Insiders' information advantage: Evidence from competition with short sellers*

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August 24, 2025

Abstract

We study the information content of corporate insiders' trades after earnings announcements. We find little evidence that insiders trade on foreknowledge of material information in the post-SOX period. Conditioning on short-selling activity as a proxy for demand of arbitrageurs who exploit short-term mispricing, we show that insiders profit from selling because of their ability to exploit short-term mispricing after earnings releases. In contrast before SOX, insiders do take advantage of foreknowledge of material information while selling. Insider purchases are based on foreknowledge of material information both before and after SOX, but they are rare and have small economic magnitude.

*We are grateful to the anonymous referee, Constantinos Antoniou, Henk Bessembinder, Viet Nga Cao, Oleg Chuprinin, Carina Cuculiza, Terry Hendershott, Dirk Jenter, Olga Klein, Adriana Korczak, Piotr Korczak, Vikas Raman, Elvira Sojli, Chendi Zhang, as well as participants at the 2017 FIRN Sydney Market Microstructure Meeting 2017, 2017 FMA Annual Meeting, 2017 EFMA Annual Meeting and research seminars at the University of Chile and Warwick Business School for providing helpful comments and suggestions.

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I. Introduction

As corporate insiders possess information that is not available to any other market participants, insider trading has attracted interest from academics and regulators to understand the impact of this trading. On the one hand, insider trades carry information, making prices more efficient and facilitating price discovery (Manne, 1966; Carlton and Fischel, 1983). Insiders possess intimate knowledge of the fundamental value of the firm and so could trade to push prices towards this ‘true’ valuation. On the other hand, insider trades can harm uninformed traders and damage market liquidity (Ausubel, 1990; Leland, 1992; Fishman and Hagerty, 1992; Bebchuk, Cohen, and Ferrell, 2002). Regulators aim to impose insider-trading restrictions, which reduce the adverse market effect but retain the efficiency effects of insider trading. In this respect, regulators wish to restrict trading on foreknowledge of material information, but at the same time to allow trading on short-term mispricings that arise due to market misinterpretation of public information releases.

In this paper, we aim to understand the source of insiders’ information advantage when trading under tight regulatory restrictions.[1] We build a simple model and test empirical predictions of whether insiders trade on foreknowledge of material information or react to short-term mispricing. Contrary to the existing literature concluding that insiders trade on foreknowledge of future material information (see Ke, Huddart, and Petroni, 2003; Cheng, Navar, and Rajan, 2007; Cohen, Malloy, and Pomorski, 2012; Ali and Hirshleifer, 2017; Akbas, Jiang, and Koch, 2020), we find little evidence of illegal insider trading on material information in the post-Sarbanes-Oxley (post-SOX) period. Insider trades correlate with future returns, but they rely on short-term mispricing.

[1]In the US, insider trading regulation has tightened and insiders are prohibited from trading when they are likely to possess material information (Bettis, Coles, and Lemmon, 2000; Lee, Lemmon, Li, and Sequeira, 2014). Following the Sarbanes-Oxley Act in 2002, insiders are required to report their trades within two business days from trading (Brochet, 2010). Many companies impose trading bans for their insiders and allow them to trade only in periods when information asymmetry is low, shortly after earnings announcements (Bettis et al., 2000; Huddart, Ke, and Shi, 2007).

Differentiating whether insiders trade on foreknowledge of material information or react to short-term mispricing is a difficult task. The existing literature often relates the ability of insider trades to predict future returns as evidence of insiders trading on foreknowledge of material undisclosed information (see, for example, Huddart et al., 2007; Cohen et al., 2012; Akbas et al., 2020). This approach may be misleading since informed traders can make profits on their trades even when they legally exploit mispricing stemming from the market's misinterpretation of publicly disclosed information. For example, suppose the market misinterprets an earnings announcement and overreacts. Shortly after the earnings announcement, an insider decides to sell to exploit the mispricing. This trade is not based on any foreknowledge of material information because the insider uses the earnings information that has just been released to the public. The trade is not illegal. Yet, the insider profits from the sale because the overpricing will eventually be reflected in a lower stock price which leads to a negative future abnormal return. This example illustrates that insiders do not need to trade on foreknowledge of material private information for their trading to be profitable and for the trade direction to forecast future stock returns. As a result, it is essential to identify and filter out insider trading on mispricing.

In order to separate the two sources of information, one needs a reliable measure of mispricing, which is a task without a suitable direct solution in the empirical finance literature so far. We opt for a highly correlated proxy: an alternative group of informed traders, whom we call arbitrageurs, who trade predominantly on short-term mispricings arising after public news releases. To fully understand interactions between arbitrageurs' and insiders' trading, we build a simple theoretical model. This model guides our empirical identification strategy.

In line with our research question, our model works with two types of information and two types of informed traders. Arbitrageurs possess information about short-term mispricing (hereafter, *short-term information*) arising after public news. An example of such information is arbitrageurs' ability to better estimate fundamental values of stocks after public news releases and to identify market under- or over-reactions. Anybody with a special information-processing skill could profit on this type of information without breaking trading rules. The short-term information is also in possession of an insider – he/she is also able to spot mispricing. In addition, the insider, but not arbitrageurs, has access to foreknowledge of material information (hereafter, *long-term information*). Future new product releases, asset sales, acquisitions, etc., are examples of information that falls into this category. Trading on the long-term information is regarded as illegal as it is material in the true sense; it is not released in a public announcement and is price-sensitive.[2]

It is noteworthy to highlight that trading on the short-term information in the model is equivalent to trading on mispricing, which takes advantage of public information and is not illegal. In contrast, trading on the long-term information relies on foreknowledge of material information, and this type of information is not available to arbitrageurs. As we are interested in unveiling whether the insider does take advantage of his/her privileged access to the long-term information, we contrast predictions of two benchmarks: a benchmark where the insider abstains from trading based on the long-term information to avoid legal prosecution, versus a benchmark where the insider trades optimally by taking into account all available information. Because the insider's information set is richer than that of arbitrageurs in the latter benchmark, any disagreement between the insider and arbitrageurs translates into a strict advantage for the insider. As a result, the insider takes advantage of buying or selling pressure coming from arbitrageurs who trade on the basis of short-term information only. Hence, in the case the long-term and short-term information disagree, the latter

[2] We discuss deviations from this strict distinction between short-term and long-term information and their implications for the interpretation of our results in Section VI.

benchmark predicts that the insider's demand is contrarian to the short-term information and arbitrageurs' demand. This is not the case for the former benchmark, where the insider trades only on the short-term information. These contrasting predictions help to identify whether the insider uses the long-term information when trading or not.

In our empirical analysis, we use short interest to proxy the demand of arbitrageurs. We argue that this is a reasonable strategy due to the nature of short sellers' trading around earnings announcements. Short sellers are informed traders with strong incentives to profit on their information advantage who trade on mispricing when the market over- or under-reacts to public news.[3] McLean, Pontiff, and Reilly (2020) show that short sellers are the only group of influential market participants, except insiders, who build positions in agreement with 130 anomaly strategies which have been shown to predict the cross-section of stock returns. Engelberg, Reed, and Ringgenberg (2012) show that short-sellers' information advantage around earnings announcements indeed comes from their superior ability to analyze publicly available information. It is also important to note that short-sellers' investment horizon is usually relatively short, which makes them unlikely to be trading on foreknowledge of future material information.[4]

Using a sample of insider trades in US stocks shortly after earnings announcements from 2006 until 2017, we conclude that although corporate insiders' purchases and sales do forecast future returns, insider *sales* are based on the short-term overpricing only. We document that insiders tend to sell overwhelmingly in agreement with short sellers; even for more informed non-routine (opportunistic) insider transactions (Cohen et al., 2012). The average monthly profit of an insider sale

[3] See, for example, Asquith, Pathak, and Ritter (2005), Cohen, Diether, and Malloy (2007), Boehmer, Jones, and Zhang (2008), Diether, Lee, and Werner (2009).

[4] Boehmer et al. (2008) estimate that the typical short seller's horizon is 37 trading days. Gamble and Xu (2017) document similar estimates for retail short sellers. This strongly suggest that short sellers are unlikely to trade on long-lasting forward-looking private information that would eventually be revealed in future earnings announcements.

when insiders agree with short sellers is \$5391, while the profit is statistically insignificant when insiders and short sellers disagree. Insider *purchases* sometimes take advantage of the long-term information, they forecast future returns when short sellers disagree by selling heavily. However, insider purchases are four times smaller than sales and disagree with intensive short selling only in about 2% of all firm-quarters in our data set. So, the economic effect of insiders exploiting undisclosed material information when buying is small, and their profit is statistically insignificant.

We also test whether it is the tighter SOX regulation that is behind the insiders' abstaining from selling on foreknowledge of private information. We extend our sample by utilizing Compustat short-selling data and compare the pre- versus post-SOX periods.[5] We show that insiders sell on foreknowledge of material information before SOX; insider sales predict negative future returns when they disagree with short sellers on the direction of trading. This predictive power decreases significantly after SOX. Insiders' dollar profits when selling are significantly higher before than after SOX. We conclude that tight regulatory restrictions after SOX are effective in mitigating insider trading on foreknowledge of material information. Insider trading still correlates with future returns but is highly aligned with short sellers' trading; insiders choose not to use more information than is in the short sellers' possession.

We contribute to the insider trading literature by adding to the discussion on what kind of information insiders use when trading under tighter regulation. Literature suggests that insider trades are motivated by either foreknowledge of future material information (Ke et al., 2003; Cheng et al., 2007; Cohen et al., 2012; Ali and Hirshleifer, 2017) or by public information (Jenter, 2005; Kolasinski and Li, 2010; Alldredge and Cicero, 2015). We contribute by using the interaction of

[5]The short-selling data in Compustat is less granular, which means that our main analysis has to rely on more precise Markit data available starting from 2006.

insiders' and short-sellers' demands to detect insider trading on foreknowledge that is not available to short sellers. Our strategy can distinguish insider trading that exploits mispricing after public news releases from insider trading on foreknowledge of material information.

We are not the first to explore the question of the information source of insider trading. Piotroski and Roulstone (2005) argue that insiders use both types of information advantage. Our results are different in three ways. The first difference is in how we identify the trading on mispricing. Piotroski and Roulstone (2005) use the book-to-market ratio. While the book-to-market ratio could be regarded as a mispricing indicator, it also reflects other firm characteristics, such as the degree of distress, growth opportunities, or expected returns.[6] We instead rely on orders of traders who are known to play the role of arbitrageurs, trading to exploit mispricing after public news releases, which is a more refined, precise, and cleaner measure of short-term mispricing, measured on a daily frequency. We also highlight the disagreement between insiders and arbitrageurs and its correlation with future returns, which is at the core of our identification strategy.

Second, our samples are different. We use a sample that follows the SOX Act in 2002, while the sample in Piotroski and Roulstone (2005) ends in 2000. Finally, our research design allows us to condition on the direction of trading and show that only insider purchases, but not insider sales, are, in some cases, based on foreknowledge of future material information. This highlights the increased legal prosecution costs since 2002 and contrasts with papers documenting that pre-SOX insiders sell on knowledge of economically significant forthcoming accounting disclosures (Ke et al., 2003). We show that insider trading restrictions are largely effective and insiders sell mostly in line with short sellers on short-term mispricing.

We also contribute to empirical literature which finds little evidence that insider sales, in con-

[6]See Loughran (1997); Lewellen (1999); Vassalou and Xing (2004).

trast to insider purchases, are profitable (Lakonishok and Lee, 2001; Jeng, Metrick, and Zeckhauser, 2003). The main explanation for these findings is that insiders often sell for liquidity and/or diversification reasons and do not use their information advantage (Lakonishok and Lee, 2001; Cheng et al., 2007). Cohen et al. (2012) show that excluding repetitive insider selling that is more likely due to liquidity/diversification reasons leads to remaining opportunistic insider sales to become profitable. They conclude that opportunistic insider sales are driven by foreknowledge of future material information. In contrast, our analysis suggests that opportunistic insider sales are profitable due to taking advantage of short-term mispricings arising after public news releases rather than due to foreknowledge of future material information. In a similar vein to Cohen et al. (2012), Akbas et al. (2020) highlight short-horizon insiders as better performing in predicting future returns than long-horizon insiders because their trades are more unexpected and more informed. However, Akbas et al.'s classification of short-horizon insiders still does not answer the question of what type of information is used by these insiders. Short-horizon insiders may rely on short-term mispricing rather than on foreknowledge of material information.

Our paper is also related to the literature on the relationship between short sales and trades of other informed investors. Massa, Qian, Xu, and Zhang (2015) explore how the potential presence of short sellers affects the incentives of insiders to trade on negative material information. They show that intensity and speed of insider sales in a given month increase with higher short-selling potential in the previous month. They conclude that insiders and short sellers compete for trading on foreknowledge of the same private information. Wang, Wang, Wei, Zhang, and Zhou (2022) show that the threat of short selling reduces opportunistic insider sales and argue that short sales exert discipline for insiders. Chakrabarty and Shkilko (2013) examine short sellers' informativeness regarding recently completed insider sales and show that short selling by non-market makers increases on days of insider selling. In contrast to these papers, we focus on the information content of insider trades. We differentiate information sets of insiders and short sellers and use the differences to identify the nature of insiders' information advantage.

The remainder of the paper proceeds as follows. Section II introduces our model and derives our testable hypotheses. Section III describes the data. Section IV presents our main findings, Section V compares pre- versus post-SOX periods, and Section VI discusses our key assumptions and their consequences for interpretation of the results. Section VII concludes.

II. Theoretical predictions and testable hypotheses

A. A simple model

We develop our testable hypotheses by relying on a simple model of insider trading with an *insider* who possesses short-term information (i.e., information stemming from mispricing, arising after misinterpretation of a public announcement by the market) and long-term information (i.e., foreknowledge of material private information). The insider trades along with *arbitrageurs* who possess only the short-term information. We assume that the long-term information is truly private: it is undisclosed, price-sensitive, and in possession exclusively by the insider. The insider could be prosecuted if trading on this long-term information. The short-term information is also available to arbitrageurs because they have a superior ability to process public news releases relative to the rest of the market. Anybody who can do this would be classified as an arbitrageur in our model. Trading on the short-term information is not illegal because it is based on public information.

In order to test our research question of whether insiders (illegally) trade on foreknowledge of long-term material information, we derive two benchmarks and formulate testable predictions corresponding to each benchmark. In the first benchmark, we assume that the insider manager abstains from trading based on the long-term information to avoid legal prosecution, and denote it the "No-Long-term-Information" (NLI) benchmark. In the second benchmark, denoted as the "All-Information" (AI) benchmark, we assume that the insider trades optimally by taking into account both the short-term and long-term information. This benchmark shows insider trading patterns in the limiting case when the insider does not care about prosecution.

The market is populated by four types of market participants: a competitive market maker, a single insider trader, n identical arbitrageurs and a group of liquidity traders. The model has three periods, which we index as $t \in \{1, 2, 3\}$. Consider a firm with an initial fundamental value of v_0, which is publicly known. We assume that the firm has one share of stock outstanding and its price is $p_0 = v_0$. The insider initially holds η shares. In period 1, the insider and arbitrageurs learn that the fundamental value of the firm changes from the initial v_0 to $v_0 + v_1$, where $v_1 \sim N(0, \sigma^2)$. Here, v_1 innovation represents the short-term information. The market maker knows only the distribution of v_1. Moreover, in period 1, the insider also learns that the fundamental firm value will change from $v_0 + v_1$ to $v_0 + v_1 + v_2$, where $v_2 \sim N(0, \sigma^2)$. Here, v_2 innovation represents the long-term information. We assume that v_1 and v_2 are independent.[7] The information about the realization of v_2 is not available to the arbitrageurs in period 1; they can only observe the distribution of v_2. In period 2, the value of v_2 becomes known to the arbitrageurs but not to the market maker. This means that the long-term information becomes after some time known to some market participants, in addition to the insider. In period 3, the firm is liquidated and the dividends are paid to all shareholders at price $p_3 = v_0 + v_1 + v_2$.

[7]We discuss implications of the independence assumption and consequences of relaxing it in Section VI.

In periods 1 and 2, some liquidity traders need to trade u_1 and u_2 shares of the stock to cover their private liquidity shocks, with $u_t \sim N(0, \sigma_u^2)$, $t = 1, 2$. We assume that variables u_1, u_2, v_1 and v_2 are mutually independent and that the two types of informed traders experience liquidity shocks during both periods. That is, at the beginning of period t, for $t = 1, 2$, the insider receives an endowment shock $w_t^i \sim N(0, \sigma_w^2)$ and each arbitrageur receives $w_t^a \sim N(0, \sigma_w^2)$.[8]

The NLI benchmark assumes the insider chooses not to trade upon signal v_2 due to being afraid to be prosecuted by the regulator. In contrast, the AI benchmark assumes that the insider takes signal v_2 fully into account and strategically trades based on both v_1 and v_2 pieces of information. Given that the insider and arbitrageurs know v_1 and v_2 in period 2 in both benchmarks, the derivation for period 2 price and demands is identical. The two benchmarks have different implications only for period 1 prices and quantities.

Let ζ_1 and ζ_2 denote the number of shares traded by the insider in period 1 and 2, respectively, and let ξ_{1j} and ξ_{2j} denote the number of shares traded by arbitrageur j in period 1 and 2, respectively. The insider optimally trades ζ_1 and ζ_2 shares to maximize his consumption

$$C^i = (\zeta_1 + \zeta_2 + \eta)p_3 - \zeta_1 p_1 - \zeta_2 p_2, \tag{1}$$

where p_t refers to the price of the stock in period t. Similarly, each arbitrageur j trades optimally ξ_{1j} and ξ_{2j} shares in periods 1 and 2 by maximizing his consumption

$$C_j^a = (\xi_{1j} + \xi_{2j})p_3 - \xi_{1j} p_1 - \xi_{2j} p_2, \qquad j = 1, ..., n. \tag{2}$$

In period 2, before the trading occurs, the market observes p_1, which is the last period's trading price. Given the linear pricing rule, Proposition 1 characterizes the equilibrium price in period 2 and the arbitrageurs' orders. All proofs are in the Internet Appendix B.

[8]We introduce the endowment shocks so that the insider and arbitrageurs demands are not perfectly correlated.

Proposition 1 (NLI and AI benchmarks): In period 2, the pricing rule and the demands are:

(3)
$$\begin{aligned} p_2 &= p_1 + \lambda_2 x_2, \\ \zeta_2 &= \frac{v_2 + v_1 + v_0 - p_1}{\lambda_2(n+2)} + \frac{w_2^i}{2}, \\ \xi_{2j} &= \frac{v_2 + v_1 + v_0 - p_1}{\lambda_2(n+2)} + \frac{w_{2j}^a}{2}, \qquad j = 1, ..., n, \end{aligned}$$

where $x_2 = \zeta_2 + \sum_{j=1}^{n} \xi_{2j} + u_2$ is the total order imbalance in period 2 and the price impact λ_2 is

(4)
$$\lambda_2 = \sqrt{\frac{(n+1)}{(n+2)^2}\left(\frac{\tilde{\sigma}^2}{\frac{n\sigma_w^2}{2} + \sigma_u^2}\right)}, \qquad \tilde{\sigma}^2 = var[v_1 + v_2 | p_1].$$

Proposition 2 characterizes the equilibrium price and the insider's and arbitrageurs' orders in period 1 in the NLI benchmark – when the insider ignores the information about v_2 in period 1.

Proposition 2 (NLI benchmark): Suppose that the insider ignores information about v_2. The pricing rule and the insider's and each arbitrageur's orders in period 1 are:

(5)
$$\begin{aligned} p_1 &= p_0 + \lambda_1 x_1, \\ \zeta_1 &= \beta_1 v_1 + \delta \lambda_1 w_1^i, \\ \xi_{1j} &= \beta_1 v_1 + \delta \lambda_1 w_{1j}^a, \qquad j = 1, ..., n, \end{aligned}$$

where $x_1 = \zeta_1 + \sum_{j=1}^{n} \xi_{1j} + u_1$ denotes the total order imbalance in period 1, the parameters β_1, δ and λ_1 solve the system of equations:

(6)
$$\begin{aligned} \lambda_1 &= \frac{(n+1)\beta_1 \sigma^2}{(n+1)^2 \beta_1^2 \sigma^2 + n\delta^2 \lambda_1^2 \sigma_w^2 + \sigma_u^2}, \\ \beta_1 &= \frac{1 - 2\alpha\lambda_1}{\lambda_1(n + 2 - 2\alpha\lambda_1(n+1))}, \\ \delta &= \frac{1 - 2\alpha\lambda_1}{2\lambda_1(1 - \alpha\lambda_1)}, \qquad \alpha = \frac{1}{(n+2)^2 \lambda_2}, \end{aligned}$$

and λ_2 is as given in Equation (4).

Finally, Proposition 3 characterizes the equilibrium price and the insider's and arbitrageurs' orders in period 1 in the AI benchmark – under the assumption that the insider does not ignore v_2 and strategically trades on this information in period 1.

Proposition 3 (AI benchmark): Suppose that the insider conditions his demand on knowledge of v_2, then the pricing rule and the insider's and each arbitrageur's orders in period 1 are:

(7)
$$\begin{aligned} p_1 &= p_0 + \lambda_1 x_1, \\ \zeta_1 &= \beta_1 v_1 + \delta v_2 + \delta\lambda_1 w_1^i, \\ \xi_{1j} &= \beta_1 v_1 + \delta\lambda_1 w_{1j}^a, \qquad j = 1, ..., n \end{aligned}$$

where $x_1 = \zeta_1 + \sum_{j=1}^{n} \xi_{1j} + u_1$ denotes the total order imbalance in period 1, and the parameters λ_1, β_1, and δ solve the system equations:

(8)
$$\begin{aligned} \lambda_1 &= \frac{((n+1)\beta_1 + \delta)\sigma^2}{((n+1)^2\beta_1^2 + \delta^2)\,\sigma^2 + n\delta^2\lambda_1^2\sigma_w^2 + \sigma_u^2}, \\ \beta_1 &= \frac{1 - 2\alpha\lambda_1}{\lambda_1(n + 2 - 2\alpha\lambda_1(n+1))}, \\ \delta &= \frac{1 - 2\alpha\lambda_1}{2\lambda_1(1 - \alpha\lambda_1)}, \qquad \alpha = \frac{1}{(n+2)^2\lambda_2}, \end{aligned}$$

and λ_2 is as given in Equation (4).

B. Hypotheses

In this section we develop testable hypotheses based on the predictions derived for the two benchmarks. From now on, we set $p_0 = 0$ and define returns as price changes. We are interested in $r_{1,3} = p_3 - p_1$, the long-term future return after the insider and arbitrageurs learn their private information. As the long-term information is observed only by the insider, we contrast return sensitivities to insider's and arbitrageurs' demands to determine whether the insider does or does not trade based on foreknowledge of future material information. We denote the observed insider's demand after he/she learns the short-term and long-term information as ζ_1 and the observed aggregate demand of the arbitrageurs after they learn the short-term information as $\xi_1 = \sum_{j=1}^{n} \xi_{1j}$.

To examine the sensitivities between the demands of the two types of informed traders and future stock returns, we consider three different tests. First, we consider return sensitivities of insider's and arbitrageurs' demands as reflected in coefficients b and c in Equation (9). Second, we differentiate the signs of insider's and arbitrageurs' demands and consider their interactions. Equation (10) regresses returns on a set of dummy variables interacting the direction of each type's net demand (for example, $\mathbb{I}_{\zeta_1>0,\xi_1<0}$ treats the case when the insider buys and arbitrageurs sell). Finally, Equation (11) considers the sensitivities of the insider's demand to the short-term and long-term information and complements the return equations.

$$(9) \qquad r_{1,3} = b_0 + b\zeta_1 + c\xi_1 + \epsilon$$

$$(10) \qquad r_{1,3} = b_{++}\mathbb{I}_{\zeta_1>0,\xi_1>0} + b_{+-}\mathbb{I}_{\zeta_1>0,\xi_1<0} + b_{-+}\mathbb{I}_{\zeta_1<0,\xi_1>0} + b_{--}\mathbb{I}_{\zeta_1<0,\xi_1<0} + \epsilon$$

$$(11) \qquad \zeta_1 = d_{++}\mathbb{I}_{v_1>0,v_2>0} + d_{+-}\mathbb{I}_{v_1>0,v_2<0} + d_{-+}\mathbb{I}_{v_1<0,v_2>0} + d_{--}\mathbb{I}_{v_1<0,v_2<0} + \epsilon$$

In order to evaluate signs and relative magnitudes of the demand sensitivities on future returns (coefficients b and c in Equation (9)), we solve the model numerically. Figure 1 presents the values of coefficients b and c as predicted by the two benchmarks for $\sigma_v^2/\sigma_u^2 = 1$, $\sigma_v^2/\sigma_w^2 = 1$ and $n = 3$.[9]

Insert Figure 1 about here

In the NLI benchmark, both types of informed traders use only the short-term information v_1, which positively correlates with the long-term fundamental value $v_0 + v_1 + v_2$. This means that the demands of both types of traders positively predict future stock returns. If insiders trade also on the

[9]Figures A1-A3 with robustness checks when the two variance ratios σ_v^2/σ_u^2 and σ_v^2/σ_w^2 range from 0.25 to 4 and the number of arbitrageurs n changes between 3 and 20 are in the Internet Appendix.

long-term information v_2, as in the AI benchmark, arbitrageurs are able to predict future returns relatively less well, and therefore the coefficient c is negative. When both v_1 and v_2 are either positive or negative, the arbitrageurs' prediction has a correct sign. However, when v_1 and v_2 have opposite signs, arbitrageurs' demands and future returns are negatively correlated. On average, the negative correlation in the latter case dominates the positive correlation in the former case, and the overall effect, as reflected in the coefficient c, is negative. In summary, our first hypothesis highlights the relative informational advantage of the insider over arbitrageurs. We formulate a null hypothesis and two alternative hypotheses corresponding to the two benchmarks.

H1$_0$ (Relative predictive power of informed trading): *Arbitrageurs' demand conditional on insider's demand does not predict future return.*

H1$_{NLI}$: *Arbitrageurs' demand conditional on insider's demand predicts positive future return.*

H1$_{AI}$**:** *Arbitrageurs' demand conditional on insider's demand predicts negative future return.*

Figure 2 provides predictions for categorical rather than continuous demand variables as reflected in Equation (10), assuming $\sigma_v^2/\sigma_u^2 = 1$, $\sigma_v^2/\sigma_w^2 = 1$, and $n = 3$. We consider separately demand sensitivities when the insider and arbitrageurs both buy or sell (b_{++} and b_{--}) versus when their demands have opposite signs (b_{+-} and b_{-+}).

Insert Figure 2 about here

Both benchmarks imply that whenever insider's and arbitrageurs' demands have the same sign, demands of the two types correctly forecast the future return: b_{++} is positive and b_{--} is negative. However, in the case of opposite signs of insider's and arbitrageurs' demands, the NLI benchmark predicts that the expected future stock return is positive whenever the arbitrageurs' aggregate demand is positive and vice versa: b_{-+} is positive, while b_{+-} is negative. The higher predictive power of arbitrageurs' demand stems from the fact that their demands are aggregated over n arbitrageurs and the noise in the arbitrageurs' demands, which is due to independent shocks to their initial endowments, is diversified away. The AI benchmark in the case of opposite signs of insider's and arbitrageurs' demands predicts that the expected future stock return is positive whenever the insider's demand is positive because the insider is informed about the long-term innovation to the fundamental value, while arbitrageurs are not. This implies that b_{+-} is positive, while b_{-+} is negative. As a result, Hypothesis 2 concerns the predictive ability of informed demands when the two types of informed traders disagree on the direction of trading.

H2$_0$ (Predictive ability of disagreement between the two types of informed traders): *When demands of the insider and arbitrageurs have opposite signs, the demands of neither type of informed traders predict future returns.*

H2$_{NLI}$: *Conditional on demands of the insider and arbitrageurs having opposite signs, the future return is positive whenever arbitrageurs buy and negative whenever they sell.*

H2$_{AI}$: *Conditional on demands of the insider and arbitrageurs having opposite signs, the future return is positive whenever the insider buys and negative whenever he/she sells.*

Hypothesis 3 is somewhat different. It does not concern *return-demand* sensitivities but focuses on the relationship between the insider's demand and the short-term and long-term information. Estimation of the direct sensitivity of insider's demand to the two types of information complements Hypothesis 2. Figure 3 presents the model's predicted sensitivities to information as represented by coefficients d_{++} to d_{--} in Equation (11). We again differentiate the NLI and AI benchmarks and assume $\sigma_v^2/\sigma_u^2 = 1$, $\sigma_v^2/\sigma_w^2 = 1$ and $n = 3$.

