,-21} \times LIQ_{itk}$, $D_{itk}^{-20,-6} \times LIQ_{itk}$, and $D_{itk}^{-5,-1} \times LIQ_{itk}$ measure how the relations between intraday shorting flows and illiquidity measures change prior to the news release relative to regular time, as we move closer to the release date. If short sellers are not only informed of future negative news but also its arrival time, then as Collin-Dufresne and Fos (2015, 2016) suggest, they may become less patient and less capable of timing the liquidity as the news release date is approaching, and coefficients on $D_{itk}^{-60,-21} \times LIQ_{itk}$, $D_{itk}^{-20,-6} \times LIQ_{itk}$, and $D_{itk}^{-5,-1} \times LIQ_{itk}$ should be positive. Similarly, the coefficients on $D_{itk}^{0} \times LIQ_{itk}$ and $D_{itk}^{1,5} \times LIQ_{itk}$ reflect how the relations between intraday shorting flows and liquidity conditions change on the day of news releases, and immediately after news releases, relative to regular non-event period. Upon the public release of negative news on day 0 and immediately afterwards, short sellers face time urgency and competition. If the aggressive trading hypothesis dominates the liquidity timing hypothesis during this period, short sellers might trade aggressively and care less about the liquidity timing, then the coefficients on $D_{itk}^{0} \times LIQ_{itk}$ and $D_{itk}^{1,5} \times LIQ_{itk}$ should be positive.

Table 9 Panel B presents the results. For the open short selling, the coefficient b_1 is significantly negative, suggesting that opening short sellers time liquidity during the regular non-event period. Coefficients on $D_{itk}^{-60,-21} \times LIQ_{itk}$, $D_{itk}^{-20,-6} \times LIQ_{itk}$, and $D_{itk}^{-5,-1} \times LIQ_{itk}$ have mixed signs, but none of them is significant. Coefficient on $D_{itk}^{0} \times LIQ_{itk}$ is positive and highly significant, suggesting that the opening short sellers' tendency to time liquidity significantly drops on day 0, possibly because time urgency outweighs the higher effective spreads. For the middle and close short selling, all coefficients on $D_{itk}^{-60,-21} \times LIQ_{itk}$, $D_{itk}^{-20,-6} \times LIQ_{itk}$, $D_{itk}^{-5,-1} \times LIQ_{itk}$, $D_{itk}^{0} \times LIQ_{itk}$ and $D_{itk}^{1,5} \times LIQ_{itk}$ are negative and mostly significant, indicating that shorting flows at middle and close exhibit a higher tendency to time liquidity during event period than regular period. We find similar results for lambda in Panel C.

To summarize, using the Ravenpack negative news events analyses, we find that when there is greater urgency to trade on the news, the aggressive trading hypothesis dominates the liquidity timing hypothesis for short sellers near the open, in the sense that they trade more aggressively and reduce their liquidity timing practice.

5. Additional Analyses

5.1 FINRA Intraday Shorting Flows

Can our results be extended to off-exchange short sales? To answer this question, we obtain data from FINRA. From the summary statistics of intraday shorting flows from FINRA reported in Internet Appendix Table 2 Panel A, both shorting during the opening and middle buckets account for around 13% of daily FINRA trading volume, similar to the 15% of daily CBOE trading volume for opening and middle short flows from CBOE. Shorts in the close bucket account for 18% of daily FINRA trading volume, significantly smaller than the 26% of daily CBOE trading volume for closing bucket in CBOE.

Internet Appendix Table 2 Panel B presents the Fama-MacBeth regression coefficients of future returns on FINRA intraday shorting flows. The evidence of short-and long-term predictive power using FINRA data is mostly consistent with those in Table 2 using CBOE data. That is, overall intraday short sellers' predictive patterns are generally consistent across different trading venues.[24]

5.2 Intraday Shorting Flows Spikes

Is the relation between short selling and future returns linear? To answer this question, we create indicators for large spikes and examine whether intraday short selling's future return predictive power varies with the spike indicators. We start by compiling a pooled panel of our intraday shorting flows to identify spikes. Since open and close periods both have 2 hours, while middle period has 2.5 hours, we first compute hourly average shorting flows for our three different intervals so they can be comparable. Next, we compute the 95% threshold value using the pooled panel. If the shorting flow for a particular day*stock*interval is above this threshold, then we define it as a "spike". Table 10 Panel A shows that spikes are more likely to happen at close, accounting for 3.64% of the pooled panel, while the likelihood of spikes for open and midday are 0.92% and 0.45%, respectively. Interestingly, many of the spikes at close are on the quadruple witching days or the last trading days of each month, suggesting that the spikes near the close are likely related to liquidity, hedging or inventory management purposes.

[Insert Table 10 about here]

We examine the non-linearity in the relation between short selling and future returns by including an interaction term between short-selling and indicators for large spikes. The indicator for a large spike for a given interval, $DSpike_{i,t}$, is equal to one if the average hourly shorting flow during that interval is above the 95% threshold defined in panel A, and zero otherwise. If the spikes have different predictive power than non-spikes, the coefficient on the interaction term would be significant. We present the empirical results in Table 10 Panel B. For shorting flows near the open,

[24] To save space, results for the four hypotheses using FINRA data are not reported here. They are qualitatively similar to our findings using CBOE data, and they are available on request.

after we add in the interaction term, the original *RSSOPEN* stays negative and mostly significant, same as in the main results. The interaction terms range between 0.0129 and 0.0389, but most are statistically insignificant. These positive coefficients show that the spikes don't improve shorts' predictive power in general, possibly because spiky observations may contain noise rather than information. Results for the middle and close are similar but stronger than the open, especially for the close. This is consistent with our earlier observation that spikes at close are possibly more related to liquidity, hedging and inventory management purposes.

5.3 Intraday Shorting Flows and Price Efficiency

The predictive power of shorts for future returns demonstrates short's relation with price discovery. It is also natural to ask how short-sales are related to market efficiency measures. Boehmer and Wu (2013) connect daily short-sales with daily information efficiency measures and find that the information efficiency of prices improves with greater daily shorting flows in a large panel of NYSE-listed stocks from January 2005 through June 2007. Following their methodology, we estimate their efficiency measures (pricing errors and absolute correlations) for our intraday time buckets, where lower pricing errors and absolute autocorrelations indicate higher information efficiency.[25]

[Insert Table 11 about here]

When we connect contemporaneous and next day intraday price efficiency measures with intraday shorting flows, as reported in Table 11, we find that *SSOPEN*, *SSMIDDLE*, and *SSCLOSE* are all significantly and negatively associated with contemporaneous and next day intraday pricing errors, but the magnitudes of coefficients gradually decrease throughout the day. That is, intraday shorting flows significantly enhance the information efficiency of prices throughout the day, but

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[25] We thank the authors of Boehmer and Wu (2013) for providing us the code of calculating price efficiency measures. Internet Appendix B provides a detailed introduction of the construction of intraday price efficiency measures.

the effect is larger near the open than near the close, suggesting that opening shorts play a more important role in enhancing price efficiency.

6. Conclusions

In this study, we consider a recent five-year sample of U.S. on-exchange and off-exchange trading by short sellers throughout the trading day to examine how short-sellers time their trades. We divide daily shorts into three time buckets: open, midday and close, and use all three components to predict short-term returns as well as long-term returns. There is a decreasing trend in the predictive power for next-day and next 12-week returns as we move short sales from the opening hours to the closing hours, suggesting the opening shorts have the strongest predictive power for future returns.

By relating intraday short sales to the release of public news and other informed sales, we first show that short flows near the open are likely informed. Then we propose three hypotheses (steady trading, aggressive trading, and liquidity-timing) based on theoretical models and carefully examine which models describe the intraday trading behaviors of short sellers. Overall, we find supportive evidence for all three theoretical models, while under different circumstances. This might not be surprising, because these models have different assumptions, suggesting that they might work in some situations but not in others. Still, by utilizing the high-frequency short sale data as more direct measures of intraday informed trading than adverse selection proxies, our paper offers many unique insights about the three classes of informed trading models at the intraday level.

There are two caveats of our study. First, all theory models considered here are symmetric, in the sense that positive and negative signals of value should have similar effect magnitudes. However, our short sale measures are limited to negative signals. Going forward, we think it would be productive to identify similar measures of positive private information to gauge whether the empirical results line up symmetrically behind these theory models. Second, albeit the advantage of being large scale and available at intraday frequency, our data are aggregate intraday shorting flows, and we don't directly observe individual short-sellers' trading activities. We leave the pursue of direct and observable measures of individual short-seller's trading to future research.

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Table 1. Summary Statistics for CBOE Shorting Flows

This table presents summary statistics for short sale trading volume at different times of the day, along with our control variables. Our sample period is January 2015 to December 2019, and our sample firms are common stocks listed on the NYSE, NYSE MKT, or Nasdaq with a share price of at least $1. Panel A presents the summary statistics of shorting and control variables. Panel B shows the autocorrelations, correlations with rank variables, and cross-correlations of shorting variables. The shorting variable *SSOPEN* is short volume over [9:30,11:30) divided by CBOE total trading volume in that stock on that day. Similarly, *SSCLOSE* is short volume over [14:00,16:00) and *SSMIDDLE* is short volume during the rest of the trading day. For the rank variables in Panel B, we sort all stocks by shorting flow variables into 100 groups, and assign the rank number to the variable. The rank variables are then computed as rank variables divided by 100. For the control variables, *Ret [-1]* is the return on the previous day using closing bid-ask averages. *Ret [-20, -2]* is the cumulative daily return in the [-20, -2] window. *Ret [-120, -21]* is the cumulative daily return over the [-120, -21] window. *Turnover* is the monthly average of daily turnover measured at the most recent month end. *Volatility* is the monthly volatility of daily return at the most recent month end. *Lsize* is log of market capitalization and *Lbm* is the log of book to market ratio, both at the most recent quarter end.

Panel A. Summary statistics

	N	Mean	Std	P25	P50	P75
SSOPEN	3,570,989	0.1586	0.1181	0.0875	0.1437	0.2062
SSMIDDLE	3,570,989	0.1494	0.1109	0.0881	0.1360	0.1881
SSCLOSE	3,570,989	0.2603	0.1471	0.1711	0.2497	0.3333
Ret [-1]	3,570,989	0.0005	0.0343	-0.0112	0.0000	0.0115
Ret [-20,-2]	3,570,989	0.0088	0.1459	-0.0514	0.0050	0.0598
Ret [-120,-21]	3,570,989	0.0366	0.3108	-0.1162	0.0214	0.1557
Lsize	3,570,989	6.9323	2.0148	5.5323	6.9152	8.2476
Lbm	3,570,989	-0.9452	1.0156	-1.4919	-0.8268	-0.3037
Volatility	3,570,989	0.0249	0.0225	0.0138	0.0198	0.0298
Turnover	3,570,989	0.0099	0.0322	0.0035	0.0063	0.0107

Panel B. Correlations

	AR(1)	Correl(.,rank)	Correlations		
			SSOPEN	SSMIDDLE	SSCLOSE
SSOPEN	0.1750	0.8528	1		
SSMIDDLE	0.0967	0.8213	-0.0929	1	
SSCLOSE	0.0317	0.8990	-0.2248	-0.1231	1

Table 2. Predicting Future Returns Using Total Intraday Shorting Flows from CBOE Exchanges

This table presents Fama-MacBeth regression coefficients of future returns on previous day shorting flow variables. Panel A reports the results on predicting the cross-section of next-day returns, and Panel B reports results predicting returns over the next 12 weeks. *RSSOPEN (RSSMIDDLE/RSSCLOSE)* is a rank variable for the corresponding shorting flow variable *SSOPEN (SSMIDDLE/SSCLOSE)*, computed as shares shorted on CBOE exchanges over the first two hours of the trading day (middle 2.5 hours/last two hours) over total daily CBOE share volume. To compute the ranks, we sort all stocks by shorting flow variables into 100 groups and assign the rank number to the variable. The *RSS* variables are then computed as rank variables divided by 100. For the control variables, *Ret [-1]* is the return on the previous day using closing bid-ask averages. *Ret [-20, -2]* is the cumulative daily return in the [-20, -2] window. *Ret [-120, -21]* is the cumulative daily return over the [-120, -21] window. *Lsize* is log of market capitalization and *Lbm* is the log of book to market ratio, both at the most recent quarter end. *Volatility* is the monthly volatility of daily return at the most recent month end. *Turnover* is the monthly average of daily turnover measured at the most recent month end. To account for potential serial correlation in the coefficients, the standard errors of the time-series are adjusted using Newey-West (1987) with eight lags. All regression coefficients are multiplied by 100 for presentation purposes.

