Strategic Insider Trading: Disguising Order Flows to Escape Trading Competition*

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Abstract

Short sellers actively exploit trading opportunities from insider sales. We argue that, in response to concern about potential order flow information leakage, insiders strategically disguise their order flows to escape trading competition. Our model predicts that, when short sellers are sensitive to order flow information, insiders are more likely to adopt a cautious trading strategy, i.e., splitting their trades over time. Empirically, we identify cautious trading by tracking consecutive transactions at the insider-strategy level. We find that, when anticipating intensive short selling potential, (1) insiders tend to trade cautiously; and (2) cautious insiders tend to reduce their initial trades. Overall, we highlight the strategic interaction between insiders and short sellers on the diffusion of order flow information.

JEL Classification: G12, G14, G23

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1. Introduction

Corporate insiders face unprecedented challenges in their monopoly of private information, given the fierce competition from sophisticated investors (e.g., short sellers). One reason is that the trades placed by insiders generate order flows into the financial market, which reveal insiders' private information and trigger trading competition from sophisticated investors. Indeed, a growing strand of literature documents that sophisticated investors learn from insiders' order flows and trade accordingly for profit (e.g., Khan and Lu, 2013; McNally, Shkilko and Smith, 2015; Chen, Cohen, Gurun, Lou and Malloy, 2020). These challenges force insiders to develop more strategic and dynamic trading approaches to stay profitable.

In this paper, we argue that, in response to concern about potential order flow information leakage, insiders strategically disguise their order flows by splitting trades over time to escape trading competition. This argument on order flow disguise echoes the observation from a speech by the Nobel Prize Laurent Prof. Joseph Stiglitz, who points out that "*the informed, knowing that there are those who are trying to extract information from observing (directly or indirectly) their actions, will go to great lengths to make it difficult for others to extract such information*" (Stiglitz, 2014, page 7).

We first propose a theoretical framework to formalize the aforementioned intuition and then provide empirical evidence to support our model prediction. We start with an extended two-period Kyle (1985) model. In this model, an insider has negative and private information on her firm and wants to sell her shares before the news becomes publicly available.[1] In period

[1] The assumption that insider sales contain negative and private information about firm fundamentals is supported by the literature. From a theoretical perspective, Marin and Olivier (2008) suggest that, due to trading constraints faced by insiders, insider sales should be largest several months before a large drop in the stock price. Empirically, they evaluate the likelihood of a subsequent stock price crash or jump after insider trading and find that the relation is particularly strong for insider sales and subsequent stock price crashes. In addition, empirical evidence from Ke, Huddart, and Petroni (2003), Jagolinzer (2009), Cohen, Malloy, and Pomorski (2012), and Fu, Kong, Tang, and Yan (2020) supports the informational view of insider sales. We thank an anonymous referee for pointing this out.

1, the insider trades against noise traders. A short seller observes the insider sale (with noise). This sell order allows the short seller to infer the insider's private information: the more the insider sells, the more precisely the short seller can infer the insider's private information. In period 2, the short seller and liquidity traders make their trades. The insider may continue to trade, but she is likely to face trading competition from the short seller. We characterize the equilibrium as the one in which the insider and the short seller maximize their own profits, given the other's trading strategy. Our model predicts that, knowing that the short seller is sensitive to the order flow information, the insider is likely to trade cautiously, i.e., splitting her trade over time.

We test our model prediction using all insider sales from 2010 to 2019 from Thomson Reuters, along with daily short volumes from the Financial Industry Regulatory Authority (FINRA). Motivated by our model, we define insider sales traded over multiple consecutive trading days as cautious strategies (for simplicity, the number of consecutive trading days for a strategy is termed as "cluster length" hereafter). In comparison, we define aggressive strategies as those in which insiders sell all of their shares in one day. By this definition, in our sample, we obtain a total of 295,008 insider trading strategies, of which 248,199 (84%) are aggressive strategies, whereas 46,809 (16%) are cautious strategies.

We start by showing that short sellers indeed learn from insiders' order flows and trade accordingly. Specifically, we compare the daily abnormal short volume dynamics with insiders' cautious trading patterns. Based on the relative size of the first trade to the last trade, we identify three different patterns of cautious strategies: (1) increasing, (2) balancing, and (3) decreasing. In Pattern (1), Pattern (2), and Pattern (3), insiders tend to increase, balance, and decrease their trading volume from the first trade to the last trade, respectively. We find that, in all three patterns, the daily abnormal short volume covaries strongly with insiders' trading volume. In other words, in Pattern (1), the daily abnormal short volume increases with insider sales; in

Pattern (2), it remains the same across insider sales; and in Pattern (3), it decreases with insider sales. These different interactions between insider sales and short selling clearly suggest that short sellers actively exploit trading opportunities from insider sales.[2]

Next, we examine the implications of such order-flow-induced short selling for insiders' trading strategies. Intuitively, knowing that there are short sellers who are trying to extract information by observing her trades, an informed insider would try to disguise her order flows to make it difficult for short sellers to extract such information. Therefore, we argue that insiders' tendency to trade cautiously increases when the expected short selling intensity is high. As one cannot disentangle the real motive for insider sales (i.e., driven by information, liquidity, or diversification needs), we perform a Heckman two-stage procedure to mitigate sample selection bias. Following Massa, Qian, Wu, and Zhang (2015), the instrument variable for this approach is a dummy variable (*Routine Insider Sell Dummy*) that equals one if there are routine insider sales in a month, and zero otherwise. The intuition is that, routine sales help to hide informed trading, as they are unrelated to private information (Cohen et al., 2012).

We first model the choice of adopting a cautious strategy using the instrument, and then model the cautious trading volume using lagged short volume in the second stage. We find that, the likelihood of taking a cautious strategy is positively related to the lagged short selling intensity. Conditional on this decision, a one-standard-deviation increase in the lagged short volume comes with a 1.27% increase in the total cautious trading volume, as a proportion of shares outstanding. For comparison, the average monthly cautious trading volume is 8.61%. Therefore, this effect is not only statistically significant but also economically large.

[2] An alternative assumption is that both short sellers and insiders have access to the same information and trade on it. However, this assumption cannot explain our findings. In Pattern (1), if short sellers knew insiders' private information before insider sales, they would short before the last insider trading day. Another plausible assumption is that insiders make their trading decisions after observing short sales. However, this assumption also contradicts with our findings. In Pattern (1) (Pattern (3)), if an insider were to observe a low (high) short selling on her first trading day, she would sell everything immediately (delay selling), as there would be no (strong) trading competition.

Our paper differs from that of Massa et al. (2015) in both its theoretical and empirical perspectives. First, although both papers view short sellers as potential competitors to insiders, Massa et al. (2015) assume that short sellers have access to the same information *ex ante* as insiders before insider sales. Therefore, the presence of short sellers induces insiders to sell more and trade faster to pre-empt the potential competition from short sellers. However, we capture the tension between insiders and short sellers from a different perspective. That is, when insiders have an information advantage over short sellers but face potential information leakage, their best response is to act more cautiously to delay short sellers' reaction. Intuitively, insiders face a crucial trade-off between trading aggressively (selling faster) and cautiously (splitting sales over time). The equilibrium outcome may be either of these two scenarios, depending on whether insiders have an information advantage. Consistent with this intuition, our model in Section 2 predicts both scenarios under different conditions. Furthermore, consistent with our model prediction, we find both scenarios in our sample.

Second, our empirical design is very different from that of Massa et al. (2015). The key difference is that Massa et al. (2015) model the probability of insider sales versus no sales, whereas our paper focuses on the probability of a cautious versus aggressive strategy, conditional on insider sales. Motivated by our theory, we aim to directly differentiate cautious strategies from aggressive strategies and the ideal approach is to explicitly classify insider sales at the insider-strategy level. In contrast, Massa et al. (2015) aggregate sales from all insiders at the monthly level. By comparing the trading patterns of both insiders and short sellers between cautious strategies and aggressive strategies, we uncover that insiders disguise their order flows by strategically allocating their trades over time when facing strong short selling intensity. Overall, we document an intriguing phenomenon that is novel to the literature.

To further establish causality between expected short selling intensity and cautious insider trading, we use the Regulation SHO Pilot Program as a quasi-natural experiment. The Pilot

Program is an experiment conducted by the Securities and Exchange Commission (SEC) to release short constraints for a randomly selected sample of firms. We expect the firms affected by this experiment to have a higher likelihood of conducting cautious trades, due to the increased short selling threat. Applying a difference-in-differences approach to analyze the effect of this experiment, we find that insiders' cautious trading volume in the treated firms is 1.40% higher than that in the control firms during the Pilot Program.

To further explore the heterogeneity among cautious strategies, we conduct an additional test to explore how insiders allocate their trading volume over time. Focusing on cautious strategies, we run another Heckman two-stage analysis. In the first stage, the dependent variable is *I(Hidden)*, a dummy variable that equals one if an insider increases her trading volume over time, and zero otherwise. In the second stage, we regress the fraction of the first trade on the expected short volume. Consistent with our model prediction, we find that, when facing strong short selling intensity, cautious insiders tend to hide their order flows by reducing their first trades.