Insert Figure 3 about here

The NLI benchmark implies that the insider's demand is positive only when the short-term information v_1 is positive. This happens because the insider does not use the long-term information v_2 and hence buys only when v_1 signal commands so. In the AI benchmark, the insider optimally forms a positive demand whenever the long-term information v_2 is positive, anticipating a positive future return. In the case of $v_1 < 0$ and $v_2 > 0$ ($v_1 > 0$ and $v_2 < 0$), the fundamental asset value is on average zero. However, the insider buys (sells) to exploit the selling (buying) pressure coming from arbitrageurs who act on the basis of v_1 only. As a result, insider's demand is contrarian to the short-term information when the short-term and long-term signals are of opposite signs.

H3$_0$ (Relationship between insider's demand and long-term information): *Conditional on the short-term and long-term information having opposite signs, the insider's demand is sensitive to neither the short-term nor long-term information.*

H3$_{NLI}$: *Conditional on the short-term and long-term information having opposite signs, the insider tends to sell when the short-term information is negative and buy when the short-term information is positive (the insider's demand is not sensitive to the long-term information).*

H3$_{AI}$: *Conditional on the short-term and long-term information having opposite signs, the insider tends to sell when the long-term information is negative and buy when it is positive.*

Overall, our hypotheses aim to establish whether insider's trading strategies take into account the short-term and/or long-term information. The main identification strategy is comparing his/her demand to the demand of traders who use only the short-term information. Using short-sellers' demand to proxy for arbitrageurs' trades, we are able to estimate the sensitivity of insider trades to the short-term versus long-term information.

III. Data

Our sample comprises firm-quarter information from July 2006 to December 2017 for 6,046 publicly listed US firms. We consider all US common stocks that are traded on the NYSE, NASDAQ, or AMEX exchanges.[10] We obtain quarterly earnings announcements from the Compustat quarterly data file and delete firm-quarters for which this data is unavailable. Compustat is also the source of accounting information. Insider trading data comes from Thomson Financial Insider Filings that contain all insider trading activity as reported in Forms 3, 4 and 5 specified in the Securities Exchange Act of 1934. The data set contains detailed information about all reported transactions, including the trading date, reporting date, insider name, insider's position in their firm, number of shares traded, transaction price, and transaction type (purchase or sale). We consider only open-market purchases and sales by officers and directors.[11] As insiders sometimes trade several times on the same day, we sum all insider transactions by the same director in the same direction (purchases/sales) within one day, but keep transactions if they are in different directions even on the same day. Data on short selling and equity-lending supply is from Markit (which acquired Data Explorers).[12] The data on insider trading and short selling around earnings announcements is matched with stock-return data from CRSP, and analyst forecast data from I/B/E/S.

The number of shares sold and bought by insiders and the daily number of stocks on loan based on shorting transactions that are initiated on the most recent business day should reflect informed trading as defined in our model in Section A. For insider trading, we define net insider selling (nis_{kt}) as the difference between the number of shares sold and bought on a given day t by all

[10] We exclude non-US incorporated firms, ADR, ETF, and REITS.

[11] Trading by large block holders is, in our view, of different nature and based on different trading incentives.

[12] Equity-lending information in Markit is collected daily from 125 large custodians and 32 prime brokers and covers more than 85% of the equity-lending market. The data is described in Saffi and Sigurdsson (2010).

insiders of a focus firm k, scaled by the number of shares outstanding. To distinguish net sales from net purchases, we also define $nispos_{kt}$ where we replace all negative values with zeros and keep all positive values – this variable represents insider sales that are larger than insider purchases. Similarly, we define $nisneg_{kt}$ by keeping negative values of nis_{kt} and then taking an absolute value for easier interpretation. This variable then represents insider purchases that exceed insider sales. Short selling ($relss_{kt}$) is measured as the number of stocks on loan based on shorting transactions of the focus firm k that are initiated on the day t, scaled by the number of shares outstanding.

Figure 4 plots averages for the relative short-selling volume $relss_t$, the net insider selling $nispos_t$, and the net insider buying $nisneg_t$ 29 days around earnings announcements. As the magnitude of insider trades is considerably smaller than the magnitude of short sales, we place the range of values for shorting transactions on the left axis and of insiders' transactions on the right axis. We can see that earnings announcements have a significant effect on the trading patterns of both types of informed traders. In line with Engelberg et al. (2012), short sales increase sharply at day -1 and gradually decrease afterwards. Insider sales peak at day +3 and their trading on day +14 is still markedly higher compared to the pre-announcement level, which is not the case for short sales. It is apparent that short sellers are faster than insiders – their trades peak immediately on the announcement day, while insiders follow only three days later for both insider sales and purchases. This insider trading lag is most likely due to restrictive "blackout" periods imposed on insiders by their employers in order to minimize their information advantage.[13] The short sales decrease smoothly since day +2 and do not seem to respond to the peak in insider trading.

Insert Figure 4 about here.

[13] Bettis et al. (2000) conduct survey regarding corporate policies and restrictions on insider trading. They find that 78% of firms in their sample have explicit blackout periods. The most common policy is to ban any trading by insiders except during a trading window from day +3 through to day +12 after any quarterly earnings announcement.

As our analysis centers around earnings announcements and focuses on the ability of informed traders to interpret public information, we need to aggregate insider and short-selling activity following quarterly earnings announcements. We consider a "response window" of (0,+5) to reflect that informed trading should be prompt, and we want to exclude the possibility of short sellers following insider trades. This could potentially happen only after 5 days from an earnings announcement; 3 days due to insider trading bans plus 2 days of reporting lag, on average. Consequently, we compute the average daily net insider sales (nis), positive net insider sales ($nispos$), and negative net insider sales ($nisneg$) within the response window. Similarly, we compute the average daily relative number of shares on loan ($relss$) within the six days. We define the buy-and-hold stock return $aret_{k,t+5,t+6+h}$ for firm k from day $t+5$ to day $t+6+h$ after the earnings announcement date t adjusted for the corresponding 5×5 size and book-to-market portfolio return.[14]

Table 1 shows firm-quarter summary statistics for all variables of interest that are defined in the Appendix. Panel A focuses on informed-trading variables over the $(0, +5)$ response window, which are (except dummy variables) reported in basis points. The average daily net insider sales are only 0.6 bps of their shares outstanding per day during the six days. The average positive and negative values for net insider sales are 0.79 bps and 0.19 bps, respectively, which indicates that insiders, on average, sell more than they buy. The quartile statistics show that both net insider sales and purchases are quite rare. In contrast, short sellers are significantly more active. The average relative fraction of shares shorted is 14 bps per day. Only 25% of firm-quarters have an average daily number of shares shorted during the (0,+5) response window smaller than 1.67 bps.

Insert Table 1 about here.

[14]In Section D with robustness checks, we also consider a response window of (0,+20) to reflect longer allowed trading periods for insiders (Bettis et al., 2000) as well as market-adjusted returns.

In order to test our hypotheses, we distinguish intensive informed trading using a set of dummy variables. First, we set intensive insider selling ($is_{k,t,t+5}$) and buying ($ip_{k,t,t+5}$) dummies to one when net insider selling is positive and negative, respectively, over the $(0, +5)$ response window. Accordingly, the dummy $noit_{k,t,t+5}$ for "no insider trading" is set to one when net insider selling is equal to zero over the response window.[15] Finally, we define firm-quarters with intensive short selling ($ssh_{k,t,t+5}$) as quarters with the relative number of shares shorted being in the top quintile and firm-quarters with low-intensity short selling ($ssl_{k,t,t+5}$) as quarters with the relative number of shares shorted being in the bottom quintile. The dummy variable $ssm_{k,t,t+5}$ corresponds to the three middle quintiles of short selling. To preserve space, we simplify notation for these variables and use is, ip, $noit$, ssh, ssm, and ssl in all tables and is_{kt}, $\ldots$, ssl_{kt} in equations. The average values for is and ip in Panel A of Table 1 show that only about 19% of all firm-quarters experience net insider selling and about 7% experience net insider buying over the $(0, +5)$ response window. No insider trading is the complement to these two groups. Statistics for ssh, ssm, and ssl are self-explanatory and therefore not tabulated.

Panels B and C of Table 1 show summary statistics for future returns and control variables, respectively. The average size- and book-to-market-adjusted return over the 20 business days just after the $(0, +5)$ response window is -0.58% and returns deteriorate further over longer horizons. The negative values are due to the size and book-to-market adjustments as the market-adjusted model shows future returns with positive values.[16] The average firm in our sample has a negative change in earnings per share relative to four quarters back of –0.37%. Nevertheless, the average market reaction to the earnings announcement is 0.16%. The past 1-year return, again with the

[15]Note that this dummy variable represents no insider trading rather than equal sales to purchases because the number of firm-quarters with an equal number of purchase and sales is almost zero.

[16]Summary statistics for the market-adjusted returns are not tabulated but are available upon request.

size and book-to-market adjustment, is –2.22%. The two measures to determine the direction of the long-term information used for testing Hypothesis 3 are based on future-quarter earnings innovations and are discussed in more detail in Section B. The first measure $\Delta earn$ takes the change in net income scaled by total assets in thousands, while the second measure $eaar$ focuses on the 3-day market reaction to future earnings announcements, again size and book-to-market adjusted. Median values for both measures are close to zero, but they both exhibit large variation.

Table 2 provides statistics for interaction terms between intensive insider and short-selling activity during the six-day response window. Insiders and short sellers sell together relatively frequently. The first set of interaction terms between insider selling and the three categories of short selling shows that insiders are net selling in about 17.7% of all quarters (is in Column 2). In 4.7% of all quarters, they net sell together with intensive short selling ($is \times ssh$), while in only 0.9% of all quarters, they net sell when the short-selling activity is very low ($is \times ssl$). The insider tendency to trade when short selling is high pertains also when considering the fraction of shares traded (5.18 bps in Column 5) or the average trade dollar value ($2.6 million in Column 7). The corresponding numbers for low short-selling intensity are 4.56 bps and $1.3 million, respectively.

Insert Table 2 and Figure 5 about here.

Net insider purchases are present in only 7.4% of quarters (ip in Column 2) and are equally likely with low and high short-selling activity. Column 6 shows that insiders buy significantly more (3.12 bps of shares outstanding) in low short-selling activity quarters than in high short-selling activity quarters (2.58 bps). However, the average dollar value purchased is at $0.4 million, almost six-fold higher in the high than in the low sort selling category (Column 8).

Finally, short selling without any insider trading activity covers 74.9% of all quarters ($noit$ in

Column 2). The intensity of short selling without any presence of insider trading activity inclines towards lower levels. The fraction of quarters with high short selling and without any insider trading activity is 13.05% ($noit \times ssh$ in Column 2). This represents 17% of all quarters without any insider trading activity ($noit \times ssh$ in Column 3) and is significantly lower than the unconditional fraction of 20% at the 1-percent level.[17] Moreover, low short-selling activity without any insider trading activity is reported in 16.5% of all quarters ($noit \times ssl$ in Column 2). This represents 22% of quarters without insider trading and is significantly higher than 20%, indicating again that short sellers are less active when insiders are not trading.

The last row in Columns 5 to 8 shows that insider sales are substantially larger than purchases both by the fraction of shares traded and dollar trade value. Insiders on average sell $1.6 million (about 0.79 bps of shares outstanding) but buy only $0.07 million (0.19 bps of shares outstanding). The average sale value during quarters of high short selling is $2.6 million, and the average purchase value during quarters of low short selling is only $0.07 million.

Figure 5 shows that the two types of informed traders sell indeed more when selling together. We graph the selling activity for 29 days around earnings announcements as in Figure 4 but now conditional on the set of informed-trading interaction categories used in Table 2 within the (0,+5) response window, not showing plots when insiders are not trading. Short-selling peaks at day 0 regardless of the direction of insider trading. Still, short sellers' trades peak higher when insiders sell rather than buy. Similarly, insider sales (purchases) peak at day +3 regardless of short-sellers' trading. The peak is sharper when insiders sell together with high short selling, but surprisingly, it seems to be sharper also with purchases when insiders and short sellers disagree.

[17]The short-selling intensity is defined based on quintiles.

IV. Empirical results

A. Predictability of future returns

To test Hypothesis 1 on the relative predictive power of informed trading, we regress future returns on insider-trading and short-selling intensity dummies simultaneously:

$$(12) \qquad aret_{k,t+5,t+6+h} \;=\; b_1\, is_{kt} + b_2\, ip_{kt} + c_1\, ssh_{kt} + c_2\, ssl_{kt} + X_{kt}\,\gamma + u_{kt},$$

where $aret_{k,t+5,t+6+h}$ denotes abnormal return in stock k from $t+5$ to $t+6+h$ relatively to the earnings announcement at t, with $h \in \{20, 40, 60, 130, 250\}$; is_{kt} and ip_{kt} denote dummy variables for intensive net insider sales and purchases, respectively, in firm k over the $(0, +5)$ response window relatively to t; and ssh_{kt} and ssl_{kt} denote short selling in the highest and lowest quintiles, respectively, in firm k over the $(0, +5)$ response window. Figure 6 shows the timings. Variables X_{kt} include firm-specific characteristics including the past 1-year return $pastret_{k,t-1y,t-2}$, the earnings announcement abnormal return $eaar_{k,t-2,t+1}$, the change in earnings-per-share $\Delta eps_{k,t-q4,t}$ as well as firm and year fixed-effect dummies. Standard errors are clustered within firms.

Hypothesis 1 highlights the relative informational advantage of insiders over short sellers in the AI benchmark. In particular, Hypothesis H1$_{AI}$ predicts that future returns are negatively correlated with short-sellers' demand, which means that c_1 should be positive and c_2 negative. In contrast, Hypothesis H1$_{NLI}$ predicts negative c_1 and positive c_2.

Insert Table 3 and Figure 6 about here.

Table 3 shows the results with the first two columns summarizing H1 predictions. Future abnormal returns are significantly more negative for stocks with insider selling and significantly more positive for stocks with insider buying. Similarly, future abnormal returns are significantly more negative for intensively shorted stocks (except for the shortest horizon $h = 20$) and significantly more positive for stocks with the lowest levels of short selling for all horizons.[18] This shows that both insiders' and short-sellers' demands predict future returns, which is in line with existing literature (Huddart et al., 2007; Akbas et al., 2020). More importantly, we reject the null hypothesis H1$_0$ for all horizons h in favor of the alternative hypothesis H1$_{NLI}$. Coefficient c_1 is significantly negative and c_2 is significantly positive at the 1-percent level after controlling for insider trading, which provides initial evidence in favor of the NLI benchmark that insiders abstain from trading on the foreknowledge of future material information, but take advantage of short-term mispricing.

To test Hypothesis 2 concerning the predictive power of a disagreement between the two types of informed traders, we interact insiders' and short sellers' intensive trading dummies:

$$\begin{aligned} aret_{k,t+5,t+6+h} &= b_{++}\,(ip_{kt} \times ssl_{kt}) + b_{+-}\,(ip_{kt} \times ssh_{kt}) \\ &+ b_{-+}\,(is_{kt} \times ssl_{kt}) + b_{--}\,(is_{kt} \times ssh_{kt}) + X_{kt}\,\gamma + u_{kt}, \end{aligned} \tag{13}$$

where matrix X_{kt} contains the same control variables as in model (12), but we add interaction terms for the no insider trading dummy $noit$ and the middle short-selling quintiles dummy ssm. The regression constant reflects the remaining category of quarters $ssm \times noit$. As we focus on the predictive power of the two informed traders' demands when they are in disagreement, Hypothesis H2$_{NLI}$ suggests a higher predictive power for short-sellers' demands: b_{+-} should be negative and b_{-+} positive. H2$_{AI}$ predicts the opposite signs as insiders' predictive power is higher when they use foreknowledge of future material information.

Panel A of Table 4 shows the results with the first two columns summarizing H2 predictions.

[18] One could argue that low levels of short sales are not as informative as high levels of short sales. If no one is short-selling a stock, it does not necessarily mean it will do well; it may just stay flat. Table 3 shows that low short selling predicts future stock returns at least as well as high short selling.

We reject the null hypothesis H2_0 at all horizons h, but this time it is rejected in favor of H2_{NLI} or H2_{AI}, depending on whether insiders buy or sell. Specifically, the coefficient b_{+-} corresponding to the interaction term $ip \times ssh$ (insiders are buying while short sellers are selling intensively) is positive and statistically significant for all horizons. This means that when insiders and short sellers disagree and insiders buy, future returns are positive – insiders predict future returns better than short sellers. Hence, insiders' demand is based on foreknowledge of future material information. The null hypothesis H2_0 is rejected in favor of the alternative H2_{AI} for insider purchases. It is noteworthy that this result applies under the assumption that short sellers are as good as insiders in processing the short-term public information. Section VI discusses alternative scenarios.

Insert Table 4 about here.

In contrast, the coefficient b_{-+} for the interaction term $is \times ssl$ (insiders are selling while short sellers are "buying") is positive for $h \geq 40$ and significant for $h = 40$. This means that when demands of insiders and short sellers have opposite signs and insiders sell, future returns are positive – insiders do not predict future returns well. Insider selling is not based on foreknowledge of future material information. In the case of insider sales, the null hypothesis $H2_0$ is rejected in favor of the alternative hypothesis $H2_{NLI}$.

Overall, Panel A suggests that when insiders and short sellers disagree in their trading, insiders tend to abstain from selling on foreknowledge of future material information. Also, insiders' sales forecast future returns when their demand is aligned with short-sellers' demand; they effectively hide behind the high short-sellers' demand. In contrast, insiders are sometimes able to take advantage of foreknowledge of future material information when buying. As shareholders are usually more determined to sue when suffering from negative returns, the differing pattern across purchases and sales minimizes insiders' chances of legal jeopardy in the future (Ke et al., 2003; Cheng and Lo, 2006; Kallunki, Kallunki, Nilsson, and Puhakka, 2018).

Still, it is important to check whether insiders are able to earn significant dollar amounts during periods of their agreement or disagreement with short sellers, as positive correlation between trades and future returns is not necessarily translated into significant dollar profits for insiders (Cziraki and Gider, 2021). This is due to variation in trading volumes that differ significantly across different categories, as we show in Table 1, but also across different percentage returns. We calculate the dollar profit for each trade within the (0,+5) response window as the inflation-adjusted dollar value expressed in 2017 US dollars and multiplied by the buy-and-hold abnormal return over the corresponding time horizon, which is size and book-to-market adjusted. In order to express profits with positive values, we multiply the resulting number for sales by -1. For each firm-quarter, we average over all trades that fall within the (0,+5) response window.

Panel B of Table 4 shows averages of dollar profits per trade across different trading categories and horizons.[19] The unconditional average dollar profit per trade in our sample (untabulated) is \$3,202 for the $h = 20$ horizon and \$23,375 for the $h = 250$ horizon. This compares to \$4,000 and \$12,000, respectively, in Cziraki and Gider (2021). Most of this profitability comes from quarters when insiders sell together with high or medium sort selling ($is \times ssh$ and $is \times ssm$ categories), that is, when insiders sell in agreement with short sellers. The average per-trade profit in the $is \times ssh$ category is \$5,391 for the 20-day horizon, while the annual profit ($h = 250$) in this category reaches \$48,105 per trade. Insiders do not make significant profits when selling in disagreement with short sellers. The average net profit in categories where insiders actively purchase shares is

[19]We cannot run dollar-profit regressions corresponding to Panel A because dollar profits are not defined in quarters when insiders do not trade.

small and insignificant, and even negative for short horizons. It seems that insiders do not purchase shares in order to make large profits. Overall, Panel B supports hypothesis $H2_{NLI}$ that insiders do not profit from using foreknowledge of private information, but they still make relatively sizable profits when selling in agreement with short sellers.

There are three other interesting points to make here. First, our results in Panel B show that even when insiders agree with short sellers, they make dollar profits only from sales and not from purchases. This suggests that insiders often have high motivation to sell due to liquidity or diversification needs, but are very cautious when making sales to avoid unnecessary losses. Insiders take every opportunity to sell when they do not face high legal jeopardy. The second point is that in Panel B, the $is \times ssm$ category also exhibits a similar and almost as strong dollar profits as the $is \times ssh$ category. This could be because our classification of high short-selling is too conservative. Alternatively, it may highlight that insiders are better at identifying public information than short sellers and use long-term information only when it is correlated with the short-term information (hiding behind short sellers). Third, insiders do not suffer losses when they sell in disagreement with short sellers; coefficients for $is \times ssl$ in Panel A are all but one (for $h = 40$) insignificant. This is in sharp contrast with positive and highly significant coefficients for $noit \times ssl$, which is for the same low short-seller trading but when insiders decide not to trade. This pattern suggests that insiders stop selling strategically.

B. Insiders' demand predictions

Finally, we test Hypothesis 3 concerning the relationship between the insiders' demand and the long-term information following Equation (11). It predicts that when the short-term and long-term information exhibit opposite signs, insiders' demand is positively correlated with the long-term private information in the AI benchmark, while it is negatively correlated with the long-term information in the NLI benchmark. We measure the direction of the short-term information using the demand of short sellers. We base this approximation on our earlier conjecture that short sellers typically trade on a superior interpretation of public news contained in earnings announcements (Engelberg et al., 2012). This conjecture is indeed confirmed in Section A above. Applying this interpretation for quintiles by short-selling demand, dummy variables ssl, ssm, and ssh correspond to positive, neutral, and negative short-term information, respectively.

To measure the direction of the long-term information, we use future realizations of earnings innovations following Piotroski and Roulstone (2005). We define future earnings innovation as $\Delta earn_{k,t,t+q4} = \frac{earn_{k,t+q4} - earn_{kt}}{TA_{kt}}$, which is the difference between earnings four quarters ahead $earn_{k,t+q4}$ and the current quarter earnings $earn_{kt}$, scaled by the firm's total assets TA_{kt} at the current quarter. We set the dummy variable $longh$ equal to one for all observations in the highest quintile by $\Delta earn_{k,t,t+q4}$. Similarly, $longl$ is equal to one for the lowest quintile and $longm$ is equal to one for the middle three quintiles by $\Delta earn_{k,t,t+q4}$.[20]

Panel A of Table 5 shows insider trading patterns depending on short-term information (short sellers' trading) and long-term information ($\Delta earn_{k,t,t+q4}$). We aim to show deviations of insider sale and purchase frequencies from their expected frequencies. The data set covers 115,997 firm-quarters, and insiders on average sell in 18.3% and purchase in 7.7% of them. 74% of firm-quarters are without any insider trading activity. Both short-term and long-term information are sorted into

[20]Table A1 in the Internet Appendix presents also estimation results with one and three quarters ahead future earnings innovation and with one, three, and four quarters ahead earnings announcement abnormal returns as an alternative measure. Using the earnings announcement abnormal returns measure ($eaar$, adjusted by the corresponding size and book-to-market portfolio return and cumulated over three days around the announcement), we assume that insiders anticipate the future earnings surprise that is concentrated in the three days around the earnings announcement and we ignore the information incorporated into prices during other days in the quarter.

three bins, where high and low bins represent around 20% of firm-quarter observations and the medium bin around 60%. Based on these frequencies, we compute the expected frequencies for all combinations of short-term information, long-term information, and insider trading. For example, the expected frequency of a quarter with insider sales when both short- and long-term information are low is $0.0071 = 0.183 \times 0.198 \times 0.196$. We then compute the realized frequency of the type (in this case, it is 0.0109), take the deviation from the expected value ($0.0038 = 0.0109 - 0.0071$), and express it as a percentage deviation ($+54\% = 0.0038/0.0071$). The interpretation of the number is that the actual frequency of quarters when insiders sell and short- and long-term information is low is 54% higher than its expected frequency.

Panel A of Table 5 shows the percentage deviations for insider sales and purchases. We can see that insider sales are clearly aligned with the short-term information: the frequency of quarters with insider sales is increased by 24 to 54 percent when the short-term information is negative (ssh), regardless of the long-term information. At the same time, the frequency of quarters with insider sales decreases between 71 and 80 percent when the short-term information is positive (ssl), again regardless of the nature of the long-term information. The bins with medium short-term information show the smallest changes, and only the bin for positive long-term information is aligned with insider sales. Purchases show a somewhat higher reliance on long-term information. For example, when short-term information is positive (ssl), insiders increase purchases when long-term information is positive, but decrease purchases when it is negative. During periods of negative short-term information, insiders tend to increase their purchases irrespective of the long-term information.

Insert Table 5 about here.

Panel B of Table 5 tests Hypothesis 3 in a multivariate setting with insider trading demand as the dependent variable. We separate insider selling and buying demands and use $nispos$ and $nisneg$, both measured in basis points, respectively. For easier interpretation, we take the absolute value of $nisneg$ so that a higher $nisneg$ means higher net purchases. We run two separate regressions:

$$\begin{aligned} nispos_{k,t,t+5} &= d_{++}\, ssl_{kt} \times longh_{kt} + d_{+-}\, ssl_{kt} \times longl_{kt} \\ &+ d_{-+}\, ssh_{kt} \times longh_{kt} + d_{--}\, ssh_{kt} \times longl_{kt} + X_{kt}\, \gamma + u_{kt}, \end{aligned} \tag{14}$$

$$\begin{aligned} nisneg_{k,t,t+5} &= d_{++}\, ssl_{kt} \times longh_{kt} + d_{+-}\, ssl_{kt} \times longl_{kt} \\ &+ d_{-+}\, ssh_{kt} \times longh_{kt} + d_{--}\, ssh_{kt} \times longl_{kt} + X_{kt}\, \gamma + u_{kt}. \end{aligned} \tag{15}$$

As before, matrix X_{kt} includes control variables $pastret_{k,t-1y,t-2}$, $eaar_{k,t-2,t+1}$, $\Delta eps_{k,t-4q,t}$, and firm and year fixed effects. It also includes the remaining interaction terms with medium short-term and long-term information dummies, ssm and $longm$. The reference category is the group of $ssm \times longm$ with neutral short-term or long-term information.

Panel B shows coefficient estimates, using $\Delta earn$ four quarters ahead as the measure of long-term information. The first two columns show H3 predictions for insider sales, followed by a column with coefficients. We can see that stocks with negative short-term information ssh and positive long-term information $longh$ experience insider selling in line with the short-term information and against the long-term information. Insiders increase their net sales: coefficient d_{-+} is positive. Similarly, for stocks with positive short-term information ssl and negative long-term information $longl$, insiders tend to decrease their net sales: coefficient d_{+-} is negative and statistically significant. Insiders follow the short-term information despite the opposite sign of the long-term information. The same pattern prevails for sales when we measure $\Delta earn$ one and three quarters ahead or use earnings announcement abnormal returns one, three, and four quarters ahead as a measure of long-term information (see Table A1 in the Internet Appendix). For insider sales, we reject the null hypothesis $H3_0$ in favor of the alternative hypothesis $H3_{NLI}$. It is noteworthy that these results for H3 are not just consistent with H2 results, but reinforce them because this time the conclusion is not based on a "non-rejection" of the null hypothesis.

Coefficients for purchases in Panel B show a different pattern. We can see that coefficient d_{+-} is negative while d_{-+} is positive. This suggests that insider purchases decrease with bad but increase with good long-term information. Even though d_{+-} is not statistically significant in Panel B, Table A1 shows statistical significance for $\Delta earn$ one quarter ahead and for all three $eaar$ specifications. We reject the null hypothesis $H3_0$ for insider purchases in favor of the alternative hypothesis $H3_{AI}$.

In summary, our results in this section suggest that insider sales versus purchases take advantage of different information. Insider sales follow closely patterns of short-selling demands, which suggests that insiders exploit short-term mispricing stemming from public information rather than foreknowledge of material information. This is not the case for insider purchases: insiders seem to trade on foreknowledge of future material information when buying. We believe the difference is due to insiders more carefully avoiding trading on the long-term undisclosed information when selling because the chances and cost of being prosecuted are higher with sales than with purchases (Ke et al., 2003; Cheng and Lo, 2006; Kallunki et al., 2018). Instead, they skillfully take advantage of the short-term mispricing stemming from public information that is not illegal but still profitable.

C. Routine versus opportunistic insider trades

Our conclusion so far is that insider sales rely on exploiting mispricing stemming from the market's misinterpretation of public information, and only insider purchases rely on foreknowledge of material information. This section explores whether this trading pattern prevails for opportunistic trades. In particular, we want to check whether our results hold even after excluding routine insider sales, which should be independent of any information (Cohen et al., 2012).If the results hold, it would reinforce the claim that sales carry higher legal jeopardy and insiders avoid using the foreknowledge of material information when selling to minimize their legal prosecution cost.

Following Cohen et al. (2012), we identify insiders who trade in the same calendar (routine) month in at least three consecutive years. We classify all trades by the insider following this three-year period as routine if they happen in the same routine month. Trades made in non-routine months are classified as opportunistic. Then, in each quarter, we add routine (opportunistic) net insider sales over the response window and set routine (opportunistic) insider selling and buying dummies to one when routine (opportunistic) net insider selling is positive and negative, respectively. This adjustment of Cohen et al. (2012) covers all quarters in our data set and fits our setting of insider trading in concise response windows. Table A2 in the Internet Appendix shows that routine insider trading is less frequent than opportunistic insider trading. In line with Table 2, both opportunistic and routine insider trading are higher when short-selling demand is in the highest and lowest quintiles than when it is in the middle three quintiles.