Panel A. Predicting next-day returns

	I		II		III		IV	
	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat
Intercept	0.0469	1.54	0.0474	1.54	0.0465	1.49	0.0794	2.64
RSSOPEN	-0.0820	-7.91					-0.0860	-8.29
RSSMIDDLE			-0.0584	-5.75			-0.0526	-5.38
RSSCLOSE					-0.0397	-3.88	-0.0493	-4.76
Ret [-1]	-0.3438	-1.84	-0.3685	-1.97	-0.3771	-2.02	-0.3230	-1.73
Ret [-20,-2]	-0.1448	-2.53	-0.1500	-2.62	-0.1497	-2.62	-0.1435	-2.52
Ret [-120,-21]	0.0066	0.28	0.0063	0.26	0.0077	0.32	0.0041	0.17
Lsize	0.0042	1.28	0.0028	0.89	0.0021	0.67	0.0071	2.22
Lbm	0.0053	0.74	0.0057	0.78	0.0065	0.90	0.0052	0.73
Volatility	0.2219	0.50	0.1514	0.34	0.0620	0.14	0.2068	0.47
Turnover	-0.6021	-2.27	-0.6573	-2.45	-0.7145	-2.66	-0.5350	-2.01
Adj.R2	0.0362		0.0358		0.0359		0.0374	

Panel B. Predicting future weekly returns

	RSSOPEN		RSSMIDDLE		RSSCLOSE	
	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat
Week 1	-0.0308	-3.66	-0.0242	-3.76	-0.0106	-1.48
Week 2	-0.0063	-0.75	-0.0043	-0.68	-0.0066	-0.97
Week 3	-0.0135	-1.62	-0.0130	-2.03	-0.0076	-1.12
Week 4	-0.0181	-2.06	-0.0149	-2.39	-0.0096	-1.49
Week 5	-0.0216	-2.46	-0.0156	-2.52	-0.0079	-1.30
Week 6	-0.0216	-2.48	-0.0110	-1.76	-0.0060	-0.93
Week 7	-0.0207	-2.44	-0.0148	-2.23	-0.0039	-0.61
Week 8	-0.0227	-2.55	-0.0178	-2.83	-0.0007	-0.11
Week 9	-0.0212	-2.48	-0.0142	-2.18	-0.0027	-0.41
Week 10	-0.0228	-2.56	-0.0121	-1.79	-0.0043	-0.68
Week 11	-0.0247	-2.62	-0.0117	-1.62	0.0015	0.21
Week 12	-0.0133	-1.44	-0.0178	-2.59	-0.0064	-0.91

Table 3. Intraday Shorting Flows and RavenPack News Events

This table presents the trading dynamics and return predictability of the intraday shorting flows and Ravenpack negative news. Firm-level news is obtained from RavenPack and negative news is defined as news with ESS (event sentiment score) <0. We require the relevance score to be 100 to keep the most relevant news and event similarity days (*SIM*) > 90 days to exclude the stale news. For intraday shoring flows respond to previous overnight negative news, the independent variable, $PreviousNegNews_{i,t}$, is equal to 1 if and only if there is a negative news that is released to the public after the market close on day t-1 but before the market opens on day t, and zero otherwise. The results are presented in Panel A as specified by the following Fama-MacBeth regression:

$$Shorting_{it} = b_{0t} + b_{1t}PreviousNegNews_{it} + b_{2t}{}'Controls_{it} + \epsilon_{it},$$

The control variables are the same as in Table 2, and we also control for previous day's short selling to control the persistence. For intraday shorting flows predict future negative news, the dependent variable, $FutureNegNews_{i,t+k}$, is equal to 1 if and only if there is a negative news that is released to the public after the market close on day $t+k$ and before the market closes on day t+k+1, and zero otherwise. The results are reported in Panel B as specified by the following Fama-MacBeth regression:

$$FutureNegNews_{i,t+k} = b_{0t} + b_{1t}Shoring_{it} + b_{2t}{}'Controls_{it} + \epsilon_{i,t+k}.$$

The control variables are the same as in Table 2, and we also control for previous overnight negative news to control the persistence. Panel C examine the return predictability of intraday shorting flows interacted with the previous overnight negative news, as specified by the following Fama-MacBeth regression:

$$Ret_{i,t+k} = b_{0t} + b_{1t}RSS_{it} + b_{2t}RSS_{it} \times PreviousNegNews_{it} + b_{3t}{}'Controls_{it} + \epsilon_{i,t+k}.$$

Controls are included and omitted from presentation. To account for potential serial correlation in the coefficients, the standard errors of the time-series are adjusted using Newey-West (1987) with eight lags. The regression coefficients of ranking shorting variables RSS_{it} in Panel C are multiplied by 100 for presentation purposes.

Panel A. Intraday shorting flows respond to previous negative news

	I		II		III	
	SSOPEN		SSMIDDLE		SSCLOSE	
	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat
PreviousNegNews	0.0099	20.89	-0.0021	-5.36	-0.0119	-18.33
Control	Yes		Yes		Yes	
Adj.R2	0.0535		0.0213		0.0849	

Panel B. Predicting future negative news using intraday shorting flows

	SSOPEN Coef.	*t*-stat	SSMIDDLE Coef.	*t*-stat	SSCLOSE Coef.	*t*-stat
FutureNegNews next day	0.0051	7.78	-0.0015	-2.37	0.0016	0.19
FutureNegNews Week 1	0.0202	12.90	0.0052	3.29	-0.0058	-0.39
FutureNegNews Week 2	0.0162	10.93	0.0109	6.93	0.0238	1.48
FutureNegNews Week 3	0.0160	10.04	0.0110	7.09	0.0097	0.67
FutureNegNews Week 4	0.0152	8.57	0.0125	7.87	0.0203	0.73
FutureNegNews Week 5	0.0151	9.38	0.0106	6.63	0.0005	0.04
FutureNegNews Week 6	0.0140	9.77	0.0119	7.86	0.0149	1.41
FutureNegNews Week 7	0.0149	9.50	0.0098	6.47	0.0164	1.23
FutureNegNews Week 8	0.0159	9.20	0.0114	7.74	-0.0039	-0.61
FutureNegNews Week 9	0.0152	10.26	0.0107	7.34	0.0168	1.06
FutureNegNews Week 10	0.0143	8.71	0.0104	6.93	-0.0030	-0.30
FutureNegNews Week 11	0.0156	10.17	0.0119	7.77	0.0071	0.73
FutureNegNews Week 12	0.0147	9.68	0.0113	7.08	0.0205	0.77

Panel C. Predicting future returns using intraday shorting flows, interacted with previous overnight negative news

	I		II		III		IV		V		VI	
	RSSOPEN		RSSOPEN *PreviousNegNews		RSSMIDDLE		RSSMIDDLE *PreviousNegNews		RSSCLOSE		RSSCLOSE *PreviousNegNews	
	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat
Next day	-0.0808	-7.75	-0.1052	-4.68	-0.0568	-5.61	-0.1302	-5.74	-0.0351	-3.35	-0.1473	-6.40
Week 1	-0.0305	-3.64	-0.0141	-1.43	-0.0242	-3.78	-0.0229	-2.12	-0.0084	-1.18	-0.0247	-2.61
Week 2	-0.0068	-0.81	0.0038	0.51	-0.0050	-0.81	0.0000	0.00	-0.0049	-0.74	-0.0072	-0.84
Week 3	-0.0135	-1.62	0.0156	1.87	-0.0131	-2.08	0.0166	1.97	-0.0108	-1.59	0.0153	1.84
Week 4	-0.0186	-2.12	0.0066	0.73	-0.0148	-2.40	0.0035	0.41	-0.0091	-1.44	0.0020	0.26
Week 5	-0.0220	-2.51	0.0227	2.38	-0.0165	-2.70	0.0259	2.77	-0.0065	-1.10	0.0174	1.94
Week 6	-0.0222	-2.56	0.0115	1.31	-0.0111	-1.81	0.0124	1.35	-0.0066	-1.03	0.0081	0.96
Week 7	-0.0201	-2.38	0.0201	2.15	-0.0145	-2.22	0.0037	0.36	-0.0039	-0.61	0.0084	0.88
Week 8	-0.0231	-2.62	0.0086	0.87	-0.0178	-2.88	0.0073	0.78	-0.0006	-0.09	0.0067	0.65
Week 9	-0.0210	-2.47	0.0004	0.05	-0.0142	-2.21	0.0001	0.01	-0.0018	-0.28	0.0036	0.39
Week 10	-0.0229	-2.59	0.0151	1.40	-0.0124	-1.84	0.0157	1.48	-0.0045	-0.73	0.0086	0.84
Week 11	-0.0239	-2.55	-0.0071	-0.74	-0.0113	-1.56	-0.0114	-1.01	0.0019	0.28	0.0000	0.00
Week 12	-0.0143	-1.55	0.0034	0.33	-0.0178	-2.61	0.0015	0.14	-0.0064	-0.87	-0.0040	-0.41

Table 4. Intraday Shorting Flows and Informed Trades

This table examines the trading dynamics and return predictability of intraday shorting flows and the insider sales and Schedule 13D trades. The insider sale data is from Thomson Reuters Insider Filings (Form 4) and we choose the insider sales transaction date as the event day. *DInsiderSale*, is a dummy equal to one if the insider sells on firm *i* on day *t*, and zero otherwise. Panel A examines intraday shorting flows and insider sales by estimating the following Fama-MacBeth regression:

$$Shorting_{it} = b_{0t} + b_{1t}DInsiderSale_{it} + b_{2t}{}'Controls_{it} + \epsilon_{it}.$$

The control variables are the same as in Table 2, and we also control for previous day's short selling to control the persistence. Panel B examines whether intraday shorting flows could predict future insider sales, as specified by the following Fama-MacBeth regression:

$$DInsiderSale_{i,t+k} = b_{0t} + b_{1t}Shorting_{it} + b_{2t}{}'Controls_{it} + \epsilon_{i,t+k}.$$

The control variables are the same as in Table 2, and we also control for previous day's insider sales to control its persistence. Panel C examines the return predictability of intraday shorting flows, and insider sales as specified in the following Fama-MacBeth regression:

$$Ret_{i,t+k} = b_{0t} + b_{1t}RSSOPEN_{it} + b_{2t}RSSMIDDLE_{it} + b_{3t}RSSCLOSE_{it} + b_{4t}DInsiderSale_{it} + b_{5t}{}'Controls_{it} + \epsilon_{i,t+k},$$

The control variables are the same as in Table 2 and omitted from presentation. To account for potential serial correlation in the coefficients, the standard errors of the time-series are adjusted using Newey-West (1987) with eight lags. The regression coefficients of Panel C are multiplied by 100 for presentation purposes. Panel D examines the return predictability of intraday shorting flows, and informed trading intensity (ITI) learned from Schedule 13D trading as specified in the following Fama-MacBeth regression:

$$Ret_{i,t+k} = b_{0t} + b_{1t}RSSOPEN_{it} + b_{2t}RSSMIDDLE_{it} + b_{3t}RSSCLOSE_{it} + b_{4t}ITI_{it} + b_{5t}{}'Controls_{it} + \epsilon_{i,t+k}.$$

The stock-day informed trading intensity (ITI) is from Bogousslavsky, Fos, and Muravyev (2024). The control variables are the same as in Table 2 and omitted from presentation. To account for potential serial correlation in the coefficients, the standard errors of the time-series are adjusted using Newey-West (1987) with eight lags. The regression coefficients of Panel D are multiplied by 100 for presentation purposes.