To provide further evidence that short sellers learn from insiders' order flows, we examine the EDGAR search volume right after insider filings. The SEC EDGAR server stores all mandatory SEC filings and maintains log files for all web visits. The log files we use include all web visits for insider sales from 2010 to 2017.[3] We define *IP Access [0,1]* as the number of EDGAR searches for an insider sale during the two-day window since the filing date (t = 0). We find that, on average, cautious strategies receive 1.20 more IP visits on the first two days since insider filing, and that such excessive IP visits are associated with strong short volumes in the next five days after the IP visits. These results help us further support our assumption that short sellers actively exploit trading opportunities from insider sales.

[3] The EDGAR log files end in 2017. Therefore, our sample size is reduced when using these log files.

Our paper contributes to the literature as follows. First, we emphasize how the strategic interaction between insiders and short sellers reshapes insiders' trading strategies. Prior studies mostly focus on how short sellers exploit trading opportunities from insider sales (Geczy and Yan, 2006; Inci, Lu, and Seyhun, 2010; Khan and Lu, 2013; Chakrabarty and Shkilko, 2013; McNally et al., 2015; Du, 2015; Chen et al., 2020). We complement this stream of literature by showing that, with the knowledge that short sellers are observing their actions, insiders can counteract short sellers to escape trading competition by disguising their order flows. In this sense, our results are related to the literature on strategic trading with multiple players (e.g., Kyle, 1985; Holden and Subrahmanyam, 1992; Foster and Viswanathan, 1993; Edmans and Manso, 2011). More specifically, our prediction echoes the recent theoretical work by Yang and Zhu (2020). In their model, fundamental investors (who possess private information) counteract back-runners (whose only information is about the past order flows of fundamental investors) by randomizing their orders to prevent back-runners from exploiting order flow information. The strategic interaction between insiders and short sellers highlighted in this paper is intuitively similar to the interaction between fundamental investors and back-runners in Yang and Zhu (2020).

Second, we are the first to show how insiders disguise their order flows from external competitors by trading cautiously. These cautious trading patterns are sharply different from aggressive strategies. In this sense, through the lens of trading competition, we provide a new way to decipher insider trading (Cohen et al., 2012; Massa et al., 2015; Wang, Wang, Wei, Zhang, and Zhou, 2019; Kacperczyk and Pagnotta, 2020; Fu, Kong, Tang, and Yan, 2020). Conceptually, our results can be extended to consecutive insider purchases as well.[4]

[4] We thank an anonymous referee for pointing this out. However, we cannot empirically test this prediction because we do not have data on daily institutional purchases. Therefore, we focus on insider sales instead.

The remainder of this paper is as follows. Section 2 presents our model and its prediction. Section 3 demonstrates how short sellers actively exploit trading opportunities from insider sales. Section 4 examines how insiders strategically counteract strong short selling by disguising their order flows. Section 5 provides further discussions and robustness tests. Section 6 concludes.

2. A Model of Strategic Insider Trading

2.1 Model Setup

In this model, we introduce three types of players in a four-period game (periods 0 to 3): one insider, one short seller, and risk-neutral liquidity traders. In period 0, the insider (e.g., manager) of a firm takes a private bad action that would benefit her but harm other shareholders. Without the bad action, the firm would be liquidated in period 3 at a value of v per share. However, with such an action, the per share value of the firm is reduced by $\hat{\delta} > 0$.

We assume that the market knows the distribution of $\hat{\delta}$ in all periods, $\hat{\delta} \sim N(\delta_t, \sigma_t^2)$. However, its precise value will only become public in period 3. In contrast, the insider observes the precise value of $\hat{\delta}$ immediately following the bad action in period 0 and trades on it in period 1. The short seller observes and interprets the insider's order flow in period 1 and trades in period 2.[5]

[5] Short sellers may infer valuable private information from insiders' order flows in the following ways. First, transaction details, such as whether a trade is conducted through automated insider trading plans (i.e., 10b5-1 plans) may indicate whether the trade is informative. Second, the direction of the order flows (buy or sell) may indicate the nature of a private signal (good news or bad news). Third, the role of the insider (e.g., CEO, CFO, or board director) and the number of shares traded may indicate the strength of the private signal. Comparing with historical insider trading patterns may also help short sellers to reach a better judgement.

Both the insider and the short seller are strategic in the sense of Kyle (1985).[6] We present the timeline and detailed model setting below.

Period 0: The insider takes a bad action that reduces the firm value by $\hat{\delta}$. The public knows $\hat{\delta} \sim N(\delta_0, \sigma_0^2)$. Let the price be $P_0 = v - \delta_0$.

Period 1: The insider fully observes $\hat{\delta}$ in period 0, and trades against liquidity traders. Liquidity traders' net order is represented by $u \sim N(0, \sigma_u^2)$. A risk-neutral market maker observes the aggregate market order flows and sets the price at P_1. The public observes P_1 and updates the distribution of $\hat{\delta} \sim N(\delta_1, \sigma_1^2)$, where $\delta_1 = E[\hat{\delta}|P_1]$ and $\sigma_1^2 = Var[\hat{\delta}|P_1]$.

The short seller observes the insider's order flow and obtains a valuable private signal, $\tilde{\eta}_L \sim N(0, \sigma_L^2)$. Hence, the total signal (public and private) that the short seller observes is $\hat{S} = \hat{\delta} + \tilde{\eta}_L$. In particular, we assume that σ_L^2 is endogenously determined by the insider's trading volume: the more the insider sells, the more precise the signal becomes (i.e., σ_L^2 decreases with the insider's trading volume). When $\sigma_L^2 \to \infty$, the short seller has no additional information. When $\sigma_L^2 \to 0$, the short seller is as informed as the insider.

Period 2: The short seller and liquidity traders make their trades. The insider may continue to trade, but she is likely to face trading competition from the short seller. The market maker sets the price at P_2.

Period 3: All uncertainties are resolved and all shorts are covered. The price becomes $P_3 = v - \hat{\delta}$.

2.2 The Equilibrium

[6] In Kyle (1985), the informed trader, whose trading is modelled as a sequence of auctions, is assumed to maximize his own expected profit. He acts as an intertemporal monopolist in the market, explicitly taking into account the effect of his trade at one auction on the price at that auction and on potential trades at future auctions.

With the above setting, we are particularly interested in the insider's trading strategy in period 1. Given its dynamic nature, the model can be solved via backward induction.

In period 2, let $X_2 = \kappa_{2I} + \kappa_s + u$ indicate the total order flows, where κ_{2I} is the trading volume of the insider, and κ_s is the trading volume of the short seller. ϕ_I and ϕ_s represent the information sets of the insider and the short seller, respectively. The equilibrium conditions in period 2 are defined as follows.[7]

(1) The market price is $P_2 = P_1 + \lambda_2 X_2$, where $\lambda_2 = \frac{\sigma_1}{6\sigma_u}\sqrt{\frac{9\sigma_L^2+8\sigma_1^2}{\sigma_L^2+\sigma_1^2}}$ is a constant.

(2) Denote $I_2 = P_3 - P_1 = \delta_1 - \hat{\delta}$ as the private information of the insider at the end of period 1. The optimal trading volume of the insider in period 2 is:

$$\kappa_{2I}^* = a_{2I} I_2 + a_L \hat{S} = \frac{1}{2\lambda_2} I_2 - \frac{1}{6\lambda_2}\frac{\sigma_1^2}{\sigma_1^2+\sigma_L^2}\hat{S} = \frac{2\sigma_1^2+3\sigma_L^2}{6\lambda_2[\sigma_1^2+\sigma_L^2]} I_2 - \frac{\sigma_1^2}{6\lambda_2[\sigma_1^2+\sigma_L^2]}\tilde{\eta}_L.$$

The optimal trading volume of the short seller in period 2 is:

$$\kappa_s^* = \beta_s E[I_2|\phi_s] + \beta_L \hat{S} = \frac{1}{4\lambda_2} E[I_2|\phi_s] + \frac{1}{12\lambda_2}\frac{\sigma_1^2}{\sigma_1^2+\sigma_L^2}\hat{S} = \frac{\sigma_1^2}{3\lambda_2[\sigma_1^2+\sigma_L^2]}[I_2 + \tilde{\eta}_L].$$

Note that I_2, κ_{2I}^* and κ_s^* are all negative.

(3) Denote constants $d_I = \frac{[2\sigma_1^2+3\sigma_L^2]^2}{36\lambda_2[\sigma_1^2+\sigma_L^2]^2}$ and $d_L = \frac{\sigma_1^4}{9\lambda_2[\sigma_1^2+\sigma_L^2]^2}$, the expected trading profit of the insider is $\pi_{2I}^* = d_I Var[I_2] + d_L Var[\tilde{\eta}_L]$, which decreases with the informativeness of the short seller.