Table A3 in the Internet Appendix replicates Tables 3 and 4 replacing is and ip with decomposed dummies for opportunistic ($isopp$ and $ipopp$) and routine ($isrt$ and $iprt$) trades. We conclude that opportunistic purchases and sales predict significantly future returns in the right direction. Insiders are informed when making their opportunistic purchases and sales. All the coefficients for routine purchases $iprt$ are insignificant, which confirms that they do not predict future abnormal returns. Routine insider sales $isrt$, however, are significantly negatively correlated with future returns for all horizons except the longest horizon. The coefficients are smaller in size than the coefficients for the opportunistic sales, but they suggest that insiders are able to sell in line with future returns even in the case they sell regularly in a particular month of the year. This is because insiders have the option not to trade in some years – our results suggest that insiders abstain from selling when future returns are particularly large and keep their pattern of trading when future returns are small.

Panel B of Table A3 tests Hypothesis 2 separately for opportunistic and routine insider trades. When insiders and short sellers disagree, future returns align with insiders' trades in case of opportunistic insider purchases, but they align with short sellers' trades in case of routine insider purchases. The null hypothesis $H2_0$ is rejected in favor of $H2_{AI}$ in the former case, but in favor of $H2_{NLI}$ in the latter case. Note that when the two types of informed traders agree, they predict future information regardless of whether insider purchases are routine or opportunistic. Focusing on insider sales, even the most informed transactions do not show any signs of usage of long-term private information. We conclude that insider sales rely on exploiting short-term mispricing.

Finally, Table A4 tests Hypothesis 3 concerning the relationship between insiders' demand and private information, again separately for opportunistic and routine insider trades. We can see that insider selling aligns with the short-term rather than the long-term information, even when we restrict to opportunistic transactions that are more informative. Routine sales do not adjust to information. Opportunistic net purchases decrease with negative long-term information and increase with positive long-term information. Again, we see evidence of insiders relying on foreknowledge of material long-term information when buying, but only opportunistically. Routine insider purchases do not adjust to long-term information. Table A5 in the Internet Appendix shows results when we measure opportunistic insider trades on the insider instead of the trade level.[21] Intuitively, this definition gains a higher fraction of routine trading. Our conclusions pertain.

[21]We identify routine insiders as the insiders who trade in the same calendar month for at least three consecutive years, and then classify all subsequent trades by these insiders as routine.

To summarize, this section suggests that insider sales exploit mispricing stemming from short-term public information rather than foreknowledge of material information, even when we drop less information-driven routine insider sales and focus on opportunistic sales. Opportunistic insider purchases tend to take advantage of foreknowledge of material information.

D. Robustness tests

In this section, we perform four robustness tests to further support our main results. First, we check that our results are not driven by high short-selling constraints. In particular, low short-selling activity, reflected in our ssl dummy, may not measure positive short-term information, but it may rather capture short sellers refraining from trading because it is too costly to do so. We classify short-selling constrained stocks as stocks with loan fees exceeding 200 bp during the response window[22] and repeat tests in Tables 4 and A1, but drop all stock-quarter observations with high loan fees. Table A6 in the Internet Appendix shows that our conclusions hold; insider purchases link with the long-term information while insider sales with the short-term information.

Second, we show that our results are not substantially affected by the fact that not all short selling is driven by speculative motives. For example, market makers, who do not want to hold costly inventory, rely on short selling during episodes of intensive public buying pressure. This part of the short-selling demand is not informationally motivated. In order to isolate short selling that is due to market making, we follow Diether et al. (2009) and define residual relative short selling as the error term in the regression: $ss_{i,t} = \alpha_i + \beta_i \times oimb^+_{it} + \varepsilon_{i,t}$, which is run for every stock i and day t and where ss is the number of shares shorted divided by the number of shares outstanding and

[22]The literature defines short-selling constraints based on lending fees in the range from 25 to 300 bp (D'Avolio, 2002; Geczy, Musto, and Reed, 2002; Cohen, Diether, and Malloy, 2006).

$oimb^+$ is the daily positive order imbalance of a stock, with negative values replaced with zeros. $oimb$ is computed as daily purchases minus sales scaled by daily volume and purchases and sales are defined as in Lee and Ready (1991). We replace relative short selling in Tables 4 and A1 by residual relative short selling ess to better proxy for informationally motivated short selling. Table A7 in the Internet Appendix shows that even the composition of short-selling quintiles changes (Panel A), our main conclusions remain broadly unchanged.

Third, we address a concern that some insider trades are not informationally motivated ex-ante and including them in our sample may add noise to our tests. In the previous section, we dropped routine insider trades but not all non-informationally motivated trades are classified as routine; many plan trades executed under Rule 10b5-1 are classified as opportunistic if they are not repeated over three consecutive years. To mitigate this concern, we exclude plan trades from opportunistic trades and test that the remaining opportunistic non-plan trades are indeed not based on foreknowledge of material information. About 7.60% of opportunistic insider sales are plan trades, while only about 0.63% of opportunistic purchases are plan trades. Table A8 in the Internet Appendix shows that the main conclusions hold for the stricter definition of opportunistic trades.

Finally, we show that our results do not change when considering a longer response window (0,+20) for informed trading and an alternative adjustment for abnormal returns. Table A9 in the Internet Appendix replicates Tables 4 and A1, but measures informed traders' demands during the (0,+20) response window. Table A10 replicates Table 4 using market-adjusted returns instead of book-to-market and size adjustment. It is worth noting that the longer response window does not affect the signs of the coefficients, but coefficient magnitudes drop somewhat. This suggests that most of the informed trading is indeed happening during the shorter response window of (0,+5).

V. Pre-SOX versus post-SOX analysis

So far, we have shown that in the post-SOX period (our data is between 2006 and 2017), insider sales are based predominantly on short-term mispricing. Now we test whether this is a consequence of the tighter SOX regulation. Ideally, we would want to show that insiders take advantage of foreknowledge of material information before SOX: insider sales would exhibit predictive ability when the two types of informed traders disagree on the direction of trading. The introduction of effective regulation should then hinder that predictive ability. Hypothesis 4 reflects this effect.

H4$_0$ (Predictive ability of disagreement before and after SOX): *The ability of insider trading to predict future returns when demands of the insider and arbitrageurs have opposite signs in the pre-SOX period is the same as the predictive ability in the post-SOX period.*

H4$_A$: *The ability of insider trading to predict future returns when demands of the insider and arbitrageurs have opposite signs is higher in the pre- than in the post-SOX period.*

To test this hypothesis, we compare the relationship between stock returns and informed traders' demands before versus after the introduction of SOX. Unfortunately, the Markit short-selling data starts only in 2006, so we have to rely on Compustat short interest data. We start in 1986, when the insider trading data starts. Compustat, however, provides data points only twice a month. It reports the snapshot of the total number of shares sold short for a given firm as of the reporting date. The key limitation of this data is its lower frequency compared to the daily short-selling data from Markit, which challenges our analysis. We want to link insider trading with short selling within six days immediately after earnings announcements, which is not possible to do precisely with the low frequency of short-interest reporting in Compustat. Apendix B describes our variable construction within the Compustat data. Note that we are not able to separate shares on loan that are initiated on the most recent business day, instead, we rely on relative short interest regardless of when it was initiated. Nevertheless, statistics in Table 6 show high similarity in short-selling patterns between the two data sources. Also, the correlation between the Compustat and Markit short interest in the $(0, +5)$ response window is 0.63 and is statistically significant at the 1-percent level.

As in our main analysis, we use a set of dummy variables based on quintiles of short interest during the $(0, +5)$ response window, relative to the earnings announcement date t, to measure intensive short selling. Firm-quarters with intensive short selling (ssh_{kt}) are quarters in the top quintile, while low-intensity short selling (ssl_{kt}) corresponds to the bottom quintile, and ssm_{kt} covers the middle quintiles. Note that the insider trading data does not change; we extend the insider trading dummies back before SOX. Based on net insider selling (nis_{kt}), which is the difference between the number of shares sold and bought by all insiders of firm k over the response window $(0, +5)$ scaled by the number of shares outstanding, we set intensive insider selling (is_{kt}) and buying (ip_{kt}) dummies to one when the net insider selling is positive and negative, respectively.

Insert Table 6 about here.

Table 6 replicates Table 2 with the new short-selling categories based on Compustat data before and after SOX in Panels A and B, respectively. Frequencies of quarters across the three main categories of insider trading in the post-SOX period remain largely consistent with Table 2. Sales are more frequent than purchases, with frequencies of 17% and 7% of all firm-quarters, respectively. Also similar to Table 2, $is \times ssm$ and $is \times ssh$ are reassuringly more than proportionately populated, while $is \times ssl$ capturing informed trading disagreement is under-represented. A comparable trend is observed for interactions between insider purchases and short selling. Notably, Column 11 (12) for $nispos$ ($nisneg$) after SOX shows higher volumes than in Table 2, which is because of higher volumes immediately after the introduction of SOX and availability of Markit data from 2006. Insiders took some time to adjust: the average $nispos$ ($nisneg$) over 2003–2006 is 1.62bp (0.24bp), while from 2006 onward it is 0.79bp (0.19bp). We are reassured that even though the measures of short selling are not directly comparable across the Compustat and Markit samples, the relative distributions across categories demonstrate a consistent pattern.

When moving from before to after SOX, insider sale quarters become more frequent at the expense of no trading quarters while insider purchase frequency drops by a small margin. Moreover, insider sales move somewhat from the category where they disagree with short sellers (decrease from 8% to 5%) to the middle category (increase from 61% to 65%). For insider purchases, we also see a slight movement towards more agreement between insiders and short sellers. Finally, insiders decrease the average daily volumes sold while they slightly increase volumes of purchases.

To capture the fact that the predictive power of the disagreement between the two types of informed traders changes from before to after SOX and test Hypothesis 4, we include interaction terms with a post-SOX dummy S_t and estimate

$$\begin{aligned} aret_{k,t+5,t+6+h} &= b_{++}(ip_{kt}\times ssl_{kt}) + b_{+-}(ip_{kt}\times ssh_{kt}) + b_{-+}(is_{kt}\times ssl_{kt}) + b_{--}(is_{kt}\times ssh_{kt}) \\ &+ c_{++}(ip_{kt}\times ssl_{kt}\times S_t) + c_{+-}(ip_{kt}\times ssh_{kt}\times S_t) + c_{-+}(is_{kt}\times ssl_{kt}\times S_t) \\ &+ c_{--}(is_{kt}\times ssh_{kt}\times S_t) + X_{kt}\,\gamma + u_{kt}, \end{aligned} \tag{16}$$

where all variables are defined in Section IV.A and X_{kt} contains control variables as in Regression (13) plus their interactions with S_t. Coefficients b_{+-} and b_{-+} measure the ability of informed traders to predict abnormal returns before SOX when insiders and short sellers disagree, while coefficients c_{+-} and c_{-+} measure the additional predictive power after SOX.

Insert Table 7 about here.

Panel A of Table 7 shows estimation results, with H2 and H4 predictions summarized in the first two columns. Coefficient b_{-+}, for $is \times ssl$ capturing scenarios when insiders sell while short sellers "buy", is negative for all horizons and statistically significant for $h = 20$ and $h = 40$. For these two horizons, we reject the null hypothesis H2_0 in favor of H2_{AI}: before SOX, insiders take advantage of foreknowledge of material information when selling. For longer horizons, we reject H2_0 in favor of H2_{NLI}; insiders are not using private information. Coefficient c_{-+} (for $is \times ssl \times S_t$) is positive and statistically significant for all but the highest horizon indicating that the usage of long-term private information for insider selling decreased after SOX. We reject H4_0 in favor of H4_A. The last row in Panel A tests for $b_{-+} + c_{-+} = 0$, measuring the overall predictive power in the post-SOX period. Across all horizons $h \geq 40$, the sum is positive and we reject H2_0 in favor of H2_{NLI}, in line with Section IV.A.

Now turning to insider purchases, the coefficient b_{+-} (for $ip \times ssh$ when insiders are buying while short sellers are selling intensively) is positive and statistically significant across all horizons h. We reject H2_0 in favor of H2_{AI} in the pre-SOX period; insider purchases are based on foreknowledge of future material information. Coefficient c_{+-} (for $ip \times ssh \times S_t$) is statistically insignificant for all horizons except $h = 250$, where it is negative and statistically significant at the 5-percent level. This implies no difference pre versus post SOX, except for the very long horizon. As even for $h = 250$ the total effect of the disagreement remains positive ($0.015 = 0.050 - 0.035$), we conclude that insider purchases rely on foreknowledge of material information in both periods.

Panel B of Table 7 focuses on insider dollar profits before versus after SOX. We run regressions with dummies for the informed traders' demand categories and add interaction terms with the post-SOX dummy S_t.[23] Columns labeled *pre* show profits before SOX, while columns labeled *post−pre* show the extra profits from before to after SOX. For insider sales before SOX, we can see significantly positive dollar profits across almost all horizons and all three selling categories. Interestingly, insiders earn higher profits when selling in disagreement with short sellers ($is \times ssl$) before SOX. This is reversed after SOX; the interaction terms $is \times ssl \times S_t$ are negative. After SOX, insiders shift their profits to using short-term public information.[24] For insider purchases, dollar profits are negative or insignificant for lower horizons $h \leq 60$ both before and after SOX. For higher horizons, we have positive profits before SOX that are lower after SOX. Still, profits remain insignificant when insider purchases are in disagreement with short sellers ($ip \times ssh$). So despite the predictive power of insider purchases for returns, as suggested by Panel A, insiders do not profit from their purchases in an economically significant way both before and after SOX.

VI. Discussion

Our model is based on a simplifying assumption that the short-term innovation to the fundamental value v_1 known to both informed parties is uncorrelated with the long-term innovation v_2 known only to insiders. In reality, this assumption may not hold. First, the short-term news, which arbitrageurs infer from public announcements, may correlate with long-term private material information. For example, earnings are usually positive in firms that subsequently receive takeover proposals. Second, v_1 may in part represent not only public information but some part of undisclosed private information that is leaked to arbitrageurs (Karpoff and Lou, 2010; Boehmer, Wu,

[23]We are not able to replicate Regression (16) because insiders' dollar profits are defined only for quarters when insiders buy or sell, we do not use any control variables.

[24]In contrast to Section IV.A, insiders make positive profits after SOX when selling in disagreement with short sellers, which is due to profits from 2003–2005, period not covered in IV.A. We see gradual adjustments in trading.

and Zhang, 2020). In these cases, the predictions of our model hold but one should modify the interpretation of v_1 and v_2. The short-term innovation v_1 represents news about v, public or private, known to arbitrageurs. The long-term innovation v_2 is then the orthogonal component of v that is not in the information set of arbitrageurs. We assume that the information set of insiders is richer than that of arbitrageurs, but this is realistic (Purnanandam and Seyhun, 2018).

Our main empirical predictions and results in Table 4 rely on disagreement between arbitrageurs and insiders about the direction of future returns. The disagreement reflects the opposite signs of arbitrageurs' and insiders' demands. Whenever arbitrageurs and insiders disagree and insiders significantly forecast future returns, it is clear that insiders rely on information that is not in the arbitrageurs' information set. In this scenario, our conclusion that insiders use private information beyond what is known to arbitrageurs holds firmly. In contrast, whenever insiders do not forecast future returns during the periods of disagreement with arbitrageurs, we have to be careful. An insignificant coefficient for insider demand could be due to the lack of power of our tests and hence does not prove that insiders do not use private information. It rather shows that we have no evidence that insiders use information beyond the information set of arbitrageurs. This is the case for insider sales. Still, the insiders' demand sensitivity tests in Table 5 provide an alternative view because we proxy the long-term information directly using future earnings surprises. We show that insiders sell less (more) when future earnings surprises are lower (higher); insiders ignore the long-term information and align with short-sellers' demand. These results are based on significant coefficients and do not suffer from the type II error problem. Moreover, corporate insiders are generally considered the most informed due to their access to non-public information (Massa et al., 2015; Purnanandam and Seyhun, 2018; Wang et al., 2022), and so, we interpret our results that insiders choose not to use v_2 when selling rather than not having any information advantage.

We should still distinguish a third case of the assumption violation, which considers that short sellers are not super-humans and they may miss some information that can be derived from public data. Insiders, in contrast, know their firms much better and exhibit an advantage also when interpreting the short-term public information. Consequently, v_1 may not cover all public information available and insiders' advantage over arbitrageurs in v_2 may include also bits of public information. Trading on v_2 is, as a result, not exclusively illegal. It is noteworthy that this violation of our assumptions would further support the effectiveness of insider trading regulation. In this case, we should be careful with conclusions in the scenario when insiders and arbitrageurs disagree, while insider purchases significantly forecast future returns, but it is unlikely that insiders would trade predominantly on public information. Firstly, short sellers sell very intensively and we do not find it plausible that the part of public short-term information that arbitrageurs miss dominates future positive returns. Secondly, Table A3 shows that routine insider purchases align with short sellers and significantly predict negative future returns, while opportunistic insider purchases predict positive future returns. These contrasting coefficients for routine versus opportunistic purchases are inconsistent with v_2 containing bits of positive public information and insider purchases relying predominantly on this piece of public information when disagreeing with short sellers.

VII. Conclusions

We study whether corporate insiders trade on foreknowledge of material information or rather on exploiting mispricing that arises after public news releases. We restrict our attention to periods immediately after earnings announcements when the private information advantage of insiders is substantially reduced. We identify the type of information insiders use by analyzing their trades in the context of the trading activity of another group of informed traders – short sellers.

We show that insider sales after SOX are based on short-term mispricing. We do not find any evidence that insiders take advantage of foreknowledge of material information when selling. After the introduction of tighter regulation, even opportunistic insider selling relies only on mispricing. Insider purchases seem to take advantage of foreknowledge of material information, but they are rare and their economic impact is small. In addition, we show a significant shift in insider selling with the introduction of SOX; insider selling shifts from taking advantage of foreknowledge of material information before SOX to relying on short-term mispricing after SOX. This shift is significant both when predicting future returns and considering insider dollar profits.

Our main contribution concerns the nature of information insiders use when trading. Given that insiders' trades predict future abnormal returns even in the post-SOX period with tighter regulation, insider trading can still be regarded as a source of information and can serve as a proxy for informed transactions in empirical studies. However, contrary to conventional opinion that insiders profit from foreknowledge of material private information, we show that the nature of the information used by insider sales comes from superior processing of public news, at least in the period after earnings announcements. This type of insider trading is also beneficial for the stock market quality because it helps to correct mispricing following earnings announcements and leads to higher information efficiency. Our evidence is, therefore, supportive of the effectiveness of insider trading regulations that motivate insiders to trade on public rather than private information.

Appendix A Variable definitions

Variable	Definition
nis_{kt}	Net insider selling is the number of shares sold less the number of shares purchased by insiders of firm k on date t, scaled by the number of shares outstanding (in basis points).
$nis_{k,t,t+5}$	Net insider selling is the average daily number of shares sold less the number of shares purchased by insiders of firm k over the $(0,+5)$ response window around the earnings announcement date t, scaled by the number of shares outstanding (in basis points).
$nispos_{kt}$	Selling side of net insider selling. Derived from nis_{kt} by keeping all positive observations and replacing negative observations by zeros.
$nispos_{k,t,t+5}$	Selling side of net insider selling. Derived from $nis_{k,t,t+5}$ by keeping all positive observations and replacing negative observations by zeros.
$nisneg_{kt}$	Buying side of net insider selling. Derived from nis_{kt} by keeping all negative observations, replacing all positive observations by zeros, and taking the absolute value.
$nisneg_{k,t,t+5}$	Buying side of net insider selling. Derived from $nis_{k,t,t+5}$ by keeping all negative observations, replacing all positive observations by zeros, and taking the absolute value.
$relss_{kt}$	Relative short selling is the number of shares shorted within 1 business day for firm k on date t, scaled by the number of shares outstanding (in basis points). In Tables 6, 7 and A12 we use the number of shares on loan at time t instead.
$relss_{k,t,t+5}$	Relative short selling is the average daily number of shares shorted within 1 business day for firm k over the $(0,+5)$ response window around the earnings announcement date t, scaled by the number of shares outstanding (in basis points). In Tables 6, 7 and A12 we use the average number of shares on loan over the $(0,+5)$ response window instead.
$is_{k,t,t+5}$ ($ip_{k,t,t+5}$)	Dummy variable equal to one for all firm-quarters with positive (negative) $nis_{k,t,t+5}$.
$isopp_{k,t,t+5}$ ($ipopp_{k,t,t+5}$)	Dummy variable equal to one for all firm-quarters with positive (negative) $nis_{k,t,t+5}$ that is opportunistic.
$isrt_{k,t,t+5}$ ($iprt_{k,t,t+5}$)	Dummy variable equal to one for all firm-quarters with positive (negative) $nis_{k,t,t+5}$ that is routine.
$noit_{k,t,t+5}$	Dummy variable equal to one for all firm-quarters with zero $nis_{k,t,t+5}$.
$ssh_{k,t,t+5}$ ($ssl_{k,t,t+5}$)	Dummy variable equal to one for all firm-quarters in the top (bottom) quintile of $relss_{k,t,t+5}$.
$ssm_{k,t,t+5}$	Dummy variable equal to one for all firm-quarters in the three middle quintiles of $relss_{k,t,t+5}$.
total sale (purchase) value	Number of shares sold (purchased) by all insiders on day t within the (0,+5) response window times the stock price on day t and then aggregated over all days in the response window.
$aret_{k,t+5,t+6+h}$	The buy-and-hold stock return for firm k from day $t+5$ to day $t+6+h$ after the earnings announcement date t adjusted for the corresponding 5×5 size and book-to-market portfolio return. Sensitivity analysis in the Internet Appendix reports results with market-adjusted returns.
$pastret_{k,t-1y,t-2}$	The buy-and-hold stock return for firm k from day -365 to day -2 after the earnings announcement date t adjusted for the corresponding 5×5 size and book-to-market portfolio return.
$eaart_{k,t-2,t+1}$	Buy-and-hold stock return for firm k three days around the earnings announcement date t adjusted for the corresponding 5×5 size and book-to-market portfolio return.
$\Delta eps_{k,t-4q,t}$	Change in net earnings before extraordinary items per share on the same quarter 1 year sooner, scaled by the share price 2 days before the earnings announcement.
net dollar profits per trade	The average over all insider trades within the $(0,+5)$ response window of the inflation-adjusted dollar value of net insider sales or purchases in 2017 US dollars multiplied by the buy-and-hold abnormal return over the corresponding horizon. The value of dollar profits for sales is multiplied by -1 to get a positive profit when future return is negative. Abnormal returns are size-and-book-to-market-adjusted.
$\Delta earn_{k,t,t+q1}$	The difference between earnings one quarter ahead $earn_{k,t+q1}$ and the current quarter earnings $earn_{kt}$, scaled by the firm's total assets at the end of the current quarter. We also consider alternatives with future earnings three and four quarters ahead.
$eaar_{k,t,t+q1}$	Buy-and-hold stock return for firm k three days around the earnings announcement one quarter ahead $t+q1$ adjusted for the corresponding 5×5 size and book-to-market portfolio return. We also consider alternatives with future earnings announcements three and four quarters ahead.
$longh_{k,t,t+q1}$	Dummy variable equal to one for all firm-quarters in the top quintile of $\Delta earn_{k,t,t+q1}$ or $eaar_{k,t,t+q1}$. Alternatives with future earnings three and four quarters ahead are also considered.
$longm_{k,t,t+q1}$	Dummy variable equal to one for all firm-quarters in the middle three quintiles of $\Delta earn_{k,t,t+q1}$ or $eaar_{k,t,t+q1}$. Alternatives with future earnings three and four quarters ahead are also considered.
$longl_{k,t,t+q1}$	Dummy variable equal to one for all firm-quarters in the bottom quintile of $\Delta earn_{k,t,t+q1}$ or $eaar_{k,t,t+q1}$. Alternatives with future earnings three and four quarters ahead are also considered.

Appendix B Compustat short interest data

Compustat provides data points typically twice a month (15^{th} and end of each month). It reports the snapshot of the total number of shares sold short for a given firm as of the reporting date. We want to link insider trading with the short-selling activity within six days immediately after earnings announcements, which is not possible to do precisely with the low frequency of short-interest reporting points in Compustat. To address this issue, we fill in missing values between two reporting dates, t_1 and t_2, by carrying *backwards* the short interest level from t_2. This method is illustrated in the figure below, where the short interest is reported on four dates around an earnings announcement, with time indicated in black and relatively to the earnings announcement. The two closest reported numbers are 80 shares five days before and 150 shares ten days after the earnings announcement. Our backward approach means that we assume the short interest to be 150 shares each day in the (0,+5) response window around the earnings announcement. As in the baseline regressions, we scale the shares on loan by the shares outstanding. We motivate the backward approach by patterns in the post-SOX data as illustrated in Figure 4: if the announcement happens between two dates that are 15 days apart, the average short selling in (0,+5) is better approximated by the relative number of shares shorted on the post-announcement date (day +10 in Figure 4) than on the pre-announcement date (day -5). As a robustness test, we use a linear interpolation between t_1 and t_2 instead of filling in backwards from t_2. Table A12 in the Internet Appendix shows that the results remain qualitatively similar. Also, we replace by zero all missing values of short interest of a firm that reports short interest at t_1 but has no reported short interest at t_2.

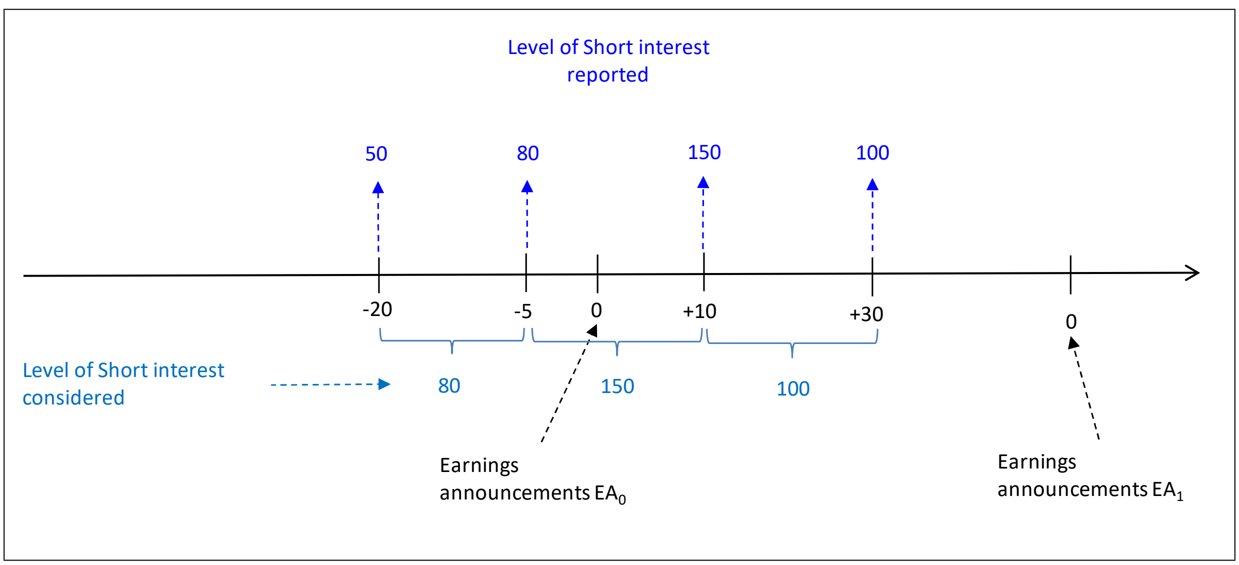

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TABLE 1

Summary statistics.