Panel A. Intraday shorting flows and insider sales

	I		II		III	
	SSOPEN		SSMIDDLE		SSCLOSE	
	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat
DInsiderSale	0.0018	5.38	-0.0012	-4.32	-0.0113	-25.73
Control	Yes		Yes		Yes	
Adj.R2	0.0533		0.0212		0.0860	

Panel B. Predicting insider sales over next 12 weeks using intraday shorting flows

	SSOPEN		SSMIDDLE		SSCLOSE	
	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat
DInsiderSale next day	0.0010	1.29	-0.0010	-1.35	-0.0090	-12.36
DInsiderSale Week 1	0.0081	5.13	-0.0003	-0.23	-0.0104	-6.40
DInsiderSale Week 2	0.0063	3.79	-0.0016	-1.03	-0.0058	-3.24
DInsiderSale Week 3	0.0035	2.13	0.0007	0.50	-0.0031	-1.70
DInsiderSale Week 4	0.0029	1.76	0.0028	1.79	-0.0014	-0.74
DInsiderSale Week 5	0.0034	1.82	0.0000	-0.02	-0.0022	-1.09
DInsiderSale Week 6	0.0024	1.28	0.0009	0.56	-0.0009	-0.42
DInsiderSale Week 7	0.0009	0.47	0.0007	0.41	0.0001	0.04
DInsiderSale Week 8	0.0028	1.52	0.0004	0.21	-0.0014	-0.63
DInsiderSale Week 9	0.0025	1.30	-0.0010	-0.63	-0.0033	-1.52
DInsiderSale Week 10	0.0016	0.85	-0.0010	-0.59	-0.0034	-1.54
DInsiderSale Week 11	-0.0017	-0.93	-0.0004	-0.25	-0.0020	-1.03
DInsiderSale Week 12	-0.0035	-1.96	-0.0007	-0.44	-0.0043	-2.37

Panel C. Predicting future returns using intraday shorting flows and insider sales

	RSSOPEN		RSSMIDDLE		RSSCLOSE		DInsiderSale	
	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat
Next day	-0.0862	-8.31	-0.0525	-5.36	-0.0496	-4.81	-0.0297	-3.24
Week 1	-0.0314	-3.77	-0.0221	-3.65	-0.0145	-2.03	-0.0365	-5.74
Week 2	-0.0071	-0.85	-0.0037	-0.63	-0.0068	-1.00	0.0048	0.90
Week 3	-0.0139	-1.70	-0.0118	-1.98	-0.0090	-1.34	0.0079	1.29
Week 4	-0.0189	-2.19	-0.0132	-2.24	-0.0123	-1.91	0.0001	0.02
Week 5	-0.0218	-2.52	-0.0140	-2.40	-0.0106	-1.76	0.0014	0.26
Week 6	-0.0225	-2.66	-0.0093	-1.57	-0.0090	-1.42	0.0099	1.90
Week 7	-0.0206	-2.45	-0.0130	-2.08	-0.0053	-0.81	0.0118	1.95
Week 8	-0.0219	-2.48	-0.0157	-2.68	-0.0023	-0.36	0.0084	1.53
Week 9	-0.0211	-2.50	-0.0122	-2.00	-0.0045	-0.68	0.0071	1.23
Week 10	-0.0241	-2.76	-0.0107	-1.70	-0.0073	-1.15	0.0096	1.27
Week 11	-0.0248	-2.65	-0.0104	-1.55	-0.0020	-0.27	0.0118	1.56
Week 12	-0.0145	-1.59	-0.0169	-2.64	-0.0084	-1.19	0.0109	1.30

Panel D. Predicting future returns using intraday shorting flows and informed trading intensity learned from Schedule 13D trading

	RSSOPEN		RSSMIDDLE		RSSCLOSE		ITI	
	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat
Next day	-0.0776	-9.49	-0.0741	-9.10	-0.0564	-6.65	0.0842	6.73
Week1	-0.0255	-4.12	-0.0263	-5.52	-0.0139	-2.35	0.0304	3.93
Week2	-0.0103	-1.69	-0.0053	-1.14	-0.0089	-1.71	0.0117	1.99
Week3	-0.0181	-2.82	-0.0108	-2.26	-0.0114	-2.01	0.0027	0.41
Week4	-0.0186	-2.76	-0.0094	-2.02	-0.0053	-0.96	0.0001	0.01
Week5	-0.0192	-3.10	-0.0135	-3.01	-0.0052	-0.95	0.0022	0.37
Week6	-0.0235	-3.56	-0.0079	-1.67	-0.0059	-1.11	0.0004	0.08
Week7	-0.0209	-3.52	-0.0111	-2.13	-0.0039	-0.71	-0.0045	-0.70
Week8	-0.0173	-2.50	-0.0120	-2.33	0.0007	0.14	-0.0033	-0.48
Week9	-0.0277	-4.20	-0.0083	-1.69	0.0010	0.18	-0.0028	-0.43
Week10	-0.0159	-2.37	-0.0129	-2.55	-0.0034	-0.61	0.0035	0.53
Week11	-0.0157	-2.18	-0.0138	-2.71	-0.0011	-0.19	0.0068	1.00
Week12	-0.0156	-2.34	-0.0114	-2.40	-0.0060	-1.05	0.0030	0.47

Table 5. Borrower Concentration of Short Sellers

This table presents the borrower concentration of short sellers. We obtain the daily borrower concentration from Markit, which measures the level of concentration of borrower demand on the securities lending market by calculating the Herfindahl index based on the market share of different borrowers' demand. To be specific, assume stock *i* on day *t*, there are N borrowers borrow shares in, borrower *n*'s borrower share is $s(i,t,n)$, and the total borrower shares are $S(i,t) = \sum_{n=1}^{N} s(i,t,n)$, then the borrower concentration is measured as $BC = \sum_{n=1}^{N} \left[\frac{s(i,t,n)}{S(i,t)}\right]^2$. This daily stock level variable is a value between 0 and 1. A very small number indicates a large number of borrowers with low borrowed values and 1 indicates a single borrower with all the broker demand. Panel A presents the summary statistics of BC. We also present the summary statistics of BC in low and high shorting fee firms, divided by the cross-sectional median. Panel B examines the intraday shorting flows and contemporaneous daily borrower concentration, as specified by the following Fama-MacBeth regression:

$$Shorting_{it} = b_{0t} + b_{1t}BC_{it} + b_{2t}{}'Controls_{it} + \epsilon_{it}.$$

The control variables are the same as in Table 2, and we also control for previous day's short selling to control the persistence. Panel C examines the return predictability of intraday shorting flows after controlling borrower concentration, as specified by the following Fama-MacBeth regression:

$$Ret_{i,t+\mathrm{k}} = b_{0t} + b_{1t}RSS_{it} + b_{2t}RSS_{it} \times DHighBC_{it} + b_{3t}{}' \; Controls_{it} + \epsilon_{i,t+\mathrm{k}}.$$

On each day, we group stocks into low and high borrower concentration (BC) groups by median, if BC is above the cross-sectional median, then $DHighBC_{it}$ equals to 1, and zero otherwise. The control variables are the same as in Table 2 and omitted from presentation. To account for potential serial correlation in the coefficients, the standard errors of the time-series are adjusted using Newey-West (1987) with eight lags. The regression coefficients of Panel C are multiplied by 100 for presentation purposes.

Panel A. Summary statistics of borrower concentration

	Mean	Std	P25	P50	P75
Borrower concentration	0.3028	0.1907	0.1692	0.2437	0.3729
Borrower concentration for low shorting fee firms	0.2901	0.1735	0.1680	0.2395	0.3574
Borrower concentration for high shorting fee firms	0.3196	0.2095	0.1709	0.2503	0.3983

Panel B. Intraday shorting flows and daily borrower concentration

	I SSOPEN Coef.	t-stat	II SSMIDDLE Coef.	t-stat	III SSCLOSE Coef.	t-stat
Borrower Concentration	-0.0390	-50.79	-0.0401	-50.06	-0.0710	-52.95
Control	Yes		Yes		Yes	
Adj.R2	0.0579		0.0265		0.0946	

Panel C. Predicting future returns using intraday shorting flows, interacted with high borrower concentration dummy

	I		II		III		IV		V		VI	
	RSSOPEN		RSSOPEN *DHighBC		RSSMIDDLE		RSSMIDDLE *DHighBC		RSSCLOSE		RSSCLOSE *DHighBC	
	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat
Next day	-0.0975	-7.68	0.0321	3.59	-0.0746	-6.15	0.0361	4.12	-0.0537	-4.83	0.0335	4.01
Week 1	-0.0440	-4.00	0.0279	3.44	-0.0385	-4.21	0.0305	3.90	-0.0226	-2.68	0.0286	3.94
Week 2	-0.0184	-1.72	0.0269	3.43	-0.0163	-1.82	0.0267	3.44	-0.0169	-2.16	0.0241	3.36
Week 3	-0.0245	-2.29	0.0236	3.07	-0.0247	-2.74	0.0255	3.33	-0.0175	-2.21	0.0236	3.34
Week 4	-0.0262	-2.33	0.0184	2.35	-0.0242	-2.70	0.0210	2.75	-0.0179	-2.38	0.0201	2.84
Week 5	-0.0307	-2.74	0.0209	2.67	-0.0267	-3.02	0.0245	3.29	-0.0182	-2.59	0.0229	3.20
Week 6	-0.0298	-2.65	0.0176	2.25	-0.0216	-2.43	0.0231	3.05	-0.0145	-2.01	0.0189	2.53
Week 7	-0.0303	-2.68	0.0209	2.54	-0.0254	-2.68	0.0223	2.81	-0.0135	-1.82	0.0216	2.97
Week 8	-0.0344	-2.95	0.0247	3.04	-0.0291	-3.23	0.0247	3.20	-0.0123	-1.64	0.0261	3.64
Week 9	-0.0364	-3.21	0.0300	3.74	-0.0272	-2.92	0.0288	3.64	-0.0133	-1.76	0.0249	3.40
Week 10	-0.0354	-3.01	0.0284	3.54	-0.0263	-2.73	0.0303	3.83	-0.0149	-2.04	0.0242	3.29
Week 11	-0.0368	-3.04	0.0258	3.31	-0.0251	-2.50	0.0307	3.96	-0.0090	-1.09	0.0253	3.40
Week 12	-0.0258	-2.15	0.0286	3.57	-0.0300	-3.16	0.0280	3.59	-0.0188	-2.36	0.0286	3.92