Given the equilibrium in period 2, we now move backward to solve the insider's trading volume in period 1. Let $X_1 = \kappa_{1I} + u$ indicate the total order flows. Denote $I_1 = P_3 - P_0$ as the insider's private information by the end of period 0. Let the optimal trading volume of the insider be $\kappa_{1I}^* = a_{1I} I_1$ and the market price be $P_1 = P_0 + \lambda_1 X_1$. The total profit of the insider

[7] The derivation of these conditions can be found in Appendix A.

from both periods is expressed as:

$$
\begin{aligned}
&\pi_I \\
&= E[\kappa_{1I}(P_3 - P_1) + \pi_{2I}^*] \\
&= E\left[\kappa_{1I}(I_1 - \lambda_1(\kappa_{1I} + u)) + d_I\big(I_1 - \lambda_1(\kappa_{1I} + u)\big)^2 + d_L F(\kappa_{1I})\right]
\end{aligned}
$$

where $F(\kappa_{1I}) = Var(\tilde{\eta}_L) = \sigma_L^2$. By assumption, $F(\kappa_{1I})$ decreases with the insider's trading volume in period 1 (i.e., $F'(\kappa_{1I}) < 0$). Furthermore, a larger absolute value of $F'(\kappa_{1I})$ means that the short seller is more sensitive to the insider's order flow information.

The first-order condition (FOC) leads to:[8]

$$I_1 - 2\lambda_1\kappa_{1I} - 2d_I\lambda_1(I_1 - \lambda_1\kappa_{1I}) + d_L F'(\kappa_{1I}) = 0 \tag{1}$$

Equation (1) characterizes the insider's optimal trading volume in period 1. Although we do not have an analytical solution for Equation (1), it clearly depicts the trade-off between trading aggressively and trading cautiously for the insider. When κ_{1I} increases, σ_L^2 decreases, which further decreases d_I and increases d_L. The reduction in d_I tends to encourage the insider to trade, which captures the aggressive trading effect in Massa et al. (2015). However, the negative value of $d_L F'(\kappa_{1I})$ tends to discourage the insider from trading, which captures order flow disguise. The optimal insider trading volume depends on the relative strength between these two effects.

2.3 Proposition and Discussion

Using two polar cases, we illustrate how the trade-off affects the insider's trading decision. In Case (i), the short seller possesses the same set of private information as the insider (i.e., $\sigma_L^2 \to 0$). In Case (ii), the short seller learns from the insider's trade, i.e., σ_L^2 is negatively

[8] The second order condition is assumed to be satisfied, i.e., $-2\lambda_1 + 2d_c\lambda_1^2 + d_L F''(\kappa_{1I}) < 0$.

related to the insider's trading volume, and the absolute value of $F'(\kappa_{1I})$ is sufficiently large.

Case (i) When $\sigma_L^2 \to 0$, $F'(\kappa_{1I}) = 0$. The short seller is as informed as the insider, regardless of the insider's trading in period 1. In other words, the insider has nothing to disguise in period 1 and the order flow disguise effect is completely turned off. In this case, the optimal strategy for the insider is to act fast and trade aggressively to avoid trading competition (Massa et al., 2015).

Case (ii) When σ_L^2 is negatively related to the insider's trading volume, and the absolute value of $F'(\kappa_{1I})$ is sufficiently large, a marginal increase in the insider's trading volume in period 1 greatly strengthens competition in period 2. Anticipating the trading competition, the insider can counteract the short seller by reducing her trade in period 1 and trading in both periods. Compared to Case (i), the insider trades cautiously.

Based on the above discussions, we make the following proposition:

Proposition: *When the short seller is sensitive to the insider's order flow information, the insider is likely to trade cautiously.*

3. Short Sellers Exploit Trading Opportunities from Insider Sales

In this section, we validate our assumption that short sellers learn from insiders' order flows and trade accordingly. We first report the patterns of insider trading based on their strategies and then examine the short selling activities around insider sales. Our sample includes companies with common shares listed on the NYSE, Nasdaq, and AMEX between 2010 and 2019. We exclude non-U.S. incorporated firms, American depositary receipts, exchange-traded funds, and real estate investment trusts from our sample.

3.1 Insider Trading Strategies by Clusters

The records of insiders' transactions are obtained from the Thomson Financial Insider Filings, which contains all insiders' trading activities reported in Forms 3, 4, and 5 as specified in the SEC Act of 1934. The data items include the transaction date, the reporting date, the insider's name, the insider's position/rank, the number of shares traded, the transaction prices, and the transaction type.

Corresponding to our research agenda that short selling responds to negative information, we consider only open-market sales made by directors, officers, and beneficial owners, while open market purchases and private transactions are excluded. If an insider sells multiple times on the same day, we sum up the sales as the number of shares traded on that day.

The key empirical design in our paper is to models the probability of a cautious versus aggressive strategy, conditional on insider sales. Motivated by our theory, we aim to directly differentiate cautious strategies from aggressive strategies. Accordingly, the ideal approach is to explicitly classify insider sales at the insider-strategy level. Therefore, we define cautious strategies as strategies in which insiders split their sales over several consecutive days. In comparison, we define aggressive strategies as strategies in which insiders sell all of their shares in one day. We group strategies based on the number of trading days (i.e., cluster length). The average trading patterns are summarized by cluster length in Table 1. *Lot Size (%)* denotes the number of shares traded on a day scaled by the number of shares outstanding. *Package Size (%)* denotes the sum of the lot sizes for each strategy. *No. of Packages* denotes the total number of strategies within each cluster length category.

[Table 1]

Table 1 uncovers some interesting patterns. First, we document that the majority of the cautious strategies are split over two to five days. The total package size increases as the cluster length increases. For example, the weighted average package size from three types of four-day-clustered cautious strategies is 0.32%, which is about twice as large as the average package size from aggressive strategies (0.16%).[9] This pattern is consistent with our argument regarding order flow disguise, as insiders become more cautious (i.e., demonstrate a longer cluster length) when they trade more shares.

Second, we explore the heterogeneity within cautious strategies, depending on the relative lot size between the first trade and the last trade: (1) First < Last; (2) First = Last; (3) First > Last (labelled as Patterns (1), (2), and (3), respectively). We discover some intriguing patterns. First, we find that in Pattern (1), the lot sizes increase from the first trade to the last trade. For example, for four-day-clustered Pattern (1), the lot size for the first trade is 0.04%, which rises to 0.15% for the last trade. In other words, 11% (45%) of the package is sold on the first (last) day. However, in Pattern (3), the lot sizes decrease from the first trade to the last trade. For example, for four-day-clustered Pattern (3), the lot size for the first trade is 0.12%, which decreases to 0.04% for the last trade. In other words, 35% (13%) of the package is sold on the first (last) day. Finally, in Pattern (2), the lot sizes are even across trades.

It is worth noting that, with the exception of two-day-clustered trades, the increasing/balancing/decreasing trading pattern is not a mechanical result. Therefore, they do capture three different patterns of cautious strategies. As far as we know, we are the first to document such insider trading patterns.

Among these three patterns of cautious strategies, Pattern (1) (increasing lot sizes) seems more aligned with order flow disguise, as insiders tend to hide their private information until the last trade. For simplicity, we refer to this pattern of cautious strategy as "hidden strategy" in our empirical tests in Section 4. However, it is worth noting that: (1) an insider can disguise

[9] 0.32% = (0.343% × 1,136 + 0.107% × 204 + 0.332% × 1,387)/(1,136+204+1,386).

her order flows by splitting her sales evenly across time; and (2) in Pattern (3), over 50% of the package is traded after the first insider sale (except for two-day-clustered strategies, which is a mechanical result by definition). Based on these two observations, we cannot rule out the possibility of some insiders disguising their order flows using Pattern (2) or (3). Considering this, we keep all three patterns of cautious strategies in our main results.

3.2 Abnormal Short Volume Around Insider Sales

We obtain data on short volume from the FINRA. Starting from September 30, 2009, the FINRA publishes monthly short sale transaction files, including the transaction time, the price, and the number of shares for every short sale transaction for all National Market System (NMS) stocks.[10]

To demonstrate that short sellers actively exploit trading opportunities from insider sales, we compare the daily abnormal short volume dynamics around insider sales. This allows us to demonstrate how short sellers track insider sales and act accordingly from the first insider trading day to the last insider trading day. Daily short volume is computed as the number of shares sold short over total shares outstanding. Following Khan and Lu (2013), *Abnormal Short Volume (%)* is measured as the difference between the daily short volume and the average daily short volume from [−60, −11], where $t = 0$ is the first insider trading day in a strategy.[11] We report the results in Table 2 with the same structure as Table 1.

[Table 2]

[10] The NMS is the national system for trading equities in the U.S. It includes all of the facilities and entities that are used by brokers-dealers to fulfil their trade orders. The FINRA's monthly short sale transaction files include trading information for short sale transactions on NMS stocks reported to the Alternative Display Facility or Trade Reporting Facility during regular and after-market hours. These files are posted on month-ends with a one-month lag. For example, the short sale data for September 2009 are posted on October 31, 2009.

[11] We exclude [t−10, t−1] from the benchmark window because evidence suggests that short sellers may front-run insider sales in a [t−10, t−1] window before insider trading (e.g., Khan and Lu, 2013; Chakrabarty and Shkilko, 2013; Sun and Yin, 2017). Therefore, we need to avoid this time window to capture the expected short volume.