This table reports summary statistics for all firm-quarters in our sample. We report informed trading statistics over the (0,+5) response window after the earnings announcement date. nis is the number of shares sold less the number of shares purchased by insiders of a firm over a particular window, scaled by the number of shares outstanding (in bps); $nispos$ is the number of shares sold by insiders of a firm over a particular window; $nisneg$ is the number of shares purchased by insiders of a firm over a particular window; is (ip) is the dummy variable equal to one for all firm-quarters with positive (negative) nis; $aret_{t+5,t+h}$ is the buy-and-hold stock return for a firm from day $t+5$ to day $t+h$ after the earnings announcement date t; $pastret$ is the buy-and-hold stock return for a firm from day -365 to day -2 after the earnings announcement date t; Δeps is the difference between earnings one quarter ahead and the current quarter earnings, scaled by the firm's total assets at the end of the current quarter; $eaar$ is the buy-and-hold stock return for a firm 3 days around the earnings announcement date t. $\Delta earn_{k,t,t+q}$ is the difference between earnings q quarters ahead $earn_{k,t+q}$ and the current quarter earnings $earn_{kt}$, scaled by the firm's total assets at the end of the current quarter. $eaar_{k,t,t+q}$ is the buy-and-hold stock return for firm k three days around the earnings announcement q quarters ahead. Abnormal returns are adjusted for the corresponding 5×5 size and book-to-market portfolio return. The sample runs from July 2006 to December 2017.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variable	Nr.obs.	mean	std.dev.	p5	p25	p50	p75	p95
Panel A: Informed trading over the $(0, +5)$ response window								
nis	132,240	0.60	3.08	-0.63	0.00	0.00	0.00	5.00
$nispos$	132,240	0.79	2.86	0.00	0.00	0.00	0.00	5.00
$nisneg$	132,240	0.19	0.99	0.00	0.00	0.00	0.00	0.63
$relss$	132,240	14.01	19.47	0.05	1.67	6.73	18.01	54.03
is	132,240	0.19	0.38	0.00	0.00	0.00	0.00	1.00
ip	132,240	0.07	0.26	0.00	0.00	0.00	0.00	1.00
Panel B: Future returns								
$aret_{t+5,t+26}$	132,240	-0.58%	10.25%	-16.86%	-5.72%	-0.77%	4.21%	16.44%
$aret_{t+5,t+46}$	132,240	-0.85%	14.42%	-23.85%	-8.44%	-1.15%	6.11%	22.98%
$aret_{t+5,t+66}$	132,240	-0.84%	18.06%	-29.40%	-10.56%	-1.32%	7.93%	29.60%
$aret_{t+5,t+136}$	132,240	-1.91%	27.23%	-43.82%	-16.77%	-2.78%	11.13%	43.97%
$aret_{t+5,t+256}$	132,240	-2.82%	32.23%	-51.94%	-20.11%	-3.88%	12.22%	51.11%
Panel C: Control variables								
Δeps	132,240	-0.37%	6.99%	-8.13%	-0.79%	0.06%	0.70%	6.49%
$eaar$	132,240	0.16%	6.93%	-11.50%	-3.77%	-0.02%	3.89%	12.44%
$pastret$	132,240	-2.22%	32.55%	-50.75%	-20.68%	-4.08%	13.00%	53.31%
$\Delta earn_{t+q1}$	129,812	0.001	0.035	-0.041	-0.005	0.000	0.006	0.042
$\Delta earn_{t+q3}$	120,466	0.001	0.039	-0.048	-0.007	0.000	0.007	0.050
$\Delta earn_{t+q4}$	115,997	0.001	0.039	-0.047	-0.005	0.000	0.007	0.046
$eaar_{t+q1}$	129,923	-0.005	0.364	-0.115	-0.038	-0.000	0.039	0.124
$eaar_{t+q3}$	120,884	-0.008	0.401	-0.115	-0.037	-0.000	0.038	0.124
$eaar_{t+q4}$	116,382	-0.008	0.409	-0.114	-0.037	-0.000	0.038	0.123

TABLE 2

Interactions in informed trading.

This table shows frequencies, relative shares traded per trading day in bps, and total trade value over the response window of $(0, +5)$ after the earnings announcement across 9 interaction categories, split into 3 sets corresponding to insider sales (is), insider purchases (ip) and no net insider trading ($noit$), respectively. Each of these insider trading variables is interacted with the short-selling categories of high short selling (ssh), medium short selling (ssm) and low short selling (ssl). The total sale (purchase) value is the number of shares sold (purchased) by all insiders on day t within the (0,+5) response window times the stock price on day t and then aggregated over all days in the response window. The sample runs from July 2006 to December 2017.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Category	# of quarters	% of all quarters	within-group fraction	$relss$	$nispos$	$nisneg$	total sale value	total purchase value
$is \times ssh$	6,161	4.66%	26.29%	45.51	5.18	0	$2,628,562	$6,079
$is \times ssm$	16,099	12.17%	68.69%	9.46	4.16	0	$2,266,129	$5,667
$is \times ssl$	1,178	0.89%	5.03%	0.42	4.56	0	$1,316,619	$4,790
is	23,438	17.72%						
$ip \times ssh$	2,187	1.65%	22.43%	48.96	0	2.58	$18,356	$420,448
$ip \times ssm$	5,531	4.18%	56.72%	8.42	0	2.39	$11,903	$219,085
$ip \times ssl$	2,034	1.54%	20.86%	0.29	0	3.12	$1,267	$72,369
ip	9,752	7.37%						
$noit \times ssh$	17,251	13.05%	17.42%	45.49	0	0		
$noit \times ssm$	60,000	45.37%	60.58%	7.90	0	0		
$noit \times ssl$	21,799	16.48%	22.01%	0.29	0	0		
$noit$	99,050	74.90%						
total	132,240	100%						
uncond. average				14.01	0.79	0.19	$1,637,135	$72,697

TABLE 3

Predictive ability of insider trading and short sales.

This table presents estimates of sensitivities between future returns and informed traders' demands from the regression:
$aret_{k,t+5,t+6+h} = b_1\ is_{kt} + b_2\ ip_{kt} + c_1\ ssh_{kt} + c_2\ ssl_{kt} + X_{kt}\gamma + u_{kt}$,
where $aret_{k,t+5,t+6+h}$ denotes abnormal return in stock k from $t+5$ to $t+6+h$ after earnings announcement t adjusted by the corresponding 5×5 size and book-to-market portfolio return (in percent). is_{kt} and ip_{kt} denote dummy variables for intensive net insider sales and purchases, respectively, in firm k over the $(0, +5)$ response window after the earnings announcement date t; and ssh_{kt} and ssl_{kt} denote short selling in the highest and lowest quintiles, respectively, in firm k over the $(0, +5)$ response window after the earnings announcement date t. Variables X_{kt} include: past 12-month return $pastret_{k,t-1y,t-2}$, current quarter earnings announcement abnormal return $eaar_{i,t-1,t+1}$, and earnings per share change $\Delta eps_{k,t-4q,t}$ as well as the firm and year fixed effects. Robust standard errors are clustered within firms. Columns H1$_{NLI}$ and H1$_{AI}$ show the predictions for the corresponding alternative hypotheses. All variables are defined in Appendix. ***, ** and * indicate significance at the 1-, 5- and 10-percent levels. The sample runs from July 2006 to December 2017.

	H1$_{NLI}$	H1$_{AI}$	$h = 20$	$h = 40$	$h = 60$	$h = 130$	$h = 250$
is			-0.006^{***}	-0.008^{***}	-0.014^{***}	-0.026^{***}	-0.031^{***}
ip			0.015^{***}	0.016^{***}	0.021^{***}	0.034^{***}	0.036^{***}
$ssh\ (c_1)$	$c_1 < 0$	$c_1 > 0$	-0.001	-0.006^{***}	-0.011^{***}	-0.023^{***}	-0.029^{***}
$ssl\ (c_2)$	$c_2 > 0$	$c_2 < 0$	0.005^{***}	0.011^{***}	0.018^{***}	0.036^{***}	0.046^{***}
$pastret$			-0.004^{***}	-0.009^{***}	-0.026^{***}	-0.050^{***}	-0.072^{***}
$eaar$			0.046^{***}	0.071^{***}	0.050^{***}	0.042^{***}	0.051^{***}
Δeps			0.033^{***}	0.024^{***}	0.022^{*}	0.001	0.005
constant			-0.106	-0.061	-0.095	-0.203	-0.234
Nr. obs.			130,240	130,240	130,240	130,240	130,240
R-squared			0.71%	0.92%	1.11%	1.83%	1.99%

TABLE 4

Predictive ability of disagreement among informed traders' demands.

Panel A presents estimates of the following regression:
$aret_{k,t+5,t+6+h} = b_{++}ip_{kt} \times ssl_{kt} + b_{+-}ip_{kt} \times ssh_{kt} + b_{-+}is_{kt} \times ssl_{kt} + b_{--}is_{kt} \times ssh_{kt} + X_{kt}\gamma + u_{kt}$,
where $aret_{k,t+5,t+6+h}$ denotes abnormal return in stock k from $t+5$ to $t+6+h$ after earnings announcement t adjusted by the corresponding 5×5 size and book-to-market portfolio return and reported in percent. is_{kt}, ip_{kt} and $noit_{kt}$ denote dummy variables for intensive net insider sales, purchases and no insider trades, respectively, in firm k over the $(0, +5)$ response window after the earnings announcement date t; and ssh_{kt}, ssl_{kt} and ssm_{kt} denote short selling in the highest, lowest and the remaining three middle quintiles, respectively, in firm k over the $(0, +5)$ response window after the earnings announcement date t. X_{kt} includes the past 12-month return $pastret$, current quarter earnings announcement abnormal return $eaar$, earnings per share change Δeps, interactions $noit \times ssl$, $noit \times ssh$, $ip \times ssm$, $is \times ssm$, as well as firm and year fixed effects. Abnormal returns are adjusted for the corresponding quintile size and book-to-market portfolio return. Columns H2$_{NLI}$ and H2$_{AI}$ show predictions of the corresponding alternative hypotheses. Robust standard errors are clustered within firms. Panel B shows constant net dollar profits per trade defined as the average over all insider trades for each category of the inflation-adjusted dollar value of net insider sales or purchases in 2017 US dollars multiplied by the abnormal return over horizon h. The value of dollar profits for sales is multiplied by -1 to get a positive profit when future return is negative. All variables are defined in Appendix. ***, ** and * indicate significance at the 1-, 5- and 10-percent levels. The sample runs from July 2006 to December 2017.

	H2$_{NLI}$	H2$_{AI}$	$h = 20$	$h = 40$	$h = 60$	$h = 130$	$h = 250$
Panel A: Predictive regression of disagreement among traders on future returns							
$ip \times ssl$ (b_{++})			0.020***	0.026***	0.037***	0.054***	0.063***
$ip \times ssh$ (b_{+-})	$b_{+-} < 0$	$b_{+-} > 0$	0.016***	0.012***	0.013***	0.021***	0.018***
$is \times ssl$ (b_{-+})	$b_{-+} > 0$	$b_{-+} < 0$	−0.001	0.007*	0.007	0.009	0.015
$is \times ssh$ (b_{--})			−0.007***	−0.014***	−0.027***	−0.053***	−0.064***
$ip \times ssm$			0.013***	0.016***	0.021***	0.037***	0.038***
$is \times ssm$			−0.006***	−0.008***	−0.014***	−0.023***	−0.029***
$noit \times ssl$			0.005***	0.011***	0.018***	0.039***	0.048***
$noit \times ssh$			−0.002*	−0.006***	−0.010***	−0.022***	−0.029***
$pastret$			−0.004***	−0.009***	−0.026***	−0.050***	−0.071***
$eaar$			0.046***	0.071***	0.050***	0.043***	0.053***
Δeps			0.033***	0.024***	0.022*	0.001	0.005
constant			−0.106	−0.061	−0.096	−0.205	−0.235
Nr. obs.			132,240	132,240	132,240	132,240	132,240
R-squared			0.70%	0.91%	1.10%	1.83%	1.99%
Panel B: Net dollar profits per trade							
$ip \times ssl$			-\$172	\$51	\$10	\$771	\$1,614
$ip \times ssm$			-\$433	-\$57	\$81	\$113	\$1,243
$ip \times ssh$			-\$1,163	-\$122	\$130	\$405	\$2,430
$is \times ssl$			\$2,683	\$1,001	-\$837	\$6,104	\$1,268
$is \times ssm$			\$4,671***	\$5,597***	\$11,244***	\$19,591***	\$28,727***
$is \times ssh$			\$5,391***	\$8,6197***	\$18,854***	\$36,417***	\$48,105***

TABLE 5

Relationship between insiders' demand and private information.

Panel A shows deviations of insider sale and purchase frequencies from their expected frequencies depending on short sellers' trading (as a proxy for short-term information) and long-term information. $longh_{k,t}$, $longl_{k,t}$, and $longm_{k,t}$ is the dummy variable equal to one for all firm-quarters in the top, bottom, and the three middle quintiles of $\Delta earn_{k,t,t+q4} = \frac{earn_{k,t+q4} - earn_{kt}}{TA_{kt}}$, respectively. ssh_{kt}, ssl_{kt} and ssm_{kt} denote short selling in the highest, lowest and the remaining three middle quintiles, respectively, in firm k over the $(0, +5)$ response window after the earnings announcement date t. We compute the expected frequencies for all combinations of short-term information, long-term information, and insider trading as a product of unconditional sample frequencies of each variable. We then compute the realized frequency of the type and take the deviation from the expected value and express it as a percentage change. Panel B presents estimates of the following regressions
$nispos_{k,t,t+5} = d_{++} ssl_{kt} \times longh_{kt} + d_{+-} ssl_{kt} \times longl_{kt} + d_{-+} ssh_{kt} \times longh_{kt} + d_{--} ssh_{kt} \times longl_{kt} + X_{kt}\gamma + u_{kt}$,
$nisneg_{k,t,t+5} = d_{++} ssl_{kt} \times longh_{kt} + d_{+-} ssl_{kt} \times longl_{kt} + d_{-+} ssh_{kt} \times longh_{kt} + d_{--} ssh_{kt} \times longl_{kt} + X_{kt}\gamma + u_{kt}$.
Dependent variable $nispos_{k,t,t+5}$ ($nisneg_{k,t,t+5}$) stands for the relative net shares sold with positive (negative) values in basis points representing insider sales (purchases). For easier interpretation, we take an absolute value of $nisneg_{k,t,t+5}$. The set of control variables X_{kt} includes the past 12-month return $pastret$, current quarter earnings announcement abnormal return $eaar$, earnings per share change Δeps, interactions $ssm \times longh$, $ssm \times longl$, $ssl \times longm$, $ssl \times longm$, as well as firm and year fixed effects. Abnormal returns are adjusted for the corresponding quintile size and book-to-market portfolio return. Robust standard errors are clustered within firms. Columns H3$_{NLI}$ and H3$_{AI}$ summarize predictions of the corresponding alternative hypotheses. All variables are defined in Appendix. ***, ** and * indicate significance at the 1-, 5- and 10-percent levels. The sample runs from July 2006 to December 2017.

Panel A: Percentage deviations from the benchmark

	Sales			*Purchases*		
	$longh$	$longm$	$longl$	$longh$	$longm$	$longl$
ssl	-79.9%	-70.7%	-74.8%	13.5%	23.4%	-8.9%
ssm	-9.1%	24.5%	-14.4%	-9.4%	-4.7%	-19.5%
ssh	48.6%	23.8%	54.1%	22.1%	3.5%	33.0%

Panel B: Multivariate regression setting

	$nispos$ (sales)			$nisneg$ (purchases)		
	H3$_{NLI}$	H3$_{AI}$	coeff.	H3$_{NLI}$	H3$_{AI}$	coeff.
$ssl \times longh$ (d_{++})			-0.140^{***}			0.016
$ssl \times longl$ (d_{+-})	$d_{+-} < 0$	$d_{+-} > 0$	-0.198^{***}	$d_{+-} > 0$	$d_{+-} < 0$	-0.025
$ssh \times longh$ (d_{-+})	$d_{-+} > 0$	$d_{-+} > 0$	0.209^{***}	$d_{-+} < 0$	$d_{-+} > 0$	0.102^{***}
$ssh \times longl$ (d_{--})			0.189^{***}			0.060^{***}
$ssm \times longh$			-0.016			0.046^{***}
$ssm \times longl$			0.037			0.024^{**}
$ssl \times longm$			-0.162^{***}			-0.048^{***}
$ssh \times longm$			0.147^{***}			0.069^{***}
$pastret$			1.050^{***}			-0.196^{***}
$eaar$			5.212^{***}			-0.881^{***}
Δeps			-0.513^{***}			-0.306^{***}
Nr. obs.			115,997			115,997
R-squared			3.48%			1.64%

TABLE 6

Interactions in informed trading: pre-SOX versus post-SOX.

This table shows frequencies and relative shares traded in basis points over the $(0, +5)$ response window across nine interaction categories, split into three sets corresponding to insider sales (is), insider purchases (ip) and no net insider trading ($noit$), respectively. Each of these variables interacts with the short-selling categories of high short selling (ssh), medium short selling (ssm) and low short selling (ssl). The table covers short-selling data from Compustat from January 1986 to December 2017. All variables are defined in Appendix.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Panel A: Pre-SOX period						*Panel B: Post-SOX period*					
Category	# of quarters	% of all quarters	within-group fraction	$relss$	$nispos$	$nisneg$	# of quarters	% of all quarters	within-group fraction	$relss$	$nispos$	$nisneg$
$is \times ssh$	3,313	3.54%	31%	9.32	12.54	0	12,232	5.01%	30%	13.58	7.80	0
$is \times ssm$	6,513	6.96%	61%	1.06	7.52	0	26,723	10.95%	65%	2.79	5.75	0
$is \times ssl$	804	0.86%	8%	0.02	11.62	0	1,976	0.81%	5%	0.09	11.04	0
is	10,630	11.36%					40,931	16.77%				
$ip \times ssh$	1,270	1.36%	18%	8.49	0	4.53	3,308	1.36%	20%	13.47	0	5.41
$ip \times ssm$	4,456	4.76%	62%	0.80	0	3.38	9,594	3.93%	59%	2.55	0	3.96
$ip \times ssl$	1,417	1.51%	20%	0.02	0	4.91	3,466	1.42%	21%	0.07	0	5.22
ip	7,143	7.63%					16,368	6.70%				
$noit \times ssh$	14,194	15.16%	19%	8.33	0	0	33,384	13.67%	18%	13.05	0	0
$noit \times ssm$	45,551	48.66%	60%	0.79	0	0	110,406	45.22%	59%	2.27	0	0
$noit \times ssl$	16,086	17.19%	21%	0.02	0	0	43,038	17.63%	23%	0.07	0	0
$noit$	75,831	81.01%					186,828	76.53%				
Total	93,604						244,127					

TABLE 7

Pre- versus post-SOX analysis

Panel A presents estimates of the regression:

$$aret_{k,t+5,t+6+h} = b_{++}(ip_{kt} \times ssl_{kt}) + b_{+-}(ip_{kt} \times ssh_{kt}) + b_{-+}(is_{kt} \times ssl_{kt}) + b_{--}(is_{kt} \times ssh_{kt}) + c_{++}(ip_{kt} \times ssl_{kt} \times S_t) + c_{+-}(ip_{kt} \times ssh_{kt} \times S_t) + c_{-+}(is_{kt} \times ssl_{kt} \times S_t) + c_{--}(is_{kt} \times ssh_{kt} \times S_t) + X_{kt}\,\gamma + u_{kt},$$

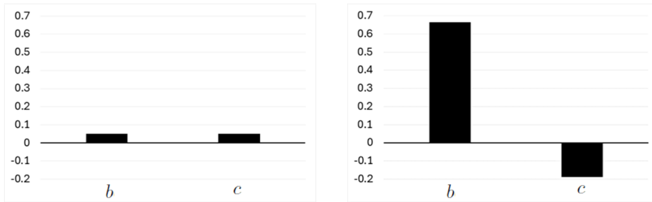
where $aret_{k,t+5,t+6+h}$ is abnormal return in stock k from $t+5$ to $t+6+h$ after earnings announcement t (in percent). is_{kt}, ip_{kt}, and $noit_{kt}$ are dummies for intensive net insider sales, purchases, and no insider trades, respectively, in firm k over the $(0, +5)$ response window after the earnings announcement date t; and ssh_{kt}, ssl_{kt}, and ssm_{kt} denote short selling in the highest, lowest and the remaining three middle quintiles, respectively. S_t is the post-SOX dummy variable equal to one for observations after July 30, 2002. X_{kt} includes the past 12-month return, current quarter earnings announcement abnormal return, earnings per share change, interactions $noit \times ssl$, $noit \times ssh$, $ip \times ssm$, $is \times ssm$, and firm and year fixed effects. Columns H2$_{AI}$ and H4$_A$ show predictions of the corresponding alternative hypotheses. Robust standard errors are clustered within firms. Columns b (c) contain coefficient estimates of variables not interacted (interacted) with S_t. Row $b_{-+} + c_{-+}$ shows the F-test for $b_{-+} + c_{-+} = 0$. This Table presents estimates for only b_{++}, b_{+-}, b_{-+} and b_{--} coefficients. The remaining coefficient estimates are in Table A11. Panel B shows constant net dollar profits per trade defined as the average total insider trades for each category of the inflation-adjusted dollar value of net insider sales or purchases in 2017 US dollars multiplied by the abnormal return over horizon h. The value of dollar profits for sales is multiplied by -1 to get a positive profit when future return is negative. Columns *pre* (*post-pre*) contain coefficient estimates of variables not interacted (interacted) with S_t. All variables are defined in Appendix. ***, ** and * indicate significance at the 1-, 5- and 10-percent levels. The estimation is based on the short-selling data from Compustat and the sample runs from January 1986 to December 2017.

	predictions		$h=20$		$h=40$		$h=60$		$h=130$		$h=250$	
Panel A: Future returns pre-SOX versus post-SOX												
	H2$_{AI}$	H4$_A$	b	c	b	c	b	c	b	c	b	c
$ip \times ssl$ $(++)$			0.007**	0.010**	0.018***	0.008	0.027***	0.013*	0.033***	0.040***	0.033***	0.079***
$ip \times ssh$ $(+-)$	$b_{+-} > 0$	$c_{+-} < 0$	0.012***	0.001	0.014***	−0.004	0.017***	−0.006	0.025***	−0.011	0.050***	−0.035**
$is \times ssl$ $(-+)$	$b_{-+} < 0$	$c_{-+} > 0$	−0.011***	0.009*	−0.014**	0.018***	−0.011	0.021**	−0.006	0.023*	0.014	0.022
$is \times ssh$ $(--)$			−0.001	−0.009***	−0.010***	−0.005*	−0.016***	−0.009**	−0.023***	−0.025***	−0.013	−0.065***
Nr. obs.			309,997		309,997		309,997		309,997		309,997	
R-squared			6.10%		6.90%		8.20%		13.40%		19.10%	
$b_{-+} + c_{-+}$			-0.002**		0.004***		0.010**		0.017		0.036	
Panel B: Net dollar profits pre-SOX versus post-SOX												
			pre	post−pre	pre	post−pre	pre	post−pre	pre	post−pre	pre	post−pre
$ip \times ssl$			\$94	−\$620*	−\$99	−\$275	\$345	−\$580	\$2,764**	−\$2,205	\$5,661***	−\$4,251**
$ip \times ssm$			−\$519***	−\$431**	−\$809**	\$338	−\$530	\$235	\$1,656**	−\$863	\$4,081***	−\$1,539
$ip \times ssh$			−\$822***	−\$1,211***	−\$1,939***	\$1,107	−\$2,541***	\$1,260	−\$1,378	\$490	−\$1,144	\$1,071
$is \times ssl$			\$2,376***	−\$1,207***	\$4,657***	−\$1,673*	\$6,325***	−\$3,392***	\$8,387***	−\$1,023	\$15,903***	−\$2,279
$is \times ssm$			\$391***	\$685***	\$4,106***	−\$991***	\$5,620***	−\$320	\$10,858***	−\$1,729***	\$18,755***	−\$4,831***
$is \times ssh$			−\$1,325***	\$2,779***	\$3,467***	−\$888**	\$1,068**	\$2,060***	\$150	\$5,768***	−\$1,127	\$10,083***

FIGURE 1

Sensitivity of future returns to order flows.

Graph A: NLI benchmark *Graph B: AI benchmark*

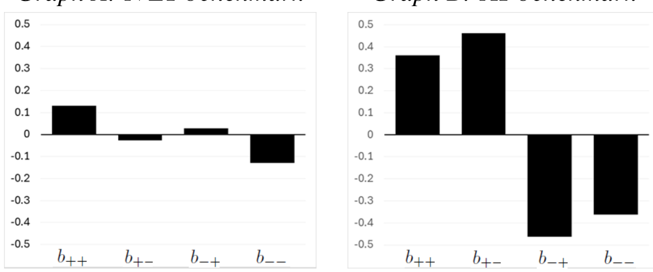


This figure plots the values of sensitivity coefficients b and c of future returns $r_{1,3}$ on insider's and informed traders' demands ζ_1 and ξ_1, respectively. The coefficients are computed based on the multivariate regression $r_{1,3} = b_0 + b\zeta_1 + c\xi_1 + \epsilon$. Graph A corresponds to the NLI benchmark of the model and Graph B corresponds to the AI benchmark. The primitive parameters are: $\sigma_v^2/\sigma_u^2 = \sigma_v^2/\sigma_w^2 = 1$ and $n = 3$. The remaining parameters are computed numerically by solving the system of equations (6) and (8) for the NLI and AI benchmark, respectively.

FIGURE 2

Future expected returns conditional on signs of order flows.

Graph A: NLI benchmark *Graph B: AI benchmark*

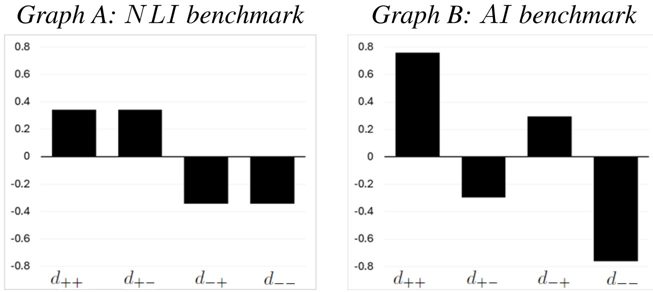


This figure plots the expectations of future returns $r_{1,3}$ conditional on signs of order flow variables ζ_1 and ξ_1. Coefficient b_{++}, b_{+-}, b_{-+} and b_{--} are computed based on the multivariate regression $r_{1,3} = b_{++}\mathbb{I}_{\zeta_1>0,\xi_1>0} + b_{+-}\mathbb{I}_{\zeta_1>0,\xi_1<0} + b_{-+}\mathbb{I}_{\zeta_1<0,\xi_1>0} + b_{--}\mathbb{I}_{\zeta_1<0,\xi_1<0} + \epsilon$. The primitive parameters are: $\sigma_v^2/\sigma_u^2 = \sigma_v^2/\sigma_w^2 = 1$ and $n = 3$. The remaining parameters are computed numerically by solving the system of equations (6) and (8) for the NLI and AI benchmark.

FIGURE 3

Expected insider's demand conditional on signs of innovations.

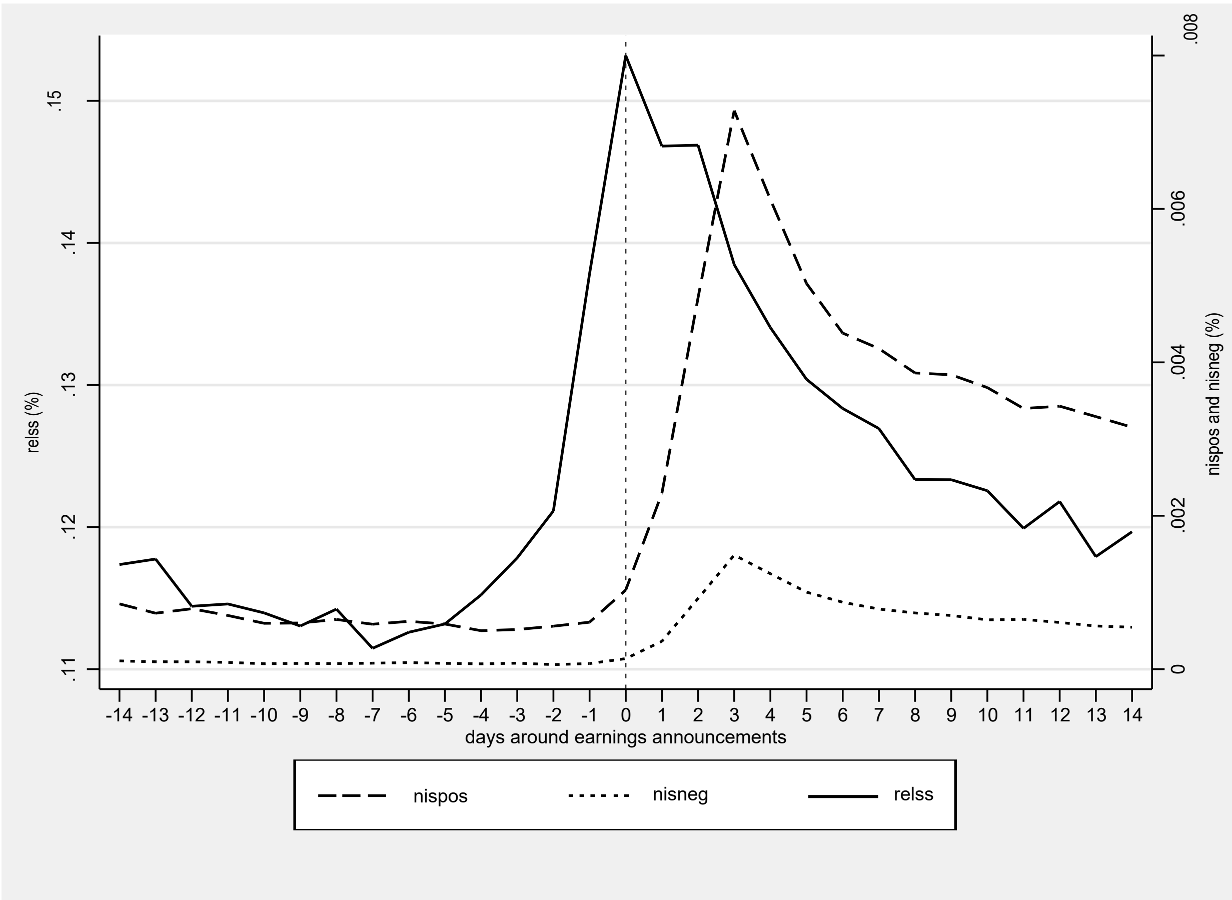
Graph A: NLI benchmark *Graph B: AI benchmark*



This figure plots the conditional expectations of insider's demand ζ_1 conditional on signs of fundamental innovations v_1 and v_2. The primitive parameters are: $\sigma_v^2/\sigma_u^2 = \sigma_v^2/\sigma_w^2 = 1$ and $n = 3$. The remaining parameters are computed numerically by solving the system of equations (6) and (8) for the NLI and AI benchmark.