Table 6. Intraday Shorting Flows, Intraday Stock Liquidity, and Noise Trading

This table examines the trading dynamics of the intraday shorting flows, intraday stock liquidity and noise trading. For liquidity measures, effective spread is the share-weighted effective spread, and lambda is the slope coefficient of $ret_{ith} = \delta_{it} + \lambda_{it}S_{ith} + \epsilon_{ith}$. *ESOPEN* (*ESMIDDLE*/*ESCLOSE*) is the effective spread calculated over the first two hours of the trading day (middle 2.5 hours/last two hours). *LAOPEN* (*LAMIDDLE*/*LACLOSE*) is the lambda estimated over the first two hours of the trading day (middle 2.5 hours/last two hours). Liquidity measures are 1% and 99% winsorized. We use retail trading to proxy for noise trading and identify the retail buy and sell volumes following the Boehmer et al. (2021) algorithm, modified by Barber et al. (2024). The *NoiseOPEN* (*NoiseMIDDLE*/*NoiseCLOSE*) are the retail buy volumes plus retail sell volumes over the first two hours of the trading day (middle 2.5 hours/last two hours) divided by the daily stock total trading volumes. Panel A presents the summary statistics of intraday liquidity and noise trading measures. Panel B to Panel D present the trading dynamics of intraday shorting flows and contemporaneous intraday illiquidity and noise trading, as specified in the following Fama-MacBeth equation,

$$Shorting_{it} = b_{0t} + b_{1t}LIQ/Noise_{it} + b_{2t}'Controls_{it} + \epsilon_{it},$$

The control variables are the same as in Table 2 and omitted from presentation. We also control for previous day *t*-1 *SSOPEN* (*SSMIDDLE*/*SSCLOSE*) to control the persistence of shorting flows. To account for potential serial correlation in the coefficients, the standard errors of the time-series are adjusted using Newey-West (1987) with eight lags.

Panel A. Intraday patterns of liquidity and noise trading measures

	Mean	Std	P25	P50	P75
ESOPEN	0.0070	0.0128	0.0010	0.0025	0.0069
ESMIDDLE	0.0033	0.0059	0.0005	0.0012	0.0033
ESCLOSE	0.0031	0.0057	0.0004	0.0010	0.0030
LAOPEN	0.0578	0.1547	0.0034	0.0148	0.0523
LAMIDDLE	0.0286	0.0649	0.0025	0.0095	0.0301
LACLOSE	0.0204	0.0547	0.0012	0.0048	0.0175
NoiseOPEN	0.0333	0.0547	0.0076	0.0160	0.0343
NoiseMIDDLE	0.0283	0.0483	0.0075	0.0145	0.0284
NoiseECLOSE	0.0306	0.0486	0.0099	0.0175	0.0310

Panel B. Intraday shorting flows from CBOE and contemporaneous intraday liquidity proxied by effective spread

	I		II		III	
	SSOPEN		SSMIDDLE		SSCLOSE	
	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat
ESOPEN	-0.4481	-22.37				
ESMIDDLE			0.6499	13.12		
ESCLOSE					0.0172	0.24
Control	Yes		Yes		Yes	
Adj.R2	0.0558		0.0243		0.0883	

Panel C. Intraday shorting flows from CBOE and contemporaneous intraday liquidity proxied by lambda

	I		II		III	
	SSOPEN		SSMIDDLE		SSCLOSE	
	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat
LAOPEN	-0.0213	-18.74				
LAMIDDLE			0.0267	8.79		
LACLOSE					-0.0557	-19.02
Control	Yes		Yes		Yes	
Adj.R2	0.0748		0.0358		0.1188	

Panel D. Intraday shorting flows from CBOE and contemporaneous intraday noise trading proxied by retail trading identified from Barber et al. (2024)

	I		II		III	
	SSOPEN		SSMIDDLE		SSCLOSE	
	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat
NoiseOPEN	0.5193	84.19				
NoiseMIDDLE			0.4126	66.19		
NoiseCLOSE					0.2603	43.43
Control	Yes		Yes		Yes	
Adj.R2	0.1055		0.0525		0.0990	

Table 7. Predicting Future Returns Using Intraday Shorting Flows from CBOE Interacted with Intraday Stock Liquidity, and Noise Trading

This table examines the return predictability of the intraday shorting flows, interacted with intraday stock liquidity and noise trading. For liquidity measures, effective spread is the share-weighted effective spread, and lambda is the slope coefficient of $ret_{ith} = \delta_{it} + \lambda_{it} S_{ith} + \epsilon_{ith}$. *ESOPEN* (*ESMIDDLE*/*ESCLOSE*) is the effective spread calculated over the first two hours of the trading day (middle 2.5 hours/last two hours). *LAOPEN* (*LAMIDDLE*/*LACLOSE*) is the lambda estimated over the first two hours of the trading day (middle 2.5 hours/last two hours). Liquidity measures are 1% and 99% winsorized. We use retail trading to proxy for noise trading and identify the retail buy and sell volumes following the Boehmer et al. (2021) algorithm, modified by Barber et al. (2024). The *NoiseOPEN* (*NoiseMIDDLE*/*NoiseCLOSE*) are the retail buy volumes plus retail sell volumes over the first two hours of the trading day (middle 2.5 hours/last two hours) divided by the daily stock total trading volumes. Panel A to Panel C examine the return predictability of intraday shorting flows, interacted with intraday liquidity and noise trading as specified in the following Fama-MacBeth regression

$$Ret_{i,t+k} = b_{0t} + b_{1t} RSS_{it} + b_{2t} RSS_{it} \times (LIQ_{it}/Noise_{it}) + b_{3t} Controls'_{it} + \epsilon_{i,t+k},$$

The control variables are the same as in Table 2 and omitted from presentation. To account for potential serial correlation in the coefficients, the standard errors of the time-series are adjusted using Newey-West (1987) with eight lags. The regression coefficients of ranking shorting variables are multiplied by 100 for presentation purposes.

Panel A. Predicting future returns using intraday shorting flows, interacted with intraday liquidity proxied by effective spread

	I RSS OPEN Coef.	*t*-stat	II RSSOPEN *ESOPEN Coef.	*t*-stat	III RSS MIDDLE Coef.	*t*-stat	IV RSSMIDDLE *ESMIDDLE Coef.	*t*-stat	V RSS CLOSE Coef.	*t*-stat	VI RSSCLOSE *ESCLOSE Coef.	*t*-stat
Next Day	-0.0949	-7.03	1.5123	2.09	-0.0802	-6.39	4.7212	3.63	-0.0586	-4.70	4.0635	2.85
Week 1	-0.0355	-3.21	0.6746	1.43	-0.0294	-3.00	1.2317	1.26	-0.0154	-1.61	1.1421	1.22
Week 2	-0.0103	-0.96	0.5928	1.27	-0.0101	-1.08	1.3522	1.35	-0.0100	-1.06	0.7255	0.76
Week 3	-0.0188	-1.73	0.6009	1.24	-0.0182	-1.88	1.1357	1.18	-0.0094	-0.99	0.4675	0.50
Week 4	-0.0201	-1.80	0.2826	0.63	-0.0175	-1.82	0.9222	0.92	-0.0130	-1.43	0.8701	0.89
Week 5	-0.0266	-2.36	0.5513	1.13	-0.0203	-2.23	1.1739	1.14	-0.0120	-1.42	1.0951	1.16
Week 6	-0.0291	-2.60	0.9135	1.93	-0.0171	-1.86	1.3690	1.36	-0.0114	-1.31	1.1184	1.18
Week 7	-0.0250	-2.23	0.5348	1.10	-0.0209	-2.17	1.3903	1.41	-0.0112	-1.24	1.6035	1.70
Week 8	-0.0301	-2.57	0.8865	1.79	-0.0245	-2.58	1.5722	1.61	-0.0118	-1.31	2.4620	2.54
Week 9	-0.0309	-2.72	1.0683	2.06	-0.0230	-2.32	2.0057	1.82	-0.0093	-1.00	1.7283	1.77
Week 10	-0.0313	-2.60	1.0716	1.88	-0.0230	-2.16	2.4201	2.07	-0.0088	-0.97	1.5633	1.50
Week 11	-0.0365	-2.92	1.5083	2.73	-0.0240	-2.25	2.9024	2.55	-0.0087	-0.91	2.6687	2.34
Week 12	-0.0260	-2.10	1.6490	2.94	-0.0287	-2.70	2.5323	2.06	-0.0156	-1.62	2.2613	2.13

Panel B. Predicting future returns using intraday shorting flows, interacted with intraday liquidity proxied by lambda

	I RSS OPEN		II RSSOPEN *LAOPEN		III RSS MIDDLE		IV RSSMIDDLE *LAMIDDLE		V RSS CLOSE		VI RSSCLOSE *LACLOSE	
	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat
Next Day	-0.1027	-9.80	0.0004	0.99	-0.0772	-7.47	0.0011	1.06	-0.0456	-4.17	0.0005	0.46
Week 1	-0.0347	-4.29	0.0000	-0.17	-0.0293	-4.66	0.0001	0.21	-0.0103	-1.25	-0.0002	-0.27
Week 2	-0.0084	-1.04	0.0003	0.85	-0.0032	-0.54	-0.0001	-0.22	-0.0052	-0.66	-0.0010	-1.36
Week 3	-0.0166	-2.03	0.0002	0.74	-0.0140	-2.23	0.0006	0.87	-0.0065	-0.81	0.0008	1.05
Week 4	-0.0163	-1.84	-0.0001	-0.49	-0.0118	-1.96	-0.0001	-0.25	-0.0059	-0.74	-0.0014	-2.11
Week 5	-0.0234	-2.79	0.0001	0.32	-0.0135	-2.49	0.0004	0.51	-0.0063	-0.85	-0.0003	-0.45
Week 6	-0.0242	-2.96	0.0001	0.22	-0.0078	-1.35	-0.0007	-1.09	-0.0057	-0.74	-0.0001	-0.12
Week 7	-0.0205	-2.47	0.0000	0.11	-0.0121	-1.94	-0.0011	-1.79	-0.0003	-0.04	-0.0007	-1.09
Week 8	-0.0238	-2.64	0.0001	0.18	-0.0160	-2.67	0.0002	0.39	0.0015	0.19	-0.0010	-1.34
Week 9	-0.0250	-2.99	0.0002	0.67	-0.0074	-1.22	-0.0009	-1.45	0.0028	0.36	-0.0014	-2.07
Week 10	-0.0193	-2.19	0.0000	-0.12	-0.0104	-1.75	0.0000	-0.02	0.0015	0.20	0.0001	0.17
Week 11	-0.0212	-2.34	0.0001	0.50	-0.0080	-1.20	-0.0005	-0.79	0.0060	0.71	-0.0007	-0.92
Week 12	-0.0124	-1.35	0.0002	0.74	-0.0161	-2.49	-0.0004	-0.77	-0.0039	-0.46	-0.0003	-0.39

Panel C. Predicting future returns using intraday shorting flows, interacted with intraday noise trading proxied by retail trading identified from Barber et al. (2024)