Table 2, along with Table 1, uncovers that there is indeed an interaction between insiders and short sellers on the diffusion of order flow information. In all cautious strategies, the abnormal short volume covaries with insider trading volume. For example, for four-day-clustered Pattern (1), the average abnormal short volume on the first insider trading day is 0.01%, which increases to 0.04% on the last insider trading day, representing almost a fourfold increase since the first trading day. For comparison, the average abnormal short volume for aggressive strategies is 0.02% on the trading day. This pattern is the same as the insider trading pattern documented in Table 1, in which insider trading volume also rises about four times from the first insider trading day to the last insider trading day. The only difference is that the abnormal short volume does not dramatically increase until the last trading day (when the private information is fully revealed). This suggests that short sellers have a delayed reaction to insider sales until the last insider trading day. Pattern (1) from other cluster lengths shows similar results.

In contrast, for the four-day-clustered Pattern (3), the average abnormal short volume on the first insider trading day is 0.04%, which decreases to 0.01% on the last insider trading day. This pattern is also the same as the insider trading pattern documented in Table 1, in which insider trading volume decreases from the first insider trading day to the last insider trading day. Compared to aggressive strategies, short sellers following Pattern (3) exhibit continuation in short selling. For aggressive strategies, we find that the average abnormal short volume quickly drops to almost zero in the subsequent three trading days after insider sales. However, for four-day-clustered Pattern (3), the average abnormal short volume gradually decreases since the first insider sale, but remains around 0.01%. This evidence suggests that short sellers underreact to the initial insider sales, compared to aggressive strategies. Pattern (3) from other cluster lengths shows similar results.

Finally, for Pattern (2), the average abnormal short volume is relatively stable from the first insider trading day to the last insider trading day, which is also consistent with the insider trading pattern. Daily abnormal short volumes for Pattern (2) are generally smaller than the abnormal short volume on the aggressive insider trading day, suggesting that the short selling intensity for Pattern (2) is relatively low.

It is worth noting that we define Patterns (1) to (3) merely based on the relative trading volume between the first insider trade and the last insider trade. Therefore, the co-movement between the abnormal short volume and the insider sales should not be a mechanical result.

The results from Tables 1 and 2 can help us fend off alternative assumptions. An alternative assumption is that both short sellers and insiders have access to the same information and trade on it. However, this assumption cannot explain our findings. In Pattern (1), if short sellers knew insiders' private information before insider sales, they would short before the last insider trading day. Another plausible assumption is that insiders make their trading decisions after observing short sales. However, this assumption also contradicts with our findings. In Pattern (1) (Pattern (3)), if an insider were to observe a low (high) short selling on her first trading day, she would sell everything immediately (delay selling) as there would be no (strong) trading competition.

Overall, the consistent dynamics between abnormal short selling and insider trading documented in Tables 1 and 2 provide strong support for our main assumption that short sellers learn from insiders' order flows and trade accordingly.

4. The Impact of Short Selling on Insiders' Trading Strategy

In this section, we examine the implications of such order-flow-induced short selling for insiders' trading strategies. Intuitively, knowing that there are short sellers who are trying to extract information by observing her trades, an informed insider would try to disguise her order flows to make it difficult for short sellers to extract such information. Therefore, we argue that insiders' tendency to trade cautiously increases when the expected short selling intensity is high. We provide causal evidence to support this argument using (1) Heckman two-stage regressions (Section 4.1), and (2) the Regulation SHO Pilot Program (Section 4.2).

4.1 Heckman Two-stage Regressions

As one cannot disentangle the real motive for insider sales (i.e., driven by information, liquidity, or diversification needs), we perform a Heckman two-stage procedure to mitigate sample selection bias. Following Massa, Qian, Wu, and Zhang (2015), the instrument variable for this approach, *Routine Insider Sell Dummy*, is a dummy variable that equals one if there are routine insider sales in a month, and zero otherwise. The intuition is that, routine sales help to hide informed trading, as they are unrelated to private information (Cohen et al., 2012). We expect to observe a high likelihood of cautious trading when there are concurrent non-informational routine transactions. In addition, routine transactions do not directly affect informed insiders' private information. Therefore, *Routine Insider Sell Dummy* satisfies both the inclusion and the exclusion requirements of Heckman (1979).

We first model the choice of adopting a cautious strategy using the instrument, and then model the cautious trading volume using lagged short volume in the second stage. The regression models are as follows:

First stage (probit) regression:

$$Cautious\_Dummy_{i,t} = \alpha + \beta \times Routine\ Insider\ Sell\ Dummy_{i,t} + \boldsymbol{\gamma} \times \boldsymbol{X}_{i,t-1} + \varepsilon_{i,t}$$

Second stage regression:

(1) $Cautious\_Fraction_{i,t} = a + b \times Shvol\_Monthly_{i,t-1} + c \times \lambda_{i,t} + \boldsymbol{d} \times \boldsymbol{X}_{i,t-1} + e_{i,t}$

$$(2)\ Hidden\_Fraction_{i,t} = a + b \times Shvol\_Monthly_{i,t-1} + c \times \lambda_{i,t} + \boldsymbol{d} \times \boldsymbol{X}_{i,t-1} + e_{i,t}$$

where t indicates the year-month and i indicates the firm. *Cautious_Dummy* is a dummy variable that equals one if a cautious strategy is taken by any insider for stock *i* in a month, and zero otherwise. *Cautious_Fraction* is the total number of shares sold by insiders from all cautious strategies for stock i in a month, as a percentage of shares outstanding. *Hidden_Fraction* is the total number of shares sold by insiders from hidden strategies (Pattern (1) from Tables 1 and 2) for stock i in a month, as a percentage of shares outstanding. *Shvol_Monthly* is the natural logarithm of the monthly short volume from the previous month. Finally, $\lambda_{i,t}$ refers to the inverse Mills' ratio estimated from the first stage regression.

$\boldsymbol{X}_{i,t-1}$ is a vector of the lagged control variables. They include: *Turnover*, the natural logarithm of monthly trading volumes; *Lagged6mret*, the cumulative stock returns for the last six months; *Dividend*, the dollar value of the dividend per share; *Price*, the stock price; *Logmv*, the natural logarithm of the market capitalization of a firm; *Book-to-Market*, the book value of equity divided by market capitalization; *Leverage*, the book value of debt divided by the book value of equity; and *Sales*, the natural logarithm of total sales.

Table 3 presents the summary statistics for our sample. *Cautious_Dummy* has a mean of 0.274, which indicates that 27.40% of the firm-month observations have cautious strategies. *Cautious_Fraction* has a mean of 0.086, which indicates that the average monthly trading volume from cautious strategies (scaled by the number of shares outstanding) is 8.60%. Similarly, *Hidden_Fraction* has a mean of 0.035, which indicates that the average monthly trading volume from hidden strategies is 3.50%.

[Table 3]

Table 4 presents the results of the Heckman two-stage regressions. Column (1) of Table 4 reports the results of the first stage regression. Consistent with our expectation, *Routine Insider*

Sell Dummy is significantly and positively associated with the tendency to apply cautious strategies. Furthermore, the likelihood of taking a cautious strategy is positively related to the lagged short selling intensity.

[Table 4]

Column (2) of Table 4 reports the results from the second stage regression using *Cautious_Fraction* as the dependent variable. The results suggest that, conditional on the insider's decision to adopt a cautious strategy, insiders trade more cautiously when facing strong short selling intensity. More specifically, a one-standard-deviation increase in the lagged monthly short volume increases cautious trading volume by 1.27%. For comparison, the average *Cautious_Fraction* is about 8.60%. Therefore, this effect is not only statistically significant but also economically large.

We conduct an additional regression to show that our results do not depend on a particular definition of cautious strategy. That is, we examine whether they still hold for hidden insider trading, characterized by strategies in which insiders gradually increase their trading volumes. We replace the dependent variable from the second stage regression with *Hidden_Fraction* and re-run the regression. Column (3) of Table 4 provides results consistent with those in Column (2). A one-standard-deviation increase in the lagged monthly short volume increases hidden trading volume by 0.73%. For comparison, the average *Hidden_Fraction* is about 3.50%. Therefore, this result is also economically meaningful.

Overall, the results in Table 4 support our proposition that insiders trade more cautiously when facing strong short selling intensity.

4.2 A Quasi-natural Experiment: The Regulation SHO Pilot Program

To further establish the causality between expected short selling intensity and cautious insider trading, we use the Regulation SHO Pilot Program as a quasi-natural experiment (Diether, Lee and Werner, 2009). The Pilot Program was announced by the SEC in 2004. Under this regulation, approximately 1,000 treated firms were randomly selected from the Russell 3000 Index, and their price restrictions on short selling (uptick rules) were lifted during the period from May 2, 2005, to August 6, 2007. We expect the treated firms to face a stronger short selling threat, as short sellers can short at any price they want. Therefore, insiders from the treated firms should demonstrate a higher likelihood of trading cautiously during the Pilot Program than insiders from the control firms.