FIGURE 4

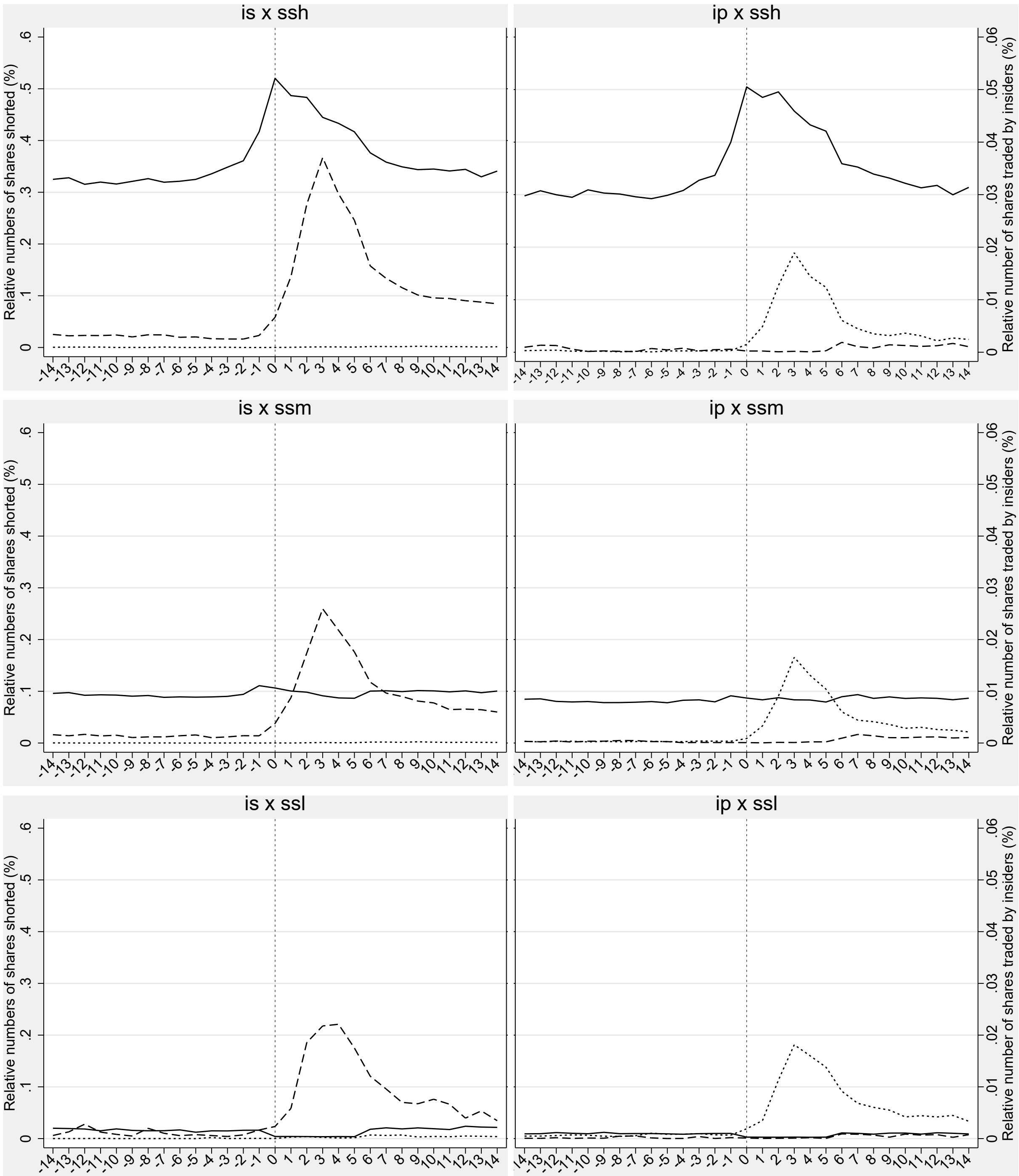
Daily shares traded by insiders and short sellers.



The figure plots the averages of daily positive net insider selling ($nispos_t$, dashed line), negative net insider selling ($nisneg_t$, dotted line) together with the relative number of shares shorted ($relss_t$, solid line) 14 day before and after earnings announcements. All shares traded are scaled by the number of shares outstanding and expressed in basis points. All variables are defined in the Appendix.

FIGURE 5

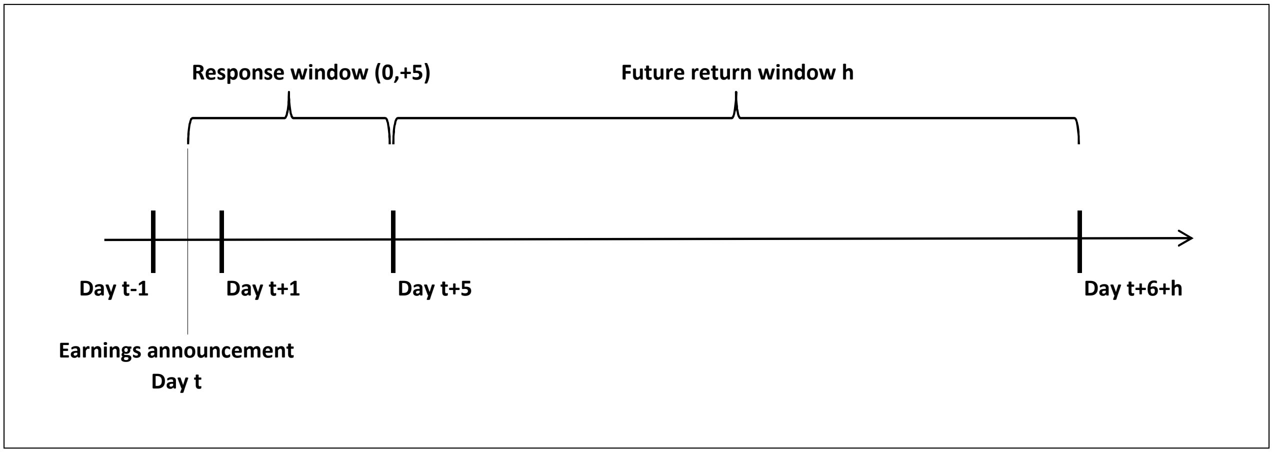
Daily shares traded by informed traders by interaction categories.



The figure plots the averages of daily positive net insider selling ($nispos_t$, dashed line), negative net insider selling ($nisneg_t$, dotted line) together with the relative number of shares shorted ($relss_t$, solid line) 14 day before and after earnings announcements by six interaction categories between insider and short-selling activity. The dummies for informed trading activity is, ip, ssh, ssm, and ssl are defined based on the (0,+5) response window. All shares traded are scaled by the number of shares outstanding and expressed in basis points. All variables are defined in the Appendix.

FIGURE 6

Timings of earnings announcements and related abnormal returns



This figure shows relative timings of informed trading during the response window and timings of future abnormal returns. Everything is arranged relatively to the earnings announcement that is set as day t. We take into account only trading days. Accordingly, we establish (i) the earnings-announcement window, which starts on day $t-1$ and ends on day $t+1$; (ii) the response window when insiders and short sellers trade, which starts on day t and ends on day $t+5$; and (iii) the future-return window, which runs between days $t+5$ and $t+6+h$.

Internet appendix to

"Insiders' information advantage: Evidence from competition with short sellers"

(not for publication)

This appendix presents supplementary results not included in the main body of the paper.

Proofs of Propositions

Proof of Proposition 1.

In period 2, the insider chooses his optimal demand ζ_2 to maximize the expected value of profit $\pi_2^i = \zeta_2(p_3 - p_2)$ given w_1^i and w_2^i:

(A.1) $$\max_{\zeta_2} \ E\left[\pi_2^M | v_1, v_2, w_2^i\right] = \max_{\zeta_2}(-\zeta_2 E[(p_3 - p_2)|v_1, v_2, w_2^i]).$$

The total order flow $x_2 = \sum_{j=1}^{n}(\xi_{2j} - w_{2j}^a) + (\zeta_2 - w_2^i) + u_2$. We solve for linear pricing in the form

(A.2) $$p_2 = p_1 + \lambda_2 x_2 = p_1 + \lambda_2 \left(\sum_{j=1}^{n}(\xi_{2j} - w_{2j}^a) + (\zeta_2 - w_2^i) + u_2\right).$$

Substituting Equation (A.2) into the expression for profit yields

$$\pi_2^i = -\zeta_2\left(p_3 - p_1 - \lambda_2\left(\zeta_2 - w_2^i + \sum_{j=1}^{n}(\xi_{2j} - w_{2j}^a)\right)\right).$$

The FOC of (A.1) becomes

$$E\left[p_3 - p_1 | v_1, v_2, w_2^i\right] - 2\lambda_2\zeta_2 + \lambda_2 w_2^i - \lambda_2 \sum_{j=1}^{n} E\left[\xi_{2j}|v_1, v_2, w_2^i\right] = 0,$$

where ξ_2 is the optimal action of each of the n arbitrageurs. We have

(A.3) $$\zeta_2 = \frac{v_2 + v_1 + v_0 - p_1}{2\lambda_2} + \frac{w_2^i}{2} - \frac{n\sum_{j=1}^{n} E\left[\xi_{2j}|v_1, v_2, w_2^i\right]}{2}.$$

The maximization problem for k's arbitrageur is

$$\text{(A.4)} \qquad \max_{\xi_{2k}} \; E[\pi^a_{2k}|v_1, v_2, w^a_{2k}] = \max_{\xi_{2k}}(-\xi_{2k}E[(p_3 - p_2)|v_1, v_2, w^a_{2k}]),$$

where $\pi^a_{2k} = -\xi_{2k}(p_3 - p_2)$ is the period 2 profit of arbitrageur k.

Substituting Equation (A.2) into the expression for profit yields

$$\text{(A.5)} \qquad \pi^a_{2k} = -\xi_{2k}\left(p_3 - p_1 - \lambda_2\left(\zeta_2 - w^i_2 + \xi_{2k} - w^a_{2k} + \sum_{j\neq k}^{n}(\xi_{2j} - w^a_{2j})\right)\right).$$

The first-order condition of (A.4) becomes

$$E\left[p_3 - p_1|v_1, v_2, w^a_{2k}\right] - 2\lambda_2\xi_{2k} + \lambda_2 w^a_{2k} - \lambda_2\sum_{j\neq k}^{n}E[\xi_{2j}|v_1, v_2, w^a_{2k}] - \lambda_2 E\left[\zeta_2|v_1, v_2, w^a_{2k}\right] = 0,$$

or

$$\xi_{2k} = \frac{E\left[v_2 + v_1 + v_0 - p_1|v_1, v_2, w^a_{2k}\right]}{2\lambda_2} + \frac{w^a_{2k}}{2} - \frac{E\left[\zeta_2|v_1, v_2, w^a_{2k}\right]}{2} - \frac{\sum_{j\neq k}^{n}E\left[\xi_{2j}|v_1, v_2, w^a_{2k}\right]}{2},$$

We conjecture that $E[\zeta_2|v_1, v_2, w^a_{2k}] = E[\xi_{2j}|v_1, v_2, w^i_2]$ for $j = 1, ..., n$, which implies that $E[\zeta_2|v_1, v_2, w^a_{2k}] = E[\xi_{2j}|v_1, v_2, w^i_2] = \frac{v_2+v_1+v_0-p_1}{\lambda_2(n+2)}$. As a result, we have

$$\text{(A.6)} \qquad \zeta_2 = \frac{v_2 + v_1 + v_0 - p_1}{\lambda_2(n+2)} + \frac{w^i_2}{2},$$

$$\text{(A.7)} \qquad \xi_{2j} = \frac{v_2 + v_1 + v_0 - p_1}{\lambda_2(n+2)} + \frac{w^a_{2j}}{2}.$$

The total order flow in period 2 is

$$x_2 = \frac{(n+1)(v_2 + v_1 + v_0 - p_1)}{(n+2)\lambda_2} - \frac{w^i_2}{2} - \sum_{j=1}^{n}\frac{w^a_{2j}}{2} + u_2 = (n+1)\beta_2(v_2 + v_1 + v_0 - p_1) - \frac{w^i_2}{2} - \sum_{j=1}^{n}\frac{w^a_{2j}}{2} + u_2,$$

where $\beta_2 = \frac{1}{(n+2)\lambda_2}$. The market maker uses x_2 to update the value of the fundamental value as

$$E[v_2 + v_1 + v_0 - p_1|x_2] = p_1 + \lambda_2 x_2,$$

where $\lambda_2 = \frac{cov[v_2+v_1,x_2]}{var[x_2]} = \frac{(n+1)\beta_2\tilde{\sigma}^2}{(n+1)^2\beta_2^2\tilde{\sigma}^2 + \frac{n\sigma^2_w}{2} + \sigma^2_u}$ with $\tilde{\sigma}^2 = var[v_1 + v_2|p_1]$. Substituting the expression for β_2 and solving for λ_2 yields

$$\text{(A.8)} \qquad \lambda_2 = \sqrt{\frac{(n+1)}{(n+2)^2}}\left(\frac{\tilde{\sigma}^2}{\frac{n\sigma^2_w}{2} + \sigma^2_u}\right),$$

$$\beta_2 = (n+2)\sqrt{(n+1)}\left(n\frac{\sigma_w^2}{2}+\sigma_u^2\right). \tag{A.9}$$

Finally, to compute period 2 expected profit

$$\begin{aligned}
E[\pi_{2k}^a|v_1, v_2, w_{2k}^a] &= \xi_{2k}E[(p_3 - p_2)|v_1, v_2, w_k^a] \\
&= \xi_{2k}\left(p_3 - p_1 - \lambda_2(n+1)E[\xi_2|v_1, v_2] + \frac{\lambda_2 w_{2k}^a}{2}\right) \\
&= \xi_{2k}\left(\frac{p_3 - p_1}{n+2} + \frac{\lambda_2 w_{2k}^a}{2}\right) = \lambda_2\left(\frac{v_2 + v_1 + v_0 - p_1}{(n+2)\lambda_2} + \frac{w_{2k}^a}{2}\right)^2.
\end{aligned}$$

Similarly,

$$E[\pi_2^i|v_1, v_2, w_2^i] = \lambda_2\left(\frac{v_2 + v_1 + v_0 - p_1}{(n+2)\lambda_2} + \frac{w_2^i}{2}\right)^2.$$

Q.E.D.

Proof of Proposition 2: Period 1 equilibrium for NLI benchmark.

In period 1, insider and arbitrageurs use only v_1 as their private information. The total order flow

$$x_1 = \sum_{j=1}^{n}(\xi_{1j} - w_{1j}^a) + \zeta_1 - w_1^i + u_1.$$

The market maker uses the order flow x_1 to set up the first-period market price as $p_1 = p_0 + \lambda_1 x_1$. The maximization problem of the insider, conditional on the second period trading profit of $E[\pi_2^i|v_1, v_2, w_2^i] = \lambda_2\left(\frac{v_2+v_1+v_0-p_1}{(n+2)\lambda_2} + \frac{w_2^i}{2}\right)^2$ becomes

$$\begin{aligned}
\max_{\zeta_1}\ E\left[\pi_1^i|v_1, w_1^i\right] &= E[\zeta_1(p_3 - p_1) + E[\pi_2^i|v_1, v_2, w_2^i]|v_1, w_1^i] \\
&= E\left[\zeta_1(v_2 + v_1 + v_0 - p_1) + \lambda_2\left(\frac{v_2 + v_1 + v_0 - p_1}{(n+2)\lambda_2} + \frac{w_2^i}{2}\right)^2 |v_1\right].
\end{aligned}$$

Because

$$\begin{aligned}
E\left[\pi_1^i|v_1, w_1^i\right] &= E\left[\zeta_1(v_2 + v_1 - \lambda_1 x_1) + \lambda_2\left(\frac{v_2 + v_1 - \lambda_1 x_1}{(n+2)\lambda_2} + \frac{w_2^i}{2}\right)^2 |v_1, w_1^i\right] \\
&= E\left[\zeta_1\left(v_2 + v_1 - \lambda_1\left(\sum_{j=1}^{k}(\xi_{1j} - w_{1j}^a) + \zeta_1 - w_1^i + u_1\right)\right)\right. \\
&+ \left.\lambda_2\left(\frac{v_2 + v_1 - \lambda_1\left(\sum_{j=1}^{k}(\xi_{1j} - w_{1j}^a) + \zeta_1 - w_1^i + u_1\right)}{(n+2)\lambda_2} + \frac{w_2^i}{2}\right)^2 |v_1, w_1^i\right],
\end{aligned}$$

the FOC is

$$0 = v_1 - \lambda_1 \left(\sum_{j=1}^{k} E\left[\xi_{1j} | v_1, w_1^i\right] \right) - 2\lambda_1 \zeta_1 + \lambda_1 w_1^i \tag{A.10}$$
$$- \frac{2\lambda_1}{(n+2)^2 \lambda_2} \left(v_1 - \lambda_1 \left(\sum_{j=1}^{k} E\left[\xi_{1j} | v_1, w_1^i\right] \right) - \lambda_1 \zeta_1 + \lambda_1 w_1^i \right)$$
$$= v_1(1 - 2\alpha\lambda_1) - \lambda_1 \left(\sum_{j=1}^{k} E\left[\xi_{1j} | v_1, w_1^i\right] \right) (1 - 2\alpha\lambda_1) - 2\lambda_1 \zeta_1 (1 - \alpha\lambda_1) + \lambda_1 w_1^i (1 - 2\alpha\lambda_1),$$

where $\alpha = \frac{1}{(n+2)^2 \lambda_2}$. We conjecture that $E\left[\xi_{1j} | v_1, w_1^i\right] = E\left[\xi_{1s} | v_1, w_1^i\right] = E$ for every $j \neq s$, and as a results, we get

$$\zeta_1 = \frac{(1 - 2\alpha\lambda_1)}{2(1 - \alpha\lambda_1)} \left(\frac{v_1}{\lambda_1} + w_1^i - nE \right). \tag{A.11}$$

The maximization problem of the ks arbitrageur, conditional on the second period trading profit of $E[\pi_{2k} | v_1, v_2, w_{2k}^a] = \lambda_2 \left(\frac{v_2 + v_1 + v_0 - p_1}{(n+2)\lambda_2} + \frac{w_{2k}^a}{2} \right)^2$ becomes

$$\max_{\xi_{1k}} E\left[\pi_{1k} | v_1, w_{1k}^a\right] = E[\xi_{1k}(p_3 - p_1) + E[\pi_{2k} | v_1, v_2, w_{2k}^a] | v_1, w_{1k}^a]$$
$$= E\left[\xi_{1k}(v_2 + v_1 + v_0 - p_1) + \lambda_2 \left(\frac{v_2 + v_1 + v_0 - p_1}{(n+2)\lambda_2} + \frac{w_{2k}^a}{2} \right)^2 | v_1, w_{1k}^a \right].$$

Because

$$E\left[\pi_{1k}^a | v_1, w_{1k}^a\right] = E\left[\xi_{1k}(v_2 + v_1 - \lambda_1 x_1) + \lambda_2 \left(\frac{v_2 + v_1 - \lambda_1 x_1}{(n+2)\lambda_2} + \frac{w_{2k}^a}{2} \right)^2 | v_1, w_{1k}^a \right]$$
$$= E\left[\xi_{1k} \left(v_2 + v_1 - \lambda_1 \left(\sum_{j \neq k}^{n} (\xi_{1j} - w_{1j}^a) + \xi_{1k} - w_{1k}^a + \zeta_1 - w_1^i + u_1 \right) \right) \right.$$
$$\left. + \lambda_2 \left(\frac{v_2 + v_1 - \lambda_1 \left(\sum_{j \neq k}^{n} (\xi_{1j} - w_{1j}^a) + \xi_{1k} - w_{1k}^a + \zeta_1 - w_1^i + u_1 \right)}{(n+2)\lambda_2} + \frac{w_2^i}{2} \right)^2 | v_1, w_{1k}^a \right],$$

the FOC is

$$
\begin{aligned}
0 &= v_1 - \lambda_1 \left(\sum_{j \neq k} E\left[\xi_{1j} | v_1, w_{1k}^a\right] \right) - 2\lambda_1 \xi_{1k} - \lambda_1 E\left[\zeta_1 | v_1, w_{1k}^a\right] + \lambda_1 w_{1k}^a \\
&- \frac{2\lambda_1}{(n+2)^2 \lambda_2} \left(v_1 - \lambda_1 \left(\sum_{j \neq k} E\left[\xi_{1j} | v_1, w_{1k}^a\right] \right) - \lambda_1 \xi_{1k} - \lambda_1 E\left[\zeta_1 | v_1, w_{1k}^a\right] + \lambda_1 w_{1k}^a \right) \\
&= v_1(1 - 2\alpha\lambda_1) - \lambda_1 n E (1 - 2\alpha\lambda_1) - 2\lambda_1 \xi_{1k}(1 - \alpha\lambda_1) + \lambda_1 w_{1k}^a (1 - 2\alpha\lambda_1).
\end{aligned}
$$

Here we used the fact that insider's and arbitrageurs' endowments are orthogonal to each other and conjectured $E\left[\xi_{1j} | v_1, w_{1k}^a\right] = E\left[\zeta_1 | v_1, w_{1k}^a\right] = E$ for every $j \neq k$. As a result, we get

$$
\xi_{1k} = \frac{(1 - 2\alpha\lambda_1)}{2(1 - \alpha\lambda_1)} \left(\frac{v_1}{\lambda_1} + w_{1k}^a - nE \right), \tag{A.12}
$$

which verifies our conjecture

$$
E\left[\xi_{1k} | v_1\right] = \frac{(1 - 2\alpha\lambda_1) v_1}{\lambda_1 (n + 2 - 2\alpha\lambda_1 (n+1)}.
$$

As a result, we get

$$
\begin{aligned}
\zeta_1 &= \frac{(1 - 2\alpha\lambda_1) v_1}{\lambda_1 (n + 2 - 2\alpha\lambda_1 (n+1))} + \frac{(1 - 2\alpha\lambda_1) w_1^i}{2(1 - \alpha\lambda_1)} = \beta_1 v_1 + \delta \lambda_1 w_1^i, \\
\xi_{1k} &= \frac{(1 - 2\alpha\lambda_1) v_1}{\lambda_1 (n + 2 - 2\alpha\lambda_1 (n+1))} + \frac{(1 - 2\alpha\lambda_1) w_{1k}^a}{2(1 - \alpha\lambda_1)} = \beta_1 v_1 + \delta \lambda_1 w_{1k}^a,
\end{aligned}
$$

where

$$
\begin{aligned}
\beta_1 &= \frac{(1 - 2\alpha\lambda_1)}{\lambda_1 (n + 2 - 2\alpha\lambda_1 (n+1))}, \\
\delta &= \frac{(1 - 2\alpha\lambda_1)}{2\lambda_1 (1 - \alpha\lambda_1)}.
\end{aligned}
$$

The order flow can be expressed as a linear function of two innovation shocks

$$
x_1 = (n+1)\beta_1 v_1 + \delta \lambda_1 \left(\sum_{j=1}^{n} w_{1j}^a + w_1^i \right) + u.
$$

The market maker can infer $E[v_1 + v_2 | x_1] = \lambda_1 x_1$, where

$$
\lambda_1 = \frac{cov[v_1 + v_2, x_1]}{var[x_1]} = \frac{(n+1)\beta_1 \sigma^2}{(n+1)^2 \beta_1^2 \sigma^2 + \frac{n(1 - 2\alpha\lambda_1)^2}{4(1 - \alpha\lambda_1)^2} \sigma_w^2 + \sigma_u^2}.
$$

Q.E.D.

Proof of Proposition 3: Period 1 equilibrium for AI benchmark.