	I RSS OPEN Coef.	*t*-stat	II RSSOPEN *NoiseOPEN Coef.	*t*-stat	III RSS MIDDLE Coef.	*t*-stat	IV RSSMIDDLE *NoiseMIDDLE Coef.	*t*-stat	V RSS CLOSE Coef.	*t*-stat	VI RSSCLOSE *NoiseCLOSE Coef.	*t*-stat
Next Day	-0.0655	-5.53	-0.2426	-2.10	-0.0745	-6.47	0.3348	3.13	-0.0482	-4.15	0.1571	1.62
Week 1	-0.0216	-2.48	-0.1401	-1.97	-0.0271	-3.45	0.0641	0.94	-0.0119	-1.35	0.0190	0.32
Week 2	-0.0035	-0.39	-0.0384	-0.50	-0.0036	-0.46	0.0147	0.20	-0.0053	-0.62	-0.0267	-0.44
Week 3	-0.0126	-1.43	0.0008	0.01	-0.0125	-1.57	0.0112	0.16	-0.0085	-0.99	0.0290	0.45
Week 4	-0.0144	-1.58	-0.0512	-0.71	-0.0162	-2.10	0.0524	0.76	-0.0107	-1.29	0.0242	0.39
Week 5	-0.0211	-2.24	-0.0191	-0.24	-0.0138	-1.90	-0.0186	-0.25	-0.0103	-1.29	0.0631	0.91
Week 6	-0.0164	-1.75	-0.0753	-1.07	-0.0101	-1.34	-0.0131	-0.18	-0.0071	-0.87	-0.0077	-0.11
Week 7	-0.0117	-1.28	-0.1516	-2.08	-0.0160	-1.94	0.0444	0.59	-0.0021	-0.24	-0.0468	-0.69
Week 8	-0.0179	-1.88	-0.0826	-1.21	-0.0145	-1.85	-0.0620	-0.91	-0.0013	-0.16	-0.0139	-0.20
Week 9	-0.0181	-1.92	-0.0570	-0.84	-0.0115	-1.48	-0.0407	-0.57	-0.0033	-0.39	0.0119	0.18
Week 10	-0.0186	-1.85	-0.0687	-0.94	-0.0154	-1.81	0.0829	1.06	-0.0048	-0.59	0.0132	0.21
Week 11	-0.0226	-2.14	-0.0246	-0.35	-0.0143	-1.67	0.0602	0.89	-0.0002	-0.02	0.0337	0.48
Week 12	-0.0142	-1.37	0.0252	0.33	-0.0170	-2.06	-0.0004	-0.01	-0.0071	-0.78	-0.0041	-0.06

Table 8. Intraday Shorting Flows, Price Impact, and Liquidity around Tick Size Pilot

This table examines the intraday shorting flows and intraday stock liquidity during the Tick Size Pilot (TSP) period. The SEC launched the TSP program on October 3, 2016, and terminated it on September 30, 2018. The TSP program divided stocks into test groups and control group, and the test groups are all subjected to the Quote rule (quoted in \$0.05 increments). Panel A to Panel C examines the intraday liquidity around the TSP events as specified in the following panel regression:

$$LIQ_{it}/Noise_{it}/Shorting_{it} = b_0 + b_1 Pilot_i \times TSP_t + b_2 Pilot_i + b_3 TSP_t + b_4{}'Controls_{it} + \epsilon_{it},$$

LIQ_{it}represents the intraday liquidity measures effective spreads and lambda, $Noise_{it}$ represents the intraday noise trading, $Shoring_{it}$ represents the intraday showing flows. Firm variable $Pilot_i$ is equal to one for the test stocks, and zero otherwise. Time variable TSP_t is equal to one between October 3 of 2016 and September 30 of 2018, and zero otherwise. The control variables are the same as in Table 2. We also control for previous day *t*-1 variables to control the persistence of liquidity and shorting flows. Standard errors are double clustered by both firm and day. Panel D report the Fama-MacBeth regression coefficients of the return prediction of intraday shorting flows over the TSP period and other period, with the standard errors are estimated using Newey-West (1987) standard errors with eight lags.

Panel A. Intraday stock liquidity around Tick Size Pilot

	ESOPEN Coef.	*t*-stat	ESMIDDLE Coef.	*t*-stat	ESCLOSE Coef.	*t*-stat	LAOPEN Coef.	*t*-stat	LAMIDDLE Coef.	*t*-stat	LACLOSE Coef.	*t*-stat
Pilot*TSP	0.0009	5.63	0.0008	11.20	0.0009	11.68	0.0129	4.30	0.0051	5.61	0.0038	4.44
Control	Yes		Yes		Yes		Yes		Yes		Yes	
Adj.R2	0.292		0.514		0.552		0.010		0.007		0.005	

Panel B. Intraday noise trading around Tick Size Pilot

	NoiseOPEN Coef.	*t*-stat	NoiseMIDDLE Coef.	*t*-stat	NoiseCLOSE Coef.	*t*-stat
Pilot*TSP	-0.0073	-14.13	-0.0059	-13.66	-0.0073	-16.17
Control	Yes		Yes		Yes	
Adj.R2	0.17		0.144		0.135	

Panel C. Intraday shorting flows around Tick Size Pilot

	SSOPEN		SSMIDDLE		SSCLOSE	
	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat
Pilot*TSP	-0.0061	-6.07	-0.0022	-2.54	0.0212	15.32
Control	Yes		Yes		Yes	
Adj.R2	0.027		0.015		0.091	

Panel D. Predicting next day returns using intraday shorting flows in TSP and Non-TSP period

	RSSOPEN		RSSMIDDLE		RSSCLOSE	
	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat
Oct2016-Sep2018 (TSP period)	-0.0757	-4.93	-0.0697	-4.70	-0.0616	-3.86
NonTSP period	-0.0862	-6.20	-0.0508	-3.72	-0.0251	-1.92

Table 9. Intraday Shorting Flows and Liquidity around RavenPack News Events

This table examines the intraday shorting flows, and their relations with liquidity around Ravenpack News Events. Firm-level news is obtained from RavenPack and negative news is defined as news with *ESS* (event sentiment score) <0. We require the relevance score to be 100 to keep the most relevant news and event similarity days (*SIM*) > 90 days to exclude the stale news. The analysis is from 60 days before the negative news and 60 days after the negative news, we require each event has at least 100 days to be included. Panel A examines the intraday shorting flows around the negative news event *k* as specified by the following panel regression:

$$Shorting_{itk} = b_0 + b_1 D_{itk}^{-60,-21} + b_2 D_{itk}^{-20,-6} + b_3 D_{itk}^{-5,-1} + b_4 D_{itk}^{0} + b_5 D_{itk}^{1,5} + b_6{}' Controls_{itk} + \eta_k + \epsilon_{itk}.$$

Here $Shorting_{it}$ represents the intraday showing flows, $D_{itk}^{-60,-21}$ equals to one for firm *i* on day *t* within the [-60,-21] days before the negative news event, and zero otherwise. $D_{itk}^{-20,-6}$ equals to one for firm *i* on day *t* within the [-20,-6] days before the negative news event, and zero otherwise. $D_{itk}^{-5,-1}$ equals one for firm *i* on day *t* within the [-5,-1] days before the negative news event, and zero otherwise. D_{itk}^{0} equals to one if firm *i* on day *t* is the negative news event day. $D_{itk}^{1,5}$ equals to one for firm *i* on day *t* within the [1,5] days after the negative news event, and zero otherwise. Panel B and Panel C examine the relation of intraday shorting flows with intraday liquidity measures, as specified by the following panel regression:

$$Shorting_{itk} = b_0 + \left[b_1 + b_2 D_{itk}^{-60,-21} + b_3 D_{itk}^{-20,-6} + b_4 D_{itk}^{-5,-1} + b_5 D_{itk}^{0} + b_6 D_{itk}^{1,5}\right] \times LIQ_{itk} + b_7 Controls_{itk} + \eta_k + \epsilon_{itk},$$

where LIQ_{itk} represents the intraday liquidity measures effective spreads and Kyle lambda. The control variables are the same as in Table 2. η_k is the event fixed effect, standard error clustered at the event level.

Panel A. Intraday shorting flows around the negative news events

	SSOPEN		SSMIDDLE		SSCLOSE	
	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat
Constant	0.1634	35.63	0.1294	32.47	0.2721	46.63
D [-60,-21]	0.0001	0.83	-0.0007	-6.11	-0.0009	-4.71
D [-20,-6]	0.0006	4.37	-0.0002	-1.40	-0.0010	-5.23
D [-5,-1]	0.0011	5.69	-0.0011	-6.40	-0.0025	-9.87
D [0]	0.0069	19.21	-0.0032	-9.88	-0.0105	-23.82
D [1,5]	0.0011	5.85	-0.0001	-0.58	-0.0026	-10.65
Control	Yes		Yes		Yes	
Event FE	Yes		Yes		Yes	
Adj.R2	0.155		0.087		0.198	

Panel B. Intraday shorting flows and intraday liquidity proxied by effective spread around the negative news events

	SSOPEN ESOPEN Coef.	*t*-stat	SSMIDDLE ESMIDDLE Coef.	*t*-stat	SSCLOSE ESCLOSE Coef.	*t*-stat
ES	-0.8264	-59.72	1.2179	25.40	0.5113	8.02
ES*D [-60,-21]	-0.0169	-0.88	-0.2349	-4.94	0.0344	0.51
ES*D [-20,-6]	0.0309	1.26	-0.0281	-0.42	-0.0491	-0.56
ES*D [-5,-1]	0.0224	0.62	-0.2600	-2.78	-0.0676	-0.55
ES*D [0]	0.4234	6.02	-0.9956	-5.21	-1.5077	-6.24
ES*D [1,5]	0.0561	1.63	-0.1526	-1.63	-0.3583	-2.91
Control	Yes		Yes		Yes	
Event FE	Yes		Yes		Yes	
Adj.R2	0.160		0.090		0.208	

Panel C. Intraday shorting flows and intraday liquidity proxied by lambda around the negative news events

	SSOPEN LAOPEN Coef.	*t*-stat	SSMIDDLE LAMIDDLE Coef.	*t*-stat	SSCLOSE LACLOSE Coef.	*t*-stat
LA	-0.0333	-41.71	0.0261	12.01	0.0759	24.41
LA*D [-60,-21]	-0.0034	-3.12	-0.0144	-5.09	-0.0119	-2.62
LA*D [-20,-6]	-0.0005	-0.34	-0.0036	-0.98	-0.0125	-2.11
LA*D [-5,-1]	-0.0044	-2.04	-0.0094	-1.69	-0.0142	-1.64
LA*D [0]	0.0296	5.84	-0.0495	-4.74	-0.1153	-7.10
LA*D [1,5]	0.0035	1.52	0.0049	0.89	-0.0359	-4.29
Control	Yes		Yes		Yes	
Event FE	Yes		Yes		Yes	
Adj.R2	0.186		0.108		0.240	

Table 10. Large Spikes in Short Selling

This table examines the large spikes in short selling. Our sample period is January 2015 to December 2019, and our sample firms are common stocks with a share price of at least $1. Since open and close periods both have 2 hours, while middle period has 2.5 hours, we first compute hourly average shorting flows for our three different intervals so they can be comparable. Next, we compute the 95% threshold value using the pooled panel. If the shorting flow for a particular day*stock*interval is above this threshold, then we define it as a large spike. Panel A presents the number of large spikes. Panel B examines the non-linearity in the relation between short selling and future returns by including interactions with indicators for large spikes. The indicator for a large spike for a given interval, *DSPIKE*, is equal to one if the average hourly shorting flow during that interval is above the 95% threshold defined in panel A, and zero otherwise. The control variables are the same as in Table 2. To account for potential serial correlation in the coefficients, the standard errors of the time-series are adjusted using Newey-West (1987) with eight lags. The regression coefficients are multiplied by 100 for presentation purposes.