We apply a difference-in-differences method to analyze the effect of the Pilot Program on cautious trading. We run the following regression:

$$Cautious\_Fraction_{i,t} = \alpha + \beta \times Treat_i \times Pilot_t + \boldsymbol{\gamma} \times \boldsymbol{X}_{i,t-1} + f_i + \tau_t + \varepsilon_{i,t} ,$$

where *Treat* is a dummy variable that equals one if a firm is selected into the program, and zero otherwise. *Pilot* is a dummy variable that equals one during the program period, and zero otherwise. $\boldsymbol{X}_{i,t-1}$ is the same set of control variables as in Table 4. f_i is firm fixed effects. Finally, τ_t is time fixed effects. As our data on short volume are only available from 2010 onwards, we cannot include short volume in the regression. The results are reported in Table 5.

[Table 5]

Table 5 shows that the fraction of cautious trades significantly increases for the treated firms during the Pilot Program across all model specifications. For example, Column (1) shows that insiders' cautious trading volume in the treated firms becomes 1.20% higher than that in the control firms during the Pilot Program. This result is robust after controlling firm and time fixed effects.

Overall, we believe that both the Heckman two-stage setup and the difference-in-differences analysis using the Pilot Program as a quasi-natural experiment help address the potential endogeneity concern and establish a causal relation between expected short selling intensity and insiders' order flow disguise.

5. Further Analysis

In Section 5.1, we further explore how cautious insiders strategically allocate their trading over time when facing strong short selling intensity. We find that, when the expected short volume is high, cautious insiders can counteract short sellers by reducing their initial trades. In Section 5.2, using the number of IP visits from the SEC's EDGAR server, we provide additional evidence supporting our assumption that short sellers learn from insiders' order flows. In Section 5.3, we provide three robustness checks to show that our results are consistent across various specifications.

5.1 The Impact of Short Selling on Lot Size Allocation

To further support our argument, we explore the heterogeneity among cautious strategies. We conduct an additional analysis to explore how insiders allocate their trading volumes over time. Based on our model, we argue that cautious insiders reduce their initial trades when facing strong short selling intensity.

To test this argument, we conduct Heckman two-stage regressions on the insider-strategy level. In the first stage, the dependent variable is a dummy variable that equals one if a strategy is a hidden strategy, and zero otherwise. In the second stage, we regress the fraction of the first trade on the expected short volume. The regression models are as follows:

First stage (probit) regression:

$$I(Hidden)_{i,t} = \alpha + \beta \times Routine\ Insider\ Sell\ Dummy_{i,t} + \boldsymbol{\gamma} \times \boldsymbol{X}_{i,t-1} + \varepsilon_{i,t}$$

Second stage regression:

$$First/Package_{i,t} = a + b \times ExpShvol_{i,[t-60,t-11]} + c \times \lambda_{i,t} + \boldsymbol{d} \times \boldsymbol{X}_{i,t-1} + e_{i,t}$$

where t indicates the first insider trading day and i indicates the firm. *I(Hidden)* is a dummy variable that equals one if a cautious strategy is a hidden strategy, and zero otherwise. *First/Package* is the first trade over package size. *ExpShvol* is the expected short volume, computed as the natural logarithm of the total short volume between [t−60, t−11], where $t = 0$ is the first insider trading day for a strategy. Finally, $\lambda_{i,t}$ refers to the inverse Mills' ratio estimated from the first stage regression.

$\boldsymbol{X}_{i,t-1}$ is a vector of the control variables. They include: *Turnover*, measured by the natural logarithm of the trading volume for stock i on day t−1; *AR* denotes the abnormal return on the first insider trading day; *CAR [-5,-1]* measures the cumulative daily abnormal returns during the five days prior to the first insider sale; *Bid-Ask Spread* is measured as the difference between the bid and the ask price divided by their average, on the day before the first insider sale. Table 6 reports the results.

[Table 6]

Consistent with our expectations, Column (1) of Table 6 shows that, in the first stage, *Routine Insider Sell Dummy* is significantly and positively associated with the tendency to apply a hidden strategy. Furthermore, the likelihood of taking a hidden strategy is positively related to the expected short selling intensity. In the second stage, we find that cautious insiders indeed reduce their first trades when facing strong short selling intensity. A one-standard-deviation increase in the expected short volume comes with a 5.43% decrease in cautious insiders' first trades relative to the total package size. For comparison, on average, the first trade is 44% of the total package with a standard deviation of 25.60%. In other words, this effect represents a 21.21% decrease relative to the standard deviation. Overall, Table 6 provides further support for our main argument that insiders disguise their order flows to escape trading competition.

5.2 EGDAR Search After Insider Filings

To provide further evidence that short sellers learn from insiders' order flows, we examine the EDGAR search volume immediately after insider filings. The SEC EDGAR server stores all mandatory SEC filings and maintains log files for all web visits. The log files we use include all web visits for insider sales from 2010 to 2017.[12] Each log entry provides the following information: the IP address of the inquiry, with the final octet of the address replaced with a unique set of three letters; the date and time of the inquiry; the Central Index Key of the person or firm that filed the requested form; and a link to the particular filing, which includes an accession number that uniquely identifies a particular filing. These features allow us to analyze the pattern of information acquisition more directly. We define *IP Access [0,1]* as the number of the EDGAR searches for an insider sale during the two-day window since the filing date ($t = 0$).

Table 7 shows that the number of IP visits to a cautious insider sale is significantly higher than to an aggressive sale. For example, Column (3) of Table 7 suggests that a cautious insider sale receives 1.20 more IP visits on the first two days since the insider filing. A similar pattern of excessive IP visits is also obtained for hidden strategies. Column (6) of Table 7 suggests that a cautious insider conducting a hidden sale receives 1.23 more IP visits on the first two days since the insider filing.

[Table 7]

[12] The EDGAR log files end in 2017. Therefore, our sample size is reduced in Tables 7 and 8.

Furthermore, Table 8 suggests that such excessive IP visits are associated with strong short volume in the next five days after the IP visits. For example, Column (1) of Table 8 suggests that a one-standard-deviation increase in *IP Access [0,1]* is associated with a 36.24% increase in the total short volume in the subsequent five trading days. Results are robust after controlling for firm and time fixed effects, as well as the same set of control variables as in Table 7.

[Table 8]

Overall, Tables 7 and 8 together provide direct evidence supporting our main assumption that short sellers indeed learn from insiders' order flows and trade accordingly.

5.3 Robustness Checks

We conduct three robustness checks to show that our results are consistent across different empirical specifications. First, throughout this paper, the analyses only explore insider sales from consecutive trading days as cautious strategies. This is a relatively clean and straightforward way to identify insider trading strategies (one-day trade vs. multiday trades). As we cannot observe the actual reason why insiders may trade with time gaps, from a conservative perspective, we make the minimum assumption in our empirical design. Still, we conduct an additional robustness test to show that our main results are robust to allowing for time gaps. Thus, we allow insiders to pause their trading for up to three days in their strategies. We reconduct our main analyses in Table 4 and report the results in Panel A of Table 9. Our main results hold under this alternative insider-strategy identification method.

[Table 9]

Second, in our empirical identification, if two or more insiders from the same firm place their trades on the same day, we identify them separately at the strategy level by insiders. Considering that insiders from the same firm may possess the same private information when they trade together, an alternative way to deal with this situation is to merge these trades into a single trade. Specifically, we aggregate all of the sales by multiple insiders from the same firm on the same day, and assign the aggregate trading volume to the insider with the biggest sale. To ensure that there is only one insider sale in a firm on each day in our sample, we delete the rest of the insider sales from the same firm on that day. Afterwards, we identify aggressive and cautious strategies in the same way as we did to obtain our main results. Using this modified sample, we reconduct our main analyses in Table 4. Panel B of Table 9 shows that our main results continue to hold.

Finally, in our main analysis, insider strategies are classified based on their trading patterns (one-day vs. multiple days). Taking a different perspective, Cohen et al. (2012) identify routine/opportunistic insiders by whether they placed a trade in the same calendar month for at least three consecutive years. As these two definitions come from different perspectives, our cautious strategies may include trades by both routine and opportunistic insiders. In our sample, most of the cautious strategies come from opportunistic insiders. Therefore, our results are not driven by routine insiders. To show that this is indeed the case, we conduct a robustness check by excluding all routine traders in our cautious strategies. We reconduct our main analysis in Table 4 and report the results in Panel C of Table 9. Panel C of Table 9 suggests that our results remain consistent.

6. Conclusion

The presence of short sellers generates strong trading competition for corporate insiders and alters insiders' trading patterns. In this paper, we document the strategic interaction between insiders and short sellers. Short sellers actively exploit trading opportunities from insider sales. As a response, when anticipating strong short selling intensity, insiders tend to counteract short sellers by disguising their order flows in the first place. Such order flow disguise is conducted by strategically splitting sales over time and reducing initial sales.