To solve for period 1 price impacts and first-period equilibrium, we note that arbitrageurs use only v_1 as their private information, while the insider uses v_1 as well as v_2. The maximization problem of the insider, conditional on the second period trading profit of $E[\pi_2^i|v_1, v_2, w_2^i] = \lambda_2 \left(\frac{v_2+v_1+v_0-p_1}{(n+2)\lambda_2} + \frac{w_2^i}{2}\right)^2$ becomes

$$\begin{aligned}
\max_{\zeta_1}\ E\left[\pi_1^i|v_1, v_2, w_1^i\right] &= E[\zeta_1(p_3 - p_1) + E[\pi_2^i|v_1, v_2, w_2^i]|v_1, v_2, w_1^i] \\
&= E\left[\zeta_1(v_2 + v_1 + v_0 - p_1) + \lambda_2\left(\frac{v_2 + v_1 + v_0 - p_1}{(n+2)\lambda_2} + \frac{w_2^i}{2}\right)^2 |v_1, v_2, w_1^i\right].
\end{aligned}$$

Because

$$\begin{aligned}
E\left[\pi_1^i|v_1, v_2, w_1^i\right] &= E\left[\zeta_1(v_2 + v_1 - \lambda_1 x_1) + \lambda_2\left(\frac{v_2 + v_1 - \lambda_1 x_1}{(n+2)\lambda_2} + \frac{w_2^i}{2}\right)^2 |v_1, v_2, w_1^i\right] \\
&= E\left[\zeta_1\left(v_2 + v_1 - \lambda_1\left(\sum_{j=1}^{k}(\xi_{1i} - w_{1i}^a) + \zeta_1 - w_1^i + u_1\right)\right)\right. \\
&+ \left.\lambda_2\left(\frac{v_2 + v_1 - \lambda_1\left(\sum_{j=1}^{k}(\xi_{1j} - w_{1j}^a) + \zeta_1 - w_1^i + u_1\right)}{(n+2)\lambda_2} + \frac{w_2^i}{2}\right)^2 |v_1, v_2, w_1^i\right],
\end{aligned}$$

the first-order condition is

$$\begin{aligned}
0 &= v_1 + v_2 - \lambda_1\left(\sum_{j\neq k} E\left[\xi_{1j}|v_1, v_2, w_1^i\right]\right) - 2\lambda_1\zeta_1 + \lambda_1 w_1^i \\
&- \frac{2\lambda_1}{(n+2)^2\lambda_2}\left(v_1 + v_2 - \lambda_1\left(\sum_{j\neq k} E\left[\xi_{1j}|v_1, v_2, w_1^i\right]\right) - \lambda_1\zeta_1 + \lambda_1 w_1^i\right) \\
&= v_1(1 - 2\alpha\lambda_1) - n\lambda_1 E\left[\xi_1|v_1\right](1 - 2\alpha\lambda_1) - 2\lambda_1\zeta_1(1 - \alpha\lambda_1) + \lambda_1 w_1^i(1 - 2\alpha\lambda_1),
\end{aligned}$$

where $\alpha = \frac{1}{(n+2)^2\lambda_2}$. Given that the arbitrageurs' demand does not depend on v_2 and w_1^i, we conjecture that $E\left[\xi_{1s}|v_1, v_2, w_1^s\right] = E\left[\xi_{1j}|v_1, v_2, w_1^i\right] = E\left[\xi_{1j}|v_1\right] = E$ for every $s \neq j$, and as a results, we get

$$\zeta_1 = \frac{(1 - 2\alpha\lambda_1)}{2(1 - \alpha\lambda_1)}\left(\frac{v_1 + v_2}{\lambda_1} + w_1^i - nE\right). \tag{A.13}$$

The maximization problem of the ks arbitrageur, conditional on the second period trading profit of $E[\pi_{2k}^a|v_1, v_2, w_{2k}^a] = \lambda_2 \left(\frac{v_2+v_1+v_0-p_1}{(n+2)\lambda_2} + \frac{w_{2k}^a}{2}\right)^2$ becomes

$$\begin{aligned}
\max_{\xi_{1k}} \ E\left[\pi_{1k}|v_1, w_{1k}^a\right] &= E[\xi_{1k}(p_3 - p_1) + E[\pi_{2k}|v_1, v_2, w_{2k}^a]|v_1, w_{1k}^a] \\
&= E\left[\xi_{1k}(v_2 + v_1 + v_0 - p_1) + \lambda_2 \left(\frac{v_2 + v_1 + v_0 - p_1}{(n+2)\lambda_2} + \frac{w_{2k}^a}{2}\right)^2 |v_1, w_{1k}^a\right].
\end{aligned}$$

Because

$$\begin{aligned}
E\left[\pi_{1k}^a|v_1, w_{1k}^a\right] &= E\left[\xi_{1k}(v_2 + v_1 - \lambda_1 x_1) + \lambda_2 \left(\frac{v_2 + v_1 - \lambda_1 x_1}{(n+2)\lambda_2} + \frac{w_{2k}^a}{2}\right)^2 |v_1, w_{1k}^a\right] \\
&= E\left[\xi_{1k}\left(v_2 + v_1 - \lambda_1 \left(\sum_{j\neq k}^{n}(\xi_{1j} - w_{1j}^a) + \xi_{1k} - w_{1k}^a + \zeta_1 - w_1^i + u_1\right)\right)\right. \\
&+ \left.\lambda_2 \left(\frac{v_2 + v_1 - \lambda_1 \left(\sum_{j\neq k}^{n}(\xi_{1j} - w_{1j}^a) + \xi_{1k} - w_{1k}^a + \zeta_1 - w_1^i + u_1\right)}{(n+2)\lambda_2} + \frac{w_2^i}{2}\right)^2 |v_1, w_{1k}^a\right],
\end{aligned}$$

the first order condition is

$$\begin{aligned}
0 &= v_1 - \lambda_1 \left(\sum_{j\neq k} E\left[\xi_{1j}|v_1, w_{1k}^a\right]\right) - 2\lambda_1\xi_{1k} - \lambda_1 E\left[\zeta_1|v_1, w_{1k}^a\right] + \lambda_1 w_{1k}^a \\
&- \frac{2\lambda_1}{(n+2)^2\lambda_2}\left(v_1 - \lambda_1 \left(\sum_{j\neq k} E\left[\xi_{1j}|v_1, w_{1k}^a\right]\right) - \lambda_1\xi_{1k} - \lambda_1 E\left[\zeta_1|v_1, w_{1k}^a\right] + \lambda_1 w_{1k}^a\right) \\
&= v_1(1 - 2\alpha\lambda_1) - \lambda_1(1 - 2\alpha\lambda_1)((n-1)E + E\left[\zeta_1|v_1\right]) - 2\lambda_1\xi_{1k}(1 - \alpha\lambda_1) + \lambda_1 w_{1k}^a(1 - 2\alpha\lambda_1).
\end{aligned}$$

The fundamental information set of all arbitrageurs is the same and w_{1k}^a is independent of the demand of other arbitrageurs and the insider, we conjecture that $E\left[\xi_{1j}|v_1, w_{1k}^a\right] = E\left[\zeta_1|v_1, w_{1k}^a\right] = E$ for every $j \neq k$. As a result, we get

$$\xi_{1k} = \frac{(1 - 2\alpha\lambda_1)}{2(1 - \alpha\lambda_1)}\left(\frac{v_1}{\lambda_1} + w_{1k}^a - nE\right),$$

which verifies that

$$E\left[\xi_{1k}|v_1\right] = \frac{(1 - 2\alpha\lambda_1)v_1}{\lambda_1(n + 2 - 2\alpha\lambda_1(n+1))}.$$

As a result,

$$\begin{aligned}
\zeta_1 &= \frac{(1 - 2\alpha\lambda_1)v_1}{\lambda_1(n + 2 - 2\alpha\lambda_1(n+1))} + \frac{(1 - 2\alpha\lambda_1)v_2}{2\lambda_1(1 - \alpha\lambda_1)} + \frac{(1 - 2\alpha\lambda_1)w_1^i}{2(1 - \alpha\lambda_1)} = \gamma v_1 + \delta v_2 + \frac{(1 - 2\alpha\lambda_1)w_1^i}{2(1 - \alpha\lambda_1)}, \\
\xi_{1k} &= \frac{(1 - 2\alpha\lambda_1)v_1}{\lambda_1(n + 2 - 2\alpha\lambda_1(n+1))} + \frac{(1 - 2\alpha\lambda_1)w_{1k}^a}{2(1 - \alpha\lambda_1)} = \beta_1 v_1 + \frac{(1 - 2\alpha\lambda_1)w_{1k}^a}{2(1 - \alpha\lambda_1)},
\end{aligned}$$

with

$$\gamma = \beta_1 = \frac{(1-2\alpha\lambda_1)}{\lambda_1(n+2-2\alpha\lambda_1(n+1))} \quad \text{and} \quad \delta = \frac{(1-2\alpha\lambda_1)}{2\lambda_1(1-\alpha\lambda_1)}.$$

Order flow can written as a linear function of two innovation shocks and liquidity orders:

$$\begin{aligned} x_1 &= n\beta_1 v_1 + \gamma v_1 + \delta v_2 + \delta\lambda_1 \left(\sum_{j=1}^{n} w_{1j}^a + w_1^i \right) + u_1 \\ &= (n\beta_1 + \gamma) v_1 + \delta v_2 + \delta\lambda_1 \left(\sum_{j=1}^{n} w_{1i}^a + w_1^i \right) + u_1. \end{aligned} \tag{A.14}$$

The market maker can infer the expected price change $E[v_1 + v_2 | x_1] = \lambda_1 x_1$, where

$$\lambda_1 = \frac{cov[v_1 + v_2, x_1]}{var[x_1]} = \frac{((n+1)\beta_1 + \delta)\sigma^2}{((n+1)^2\beta_1^2 + \delta^2)\,\sigma^2 + n\delta^2\lambda_1^2\sigma_w^2 + \sigma_u^2}.$$

Q.E.D.

Internet Appendix: Tables

TABLE A1

Insiders' demand and long-term information with alternative measures.

This table presents estimates of regression
$nisneg_{k,t,t+5} = d_{++}ssl_{kt} \times longh_{kt} + d_{+-}ssl_{kt} \times longl_{kt} + d_{-+}ssh_{kt} \times longh_{kt} + d_{--}ssh_{kt} \times longl_{kt} + X_{kt}\gamma + u_{kt}$
in odd columns and
$nispos_{k,t,t+5} = d_{++}ssl_{kt} \times longh_{kt} + d_{+-}ssl_{kt} \times longl_{kt} + d_{-+}ssh_{kt} \times longh_{kt} + d_{--}ssh_{kt} \times longl_{kt} + X_{kt}\gamma + u_{kt}$
in even columns, where $nispos_{k,t,t+5}$ ($nisneg_{k,t,t+5}$) stands for the relative net shares sold with positive (negative) values in basis points representing insider sales (purchases). For easier interpretation, $nisneg_{k,t,t+5}$ are in absolute values. We include firm and year fixed effects. Robust standard errors are clustered within firms. All variables are defined in Appendix in the main text. ***, ** and * indicate significance at the 1-, 5- and 10-percent levels. The sample runs from July 2006 to December 2017.

	q1		q3		q4	
	$nispos$	$nisneg$	$nispos$	$nisneg$	$nispos$	$nisneg$
	Panel A: $\Delta earn$ as measure of long-term information					
$ssl \times longh$ (d_{++})	−0.148***	−0.016	−0.142***	−0.003	−0.140***	0.016
$ssl \times longl$ (d_{+-})	−0.146***	−0.054***	−0.233***	−0.007	−0.198***	−0.025
$ssh \times longh$ (d_{-+})	0.149***	0.127***	0.191***	0.117***	0.209***	0.102***
$ssh \times longl$ (d_{--})	0.109**	0.095***	0.197***	0.070***	0.189***	0.060***
$ssm \times longh$	−0.046	0.052***	−0.068**	0.049***	−0.016	0.046***
$ssm \times longl$	0.030	0.023**	0.059**	0.016	0.037	0.024**
$ssl \times longm$	−0.169***	−0.021	−0.152***	−0.048***	−0.162***	−0.048***
$ssh \times longm$	0.168***	0.052***	0.124***	0.060***	0.147***	0.069***
$pastret$	0.982***	−0.191***	1.030***	−0.195***	1.050***	−0.196***
$eaar$	5.061***	−0.872***	5.152***	−0.864***	5.212***	−0.881***
Δeps	−0.508***	−0.251***	−0.533***	−0.293***	−0.513***	−0.306***
Nr. obs.	129,812	129,812	120,466	120,466	115,997	115,997
R-squared	3.32%	1.61%	3.45%	1.62%	3.48%	1.64%
	Panel B: $eaar$ as measure of long-term information					
$ssl \times longh$ (d_{++})	−0.179***	−0.013	−0.170***	−0.020	−0.136***	−0.038
$ssl \times longl$ (d_{+-})	−0.103***	−0.060***	−0.175***	−0.061***	−0.150***	−0.051**
$ssh \times longh$ (d_{-+})	0.149***	0.111***	0.204***	0.073***	0.219***	0.078***
$ssh \times longl$ (d_{--})	0.268***	0.055***	0.217***	0.048***	0.207***	0.064***
$ssm \times longh$	−0.001	0.025***	0.016	0.010	−0.001	0.001
$ssm \times longl$	0.081***	0.005***	0.066**	−0.015	0.048*	0.001
$ssl \times longm$	−0.139***	−0.037***	−0.132***	−0.049***	−0.164***	−0.041***
$ssh \times longm$	0.137***	0.055***	0.144***	0.057***	0.142***	0.051***
$pastret$	0.980***	−0.189***	1.024***	−0.192***	1.043***	−0.194***
$eaar$	5.071***	−0.874***	5.163***	−0.869***	5.225***	−0.879***
Δeps	−0.464***	−0.294***	−0.477***	−0.339***	−0.491***	−0.365***
Nr. obs.	116,379	116,359	120,881	120,868	129,923	129,909
R-squared	3.33%	1.59%	3.43%	1.60%	3.47%	1.61%

TABLE A2

Routine versus opportunistic insider trades: summary statistics.

This table shows frequencies and means for routine and opportunistic insider sales ($nispos$) and purchases ($nisneg$ in absolute value). We identify insiders who trade in the same calendar month in at least 3 consecutive years. Then, we classify all trades by the insider following this three year period as routine if they happen in the same month. Trades made in non-routine months are classified as opportunistic. Then in each quarter, we compute routine (opportunistic) net insider sales over the response window and set routine (opportunistic) insider selling and buying dummies to one when routine (opportunistic) net insider selling is positive and negative, respectively. The complementary group of routine (opportunistic) $noit$ includes all firm-quarters that do not contain any routine (opportunistic) sales or purchases. Relative shares traded over the $(0, +5)$ response window are reported in basis points. The interaction terms in Panel B are for insider sales (is) and insider purchases (ip) with three short-selling categories of high (ssh), medium (ssm), and low short selling (ssl). All variables are defined in Appendix. The sample runs from July 2006 to December 2017.

Panel A: Basic statistics

	# of quarters	% of all quarters	% of quarters with trades	relative shares traded
all classified quarters	132,240	100%		
routine $nispos$	4,904	3.7%	77.2%	1.53
routine $nisneg$	1,446	1.1%	22.8%	0.60
routine $noit$	125,890	95.2%	n.a.	n.a.
opportunistic $nispos$	20,423	15.4%	73.8%	5.00
opportunistic $nisneg$	7,264	5.5%	26.2%	3.11
opportunistic $noit$	104,553	79.1%	n.a.	n.a.

Panel B: Relative shares traded by interaction categories

	routine		opportunistic	
	$nispos$ (sales)	$nisneg$ (purchases)	$nispos$ (sales)	$nisneg$ (purchases)
$is \times ssh$	1.64	0	6.07	0
$is \times ssm$	1.47	0	4.57	0
$is \times ssl$	1.59	0	5.12	0
$ip \times ssh$	0	0.64	0	3.04
$ip \times ssm$	0	0.58	0	2.87
$ip \times ssl$	0	0.65	0	3.81

TABLE A3

Routine versus opportunistic insider trading and future returns.

This table presents estimates of sensitivities between future returns and informed traders' demands splitting insider demands into opportunistic versus routine. We identify insiders who trade in the same calendar month in at least 3 consecutive years. Then, we classify all trades by the insider following this 3-year period as routine if they happen in the same month. Trades made in non-routine months are classified as opportunistic. Panel A presents estimates of regression
$aret_{k,t+5,t+6+h} = b_1\ isopp_{kt} + b_2\ ipopp_{kt} + b_3\ isrt_{kt} + b_4\ iprt_{kt} + c_1\ ssh_{kt} + c_2\ ssl_{kt} + X_{kt}\gamma + u_{kt}$
and Panel B of two regressions for opportunistic and routine insider trades, respectively
$aret_{k,t+5,t+6+h} = b_{++} ipopp_{kt} \times ssl_{kt} + b_{+-} ipopp_{kt} \times ssh_{kt} + b_{-+} isopp_{kt} \times ssl_{kt} + b_{--} isopp_{kt} \times ssh_{kt} + X_{kt}\gamma + u_{kt}$
and
$aret_{k,t+5,t+6+h} = b_{++} iprt_{kt} \times ssl_{kt} + b_{+-} iprt_{kt} \times ssh_{kt} + b_{-+} isrt_{kt} \times ssl_{kt} + b_{--} isrt_{kt} \times ssh_{kt} + X_{kt}\gamma + u_{kt}$
$aret_{k,t+5,t+6+h}$ is abnormal return in stock k from $t+5$ to $t+6+h$ after earnings announcement t (in percent). $isopp_{kt}$ and $ipopp_{kt}$ ($isrt_{kt}$ and $iprt_{kt}$) denote dummy variables for intensive opportunistic (routine) net insider sales and purchases, respectively, in firm k over the $(0, +5)$ response window after the earnings announcement date t. $noit_{kt}$ refers to no insider trades, ssh_{kt}, ssl_{kt} and ssm_{kt} to short selling in the highest, lowest and the remaining three middle quintiles, respectively, in firm k over the $(0, +5)$ response window after the earnings announcement date t. X_{kt} includes the past 12-month return $pastret$, current quarter earnings announcement abnormal return $eaar$, earnings per share change Δeps, interactions $noit \times ssl$, $noit \times ssh$, $ip \times ssm$, $is \times ssm$, as well as firm and year fixed effects. Abnormal returns are adjusted for the corresponding 5×5 size and book-to-market portfolio return. Robust standard errors are clustered within firms. All variables are defined in Appendix. ***, ** and * indicate significance at the 1-, 5- and 10-percent levels. The sample runs from July 2006 to December 2017.

Panel A: insider's and short-sellers' demands					
	$h = 20$	$h = 40$	$h = 60$	$h = 130$	$h = 250$
$isopp$	-0.006^{***}	-0.009^{***}	-0.017^{***}	-0.030^{***}	-0.051^{***}
$ipopp$	0.012^{***}	0.013^{***}	0.016^{***}	0.026^{***}	0.027^{***}
$isrt$	-0.003^{**}	-0.005^{**}	-0.008^{***}	-0.011^{***}	-0.006
$iprt$	0.002	0.003	0.005	0.004	-0.005
ssh	-0.003^{***}	-0.009^{***}	-0.014^{***}	-0.034^{***}	-0.058^{***}
ssl	0.005^{***}	0.012^{***}	0.022^{***}	0.049^{***}	0.095^{***}
$pastret$	-0.006^{***}	-0.012^{***}	-0.027^{***}	-0.068^{***}	-0.130^{***}
$eaar$	0.034^{***}	0.053^{***}	0.029^{***}	-0.019	-0.079^{***}
Δeps	0.018^{**}	-0.008	-0.030^{**}	-0.094^{***}	-0.168^{***}
constant	-0.090	-0.059	-0.092	-0.205	-0.427^{*}
Nr. obs.	132,019	132,019	132,019	132,019	132,019
R-squared	1.1%	2.0%	2.6%	4.1%	5.6%

TABLE A3 CONTINUED.

	$h = 20$	$h = 40$	$h = 60$	$h = 130$	$h = 250$
Panel B: disagreement between informed traders					
	opportunistic trades				
$ipopp \times ssl$ (b_{++})	0.019***	0.025***	0.034***	0.042***	0.049***
$ipopp \times ssh$ (b_{+-})	0.014***	0.015***	0.014**	0.014*	0.006
$isopp \times ssl$ (b_{-+})	−0.002	0.008*	0.009*	0.011	0.017
$isopp \times ssh$ (b_{--})	−0.006***	−0.013***	−0.028***	−0.053***	−0.064***
$ipopp \times ssm$	0.011***	0.012***	0.016***	0.029***	0.029***
$isopp \times ssm$	−0.007***	−0.009***	−0.014***	−0.023***	−0.030***
$noit \times ssl$	0.005***	0.011***	0.018***	0.038***	0.048***
$noit \times ssh$	−0.002**	−0.007***	−0.010***	−0.022***	−0.028***
$pastret$	−0.005***	−0.010***	−0.026***	−0.051***	−0.073***
$eaar$	0.045***	0.069***	0.047***	0.037***	0.046***
Δeps	0.033***	0.024***	0.021*	0.001	0.005
constant	−0.105	−0.059	−0.095	−0.203	−0.233
Nr. obs.	132,240	132,240	132,240	132,240	132,240
R-sq.	0.7%	0.8%	1.0%	1.7%	1.9%
	routine trades				
$iprt \times ssl$ (b_{++})	0.017**	0.023**	0.033**	0.049***	0.051**
$iprt \times ssh$ (b_{+-})	0.000	−0.009	−0.021**	−0.037**	−0.055***
$isrt \times ssl$ (b_{-+})	−0.006	−0.005	−0.005	0.003	0.004
$isrt \times ssh$ (b_{--})	−0.009***	−0.015***	−0.028***	−0.043***	−0.049***
$iprt \times ssm$	−0.001	0.006	0.010*	0.013	0.015
$isrt \times ssm$	−0.004***	−0.007***	−0.012***	−0.021***	−0.025***
$noit \times ssl$	0.005***	0.011***	0.018***	0.037***	0.047***
$noit \times ssh$	−0.001	−0.005***	−0.010***	−0.022***	−0.028***
$pastret$	−0.006***	−0.011***	−0.028***	−0.055***	−0.077***
$eaar$	0.039***	0.062***	0.036***	0.018	0.024
Δeps	0.033***	0.024***	0.022*	0.002	0.005
constant	−0.108	−0.064	−0.101	−0.212	−0.245
Nr. obs.	132,240	132,240	132,240	132,240	132,240
R-sq.	0.6%	0.7%	0.9%	1.6%	1.7%

TABLE A4

Routine versus opportunistic insiders' demand and private information.

This table presents the estimates of the relationships between insiders' demand and private information (14) and (15) separately for opportunistic and routine insider trades. We use two different measures of long-term information $\Delta earn$ and $eaar$ for three horizons: 1, 2, and 4 quarters ahead. The dependent variables $nisneg$ and $nispos$ are measured in basis points and are split into opportunistic and routine trades. We identify insiders who trade in the same calendar month (the routine month) in at least three consecutive years. Then, we classify all trades by the insider following this three year period as routine if they happen in the same (routine) month. Trades made in non-routine months are classified as opportunistic. Then in each quarter, we compute routine (opportunistic) net insider sales ($nispos$) over the response window and set routine (opportunistic) insider selling and buying dummies to one when routine (opportunistic) net insider selling is positive and negative, respectively. We include firm and year fixed effects. Robust standard errors are clustered within firms. All variables are defined in Appendix in the main text. ***, ** and * indicate significance at the 1-, 5- and 10-percent levels. The sample runs from July 2006 to December 2017.

Panel A: Opportunistic insiders' demand and private information

	q1		q3		q4	
	$nispos$	$nisneg$	$nispos$	$nisneg$	$nispos$	$nisneg$
	$\Delta earn$ as measure of long-term information					
$ssl \times longh$ (d_{++})	-0.186^{***}	-0.029	-0.180^{***}	-0.010	-0.169^{***}	-0.015
$ssl \times longl$ (d_{+-})	-0.194^{***}	-0.077^{***}	-0.294^{***}	-0.025	-0.251^{***}	-0.030
$ssh \times longh$ (d_{-+})	0.212^{***}	0.105^{***}	0.298^{***}	0.093^{***}	0.340^{***}	0.085^{***}
$ssh \times longl$ (d_{--})	0.192^{***}	0.063^{***}	0.277^{***}	0.067^{***}	0.246^{***}	0.066^{***}
$ssm \times longh$	-0.054	0.038^{***}	-0.060^{*}	0.047^{***}	0.028	0.043^{***}
$ssm \times longl$	0.032	0.021^{*}	0.070^{*}	0.009	0.071^{*}	0.022^{*}
$ssl \times longm$	-0.194^{***}	-0.032^{*}	-0.181^{***}	-0.071^{***}	-0.184^{***}	-0.068^{***}
$ssh \times longm$	0.235^{***}	0.044^{***}	0.190^{***}	0.048^{***}	0.233^{***}	0.060^{***}
$pastret$	5.287^{***}	-0.685^{***}	5.656^{***}	-0.697^{***}	5.848^{***}	-0.722^{***}
$eaar$	1.081^{***}	-0.152^{***}	1.170^{***}	-0.164^{***}	1.212^{***}	-0.167^{***}
Δeps	-0.496^{***}	-0.235^{***}	-0.530^{***}	-0.258^{***}	-0.497^{***}	-0.288^{***}
constant	16.451	0.210^{***}	16.313	0.215^{***}	16.282	0.215^{***}
Nr. obs.	129,812	129,812	120,466	120,466	115,997	115,997
R-squared	2.9%	1.0%	2.8%	0.9%	2.8%	0.8%
	$eaar$ as a measure of long-term information					
$ssl \times longh$ (d_{++})	0.239^{***}	0.081^{***}	0.292^{***}	0.057^{***}	0.291^{***}	0.058^{***}
$ssl \times longl$ (d_{+-})	0.023^{***}	0.023^{**}	0.041	0.016	-0.011	0.003
$ssh \times longh$ (d_{-+})	-0.197^{***}	-0.018	-0.219^{***}	-0.032	-0.186^{***}	-0.046
$ssh \times longl$ (d_{--})	0.216^{***}	0.049^{***}	0.209^{***}	0.041^{***}	0.217^{***}	0.050^{***}
$ssm \times longh$	-0.160^{***}	-0.048^{***}	-0.159^{***}	-0.072^{***}	-0.208^{***}	-0.060^{***}
$ssm \times longl$	0.339^{***}	0.050^{***}	0.312^{***}	0.052^{***}	0.260^{***}	0.059^{***}
$ssl \times longm$	0.096^{***}	0.011	0.076^{**}	-0.026^{**}	0.049	0.000
$ssh \times longm$	-0.146^{***}	-0.068^{***}	-0.225^{***}	-0.064^{**}	-0.223^{***}	-0.078^{***}
$pastret$	5.293^{***}	-0.685^{***}	5.638^{***}	-0.703^{***}	5.837^{***}	-0.720^{***}
$eaar$	1.080^{***}	-0.150^{***}	1.167^{***}	-0.162^{***}	1.208^{***}	-0.166^{***}
Δeps	-0.430^{***}	-0.272^{***}	-0.483^{***}	-0.303^{***}	-0.515^{***}	-0.328^{***}
constant	16.421	0.205^{***}	16.402	0.242^{***}	16.340	0.238^{***}
Nr. obs.	129,923	129,923	120,884	120,884	116,382	116,382
R-squared	2.9%	1.0%	2.8%	0.9%	2.8%	0.8%

TABLE A4 CONTINUED.

Panel B: Routine insiders' demand and private information	q1		q3		q4	
	$nispos$	$nisneg$	$nispos$	$nisneg$	$nispos$	$nisneg$
	$\Delta earn$ *as measure of long-term information*					
$ssl \times longh$ (d_{++})	-0.003	0.002	-0.006	0.001	-0.001	0.001
$ssl \times longl$ (d_{+-})	-0.004	-0.001	-0.004	0.000	-0.008^{**}	0.002
$ssh \times longh$ (d_{-+})	0.003	0.000	0.009	0.000	0.010	-0.001
$ssh \times longl$ (d_{--})	0.010	-0.001	0.013	0.001	0.014^{*}	0.001
$ssm \times longh$	-0.007^{*}	0.001	-0.008	0.001	-0.007	0.001^{*}
$ssm \times longl$	0.001	0.000	-0.003	0.000	-0.008^{*}	0.001
$ssl \times longm$	0.001	-0.001^{*}	0.001	-0.001	-0.001	-0.002^{**}
$ssh \times longm$	0.011^{**}	0.000	0.006	0.000	0.004	0.000
$pastret$	0.261^{***}	0.003	0.278^{***}	0.003	0.285^{***}	0.005
$eaar$	0.039^{***}	0.002^{**}	0.041^{***}	0.002^{**}	0.043^{***}	0.002^{**}
Δeps	-0.047^{***}	-0.005^{*}	-0.044^{***}	-0.005^{*}	-0.036^{***}	-0.007^{**}
constant	0.038^{***}	0.007^{***}	0.039^{***}	0.007^{***}	0.043^{***}	0.007^{***}
Nr. obs.	129,812	129,812	120,466	120,466	115,997	115,997
R-squared	0.7%	0.1%	0.7%	0.1%	0.6%	0.1%
	$eaar$ *as a measure of long-term information*					
$ssl \times longh$ (d_{++})	0.003	-0.001	0.019^{**}	0.000	0.023^{**}	0.000
$ssl \times longl$ (d_{+-})	-0.013^{***}	0.000	-0.008^{*}	-0.001	0.002	-0.001
$ssh \times longh$ (d_{-+})	-0.003	-0.002	0.002	-0.003^{*}	0.001	-0.002^{*}
$ssh \times longl$ (d_{--})	0.006	0.000	0.003	-0.001	0.004	-0.001
$ssm \times longh$	-0.002	-0.001	0.000	-0.001	0.001	-0.001
$ssm \times longl$	0.009	0.000	0.014	0.000	0.018^{**}	0.000
$ssl \times longm$	-0.007	-0.001	0.003	0.000	0.001	0.000
$ssh \times longm$	-0.006^{*}	0.000	-0.004	-0.001	0.004	0.000
$pastret$	0.264^{***}	0.003	0.278^{***}	0.003	0.285^{***}	0.005
$eaar$	0.039^{***}	0.002^{**}	0.041^{***}	0.002^{**}	0.043^{***}	0.002^{**}
Δeps	-0.041^{***}	-0.006^{**}	-0.038^{***}	-0.007^{**}	-0.037^{***}	-0.008^{***}
constant	0.042^{***}	0.007^{***}	0.039^{***}	0.008^{***}	0.034^{***}	0.008^{***}
Nr. obs.	129,923	129,923	120,884	120,884	116,382	116,382
R-squared	0.7%	0.1%	0.7%	0.1%	0.6%	0.1%

TABLE A5

Classifying routine trades at the insider level.

This table replicates Tables A2 (Panel A), A3 (Panel B), and A4 (Panel C) classifying routine and opportunistic trades at the insider level. We classify all subsequent trades of a routine insider as routine trades regardless of whether they appear at the routine month or not. Opportunistic trades are trades by insiders who are not classified as routine. All variables are defined in the Appendix in the main text. We include firm and year fixed effects. Robust standard errors are clustered within firms. ***, ** and * indicate significance at the 1-, 5- and 10-percent levels. The sample runs from July 2006 to December 2017.