Panel A. Large spikes of shorting flows in open, middle and close period

	Nobs	# Large Spikes	% Large Spikes
Open Period	3,570,989	98,262	0.92%
Middle Period	3,570,989	47,737	0.45%
Close Period	3,570,989	389,649	3.64%
Total	10,712,967	535,648	5.00%

Panel B. Predicting future returns using intraday shorting flows, interacted with indicators for large spikes

	RSSOPEN		RSSOPEN *DSPIKE		RSSMIDDLE		RSSMIDDLE *DSPIKE		RSSCLOSE		RSSCLOSE *DSPIKE	
	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat
Next day	-0.0853	-6.93	0.0146	0.70	-0.0616	-5.47	0.0381	1.62	-0.0539	-4.28	0.0272	2.79
Week 1	-0.0332	-3.24	0.0129	0.96	-0.0264	-3.50	0.0236	1.48	-0.0175	-1.95	0.0127	1.94
Week 2	-0.0102	-1.01	0.0214	1.59	-0.0064	-0.88	0.0269	1.63	-0.0091	-1.09	0.0060	0.97
Week 3	-0.0190	-1.90	0.0294	2.25	-0.0149	-1.98	0.0200	1.22	-0.0105	-1.21	0.0067	1.00
Week 4	-0.0207	-1.99	0.0140	1.17	-0.0187	-2.53	0.0380	2.30	-0.0145	-1.73	0.0076	1.09
Week 5	-0.0285	-2.69	0.0389	2.85	-0.0176	-2.41	0.0303	1.82	-0.0143	-1.87	0.0118	1.73
Week 6	-0.0246	-2.31	0.0157	1.14	-0.0134	-1.83	0.0244	1.48	-0.0113	-1.42	0.0102	1.55
Week 7	-0.0254	-2.43	0.0232	1.63	-0.0179	-2.30	0.0329	1.74	-0.0103	-1.25	0.0136	2.16
Week 8	-0.0289	-2.61	0.0328	2.30	-0.0214	-2.90	0.0411	2.53	-0.0089	-1.08	0.0152	2.33
Week 9	-0.0288	-2.77	0.0380	2.70	-0.0206	-2.68	0.0664	3.70	-0.0100	-1.16	0.0148	2.12
Week 10	-0.0276	-2.46	0.0250	1.66	-0.0169	-2.12	0.0505	2.75	-0.0143	-1.69	0.0177	2.35
Week 11	-0.0310	-2.66	0.0303	2.05	-0.0157	-1.85	0.0395	2.25	-0.0120	-1.37	0.0234	3.07
Week 12	-0.0192	-1.66	0.0304	2.04	-0.0199	-2.47	0.0204	1.08	-0.0178	-2.04	0.0210	2.69

Table 11. Intraday Short Selling and Price Efficiency

This table examines intraday shorting flows and price efficiency. Our sample period is January 2015 to December 2019, and our sample firms are common stocks with a share price of at least $1. Internet Appendix B provides details about the construction of intraday price efficiency measures: pricing errors $\frac{\sigma(s)}{\sigma(p)}$ and absolute autocorrelations |AR5|. Panel A and Panel B present Fama-MacBeth regression coefficients of contemporaneous and next day intraday price efficiency measures on the shorting flow variables of the same interval. Control variables are the same as in Table 2. To account for the potential serial correlation in the coefficients, the standard errors of the time-series are adjusted using Newey-West (1987) with eight lags.

Panel A. Intraday shorting flows and contemporaneous price efficiency

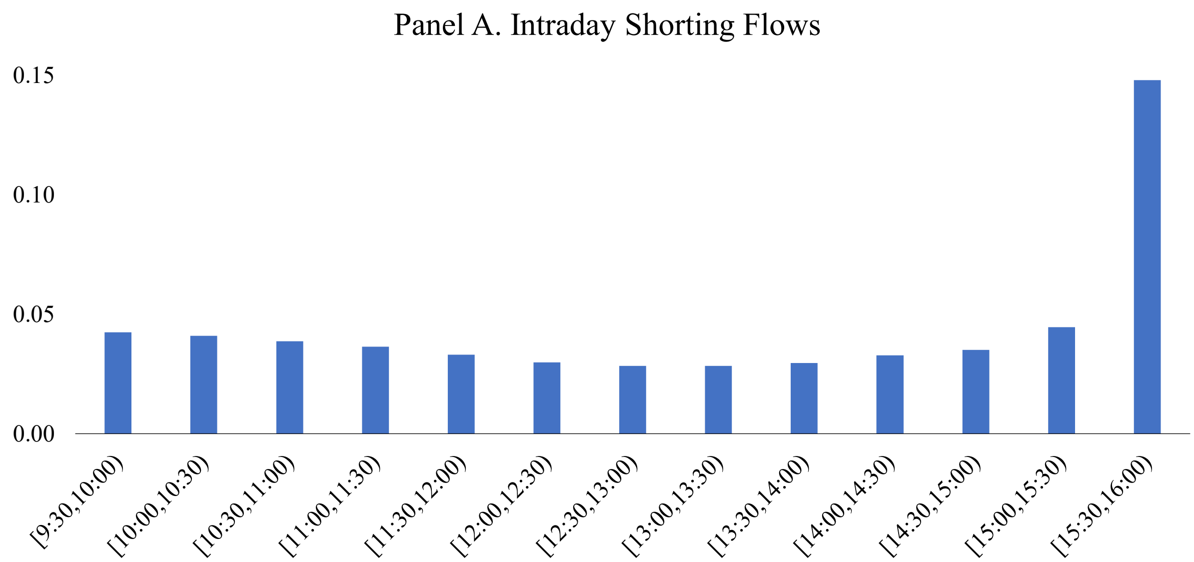
	I		II		III		IV		V		VI	
	$\frac{\sigma(s)}{\sigma(p)}$ OPEN(*t*)		$\frac{\sigma(s)}{\sigma(p)}$ MIDDLE(*t*)		$\frac{\sigma(s)}{\sigma(p)}$ CLOSE(*t*)		|AR5| OPEN(*t*)		|AR5| MIDDLE(*t*)		|AR5| CLOSE(*t*)	
	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat
SSOPEN(*t*)	-0.1514	-41.60					-0.0488	-32.78				
SSMIDDLE(*t*)			-0.0926	-24.46					-0.0318	-15.50		
SSCLOSE(*t*)					-0.0768	-37.61					-0.0003	-0.15
Control	Yes		Yes		Yes		Yes		Yes		Yes	
Adj.R2	0.1867		0.1874		0.1942		0.0170		0.0307		0.0246	

Panel B. Intraday shorting flows and next day price efficiency

	I		II		III		IV		V		VI	
	$\frac{\sigma(s)}{\sigma(p)}$ OPEN(*t*+1)		$\frac{\sigma(s)}{\sigma(p)}$ MIDDLE(*t*+1)		$\frac{\sigma(s)}{\sigma(p)}$ CLOSE(*t*+1)		|AR5| OPEN(*t*+1)		|AR5| MIDDLE(*t*+1)		|AR5| CLOSE(*t*+1)	
	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat
SSOPEN(*t*)	-0.0856	-23.17					-0.0368	-26.12				
SSMIDDLE(*t*)			-0.0438	-15.66					-0.0214	-12.50		
SSCLOSE(*t*)					-0.0572	-27.95					0.0094	5.64
Control	Yes		Yes		Yes		Yes		Yes		Yes	
Adj.R2	0.1796		0.1830		0.1898		0.0165		0.0305		0.0245	

Figure 1. Intraday Shorting Patterns

Panel A presents the average CBOE short volume during each half hour of the trading day for all sample firms. Panel B presents the average intraday shorting flows on CBOE exchanges on each date in our sample. Short includes all trades with a short seller. *SSOPEN* (*SSMIDDLE*/*SSCLOSE*) indicates the shorting flow over [9:30,11:30), [11:30,14:00), and [14:00,16:00), respectively. All CBOE short volumes are scaled by the total CBOE trading volume of the day.



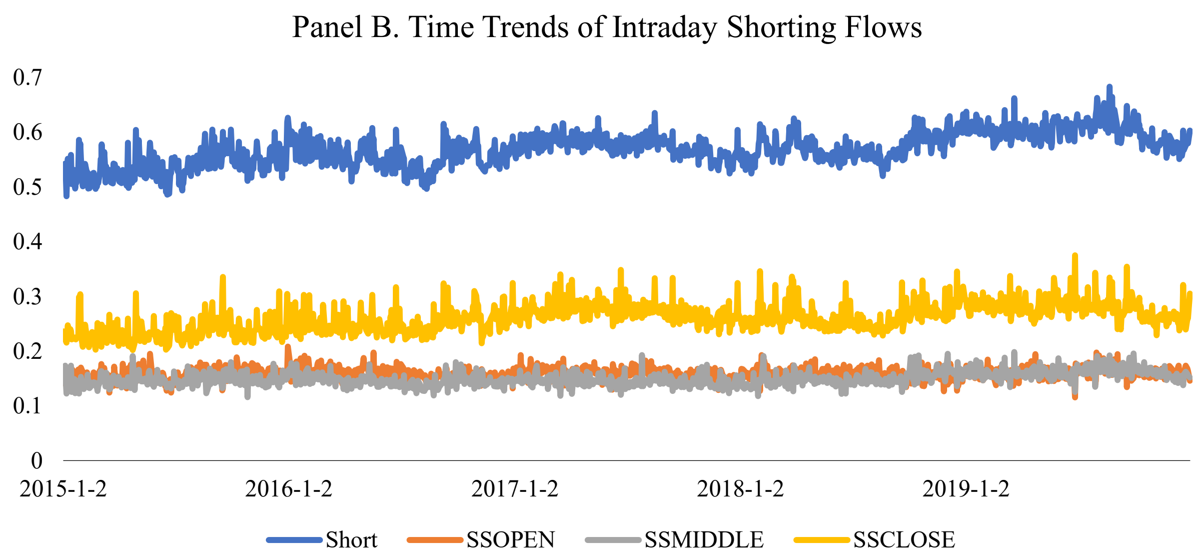


Figure 2. Time-series of Fama-MacBeth regression coefficients

This figure presents daily CBOE Fama-Macbeth regression coefficients (multiplied by 100 for presentation) for next-day predictive regressions during our sample period. The variable of interest *RSSOPEN*, *RSSMIDDLE* or *RSSCLOSE* indicates the ranked shorting flow over [9:30,11:30), [11:30,14:00), and [14:00,16:00), respectively. To smooth the time-series, here we report the 20-day moving average of the coefficients.