As far as we know, we are the first to show how insiders disguise their order flows from external competitors. We view consecutive insider sales as a cautious strategy rather than separate sales. By comparing the trading patterns of cautious and aggressive strategies, we provide a new way to decipher insider trading, through the lens of trading competition.

Our findings have important implications. First, for investors, our paper suggests that consecutive insider trading may reflect insiders' private information not yet revealed in price. Therefore, it may be more profitable to trade alongside cautious insiders than aggressive insiders. Second, for regulators, our results reinforce the increasing concern that insiders manage trade sizes and timing according to the nature of information. This represents a regulatory challenge, and our results suggest that regulators need to take insiders' cautious trading strategies into consideration when identifying illegal insider trading. Finally, from the perspective of information diffusion, our results suggest that, although the presence of short sellers may accelerate the rate at which private information is revealed to the market via insider trading, insiders can still manipulate their trading patterns to delay price discovery.

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Table 1 Insider Trading Strategies by Clusters

This table presents the summary statistics of insider trading strategies by clusters. Cluster length refers to the number of consecutive trading days in a strategy. We define aggressive strategies as insider sales with cluster length equal to one. We define cautious strategies as insider sales with cluster length bigger than one. *Lot Size (%)* denotes the number of shares traded in a day scaled by the number of shares outstanding. *Package Size (%)* denotes the sum of all the lot sizes in a strategy. We further divide all cautious strategies into three patterns based on the relative lot size between the first trade and the last trade. *No. of Packages* denotes the number of strategies within each cluster-strategy category.

Cluster length		*Lot Size (%)*							
		Trade Day						*Package Size (%)*	*No. of Packages*
1 Day	Aggressive	0.163						0.163	248,199
		First Day	Last Day					*Package Size (%)*	*No. of Packages*
2 Days	(1) First < Last	0.031	0.083					0.114	12,000
	(2) First = Last	0.041	0.041					0.081	4,850
	(3) First > Last	0.097	0.032					0.129	14,088
		First Day	First Day+1	Last Day				*Package Size (%)*	*No. of Packages*
3 Days	(1) First < Last	0.047	0.075	0.120				0.241	3,607
	(2) First = Last	0.030	0.031	0.030				0.091	734
	(3) First > Last	0.133	0.085	0.050				0.268	4,567
		First Day	First Day+1	First Day+2	Last Day			*Package Size (%)*	*No. of Packages*
4 Days	(1) First < Last	0.039	0.064	0.086	0.154			0.343	1,136
	(2) First = Last	0.026	0.027	0.028	0.026			0.107	204
	(3) First > Last	0.117	0.101	0.072	0.042			0.332	1,387
		First Day	First Day+1	First Day+2	First Day+3	Last Day		*Package Size (%)*	*No. of Packages*
5 Days	(1) First < Last	0.075	0.112	0.093	0.088	0.188		0.557	616
	(2) First = Last	0.037	0.037	0.038	0.040	0.037		0.189	116
	(3) First > Last	0.124	0.089	0.085	0.114	0.043		0.455	762
		First Day	First Day+1	First Day+2	First Day+3	···	Last Day	*Package Size (%)*	*No. of Packages*
≥6 Days	(1) First < Last	0.048	0.070	0.082	0.081	···	0.169	0.837	1,048
	(2) First = Last	0.021	0.024	0.024	0.021	···	0.021	0.353	220
	(3) First > Last	0.135	0.092	0.099	0.090	···	0.048	0.838	1,474

Table 2 Abnormal Short Volume Around Insider Sales

This table reports abnormal short selling activities around insider sales within each cluster-strategy category. Cluster length refers to the number of consecutive trading days in a strategy. We define aggressive strategies as insider sales with cluster length equal to one. We define cautious strategies as insider sales with cluster length bigger than one. Daily short volume is computed as the number of shares sold short over total shares outstanding. *Abnormal Short Volume (%)* is measured as the difference between daily short volume and the average daily short volume from [−60, −11], where t = 0 is the first insider trading day. Trade Day denotes the day of insider sales for aggressive strategies. First Day (Last Day) denotes the first (last) insider trading day in a cautious strategy. t-statistics are provided in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Cluster Length		*Abnormal Short Volume (%)*							
		Trade Day	[+1, +3]						
1 Day	Aggressive	0.021	0.004						
		First Day	Last Day					Last Day − First Day	(t-Value)
	(1) First<Last	0.018	0.025					0.007***	(6.11)
2 Days	(2) First=Last	0.010	0.009					-0.001	(-0.37)
	(3) First>Last	0.027	0.014					-0.013***	(-11.44)
		First Day	First Day+1	Last Day				Last Day − First Day	(t-Value)
	(1) First<Last	0.015	0.013	0.030				0.015***	(5.89)
3 Days	(2) First=Last	0.016	0.014	0.014				-0.001	(-0.25)
	(3) First>Last	0.038	0.014	0.011				-0.027***	(-12.51)
		First Day	First Day+1	First Day+2	Last Day			Last Day − First Day	(t-Value)
	(1) First<Last	0.012	0.011	0.020	0.041			0.029***	(6.32)
4 Days	(2) First=Last	0.008	0.001	0.014	0.007			-0.001	(-0.16)
	(3) First>Last	0.036	0.013	0.009	0.006			-0.029***	(-7.23)
		First Day	First Day+1	First Day+2	First Day+3	Last Day		Last Day − First Day	(t-Value)
	(1) First<Last	0.005	-0.001	-0.002	0.008	0.023		0.018***	(3.09)
5 Days	(2) First=Last	-0.019	-0.009	0.005	0.010	-0.014		0.005	(0.45)
	(3) First>Last	0.034	0.015	0.006	0.009	0.005		-0.030***	(-6.12)
		First Day	First Day+1	First Day+2	First Day+3	···	Last Day	Last Day − First Day	(t-Value)
	(1) First<Last	0.011	0.008	0.010	0.008	···	0.023	0.012***	(2.68)
>=6 Days	(2) First=Last	0.031	0.005	0.011	0.005	···	0.005	-0.027***	(-2.87)
	(3) First>Last	0.033	0.014	0.006	0.003	···	0.004	-0.030***	(-8.28)

Table 3 Summary Statistics

This table reports the summary statistics for dependent variables, independent variables and control variables at monthly level and strategy level, respectively.

Variables (Monthly)	N	Mean	P25	P50	P75	Std. Dev
Cautious_Dummy	97,728	0.274	0.000	0.000	1.000	0.446
Cautious_Fraction	97,728	0.086	0.000	0.000	0.006	1.435
Hidden_Fraction	97,728	0.035	0.000	0.000	0.000	0.726
Routine Insider Sell Dummy	97,728	0.169	0.000	0.000	0.000	0.375
Shvol_Monthly	97,728	13.714	12.647	13.829	14.923	1.819
Turnover	97,728	16.032	15.025	16.131	17.200	1.756
Lagged6mret	97,728	0.121	-0.015	0.106	0.239	0.243
Dividend	97,728	0.045	0.000	0.000	0.000	0.312
Price	97,728	3.475	2.906	3.547	4.096	0.950
Logmv	97,728	21.473	20.295	21.435	22.693	1.848
Book-to-Market	97,728	0.451	0.194	0.363	0.612	0.554
Leverage	97,728	0.565	0.369	0.555	0.740	0.362
Sales	97,728	20.513	19.438	20.717	22.057	2.934
Variables (Strategy)						
I(Hidden)	46,806	0.393	0.000	0.000	1.000	0.488
First/Package	46,806	0.440	0.238	0.463	0.606	0.256
ExpShvol	295,008	14.825	13.824	14.891	15.933	1.697
Turnover	295,008	13.271	12.311	13.346	14.373	1.646
AR	295,008	0.004	-0.008	0.002	0.014	0.024
CAR [−5, −1]	295,008	0.015	-0.012	0.012	0.039	0.053
Bid-Ask Spread	295,008	-0.001	-0.001	0.000	0.000	0.002
IP Access [0,1]	207,466	9.706	3.000	6.000	11.000	15.756
Shvol [2,6]	207,466	11.500	10.415	11.549	12.671	1.783