Panel A: Basic statistics

	# of quarters	% of all quarters	% quarters w. trades	rel. shares traded (bp)
routine $nispos$	8,996	6.80%	76.81%	2.06
routine $nisneg$	2,716	2.05%	23.19%	1.36
routine $noit$	120,528	91.14%		
opportunistic $nispos$	18,660	14.11%	72.46%	4.75
opportunistic $nisneg$	7,091	5.36%	27.54%	3.04
opportunistic $noit$	106,489	80.53%		

Panel B: Disagreement between informed traders

	h=20	h=40	h=60	h=130	h=250
	opportunistic trades				
$ipopp \times ssl$ (b_{++})	0.021***	0.024***	0.035***	0.045***	0.054***
$ipopp \times ssh$ (b_{+-})	0.014***	0.015***	0.014**	0.013	0.004
$isopp \times ssl$ (b_{-+})	-0.003	0.006	0.009	0.011	0.016
$isopp \times ssh$ (b_{--})	-0.007***	-0.014***	-0.028***	-0.052***	-0.064***
$isopp \times ssm$	-0.007***	-0.009***	-0.014***	-0.023***	-0.030***
$ipopp \times ssm$	0.011***	0.013***	0.016***	0.029***	0.030***
$noit \times ssh$	-0.002*	-0.006***	-0.010***	-0.022***	-0.028***
$noit \times ssl$	0.005***	0.011***	0.018***	0.038***	0.047***
$pastret$	-0.005***	-0.010***	-0.026***	-0.052***	-0.073***
$eaar$	0.045***	0.069***	0.047***	0.036***	0.045***
Δesp	0.033***	0.024***	0.021*	0.001	0.005
constant	-0.105	-0.060	-0.095	-0.204	-0.234
Nr. obs.	132,240	132,240	132,240	132,240	132,240
R-squared	0.7%	0.8%	1.0%	1.7%	1.9%
	routine trades				
$iprt \times ssl$ (b_{++})	0.008	0.015**	0.015	0.025*	0.023
$iprt \times ssh$ (b_{+-})	-0.001	-0.012*	-0.026***	-0.039***	-0.060***
$isrt \times ssl$ (b_{-+})	-0.003	0.004	0.005	0.005	0.015
$isrt \times ssh$ (b_{--})	-0.005***	-0.013***	-0.027***	-0.052***	-0.060***
$isrt \times ssm$	-0.004***	-0.006***	-0.012***	-0.021***	-0.028***
$iprt \times ssm$	-0.002	-0.001	-0.001	0.002	-0.001
$noit \times ssh$	-0.001	-0.005***	-0.010***	-0.021***	-0.028***
$noit \times ssl$	0.005***	0.011***	0.018***	0.037***	0.047***
$pastret$	-0.006***	-0.011***	-0.028***	-0.054***	-0.076***
$eaar$	0.040***	0.063***	0.038***	0.022	0.028*
Δesp	0.033***	0.024***	0.021*	0.001	0.005
constant	-0.108	-0.064	-0.100	-0.212	-0.245
Nr. obs.	132,240	132,240	132,240	132,240	132,240
R-squared	0.5%	0.7%	0.9%	1.6%	1.8%

TABLE A5 CONTINUED.

	q1		q3		q4	
	$nispos$	$nisneg$	$nispos$	$nisneg$	$nispos$	$nisneg$
Panel C: Opportunistic insiders' demand and private information						
$\Delta earn$ *as measure of long-term information*						
$ssl{\times}longh$ (d_{++})	-0.169***	-0.032	-0.165***	-0.012	-0.155***	-0.019
$ssl{\times}longl$ (d_{+-})	-0.176***	-0.078***	-0.264***	-0.036	-0.232***	-0.032
$ssh{\times}longh$ (d_{-+})	0.182***	0.106***	0.257***	0.093***	0.314***	0.085***
$ssh{\times}longl$ (d_{--})	0.171***	0.061***	0.253***	0.068***	0.210***	0.068***
$ssm{\times}longh$	-0.039	0.038***	-0.036	0.049***	0.031	0.044***
$ssm{\times}longl$	0.220***	0.045***	0.179***	0.048***	0.214***	0.060***
$ssl{\times}longm$	-0.179***	-0.034**	-0.166***	-0.069***	-0.170***	-0.068***
$ssh{\times}longm$	0.028	0.021*	0.058*	0.008	0.059	0.022*
$pastret$	0.968***	-0.149***	1.046***	-0.161***	1.084***	-0.164***
$eaar$	4.691***	-0.668***	5.014***	-0.678***	5.180***	-0.700***
Δeps	-0.419***	-0.216***	-0.438***	-0.236***	-0.404***	-0.270***
constant	15.51	0.201***	15.37	0.202***	15.35	0.203***
Nr. obs.	129,812	129,812	120,466	120,466	115,997	115,997
R-squared	2.7%	1.0%	2.6%	0.9%	2.6%	0.8%
$eaar$ *as measure of long-term information*						
$ssl{\times}longh$ (d_{++})	-0.174***	-0.021	-0.198***	-0.036	-0.168***	-0.048*
$ssl{\times}longl$ (d_{+-})	-0.129***	-0.064***	-0.208***	-0.072***	-0.215***	-0.082***
$ssh{\times}longh$ (d_{-+})	0.227***	0.081***	0.259***	0.056***	0.244***	0.058***
$ssh{\times}longl$ (d_{--})	0.302***	0.049***	0.292***	0.052***	0.222***	0.057***
$ssm{\times}longh$	0.024	0.022**	0.042	0.015	-0.023	0.003
$ssm{\times}longl$	0.092***	0.012	0.076**	-0.027**	0.039	-0.001
$ssl{\times}longm$	-0.150***	-0.051***	-0.144***	-0.072***	-0.195***	-0.061***
$ssh{\times}longm$	0.197***	0.049***	0.192***	0.041***	0.202***	0.051***
$pastret$	0.967***	-0.147***	1.044***	-0.159***	1.080***	-0.163***
$eaar$	4.696***	-0.668***	4.996***	-0.684***	5.168***	-0.698***
Δeps	-0.361***	-0.253***	-0.407***	-0.284***	-0.431***	-0.309***
constant	15.48	0.195***	15.47	0.231***	15.41	0.227***
Nr. obs.	129,923	129,923	120,884	120,884	116,382	116,382
R-squared	2.7%	1.0%	2.6%	0.9%	2.6%	0.8%

TABLE A5 CONTINUED.

Panel D: Routine insiders' demand and private information

	q1		q3		q4	
	$nispos$	$nisneg$	$nispos$	$nisneg$	$nispos$	$nisneg$
	$\Delta earn$ *as measure of long-term information*					
$ssl{\times}longh$ (d_{++})	-0.014	0.001	-0.014	0.001	0.005	0.003
$ssl{\times}longl$ (d_{+-})	-0.011	-0.005	-0.016*	0.004	0.016*	0.006
$ssh{\times}longh$ (d_{-+})	0.029*	0.002	0.042**	-0.002	-0.036*	-0.001
$ssh{\times}longl$ (d_{--})	0.024	-0.001	0.030*	0.006	-0.035**	0.010*
$ssm{\times}longh$	-0.020***	-0.001	-0.027***	-0.001	0.008	0.004
$ssm{\times}longl$	0.015	0.003	0.011	0.003	-0.016	0.004
$ssl{\times}longm$	-0.007	-0.004	-0.007	-0.007*	0.006	-0.006
$ssh{\times}longm$	0.001	-0.001	0.008	0.002	0.001	0.005*
$pastret$	0.128***	0.014***	0.139***	0.015***	-0.144***	0.016***
$eaar$	0.745***	0.029**	0.798***	0.028**	-0.828***	0.032**
Δeps	-0.119***	-0.020*	-0.133***	-0.026**	0.120***	-0.027**
constant	0.082***	0.031***	0.087***	0.029***	-0.084***	0.029***
Nr. obs.	129,812	129,812	120,466	120,466	115,997	115,997
R-squared	1.1%	0.2%	1.0%	0.2%	1.0%	0.1%
	$eaar$ *as measure of long-term information*					
$ssl{\times}longh$ (d_{++})	-0.014*	-0.004	-0.009	-0.005	-0.005	-0.002
$ssl{\times}longl$ (d_{+-})	-0.010	-0.007	-0.012	0.001	0.002	-0.003
$ssh{\times}longh$ (d_{-+})	0.006	0.003	0.043**	0.001	0.057***	0.009*
$ssh{\times}longl$ (d_{--})	0.039**	0.006	0.026	0.003	0.052***	0.003
$ssm{\times}longh$	-0.012	0.003	-0.011	0.002	0.014	0.001
$ssm{\times}longl$	-0.003	-0.001	0.003	-0.002	0.009	-0.001
$ssl{\times}longm$	-0.006	-0.001	-0.007	-0.004	-0.002	-0.003
$ssh{\times}longm$	0.019*	0.002	0.014	0.003	0.012	0.001
$pastret$	0.128***	0.014***	0.138***	0.015***	0.144***	0.016***
$eaar$	0.748***	0.028**	0.798***	0.028**	0.828***	0.032**
Δeps	-0.108***	-0.021**	-0.114***	-0.022*	-0.119***	-0.026**
constant	0.083***	0.026***	0.076***	0.028***	0.065***	0.030***
Nr. obs.	129,923	129,923	120,884	120,884	116,382	116,382
R-squared	1.1%	0.2%	1.0%	0.2%	1.0%	0.1%

TABLE A6

Abnormal returns and insiders' demand: unconstrained short selling.

This table shows results for a sample of firm-quarters without short-selling constraints. We drop firm-quarter observations with loan fees exceeding 200 basis points during the $(0,+5)$ response window after earnings announcements. Panel A presents estimates of sensitivities between future returns and informed traders' demands (as in Panel A of Table 4), while Panel B of sensitivities between net insider sales and short- and long-term information (as in Table A1). As in previous specifications, we include firm and year fixed effects and we compute robust standard errors that are clustered within firms. All variables are defined in Appendix in the main text. ***, ** and * indicate significance at the 1-, 5- and 10-percent levels. The sample runs from July 2006 to December 2017.

Panel A: Future returns and disagreement between informed traders

	h=20	h=40	h=60	h=130	h=250
$ip{\times}ssl$ (b_{++})	0.021***	0.029***	0.039***	0.059***	0.068***
$ip{\times}ssh$ (b_{+-})	0.013***	0.011***	0.012**	0.021***	0.018**
$is{\times}ssl$ (b_{-+})	0.000	0.007	0.007	0.006	0.008
$ip{\times}ssh$ (b_{--})	−0.004***	−0.011***	−0.025***	−0.048***	−0.058***
$noit{\times}ssl$	0.005***	0.010***	0.015***	0.033***	0.041***
$noit{\times}ssh$	−0.001	−0.004***	−0.008***	−0.017***	−0.024***
$ip{\times}ssm$	0.013***	0.014***	0.020***	0.035***	0.039***
$is{\times}ssm$	−0.005***	−0.008***	−0.013***	−0.022***	−0.028***
$pastret$	−0.007***	−0.012***	−0.030***	−0.059***	−0.081***
$eaar$	0.043***	0.058***	0.034***	0.024*	0.032**
Δeps	0.027***	0.012	−0.009	−0.047**	−0.055**
constant	0.001	0.119***	0.111***	0.110***	0.162***
Nr. obs.	113,109	113,109	113,109	113,109	113,109
R-squared	0.7%	0.8%	1.1%	1.8%	2.0%

TABLE A6 CONTINUED.

Panel B: Insiders' demand and private information

	q1		q3		q4	
	$nispos$	$nisneg$	$nispos$	$nisneg$	$nispos$	$nisneg$
	$\Delta earn$ *as measure of long-term information*					
$ssl \times longh$ (d_{++})	-0.167***	-0.024	-0.149***	0.009	-0.160***	0.021
$ssl \times longl$ (d_{+-})	-0.142***	-0.047*	-0.244***	-0.004	-0.205***	-0.025
$ssh \times longh$ (d_{-+})	0.175***	0.107***	0.261***	0.116***	0.243***	0.100***
$ssh \times longl$ (d_{--})	0.114**	0.113***	0.227***	0.083***	0.211***	0.067***
$ssm \times longh$	-0.052*	0.046***	-0.071**	0.053***	-0.011	0.053***
$ssm \times longl$	0.044	0.018*	0.089***	0.011	0.057*	0.019*
$ssl \times longm$	-0.173***	-0.007	-0.150***	-0.034**	-0.153***	-0.030*
$ssh \times longm$	0.182***	0.050***	0.127***	0.059***	0.164***	0.071***
$pastret$	1.100***	-0.194***	1.144***	-0.196***	1.161***	-0.197***
$eaar$	5.689***	-0.899***	5.716***	-0.875***	5.747***	-0.894***
Δeps	-0.593***	0.316***	-0.600***	-0.324***	-0.552***	-0.337***
constant	18.662***	0.228***	18.789***	0.230***	18.729***	0.231***
Nr. obs.	111,354	111,354	104,036	104,036	100,504	100,504
R-squared	3.7%	1.8%	3.8%	1.7%	3.8%	1.8%

	$eaar$ *as a measure of long-term information*					
$ssl \times longh$ (d_{++})	-0.192***	0.018	-0.190***	0.022	-0.144***	-0.027
$ssl \times longl$ (d_{+-})	-0.151***	-0.037	-0.162***	-0.044	-0.142***	-0.024
$ssh \times longh$ (d_{-+})	0.156***	0.103***	0.212***	0.079***	0.239***	0.084***
$ssh \times longl$ (d_{--})	0.285***	0.067***	0.237***	0.053***	0.237***	0.069***
$ssm \times longh$	-0.018	0.026***	0.018	0.012	0.008	0.002
$ssm \times longl$	0.067**	0.004	0.069**	-0.015	0.043	0.005
$ssl \times longm$	-0.146***	-0.034**	-0.140***	-0.044***	-0.168***	-0.032**
$ssh \times longm$	0.140***	0.054***	0.164***	0.058***	0.153***	0.053***
$pastret$	1.098***	-0.192***	1.138***	0.193***	1.155***	-0.196***
$eaar$	5.693***	-0.900***	5.735***	-0.878***	5.773***	-0.891***
Δeps	-0.528***	-0.352***	-0.535***	-0.369***	-0.513***	-0.392***
constant	18.691***	0.249***	18.605***	0.277***	18.547***	0.275***
Nr. obs.	111,482	111,482	104,415	104,415	100,840	100,840
R-squared	3.7%	1.7%	3.8%	1.7%	3.8%	1.7%

TABLE A7

Predictability of informed trading using residual relative short selling.

This table presents results of informed traders' demands considering residual relative short selling (ess). As in Diether et al. (2009), we compute ess as the residual of regression $ss_{i,t}=\alpha_i+\beta_i\times oimb^+_{it}+\varepsilon_{i,t}$, which is run every day for every stock. ss is the relative short selling corresponding to the number of shares shorted divided by the number of shares outstanding and $oimb^+$ is the daily positive order imbalance of a stock with negative values replaced with zeros. $oimb$ is computed as daily purchases minus sales scaled by daily volume. Purchases and sales are defined as in Lee and Ready (1991). Panel A compares the distribution of residual relative short selling and insider trading with our original classification. Panel B presents estimates of sensitivities between future returns and informed traders' demands (as in Panel A of Table 4) considering ess. Panel C presents estimates of sensitivities between net insider sales and short- and long-term information (as in Table A1) considering ess. As in previous specifications, we include firm and year fixed effects and we compute robust standard errors that are clustered within firms. All variables are defined in Appendix in the main text. ***, ** and * indicate significance at the 1-, 5- and 10-percent levels. The sample runs from July 2006 to December 2017.

Panel A: Distribution of categories across the sample

residual categories	# of quarters	*original relative short selling and insider trading categories*								
		$ip\times ssh$	$ip\times ssm$	$ip\times ssl$	$is\times ssh$	$is\times ssm$	$is\times ssl$	$noit\times ssh$	$noit\times ssm$	$noit\times ssl$
$ip\times essh$	1,887	78.17%	21.67%	0.16%						
$ip\times essm$	4,995	7.99%	67.37%	24.64%						
$ip\times essl$	1,338	7.32%	78.18%	14.50%						
$is\times essh$	5,219				76.76%	23.17%	0.08%			
$is\times essm$	11,538				11.96%	81.46%	6.58%			
$is\times essl$	4,735				8.34%	87.69%	3.97%			
$noit\times essh$	14,781							74.51%	25.36%	0.13%
$noit\times essm$	49,073							7.29%	69.66%	23.05%
$noit\times essl$	14,990							6.53%	82.09%	11.37%
$Total$	108,556									

Panel B: Informed traders' demand interactions

	h=20	h=40	h=60	h=130	h=250
$ip\times essl$ (b_{++})	0.022***	0.029***	0.041***	0.064***	0.077***
$ip\times essh$ (b_{+-})	0.011***	0.011***	0.016***	0.028***	0.028***
$is\times essl$ (b_{-+})	-0.003**	-0.001	-0.002	-0.006	-0.005
$is\times essh$ (b_{--})	-0.007***	-0.012***	-0.022***	-0.039***	-0.047***
$is\times essm$	-0.005***	-0.010***	-0.014***	-0.023***	-0.028***
$ip\times essm$	0.013***	0.014***	0.017***	0.031***	0.031***
$noit\times essh$	-0.002	-0.005***	-0.007***	-0.014***	-0.018***
$noit\times essl$	0.001	0.006***	0.012***	0.025***	0.035***
$pastret$	-0.005***	-0.010***	-0.028***	-0.053***	-0.074***
$eaar$	0.044***	0.067***	0.044***	0.026*	0.037**
Δeps	0.039***	0.036***	0.028**	0.004	-0.003
Constant	-0.103	-0.056	-0.090	-0.193	-0.222
Nr. obs.	108,556	108,556	108,556	108,556	108,556
R-squared	0.7%	0.9%	1.0%	1.7%	1.9%

TABLE A7 CONTINUED.

Panel C: Insiders' demand and private information

	q1		q3		q4	
	$nispos$	$nisneg$	$nispos$	$nisneg$	$nispos$	$nisneg$
	$\Delta earn$ as measure of long-term information					
$essl{\times}longh$ (d_{++})	-0.150***	0.049***	-0.138**	0.034*	-0.075	0.042**
$essl{\times}longl$ (d_{+-})	-0.078	0.002	-0.138***	0.000	-0.118**	0.020
$essh{\times}longh$ (d_{-+})	0.104*	0.127***	0.144***	0.118***	0.137**	0.102***
$essh{\times}longl$ (d_{--})	0.069	0.094***	0.151**	0.071***	0.122**	0.056***
$essm{\times}longh$	-0.018***	0.048***	-0.028	-0.044***	0.019	0.044***
$essm{\times}longl$	0.049	0.020*	0.081**	0.014	0.085**	0.030**
$essl{\times}longm$	-0.079**	-0.010	-0.057	-0.006	-0.078**	-0.012
$essh{\times}longm$	0.138***	0.044***	0.100***	0.049***	0.140***	0.060***
$pastret$	1.096***	-0.196***	1.147***	-0.202***	1.170***	-0.203***
$eaar$	5.589***	-0.921***	5.677***	-0.910***	5.737***	-0.924***
Δeps	-0.621***	-0.296***	-0.645***	-0.321***	-0.622***	-0.344***
constant	9.087	0.222***	9.105	0.239***	9.102	0.236***
Nr. obs.	106,845	106,845	99,549	99,549	96,018	96,018
R-squared	3.7%	1.8%	3.8%	1.8%	3.8%	1.8%
	$eaar$ as a measure of long-term information					
$essl{\times}longh$ (d_{++})	-0.071	0.017	-0.122**	0.001	-0.123**	-0.000
$essl{\times}longl$ (d_{+-})	-0.072	-0.002	-0.029	-0.022	-0.058	-0.007
$essh{\times}longh$ (d_{-+})	0.081	0.099***	0.156***	0.074***	0.166***	0.061***
$essh{\times}longl$ (d_{--})	0.204***	0.060***	0.160***	0.044**	0.144**	0.061***
$essm{\times}longh$	-0.005	0.026**	0.009	0.015	0.018	0.004
$essm{\times}longl$	0.132***	0.002	0.023	-0.009	0.055*	-0.008
$essl{\times}longm$	-0.072**	-0.011	-0.104***	-0.004	-0.087**	-0.015
$essh{\times}longm$	0.136***	0.050***	0.088**	0.055***	0.112***	0.044***
$pastret$	1.093***	-0.195***	1.141***	-0.200***	1.160***	-0.201***
$eaar$	5.598***	-0.922***	5.688***	-0.910***	5.748***	-0.920***
Δeps	-0.573***	-0.338***	-0.575***	-0.368***	-0.586***	-0.392***
constant	9.122	0.228***	9.078	0.262***	9.017	0.259***
Nr. obs.	106,959	106,959	99,904	99,904	96,342	96,342
R-squared	3.7%	1.8%	3.8%	1.8%	3.8%	1.8%

TABLE A8

Opportunistic insider trading: removing plan trades.

This table replicates the results of Table A3 (Panel B) and Table A4 for opportunistic insider trades that are not classified as plan trades. We identify insiders who trade in the same calendar month in at least 3 consecutive years. Then, we classify all trades by the insider following this 3-year period as routine if they happen in the same month. Trades made in non-routine months are classified as opportunistic. Then we drop trades that are executed under Rule 10b5-1. Panel A presents estimates of regression
$aret_{k,t+5,t+6+h}=b_{++}ipopp_{kt}\times ssl_{kt}+b_{+-}ipopp_{kt}\times ssh_{kt}+b_{-+}isopp_{kt}\times ssl_{kt}+b_{--}isopp_{kt}\times ssh_{kt}+X_{kt}\gamma+u_{kt}$.
Panel B presents estimates of two regressions
$nisneg_{k,t,t+5}=d_{++}ssl_{kt}\times longh_{kt}+d_{+-}ssl_{kt}\times longl_{kt}+d_{-+}ssh_{kt}\times longh_{kt}+d_{--}ssh_{kt}\times longl_{kt}+X_{kt}\gamma+u_{kt}$
and
$nispos_{k,t,t+5}=d_{++}ssl_{kt}\times longh_{kt}+d_{+-}ssl_{kt}\times longl_{kt}+d_{-+}ssh_{kt}\times longh_{kt}+d_{--}ssh_{kt}\times longl_{kt}+X_{kt}\gamma+u_{kt}$,
where $nisneg$ and $nispos$ in basis points are for opportunistic non-plan trades. $aret_{k,t+5,t+6+h}$ is abnormal return in stock k from t+5 to t+6+h after earnings announcement t (in percent). $isopp_{kt}$ and $ipopp_{kt}$ ($isrt_{kt}$ and $iprt_{kt}$) denote dummy variables for intensive opportunistic (routine) net insider sales and purchases, respectively, in firm k over the $(0,+5)$ response window after the earnings announcement date t. $noit_{kt}$ refers to no insider trades, ssh_{kt}, ssl_{kt} and ssm_{kt} to short selling in the highest, lowest and the remaining three middle quintiles, respectively, in firm k over the $(0,+5)$ response window after the earnings announcement date t. In Panel A, X_{kt} includes the past 12-month return $pastret$, current quarter earnings announcement abnormal return $eaar$, earnings per share change Δeps, interactions $noit\times ssl$, $noit\times ssh$, $ip\times ssm$, $is\times ssm$, as well as firm and year fixed effects. In Panel B, X_{kt} includes the past 12-month return $pastret$, current quarter earnings announcement abnormal return $eaar$, earnings per share change Δeps, interactions $ssm\times longh$, $ssm\times longl$, $ssl\times longm$, $ssl\times longm$, and firm and year fixed effects. Abnormal returns are adjusted for the corresponding 5×5 size and book-to-market portfolio return. Robust standard errors are clustered within firms. All variables are defined in Appendix in the main text. ***, ** and * indicate significance at the 1-, 5- and 10-percent levels. The sample runs from July 2006 to December 2017.

Panel A: Disagreement between informed traders

	h=20	h=40	h=60	h=130	h=250
$ipopp\times ssl$ (b_{++})	0.021***	0.027***	0.038***	0.056***	0.064***
$ipopp\times ssh$ (b_{+-})	0.015***	0.012***	0.013***	0.021***	0.018***
$isopp\times ssl$ (b_{-+})	−0.002	0.006	0.006	0.007	0.013
$isopp\times ssh$ (b_{--})	−0.007***	−0.013***	−0.027***	−0.053***	−0.064***
$ipopp\times ssm$	0.013***	0.016***	0.021***	0.036***	0.037***
$isopp\times ssm$	−0.006***	−0.008***	−0.013***	−0.022***	−0.029***
$noit\times ssl$	0.005***	0.011***	0.018***	0.039***	0.048***
$noit\times ssh$	−0.002*	−0.006***	−0.010***	−0.022***	−0.029***
$pastret$	−0.004***	−0.009***	−0.026***	−0.050***	−0.071***
$eaar$	0.046***	0.071***	0.050***	0.043***	0.052***
Δeps	0.033***	0.024***	0.022*	0.001	0.005
constant	−0.106	−0.061	−0.097	−0.206	−0.236
Nr. obs.	132,240	132,240	132,240	132,240	132,240
R-sq.	0.7%	0.9%	1.1%	1.8%	1.9%

TABLE A8 CONTINUED.

Panel B: Opportunistic insiders' demand and private information

	$nispos$ (sales)	$nisneg$ (purchases)
$ssl{\times}longh$ (d_{++})	-0.124^{***}	0.013
$ssl{\times}longl$ (d_{+-})	-0.177^{***}	-0.025
$ssh{\times}longh$ (d_{-+})	0.183^{***}	0.103^{***}
$ssh{\times}longl$ (d_{--})	0.153^{***}	0.059^{***}
$ssm{\times}longh$	-0.004	0.044^{***}
$ssm{\times}longl$	0.054^{*}	0.024^{**}
$ssl{\times}longm$	-0.153^{***}	-0.046^{***}
$ssh{\times}longm$	0.125^{***}	0.069^{***}
$pastret$	0.961^{***}	-0.196^{***}
$eaar$	4.630^{***}	-0.873^{***}
Δeps	-0.444^{***}	-0.310^{***}
constant	8.486	0.232^{***}
Nr. obs.	115,997	115,997
R-squared	3.3%	1.6%

TABLE A9

Results with response window (0,+20).

Panel A shows frequencies and relative shares traded in basis points over the $(0,+20)$ response window across nine interaction categories, split into three sets corresponding to insider sales (is), insider purchases (ip) and no net insider trading ($noit$), respectively. Each of these variables is interacted with the short-selling categories of high short selling (ssh), medium short selling (ssm) and low short selling (ssl). Panels B and C replicate the results in Table 4 (Panel A) and Table A1, respectively, considering insider and short-selling activity in the $(0,+20)$ response window. Due to the different response window, abnormal returns adjusted by the corresponding quintile size and book-to-market portfolio return are compounded starting at day 21 after earnings announcement and ending h days later. All variables are defined in the Appendix in the main text. All regressions include firm and year fixed effects. Robust standard errors are clustered within firms. ***, ** and * indicate significance at the 1-, 5- and 10-percent levels. The sample runs from July 2006 to December 2017.

Panel A: Summary statistics

Category	# of quarters	% of all quarters	within group fraction	$relss$	$nispos$	$nisneg$
$is \times ssh$	10,208	7.72%	25.26%	37.71	5.06	0.00
$is \times ssm$	28,022	21.19%	69.33%	8.96	3.95	0.00
$is \times ssl$	2,186	1.65%	5.41%	0.55	5.46	0.00
is	40,416	30.56%				
$ip \times ssh$	3,373	2.55%	19.65%	38.63	0.00	0.00
$ip \times ssm$	9,805	7.41%	57.13%	7.98	0.00	0.00
$ip \times ssl$	3,986	3.01%	23.22%	0.40	0.00	0.00
ip	17,164	12.97%				
$noit \times ssh$	11,995	9.07%	16.07%	38.13	0.00	0.00
$noit \times ssm$	44,389	33.57%	59.45%	7.40	0.00	0.00
$noit \times ssl$	18,276	13.82%	24.48%	0.41	0.00	0.00
$noit$	74,660	56.46%				
total	132,240	100%				
unconditional average				12.41	1.32	0.37

Panel B: Inform traders' demand interactions

	h=20	h=40	h=60	h=130	h=250
$ip \times ssl$ (b_{++})	0.005***	0.008***	0.037***	0.057***	0.071***
$ip \times ssh$ (b_{+-})	0.005***	0.004*	0.015***	0.033***	0.044***
$is \times ssl$ (b_{-+})	0.002	0.004	0.003	-0.001	-0.007
$is \times ssh$ (b_{--})	-0.006***	-0.010***	-0.032***	-0.054***	-0.064***
$ssm \times is$	-0.003***	-0.005***	-0.016***	-0.025***	-0.031***
$ssm \times ip$	0.004***	0.005***	0.015***	0.024***	0.024***
$noit \times ssh$	-0.003***	-0.008***	-0.016***	-0.028***	-0.035***
$noit \times ssl$	0.005***	0.006***	0.020***	0.045***	0.057***
constant	-0.001	-0.003	-0.115	-0.211	-0.200
Nr. obs.	132,240	132,240	132,240	132,240	132,240
R-squared	0.5%	0.7%	1.4%	2.0%	2.0%

TABLE A9 CONTINUED.