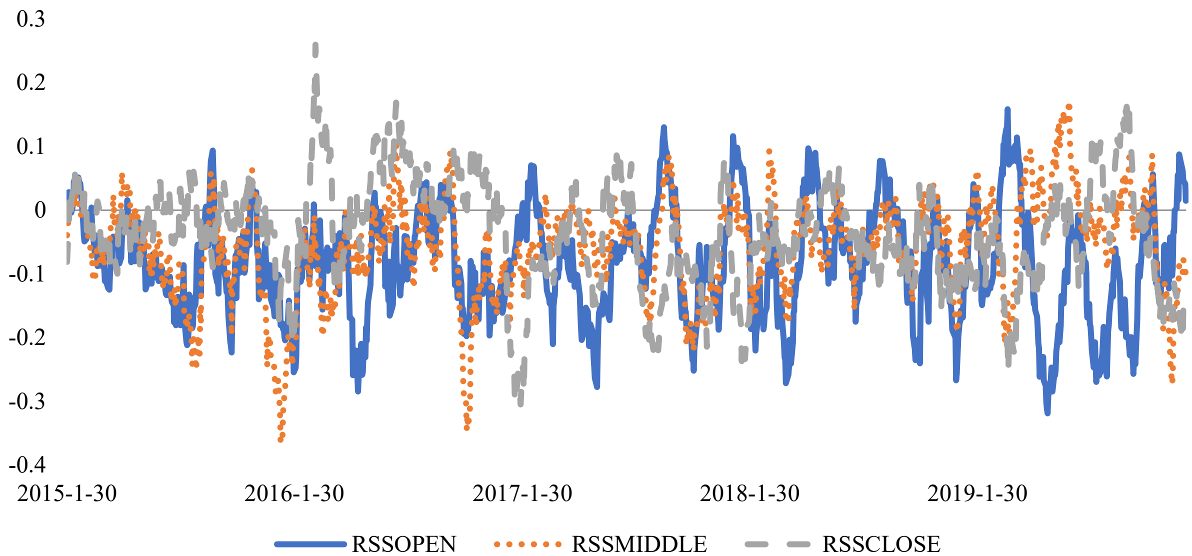
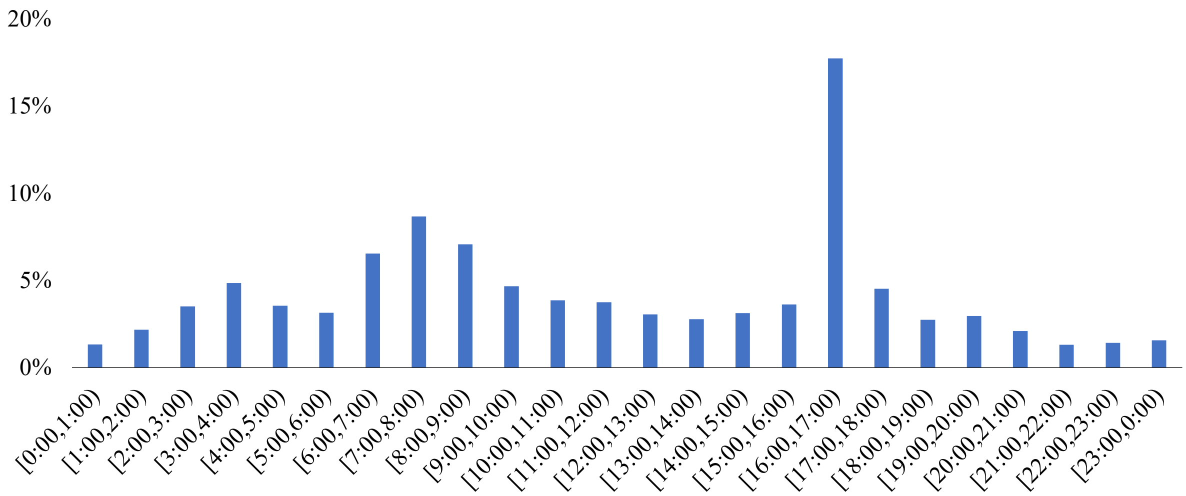


Figure 3. News Arrival Time

This figure presents the percentage of public news items that arrive in each hour of a 24-hour day. Panel A includes all public news from the RavenPack Equity Module and shows the number of news items in each time bucket across all sample firms and all days and calculate the percentage of items in each bucket relative to all news. Panel B presents the percentage of earnings-related public news that arrives in each hour of a 24-hour day. We obtain earnings announcements and management guidance (EA news) as well as analyst recommendations (REC news) from I\B\E\S.

Panel A. All Public News



Panel B. Earnings/ Analyst News

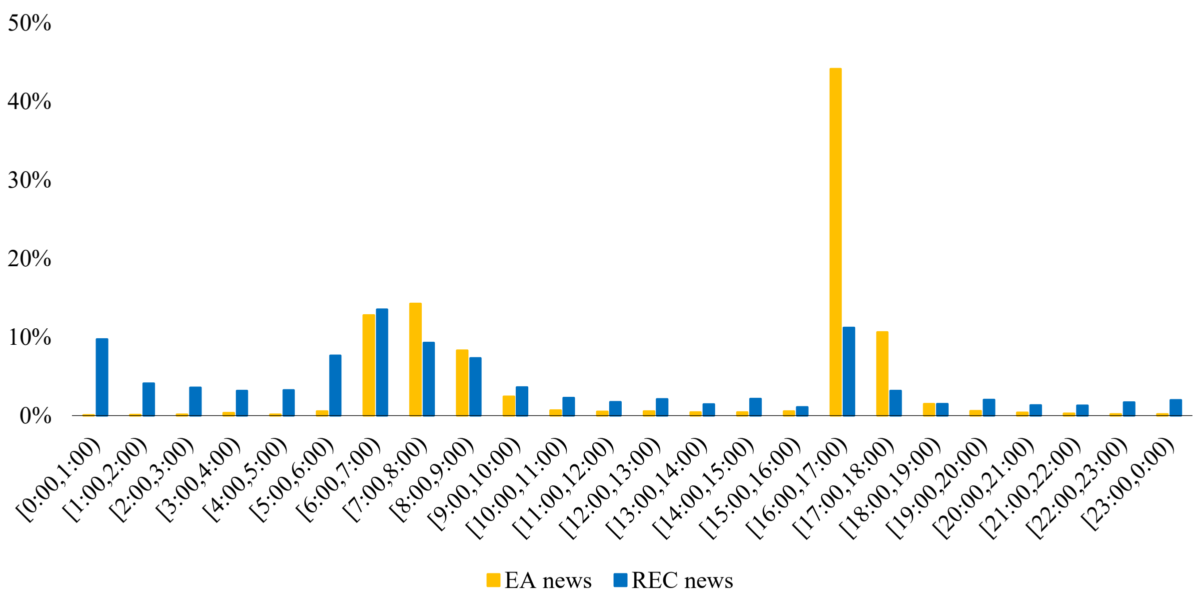
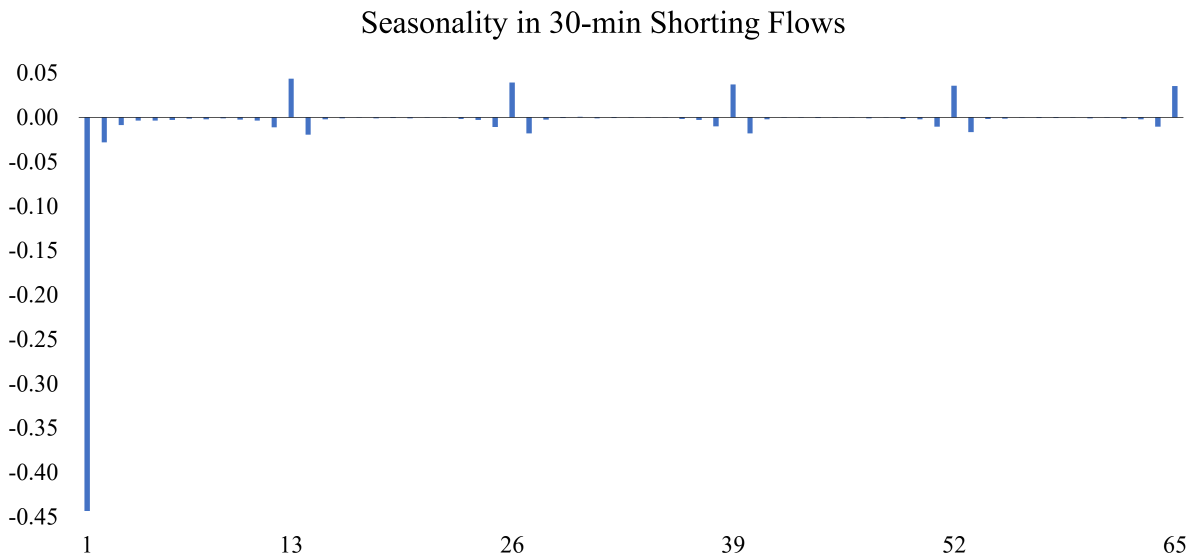


Figure 4. Seasonality of Intraday Shorting Flows

This figure plots the seasonality of half-hour shorting flows that are at exact multiples of a trading day. We regress changes in shorting volume in each half an hour on its lags (over past 5 days covering 65 lagged half-an-hour intervals) and plot the cross-sectional coefficients.



Internet Appendix of "When Do Short Sellers Trade?
Evidence from Intraday Data and Implications for Informed Trading Models"

by Danqi Hu, Charles M. Jones, Xiaoyan Zhang, and Xinran Zhang

April 2025

Internet Appendix A. The FINRA Data

The FINRA short sale sample consists of all short sale transactions that are executed off-exchange and reported to the consolidated tape. All of the transactions are reported via a FINRA Trade Reporting Facility (TRF), and the time-stamped details of the transaction (mainly price and size) are available to market participants in real time via a Securities Information Processor (SIP). By the start of the next trading day, the transaction details are also included in the daily TAQ database used by many researchers. But users of the real-time SIP transaction feed or the daily TAQ database cannot observe whether the seller in a reported off-exchange transaction is a short seller. By the start of the next trading day, FINRA posts on its website a summary for each ticker symbol of the total reported off-exchange trading volume that day and the number of those reported shares that were sold by a short seller. There is no transaction-by-transaction short sale information included in these daily summaries. Two weeks or so after the end of each month, FINRA posts all off-exchange transactions for that month that involve a short seller, and this trade-by-trade short sale dataset, which is similar to the CBOE dataset, is the one that we use.

There are lags between real transactions and data posting. For CBOE, the data become available on the same night, while FINRA does not post the trade-by-trade time-stamped short sale dataset until the middle of the following month. Due to the publication lags, market participants would not have the time stamps or the individual short sale trade prices and sizes in their information sets right away. Therefore, the cross-sectional predictability that we find from time-stamped trade-by-trade short sales, at intraday horizons for CBOE and short horizons for FINRA, should be interpreted as a measure of short sale information content rather than as a signal that can be used in real time to implement a trading strategy. For FINRA shorting flows, the numerators are the total shares sold short in FINRA's short-sale transaction files, and the denominator is that stock-day's total off-exchange trading volume reported by FINRA (Wang, Yan and Zheng, 2020).

Internet Appendix B. Intraday Price Efficiency Measures

B.1 Hasbrouck (1993) Pricing Errors

Hasbrouck assumes that the observed (log) transaction price at time *t*, p_t, can be decomposed into an efficient price, m_t, and the pricing error, s_t:

$$p_t = m_t + s_t \tag{A1}$$

where m_t is defined as the security's expected value conditional on all available information at transaction time *t*. By definition, m_t only moves in response to new information and is assumed to follow a random walk. The pricing error s_t measures the deviation relative to the efficient price. It captures non-information-related market frictions (such as price discreteness and inventory control effects, etc). s_t is assumed to be a zero-mean covariance-stationary process, and it can be serially correlated or correlated with the innovation from the random walk of efficient prices. Because the expected value of the deviation is zero, the standard deviation of the pricing error, $\sigma(s)$, measures the magnitude of deviation from the efficient price and can be interpreted as a measure of price efficiency for the purpose of assessing market quality.