Table 4 The Impact of Short Selling on Insiders' Trading Strategy

This table reports the Heckman two-stage regression results to examine the impact of short selling on insiders' trading strategy based on monthly frequency. We define cautious strategies as insider sales with cluster length bigger than one. *Cautious_Dummy* is a dummy variable that equals one if a cautious strategy is taken by any insider for stock *i* in a month, and zero otherwise. *Cautious_Fraction* denotes the aggregated number of shares sold by insiders from all cautious strategies for stock *i* in a month, as a percentage of shares outstanding. *Hidden_Fraction* denotes the aggregated number of shares sold by insiders from cautious strategies whose first trade is smaller than its last trade for stock *i* in a month, as a percentage of shares outstanding. The independent variable is the *Shvol_Monthly*, denoted as the natural logarithm of monthly short volume from the previous month. *Turnover* is the natural logarithm of monthly trading volume. *Lagged6mret* denotes the cumulative stock returns for the last six months. *Dividend* is the dollar value of the dividend per share. *Price* is the share price. *Logmv* denotes the natural logarithm of the market capitalization of the firm; *Book-to-Market* is the book value of equity divided by market capitalization. *Leverage* is the book value of debt divided by the book value of equity. *Sales* is the natural logarithm of total sales. *Routine Insider Sell Dummy* equals one if there is a routine open market sale by an insider in the same month, and zero otherwise. The standard errors reported in parentheses are heteroskedasticity-consistent and clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	1^{st} Stage	2^{nd} Stage	
	Cautious_Dummy	(1) *Cautious_Fraction*	(2) *Hidden_Fraction*
Routine Insider Sell Dummy	0.236***		
	(0.012)		
Shvol_Monthly	0.049***	0.007***	0.004***
	(0.011)	(0.002)	(0.001)
Turnover	-0.146***	-0.000	-0.005***
	(0.014)	(0.004)	(0.001)
Lagged6mret	0.003***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)
Dividend	-0.342***	0.013**	-0.006**
	(0.044)	(0.006)	(0.003)
Price	-0.115***	-0.004	-0.001
	(0.009)	(0.004)	(0.001)
Logmv	-0.010	-0.018***	-0.007***
	(0.007)	(0.005)	(0.001)
Book-to-Market	-0.310***	-0.037***	-0.011***
	(0.014)	(0.010)	(0.002)
Leverage	-0.348***	-0.003	-0.010***
	(0.018)	(0.013)	(0.002)
Sales	0.009***	-0.003**	0.000
	(0.002)	(0.001)	(0.000)
Inverse Mills' Ratio		-0.027*	0.008
		(0.014)	(0.005)
Firm Fixed Effects	No	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
N	97,728	97,728	97,728
Adj. R-squared		0.226	0.152

Table 5 A Quasi-natural Experiment: The Regulation SHO Pilot Program

This table reports the impact of changing short selling intensity on insiders' trading strategy using the Pilot Program as a quasi-natural experiment. We define cautious strategies as insider sales with cluster length bigger than one. *Cautious_Fraction* denotes the aggregated number of shares sold by insiders from all cautious strategies for stock *i* in a month, as a percentage of shares outstanding. *Treat* is a dummy variable that equals one if firm *i* is selected for the Pilot Program, and zero otherwise. *Pilot* is a dummy variable that equals one during the Pilot Program period (from 2005.05 to 2007.08), and zero otherwise. *Turnover* is the natural logarithm of monthly trading volumes. *Lagged6mret* denotes the cumulative stock returns for the last six months. *Dividend* is the dollar value of the dividend per share. *Price* is the share price. *Logmv* denotes the natural logarithm of the market capitalization of the firm; *Book-to-Market* is the book value of equity divided by market capitalization. *Leverage* is the book value of debt divided by the book value of equity. *Sales* is the natural logarithm of total sales. The standard errors reported in parentheses are heteroskedasticity-consistent and clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Cautious_Fraction		
	(1)	(2)	(3)
Treat × Pilot	0.012**	0.014**	0.013**
	(0.006)	(0.006)	(0.006)
Pilot	0.003	0.004	
	(0.003)	(0.003)	
Treat	-0.011*		
	(0.006)		
Turnover	-0.019***	-0.011***	-0.010***
	(0.001)	(0.002)	(0.002)
Lagged6mret	0.001***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Dividend	-0.050***	-0.013	-0.000
	(0.010)	(0.010)	(0.010)
Price	-0.020***	-0.007**	-0.007**
	(0.002)	(0.003)	(0.004)
Logmv	-0.018***	-0.020***	-0.008**
	(0.002)	(0.004)	(0.004)
Book-to-Market	-0.054***	-0.045***	-0.030***
	(0.004)	(0.006)	(0.007)
Leverage	-0.097***	-0.059***	-0.032***
	(0.004)	(0.010)	(0.011)
Sales	0.012***	-0.003	0.002
	(0.001)	(0.003)	(0.003)
Firm Fixed Effects	No	Yes	Yes
Time Fixed Effects	No	No	Yes
N	113,123	113,123	113,123
Adj. R-squared	0.035	0.133	0.136

Table 6 The Impact of Short Selling on Lot Size Allocation

This table reports the Heckman two-stage regression results to examine the impact of short selling on insiders' trading strategy at strategy level for all cautious trades. We define cautious strategies as insider sales with cluster length bigger than one. *I(Hidden)* is a dummy variable that equals one if a strategy is a cautious strategy and its first trade is smaller than its last trade, and zero otherwise. *First/Package* denotes the number of shares sold on the first insider trading day as a percentage of the aggregated number of shares sold in a package for a cautious strategy. *ExpShvol* is the expected short volume, computed as the natural logarithm of the total short volume between [t−60, t−11], where t = 0 is the first insider trading day for a strategy. *Turnover* is measured by the natural logarithm of the trading volume. *AR* denotes the abnormal return. *CAR [−5, −1]* measures the cumulative daily abnormal returns during the five days prior to the first insider trading day. *Bid-Ask Spread* is measured as the difference in the daily bid and ask price, divided by the average of the bid and ask prices. *Routine Insider Sell Dummy* equals one if there is a routine open market sale by an insider in the same month, and zero otherwise. The standard errors reported in parentheses are heteroskedasticity-consistent and clustered at the insider level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	1st Stage	2nd Stage
	I(Hidden)	*First/Package*
Routine Insider Sell Dummy	0.030**	
	(0.014)	
ExpShvol	0.086***	-0.032***
	(0.008)	(0.011)
Turnover	-0.143***	0.074***
	(0.009)	(0.018)
AR	-0.054	0.041
	(0.244)	(0.052)
CAR [−5, −1]	0.218**	-0.022
	(0.111)	(0.035)
Bid-Ask Spread	-3.656	0.930
	(3.557)	(1.201)
Inverse Mills' Ratio		-0.238
		(0.179)
Firm Fixed Effects	No	Yes
Time Fixed Effects	Yes	Yes
N	46,806	46,806
Adj. R-squared		0.162

Table 7 The EDGAR Searches After Insider Filings

This table documents the number of the EDGAR searches after insider filings for different insider trading strategies. *IP Access [0,1]* is the number of the EDGAR searches for insider filings during the two-day window since insider filings, where $t = 0$ is the filing date. We define cautious strategies as insider sales with cluster length bigger than one. *I(Cautious)* is a dummy variable that equals one if a strategy is a cautious strategy, and zero otherwise. *I(Hidden)* is a dummy variable that equals one if a strategy is a cautious strategy and its first trade is smaller than its last trade, and zero otherwise. *Turnover* is measured by the natural logarithm of the trading volume in stock i. *AR* denotes the abnormal return. *CAR [−5, −1]* measures the cumulative daily abnormal returns during the five days prior to the first insider trading day. *Bid-Ask Spread* is measured as the difference in the daily bid and ask price, divided by the average of the bid and ask prices. The standard errors reported in parentheses are heteroskedasticity-consistent and clustered at the insider level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	IP Access [0,1]					
	(1)	(2)	(3)	(4)	(5)	(6)
I(Cautious)	0.928***	1.628***	1.200***			
	(0.123)	(0.115)	(0.082)			
I(Hidden)				0.806***	1.645***	1.231***
				(0.143)	(0.134)	(0.108)
Turnover		1.242***	0.957***		1.219***	0.962***
		(0.043)	(0.046)		(0.043)	(0.046)
AR		-0.081***	-0.040***		-0.082***	-0.041***
		(0.014)	(0.012)		(0.014)	(0.012)
CAR [−5, −1]		0.022***	0.026***		0.022***	0.026***
		(0.006)	(0.005)		(0.006)	(0.005)
Bid-Ask Spread		-4.435***	-0.507*		-4.530***	-0.471
		(0.301)	(0.289)		(0.299)	(0.288)
Firm Fixed Effects	No	No	Yes	No	No	Yes
Time Fixed Effects	No	Yes	Yes	No	Yes	Yes
N	207,466	207,466	207,466	207,466	207,466	207,466
Adj. R-squared	0.001	0.081	0.236	0.000	0.079	0.236

Table 8 The EDGAR Searches and Subsequent Short Selling

This table documents the effect of the EDGAR searches after insider filings on subsequent short selling intensity. *IP Access [0,1]* is the number of the EDGAR searches for insider filings during a two-day window since insider filings, where $t = 0$ is the insider filing day. *Shvol [2,6]* is the natural logarithm of the total short volume during the five-day window after the IP visits. *Turnover* is measured by the natural logarithm of the trading volume in stock *i*. *AR* denotes the abnormal return. *CAR [−5, −1]* measures the cumulative daily abnormal returns during the five days prior to the first insider trading day. *Bid-Ask Spread* is measured as the difference in the daily bid and ask price, divided by the average of the bid and ask prices. The standard errors reported in parentheses are heteroskedasticity-consistent and clustered at the insider level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Shvol [2, 6]		
	(1)	(2)	(3)
IP Access [0,1]	0.023***	0.004***	0.001***
	(0.002)	(0.001)	(0.000)
Turnover		0.967***	0.468***
		(0.010)	(0.011)
AR		-2.583***	-0.425***
		(0.149)	(0.116)
CAR [−5, −1]		-0.610***	-0.007
		(0.065)	(0.056)
Bid-Ask Spread		0.334***	0.479***
		(0.074)	(0.077)
Firm Fixed Effects	No	No	Yes
Time Fixed Effects	No	Yes	Yes
N	207,466	207,466	207,466
Adj. R-squared	0.021	0.763	0.827