In the empirical implementation, Hasbrouck (1993) estimates the following vector autoregression (VAR) system with five lags:

$$\begin{aligned} r_t &= a_1 r_{t-1} + a_2 r_{t-2} + \cdots + b_1 x_{t-1} + b_2 x_{t-2} + \cdots + v_{1,t} \\ x_t &= c_1 r_{t-1} + c_2 r_{t-2} + \cdots + d_1 x_{t-1} + d_2 x_{t-2} + \cdots + v_{2,t} \end{aligned} \tag{A2}$$

where r_t is the difference in (log) prices p_t, and x_t is a column vector of trade-related variables: a trade sign indicator, signed trading volume, and signed square root of trading volume to allow for concavity between prices and trades. $v_{1,t}$ and $v_{2,t}$ are zero-mean, serially uncorrelated disturbances from the return equation and trade equation, respectively.

The above VAR can be inverted to obtain its vector moving average (VMA) representation that expresses the variables in terms of contemporaneous and lagged disturbances:

$$\begin{aligned} r_t &= a_0^* v_{1,t} + a_1^* v_{1,t-1} + a_2^* v_{1,t-2} + \cdots + b_0^* v_{2,t} + b_1^* v_{2,t-1} + b_2^* v_{2,t-2} + \cdots \\ x_t &= c_0^* v_{1,t} + c_1^* v_{1,t-1} + c_2^* v_{1,t-2} + \cdots + d_0^* v_{2,t} + d_1^* v_{2,t-1} + d_2^* v_{2,t-2} + \cdots \end{aligned} \tag{A3}$$

To calculate the pricing error, only the return equation in (A3) is used. The pricing error under Beveridge and Nelson's (1981) identification restriction can be expressed as

$$s_t = \alpha_0 v_{1,t} + \alpha_1 v_{1,t-1} + \cdots + \beta_0 v_{2,t} + \beta_1 v_{2,t-1} + \cdots \tag{A4}$$

where $\alpha_j = -\sum_{k=j+1}^{\infty} a_k^*$, $\beta_j = -\sum_{k=j+1}^{\infty} b_k^*$. The variance of the pricing error is then computed as

$$\sigma_{(s)}^2 = \sum_{j=0}^{\infty} \left[\alpha_j, \beta_j\right] Cov(v) \begin{bmatrix} \alpha_j \\ \beta_j \end{bmatrix}. \tag{A5}$$

Following Hasbrouck (1993) and Boehmer and Wu (2013), we exclude overnight returns. We use Lee and Ready's (1991) algorithm to assign trade directions. To make comparisons across stocks meaningful, $\sigma(s)$ is scaled by the standard deviation of p_t, $\sigma(p)$ to control for cross-sectional differences in the return variance. This ratio $\frac{\sigma(s)}{\sigma(p)}$ reflects the proportion of deviations from the efficient price in the total variability of the observable transaction price process, and a smaller ration means a more efficient stock price. We estimate the pricing errors within each of our three time buckets, and the measures are $\frac{\sigma(s)}{\sigma(p)} OPEN$, $\frac{\sigma(s)}{\sigma(p)} MIDDLE$, $\frac{\sigma(s)}{\sigma(p)} CLOSE$.

B.2 Absolute Autocorrelations

Our second short-term measure of relative price efficiency is the absolute value of quote midpoint return autocorrelations. The intuition is that if the quote midpoint is the market's best estimate of the equilibrium value of the stock at any point in time, an efficient price process implies that quote midpoints follow a random walk, and a smaller absolute value of autocorrelation indicates greater price efficiency. We choose a five-minute return intervals and estimate the intraday quote midpoint return autocorrelations within each of our three time buckets, and the measures are $|AR5|OPEN$, $|AR5|MIDDLE$, and $|AR5|CLOSE$.

Internet Appendix Table 1. Alternative Specifications of Intraday Shorting Flows and Future Returns

This table presents results of Fama-MacBeth regression coefficients from the baseline equation (3), examining alternative specifications of intraday short flows and future returns. Our sample period is January 2015 to December 2019, and our sample firms are common stocks with a share price of at least $1. In Panel A, we consider an alternative specification of intraday shorting flows: *SSOPEN* is defined as short volume over [9:30,10:00) divided by CBOE total trading volume. Similarly, *SSCLOSE* is short volume over [15:30,16:00), while *SSMIDDLE* is short volume during the rest of the trading day. The future returns are next day returns and next 12 weeks returns. In Panel B, shorting flows are computed for each 30-min interval, and the future returns are next day returns. In Panel C, we modify the specification of future returns. Specifically, the dependent variables are next 24-hour return, and the independent variables are corresponding shorting flows. To compute the ranks, we sort all stocks by shorting flow variables into 100 groups and assign the rank number to the variable. The *RSS* variables are then computed as rank variables divided by 100. Control variables are the same as in prior tables but are not displayed here. To account for potential serial correlation in the coefficients, the standard errors of the time-series are adjusted using Newey-West (1987) with eight lags. The regression coefficients of ranking shorting variables are multiplied by 100 for presentation purposes.

Panel A. Predicting future returns, using first and last 30 minutes as open and close shoring flow variables

	RSSOPEN [9:30-10:00)		RSSMIDDLE [10:00-15:30)		RSSCLOSE [15:30-16:00)	
	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat
Next day	-0.0745	-5.89	-0.0740	-8.17	-0.0350	-3.07
Week 1	-0.0375	-3.68	-0.0233	-3.98	-0.0133	-1.55
Week 2	-0.0182	-1.74	-0.0006	-0.11	-0.0069	-0.82
Week 3	-0.0199	-2.00	-0.0065	-1.09	-0.0120	-1.48
Week 4	-0.0192	-1.77	-0.0121	-2.11	-0.0120	-1.50
Week 5	-0.0212	-2.01	-0.0156	-2.79	-0.0079	-1.07
Week 6	-0.0209	-1.93	-0.0144	-2.54	-0.0047	-0.59
Week 7	-0.0269	-2.61	-0.0146	-2.39	-0.0034	-0.43
Week 8	-0.0286	-2.61	-0.0111	-1.86	-0.0063	-0.81
Week 9	-0.0287	-2.76	-0.0073	-1.16	-0.0054	-0.65
Week 10	-0.0271	-2.37	-0.0115	-1.88	-0.0054	-0.66
Week 11	-0.0277	-2.38	-0.0074	-1.07	-0.0023	-0.27
Week 12	-0.0194	-1.69	-0.0138	-2.13	-0.0073	-0.82

Panel B. Predicting future close-to-close returns, using 30-minute shoring flow variables

Shorting hours	Return hours	Coef.	*t*-stat
[9:30,10:00)	(16:00, next day 16:00]	-0.0745	-5.89
[10:00,10:30)	(16:00, next day 16:00]	-0.0555	-4.74
[10:30,11:00)	(16:00, next day 16:00]	-0.0582	-4.95
[11:00,11:30)	(16:00, next day 16:00]	-0.0481	-4.19
[11:30,12:00)	(16:00, next day 16:00]	-0.0521	-4.57
[12:00,12:30)	(16:00, next day 16:00]	-0.0498	-4.46
[12:30,13:00)	(16:00, next day 16:00]	-0.0497	-4.32
[13:00,13:30)	(16:00, next day 16:00]	-0.0501	-4.62
[13:30,14:00)	(16:00, next day 16:00]	-0.0313	-2.72
[14:00,14:30)	(16:00, next day 16:00]	-0.0297	-2.63
[14:30,15:00)	(16:00, next day 16:00]	-0.0345	-3.51
[15:00,15:30)	(16:00, next day 16:00]	-0.0397	-3.92
[15:30,16:00)	(16:00, next day 16:00]	-0.0350	-3.07

Panel C. Predicting next 24-hour returns, using 30-minute shoring flow variables

Shorting hours	Return hours	Coef.	*t*-stat
[9:30,10:00)	(10:00, next day 10:00]	-0.2092	-10.73
[10:00,10:30)	(10:30, next day 10:30]	-0.1561	-14.66
[10:30,11:00)	(11:00, next day 11:00]	-0.1190	-10.87
[11:00,11:30)	(11:30, next day 11:30]	-0.0945	-9.26
[11:30,12:00)	(12:00, next day 12:00]	-0.0968	-10.53
[12:00,12:30)	(12:30, next day 12:30]	-0.0746	-8.00
[12:30,13:00)	(13:00, next day 13:00]	-0.0705	-6.96
[13:00,13:30)	(13:30, next day 13:30]	-0.0731	-7.42
[13:30,14:00)	(14:00, next day 14:00]	-0.0452	-4.35
[14:00,14:30)	(14:30, next day 14:30]	-0.0320	-3.11
[14:30,15:00)	(15:00, next day 15:00]	-0.0380	-3.99
[15:00,15:30)	(15:30, next day 15:00]	-0.0338	-3.62
[15:30,16:00)	(16:00, next day 16:00]	-0.0350	-3.07

Internet Appendix Table 2. Intraday FINRA Shorting Flows

This table presents robust results for intraday shorting flows from FINRA. Our sample period is January 2015 to December 2019, and our sample firms are common stocks with a share price of at least $1. Panel A presents variables related to short sale volume from FINRA. The variable *SSOPEN* is short volume over [9:30,11:30) divided by FINRA total trading volume. Similarly, *SSCLOSE* is short volume over [14:00,16:00) and *SSMIDDLE* is short volume during the rest of the trading day. Panel B presents Fama-MacBeth regression coefficients of future returns on FINRA shorting flow variables as in equation (3). *SSOPEN* (*SSMIDDLE*/*SSCLOSE*) are rank transformed to be between zero and one as in previous specifications. Control variables are the same as in Table 2. To account for potential serial correlation in the coefficients, the standard errors of the time-series are adjusted using Newey-West (1987) with eight lags. The regression coefficients of ranking shorting variables are multiplied by 100 for presentation purposes.

Panel A. Summary statistics for intraday shorting flows from FINRA

	N	Mean	Std	p25	p50	p75
SSOPEN	3,533,969	0.1350	0.1158	0.0573	0.1112	0.1827
SSMIDDLE	3,533,969	0.1218	0.1065	0.0554	0.1005	0.1589
SSCLOSE	3,533,969	0.1808	0.1347	0.0906	0.1554	0.2402

Panel B. Predicting future returns using intraday shorting flows from FINRA

	RSSOPEN		RSSMIDDLE		RSSCLOSE	
	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat
Next Day	-0.0667	-6.59	-0.0218	-2.67	0.0258	2.66
Week 1	-0.0211	-2.66	-0.0037	-0.58	0.0026	0.39
Week 2	-0.0113	-1.52	-0.0066	-1.13	-0.0108	-1.69
Week 3	-0.0160	-1.99	-0.0111	-1.79	-0.0104	-1.63
Week 4	-0.0136	-1.69	-0.0151	-2.52	-0.0138	-2.23
Week 5	-0.0170	-2.13	-0.0152	-2.63	-0.0150	-2.62
Week 6	-0.0205	-2.74	-0.0176	-2.92	-0.0084	-1.48
Week 7	-0.0208	-2.61	-0.0153	-2.41	-0.0129	-2.19
Week 8	-0.0179	-2.28	-0.0179	-2.92	-0.0077	-1.29
Week 9	-0.0226	-2.81	-0.0158	-2.50	-0.0121	-1.86
Week 10	-0.0194	-2.32	-0.0130	-2.02	-0.0091	-1.52
Week 11	-0.0203	-2.41	-0.0143	-2.25	-0.0092	-1.43
Week 12	-0.0142	-1.63	-0.0123	-1.88	-0.0101	-1.60

Internet Appendix Figure 1. Intraday Half Hour Effective Spread

This figure presents the times series average of cross sectional mean of effective spread during each half hour of the trading day for all sample firms. Our sample period is January 2015 to December 2019, and our sample firms are common stocks with a share price of at least $1. The effective spread is the share-weighted effective spread.