Table 9 Robustness Checks

This table reports the Heckman two-stage regression results to examine the impact of short selling on insiders' trading strategy based on monthly frequency. We define cautious strategies as insider sales with cluster length bigger than one. In Panel A, we allow insiders to pause their trading for up to three days in their strategies. In Panel B, we aggregate trading volume placed by multiple insiders in the same day in each firm and assign the aggregate trading volume to the one with the largest trading volume. In Panel C, we exclude routine traders. *Cautious_Dummy* is a dummy variable that equals one if a cautious strategy is taken by any insider for stock *i* in a month, and zero otherwise. *Cautious_Fraction* denotes the aggregated number of shares sold by insiders from all cautious strategies for stock *i* in a month, as a percentage of shares outstanding. *Hidden_Fraction* denotes the aggregated number of shares sold by insiders from cautious strategies whose first trade is smaller than its last trade for stock *i* in a month, as a percentage of shares outstanding. The independent variable is the *Shvol_Monthly*, denoted as the natural logarithm of monthly short volume from the previous month. *Turnover* is the natural logarithm of monthly trading volume. *Lagged6mret* denotes the cumulative stock returns for the last six months. *Dividend* is the dollar value of dividend per share. *Price* is the share price. *Logmv* denotes the natural logarithm of the market capitalization of the firm; *Book-to-Market* is the book value of equity divided by market capitalization. *Leverage* is the book value of debt divided by the book value of equity. *Sales* is the natural logarithm of total sales. *Routine Insider Sell Dummy* equals one if there is a routine open market sale by an insider in the same month, and zero otherwise. The standard errors reported in parentheses are heteroskedasticity-consistent and clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Allow Trading Pause			
	1st Stage	2nd Stage	
	Cautious_Dummy	(1) *Cautious_Fraction*	(2) *Hidden_Fraction*
Routine Insider Sell Dummy	0.301***		
	(0.011)		
Shvol_Monthly	0.036***	0.008***	0.004***
	(0.011)	(0.003)	(0.001)
Inverse Mills' Ratio		-0.026*	0.003
		(0.014)	(0.005)
Control	Yes	Yes	Yes
Firm Fixed Effects	No	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
N	97,728	97,728	97,728
Adj. R-squared		0.226	0.156

Panel B: Aggregate Multiple Insiders			
	1st Stage	2nd Stage	
	Cautious_Dummy	(1) *Cautious_Fraction*	(2) *Hidden_Fraction*
Routine Insider Sell Dummy	0.163***		
	(0.012)		
Shvol_Monthly	0.032***	0.007***	0.004***
	(0.012)	(0.002)	(0.001)
Inverse Mills' Ratio		-0.035*	0.013*
		(0.020)	(0.008)
Control	Yes	Yes	Yes
Firm Fixed Effects	No	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
N	97,728	97,728	97,728
Adj. R-squared		0.224	0.152

Panel C: Exclude Routine Traders			
	1st Stage	2nd Stage	
	Cautious_Dummy	(1) *Cautious_Fraction*	(2) *Hidden_Fraction*
Routine Insider Sell Dummy	0.039***		
	(0.014)		
Shvol_Monthly	0.048***	0.018***	0.004***
	(0.012)	(0.004)	(0.002)
Inverse Mills' Ratio		0.276***	0.074**
		(0.079)	(0.030)
Control	Yes	Yes	Yes
Firm Fixed Effects	No	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
N	97,728	97,728	97,728
Adj. R-squared		0.229	0.155

Appendix A

Derivations of the Equilibrium in Period 2

Since the short seller observes the private information (though noisy) from the insider's trade, the information set of the insider includes the short seller's inferred information $\hat{S}$. Hence, we conjecture that the order flow of the insider is $\kappa_{2I} = a_{2I}I_2 + a_L\hat{S}$. For the short seller, his information set contains his estimation of the insider's private information. Therefore, we conjecture that the short seller's order flow is $\kappa_s = \beta_s E[I_2|\phi_s] + \beta_L\hat{S}$. Accordingly, the profit for the insider in Period 2 is

$$\pi_{2I} = E[\kappa_{2I}(P_3 - P_2)|\phi_I] = E[\kappa_{2I}(I_2 - \lambda_2(\kappa_{2I} + \kappa_s + u))|\phi_I].$$

The first-order condition (FOC) leads to

$$2\lambda_2\kappa_{2I} + \lambda_2 E[\kappa_s|\phi_I] = I_2.$$

Plugging the conjectures into the above FOC and employing the Projection Theorem, we have

$$a_{2I} = \frac{1}{2\lambda_2} \text{ and } a_L = -\frac{1}{6\lambda_2}\frac{\sigma_1^2}{\sigma_1^2+\sigma_L^2}.$$

The profit for the short seller in period 2 is

$$\pi_s = E[\kappa_s(P_3 - P_2)|\phi_s] = E[\kappa_s(I_2 - \lambda_2(\kappa_{2I} + \kappa_s + u))|\phi_s].$$

The FOC leads to

$$2\lambda_2\kappa_s + \lambda_2 E[\kappa_I|\phi_s] = E[I_2|\phi_s].$$

Again, plugging in the conjectures and $E[I_2|\phi_s] = \frac{\sigma_1^2}{\sigma_1^2+\sigma_L^2}\hat{S}$ (from the Projection Theorem), we have

$$\beta_s = \frac{1}{4\lambda_2} \text{ and } \beta_L = \frac{1}{12\lambda_2}\frac{\sigma_1^2}{\sigma_1^2+\sigma_L^2}.$$

Given the total order flow, $X_2 = \kappa_{2I}^* + \kappa_s^* + u = \frac{4\sigma_1^2+3\sigma_L^2}{6\lambda_2[\sigma_1^2+\sigma_L^2]}I_2 + \frac{\sigma_1^2}{6\lambda_2[\sigma_1^2+\sigma_L^2]}\tilde{\eta}_L + u$, we have

$$\lambda_2 = \frac{Cov(S_2,X)}{Var(X)} = \frac{\sigma_1}{6\sigma_u}\sqrt{\frac{9\sigma_1^2+8\sigma_L^2}{\sigma_1^2+\sigma_L^2}}.$$

Finally,

$$\pi_{2I}^* = \lambda_2 Var[\kappa_{2I}] = \frac{[2\sigma_1^2+3\sigma_L^2]^2}{36\lambda_2[\sigma_1^2+\sigma_L^2]^2}Var[I_2] + \frac{\sigma_1^4}{9\lambda_2[\sigma_1^2+\sigma_L^2]^2}Var[\tilde{\eta}_L].$$

Appendix B

Variable Definitions

Variables (Monthly)	Definition
Cautious_Dummy	A dummy variable that equals one if a cautious strategy is taken by any insider for stock i in a given month, and zero otherwise. A cautious strategy is a strategy in which insiders split their sales over consecutive days.
Cautious_Fraction	The aggregated number of shares sold by insiders from all cautious strategies for stock i in a month, as a percentage of shares outstanding.
Hidden_Fraction	The aggregated number of shares sold by insiders from cautious strategies whose first trade is smaller than its last trade size for stock i in a month, as a percentage of shares outstanding.
Routine Insider Sell Dummy	A dummy variable that equals one if there is a routine open market sale by an insider in the same month, and zero otherwise.
Shvol_Monthly	The natural logarithm of monthly short volume.
Turnover	The natural logarithm of monthly trading volume.
Lagged6mret	The cumulative stock returns for the last six months.
Dividend	The dollar value of the dividend per share.
Price	The share price.
Logmv	The natural logarithm of the market capitalization.
Book-to-Market	The book value of equity divided by market capitalization.
Leverage	The book value of debt divided by the book value of equity.
Sales	The natural logarithm of total sales.
Variables (Strategy)	
I(Hidden)	A dummy variable that equals one if a strategy is a cautious strategy and its first trade is smaller than its last trade.
First/Package	The number of shares sold on the first insider trading day as a percentage of the aggregated number of shares sold in a package for a cautious strategy.
ExpShvol	The natural logarithm of the total short volume between [t−60, t−11], where t = 0 is the first insider trading day for a strategy.
Turnover	The natural logarithm of the trading volume on the first insider trading day.
AR	The abnormal return on the first insider trading day. The abnormal return is calculated using the daily return minus the market return.
CAR [-5,-1]	The cumulative abnormal returns during the five days prior to the first insider trading day.
Bid-Ask Spread	The daily bid price minus the daily ask price, divided by the average of the daily bid and ask prices on the first insider trading day.
IP Access [0,1]	The number of the EDGAR searches for insider filings during the two-day window since insider filings, where t = 0 is the filing date.
Shvol [2,6]	The natural logarithm of the total short volume during the five-day window after the IP visits.