Panel C: Insiders' demand and private information	q1		q3		q4	
	$nispos$	$nisneg$	$nispos$	$nisneg$	$nispos$	$nisneg$
	$\Delta earn$ as measure of long-term information					
$ssl{\times}longh$ (d_{++})	-0.310***	0.037	-0.333***	0.061	-0.347***	0.086**
$ssl{\times}longl$ (d_{+-})	-0.295***	-0.033	-0.360***	-0.009	-0.369***	-0.020
$ssh{\times}longh$ (d_{-+})	0.299***	0.187***	0.243***	0.162***	0.426***	0.202***
$ssh{\times}longl$ (d_{--})	0.320***	0.111***	0.372***	0.076***	0.333***	0.073***
$ssm{\times}longh$	-0.098**	0.053***	-0.094**	0.056***	-0.060	0.059***
$ssm{\times}longl$	0.060	0.041***	0.031	0.013***	0.014	0.041**
$ssl{\times}longm$	-0.360***	-0.016	-0.344***	-0.030	-0.336***	-0.022
$ssh{\times}longm$	0.373***	0.068***	0.374***	0.087***	0.323***	0.084***
$pastret$	1.437***	-0.341***	1.509***	-0.346***	1.543***	-0.351***
$eaar$	5.799***	-1.274***	5.895***	-1.262***	5.974***	-1.284***
Δeps	-0.315**	-0.446***	-0.216	-0.521***	-0.232	-0.562***
constant	7.151	0.398***	7.063	0.420***	7.0681	0.401
Nr. obs.	129,812	129,812	120,466	120,466	115,997	115,997
R-squared	3.3%	2.1%	3.4%	2.1%	3.4%	2.1%
	$eaar$ as measure of long-term information					
$ssl{\times}longh$ (d_{++})	-0.316***	-0.031	-0.348***	0.073*	-0.295***	0.001
$ssl{\times}longl$ (d_{+-})	-0.290***	-0.067*	-0.381***	-0.005	-0.387***	-0.001
$ssh{\times}longh$ (d_{-+})	0.423***	0.159***	0.440***	0.112***	0.368***	0.113***
$ssh{\times}longl$ (d_{--})	0.485***	0.072***	0.442***	0.066**	0.362***	0.066**
$ssm{\times}longh$	-0.037	0.049***	0.030	0.018	0.0101	-0.001
$ssm{\times}longl$	0.162***	0.006	0.100***	-0.007	0.058	-0.011
$ssl{\times}longm$	-0.298***	-0.000	-0.273***	-0.046*	-0.306***	-0.030
$ssh{\times}longm$	0.309***	0.076***	0.343***	0.084***	0.373***	0.072***
$pastret$	1.437***	-0.340***	1.497***	-0.340***	1.535***	-0.346***
$eaar$	5.834***	-1.276***	5.923***	-1.269***	5.970***	-1.276***
Δeps	-0.234*	-0.505***	-0.078	-0.595***	-0.204	-0.663***
constant	7.122	0.376***	7.099	0.438***	6.995	0.444***
Nr. obs.	129,923	129,923	120,884	120,884	116,382	116,382
R-squared	3.3%	2.1%	3.4%	2.1%	3.4%	2.1%

TABLE A10

Results with market-adjusted returns.

This table replicates Table 4 using market-adjusted buy-and-hold abnormal returns as the dependent variable. Abnormal returns are computed by subtracting the market index return from the stock return and are compounded starting on day 6 after earnings announcement and ending h days later. All regressions include firm and year fixed effects. All variables are defined in the Appendix in the main text. Robust standard errors are clustered within firms. ***, ** and * indicate significance at the 1-, 5- and 10-percent levels. The sample runs from July 2006 to December 2017.

	Informed traders' demand interactions				
	h=20	h=40	h=60	h=130	h=250
$ip{\times}ssl$ (b_{++})	0.021***	0.028***	0.042***	0.069***	0.105***
$ip{\times}ssh$ (b_{+-})	0.016***	0.012***	0.011**	0.013	0.007
$is{\times}ssl$ (b_{-+})	-0.002	0.005	0.005	0.010	0.038***
$is{\times}ssh$ (b_{--})	-0.008***	-0.018***	-0.034***	-0.068***	-0.110***
$ssm{\times}is$	-0.006***	-0.010***	-0.016***	-0.027***	-0.047***
$ssm{\times}ip$	0.012***	0.015***	0.021***	0.039***	0.047***
$noit{\times}ssh$	-0.003**	-0.009***	-0.015***	-0.031***	-0.057***
$noit{\times}ssl$	0.006***	0.013***	0.023***	0.053***	0.100***
constant	-0.091	-0.060	-0.093	-0.210	-0.431*
Nr. obs.	132,185	132,185	132,185	132,185	132,185
R-squared	1.2%	2.1%	2.6%	4.2%	5.6%

TABLE A11

Pre- versus post-SOX analysis

Panel A presents estimates of the regression:
$aret_{k,t+5,t+6+h}{=}b_{++}(ip_{kt}{\times}ssl_{kt}){+}b_{+-}(ip_{kt}{\times}ssh_{kt}){+}b_{-+}(is_{kt}{\times}ssl_{kt}){+}b_{--}(is_{kt}{\times}ssh_{kt}){+}c_{++}(ip_{kt}{\times}ssl_{kt}{\times}S_t)$
${+}c_{+-}(ip_{kt}{\times}ssh_{kt}{\times}S_t){+}c_{-+}(is_{kt}{\times}ssl_{kt}{\times}S_t){+}c_{--}(is_{kt}{\times}ssh_{kt}{\times}S_t){+}X_{kt}\,\gamma{+}u_{kt},$
where $aret_{k,t+5,t+6+h}$ denotes abnormal return in stock k from t+5 to t+6+h after earnings announcement t (in percent). is_{kt}, ip_{kt}, and $noit_{kt}$ denote dummies for intensive net insider sales, purchases, and no insider trades, respectively, in firm k over the $(0,{+}5)$ response window after the earnings announcement date t; and ssh_{kt}, ssl_{kt}, and ssm_{kt} denote short selling in the highest, lowest and the remaining three middle quintiles, respectively, in firm k over the $(0,{+}5)$ response window after the earnings announcement date t. S_t is the post-SOX dummy variable equal to one for observations after July 30, 2002. X_{kt} includes the past 12-month return $pastret$, current quarter earnings announcement abnormal return $eaar$, earnings per share change Δeps, interactions $noit{\times}ssl$, $noit{\times}ssh$, $ip{\times}ssm$, $is{\times}ssm$, and firm and year fixed effects. Robust standard errors are clustered within firms. Columns b (c) contain coefficient estimates of variables not interacted (interacted) with S_t. Row $b_{-+}{+}c_{-+}$ shows the F-test for $b_{-+}{+}c_{-+}{=}0$. Panel B shows constant net dollar profits per trade defined as the average total insider trades for each category of the inflation-adjusted dollar value of net insider sales or purchases in 2017 US dollars multiplied by the abnormal return over horizon h. The value of dollar profits for sales is multiplied by -1 to get a positive profit when future return is negative. Categories for no insider trading are not defined and the regressions do not include any control variables. Columns *pre* (*post-pre*) contain coefficient estimates of variables not interacted (interacted) with S_t. All variables are defined in Appendix. ***, ** and * indicate significance at the 1-, 5- and 10-percent levels. The estimation is based on the short-selling data from Compustat and the sample runs from January 1986 to December 2017.

	h=20		h=40		h=60		h=130		h=250	
	Panel A: Future returns pre-SOX versus post-SOX									
	b	c	b	c	b	c	b	c	b	c
$ip{\times}ssl$	0.007**	0.010**	0.018***	0.008	0.027***	0.013*	0.033***	0.040***	0.033***	0.079***
$ip{\times}ssh$	0.012***	0.001	0.014***	−0.004	0.017***	−0.006	0.025***	−0.011	0.050***	−0.035**
$is{\times}ssl$	−0.011***	0.009*	−0.014**	0.018***	−0.011	0.021**	−0.006	0.023*	0.014	0.022
$is{\times}ssh$	−0.001	−0.009***	−0.010***	−0.005*	−0.016***	−0.009**	−0.023***	−0.025***	−0.013	−0.065***
$noit{\times}ssh$	0.000	−0.003**	−0.004**	−0.004**	−0.003	−0.010***	−0.002	−0.023***	0.001	−0.041***
$noit{\times}ssl$	−0.003**	0.004***	−0.001	0.011***	0.002	0.017***	0.013***	0.034***	0.023***	0.061***
$is{\times}ssm$	−0.004***	−0.001	−0.009***	0.001	−0.012***	−0.001	−0.018***	−0.007*	−0.027***	−0.018***
$ip{\times}ssm$	0.011***	0.002	0.017***	−0.005*	0.019***	−0.002	0.019***	0.005	0.015**	0.019**
$pastret$	0.003***	−0.009***	0.009***	−0.016***	0.010***	−0.023***	0.009**	−0.043***	−0.028***	−0.042***
$eaar$	0.043***	0.005	0.095***	−0.020	0.140***	−0.072**	0.207***	−0.143***	0.184***	−0.122**
Δeps	0.035***	−0.005	0.051***	−0.014	0.067***	−0.028**	0.099***	−0.058***	0.140***	−0.099***
constant	−0.010***	0.007	−0.010**	0.001	−0.017***	0.006	−0.040**	0.016	−0.068***	0.023
Nr. obs.	309,997		309,997		309,997		309,997		309,997	
R-sq.	6.10%		6.90%		8.20%		13.40%		19.10%	
$b_{-+}{+}c_{-+}$	-0.002**		0.004***		0.010**		0.017		0.036	
	Panel B: Net dollar profits pre-SOX versus post-SOX									
	pre	post−pre	pre	post−pre	pre	post−pre	pre	post−pre	pre	post−pre
$ip{\times}ssl$	$94	−$620*	−$99	−$275	$345	−$580	$2,764**	−$2,205	$5,661***	−$4,251**
$ip{\times}ssm$	−$519***	−$431**	−$809**	$338	−$530	$235	$1,656**	−$863	$4,081***	−$1,539
$ip{\times}ssh$	−$822***	−$1,211***	−$1,939***	$1,107	−$2,541***	$1,260	−$1,378	$490	−$1,144	$1,071
$is{\times}ssl$	$2,376***	−$1,207***	$4,657***	−$1,673*	$6,325***	−$3,392***	$8,387***	−$1,023	$15,903***	−$2,279
$is{\times}ssm$	$391***	$685***	$4,106***	−$991***	$5,620***	−$320	$10,858***	−$1,729***	$18,755***	−$4,831***
$is{\times}ssh$	−$1,325***	$2,779***	$3,467***	−$888**	$1,068**	$2,060***	$150	$5,768***	−$1,127	$10,083***

TABLE A12

Pre- vs post-SOX: Interpolated short selling activity

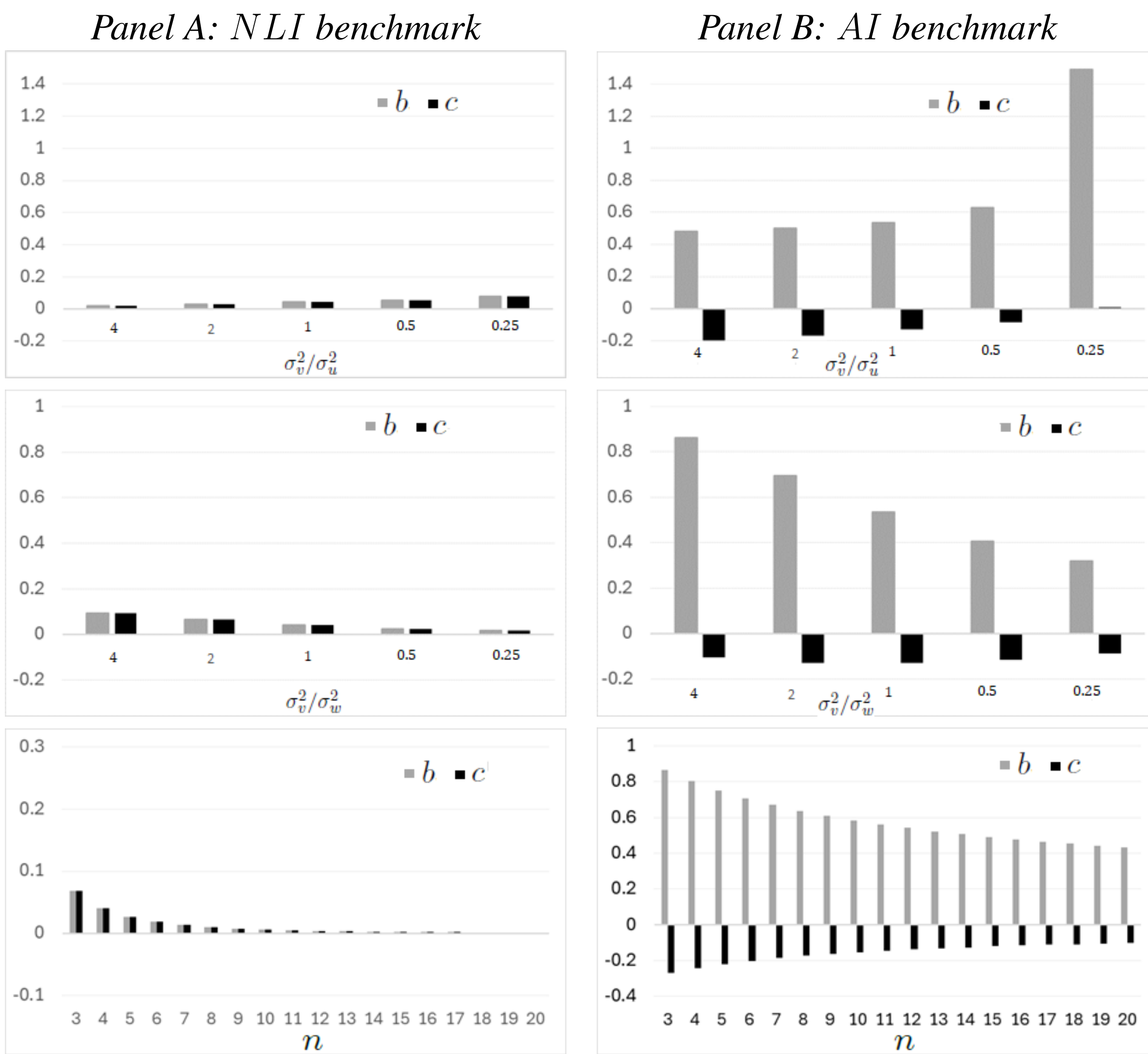
Panel A presents estimates of regression
$aret_{k,t+5,t+6+h}$=$b_{++}(ip_{kt}\times ssl_{kt})$+$b_{+-}(ip_{kt}\times ssh_{kt})$+$b_{-+}(is_{kt}\times ssl_{kt})$+$b_{--}(is_{kt}\times ssh_{kt})$+$c_{++}(ip_{kt}\times ssl_{kt}\times S_t)$
+$c_{+-}(ip_{kt}\times ssh_{kt}\times S_t)$+$c_{-+}(is_{kt}\times ssl_{kt}\times S_t)$+$c_{--}(is_{kt}\times ssh_{kt}\times S_t)$+$X_{kt}\,\gamma$+$u_{kt}$,
where $aret_{k,t+5,t+6+h}$ denotes abnormal return in stock k from t+5 to t+6+h after earnings announcement t. is_{kt}, ip_{kt} and $noit_{kt}$ denote dummy variables for intensive net insider sales, purchases and no insider trades, respectively, in firm k over the $(0,+5)$ response window after the earnings announcement date t; and ssh_{kt}, ssl_{kt} and ssm_{kt} denote short selling in the highest, lowest and the remaining three middle quintiles, respectively. S_t is the post-SOX dummy variable equal to one for observations after July 30, 2002. X_{kt} includes the past 12-month return $pastret$, current quarter earnings announcement abnormal return $eaar$, earnings per share change Δeps, interactions $noit\times ssl$, $noit\times ssh$, $ip\times ssm$, $is\times ssm$, and firm and year fixed effects. Abnormal returns are adjusted for the corresponding 5×5 size and book-to-market portfolio return. Robust standard errors are clustered within firms. Columns b (c) contain coefficient estimates of informed trading categories not interacted (interacted) with S_t. Row b_{-+}+c_{-+} contains p-values of the F-test for b_{-+}+c_{-+}=0 restriction. Panel B shows constant net dollar profits per trade defined as the average over all insider trades for each category of the inflation-adjusted dollar value of net insider sales or purchases in 2017 US dollars multiplied by the abnormal return over horizon h. The value of dollar profits for sales is multiplied by -1 to get a positive profit when future return is negative. Categories for no insider trading are not defined and the regressions do not include any control variables. Columns *pre* contain coefficient estimates of variables not interacted with S_t while columns *post-pre* contain coefficient estimates of variables interacted with S_t. All variables are defined in Appendix in the main text. ***, ** and * indicate significance at the 1-, 5- and 10-percent levels. The estimation is based on the short-selling data from Compustat and the sample runs from July 1973 to December 2017.

	h=20		h=40		h=60		h=130		h=250	
Panel A: Predictive regression on future returns: pre-SOX vs. post-SOX periods										
	b	c	b	c	b	c	b	c	b	c
$ip\times ssl$	0.008***	0.010***	0.018***	0.009*	0.027***	0.015**	0.033***	0.040***	0.032***	0.079***
$ip\times ssh$	0.010***	0.002	0.014***	−0.005	0.018***	−0.008	0.027***	−0.016	0.054***	−0.042**
$is\times ssl$	−0.005	0.006	−0.011*	0.017***	−0.001	0.014*	0.008	0.011	0.027	0.010
$is\times ssh$	−0.003*	−0.008***	−0.012***	−0.005*	−0.015***	−0.010***	−0.022***	−0.026***	−0.015	−0.065***
$is\times ssm$	0.001	0.002	0.003*	0.008***	0.005**	0.015***	0.015***	0.032***	0.026***	0.058***
$ip\times ssm$	−0.002**	−0.002	−0.005***	−0.004**	−0.003	−0.011***	−0.002	−0.025***	0.002	−0.044***
$noit\times ssh$	0.012***	0.001	0.018***	−0.006**	0.020***	−0.003	0.019***	0.006	0.016**	0.020**
$noit\times ssl$	−0.004***	−0.002	−0.008***	0.000	−0.013***	−0.001	−0.019***	−0.006	−0.027***	−0.019***
$pastret$	0.003***	−0.009***	0.009***	−0.017***	0.010***	−0.023***	0.009***	−0.044***	−0.028***	−0.042***
$eaar$	0.043***	0.004	0.095***	−0.021	0.140***	−0.072**	0.206***	−0.143***	0.183***	−0.122**
Δeps	0.035***	−0.005	0.051***	−0.014	0.066***	−0.028**	0.098***	−0.058***	0.139***	−0.099***
Constant	−0.010***	0.007	−0.011**	0.001	−0.018***	0.007	−0.041***	0.017	−0.069***	0.024
Nr. obs.	309,997		309,997		309,997		309,997		309,997	
R-sq.	6.10%		6.90%		8.30%		13.40%		19.10%	
b_{-+}+c_{-+}	0.011		0.028***		0.015		0.003		-0.017	
Panel B: Net dollar profits: pre-SOX vs. post-SOX periods										
	pre	post−pre	pre	post−pre	pre	post−pre	pre	post−pre	pre	post−pre
$ip\times ssl$	$1	−$569	−$88	−$336	$571	−$872	$3,145***	−$2,626*	$6,471***	−$5,054**
$ip\times ssm$	−$541***	−$403*	−$871**	$366	−$617	$273	$1,495**	−$828	$3,798***	−$1,468
$ip\times ssh$	−$637**	−$1,371***	−$1,726***	$1,045	−$2,477***	$1,403	−$1,219	$739	−$1,020	$1,562
$is\times ssl$	$1,765***	−$706	$4,632***	−$1,837**	$5,462***	−$2,797**	$6,914***	$385	$14,496***	−$763
$is\times ssm$	$146	$890***	$3,782***	−$777**	$5,477***	−$225	$10,511***	−$1,469**	$18,351***	−$4,505***
$is\times ssh$	−$754***	$2,311***	$4,077***	−$1,228***	$1,562**	$1,739***	$1,332	$4,810***	$172	$8,950***

Internet Appendix: Figures

FIGURE A1

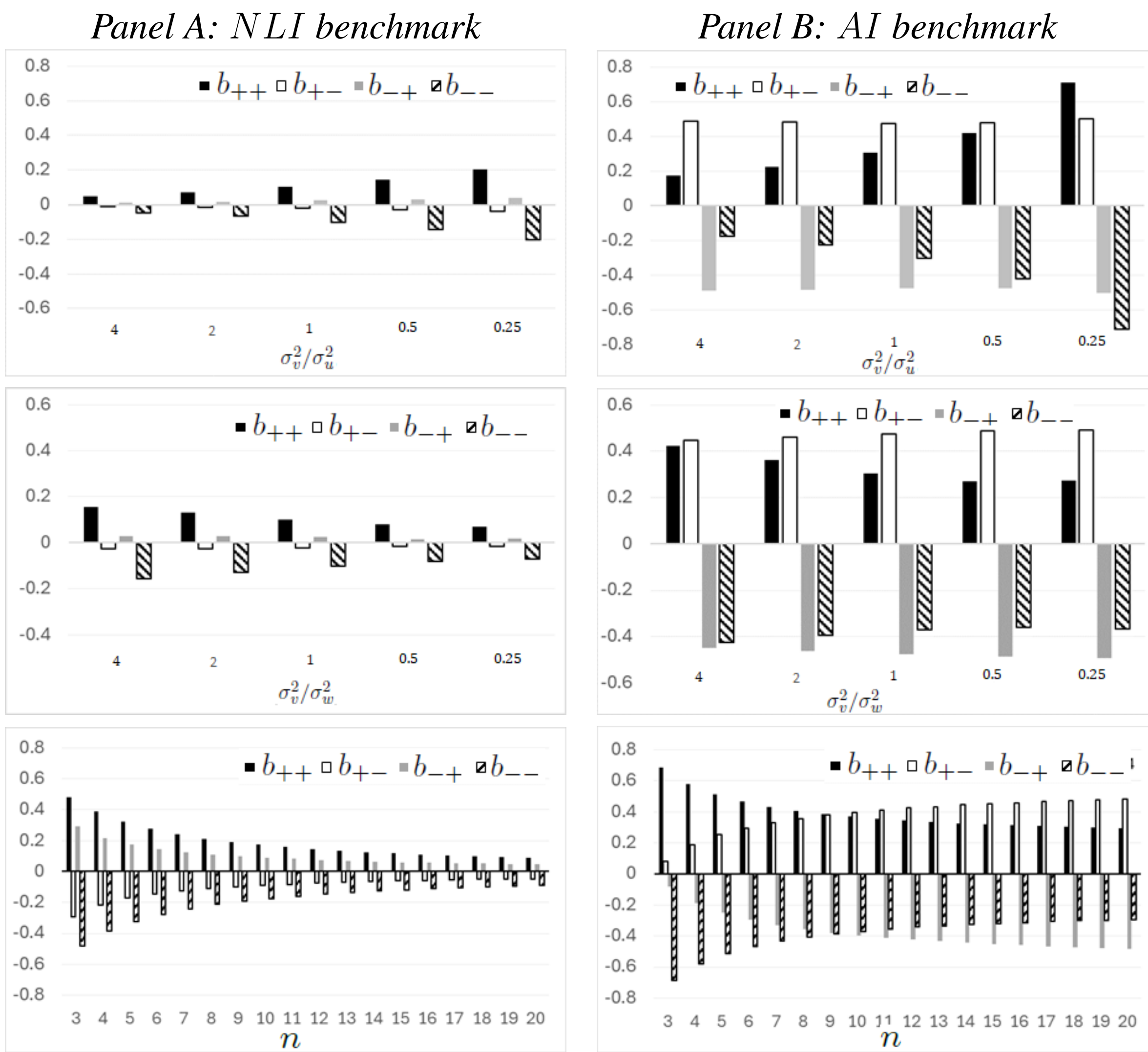
Sensitivity of future returns to order flows in a multivariate regression.



This figure plots the values of sensitivity coefficients b and c of future returns $r_{1,3}$ on insider's and informed traders demands ζ_1 and ξ_1, respectively. The coefficients are computed based on the multivariate regression $r_{1,3}{=}b_0{+}b\zeta_1{+}c\xi_1{+}\epsilon$. Panel A corresponds to the NLI benchmark of the model and Panel B corresponds to the AI benchmark. The primitive parameters are as follows: for the two top graphs $\sigma_v^2/\sigma_w^2{=}1$ and $n{=}3$ while σ_v^2/σ_u^2 changes from 4 down to 0.25; for the two middle graphs $\sigma_v^2/\sigma_u^2{=}1$ and $n{=}3$ while σ_v^2/σ_w^2 changes from 4 down to 0.25; for the two bottom graphs $\sigma_v^2/\sigma_u^2{=}1$ and $\sigma_v^2/\sigma_w^2{=}1$ while n changes from 3 to 20. The rest of the parameters in the models are computed numerically by solving the system of equations (6) and (8) for the NLI and AI benchmark, respectively.

FIGURE A2

Future expected returns conditional on signs of order flows.

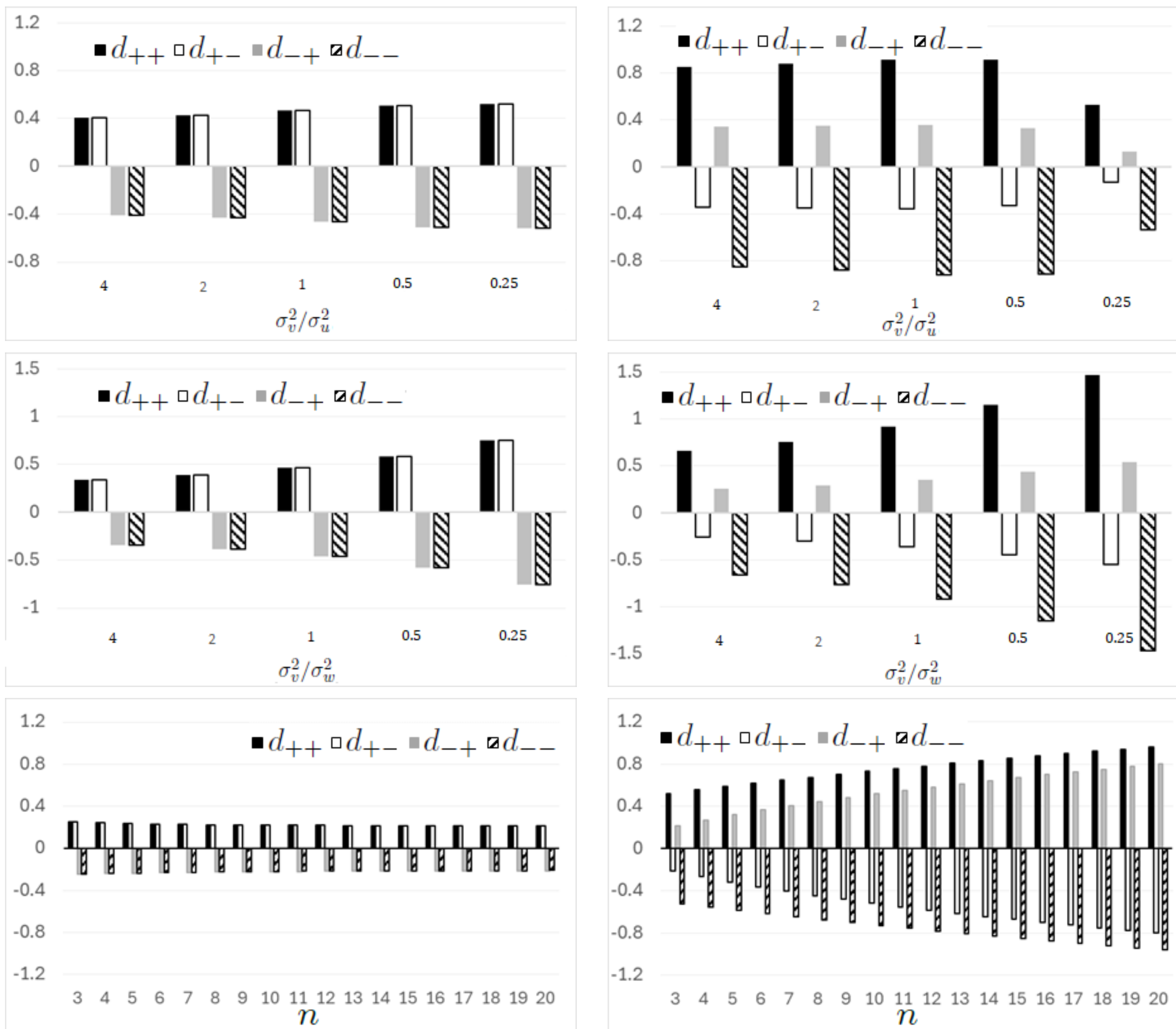


This figure plots the conditional expectations of future returns $r_{1,3}$ conditional on signs of order flow variables ζ_1 and ξ_1. Coefficient b_{++}, b_{+-}, b_{-+} and b_{--} are computed based on the multivariate regression $r_{1,3}=b_{++}\mathbb{I}_{\zeta_1>0,\xi_1>0}+b_{+-}\mathbb{I}_{\zeta_1>0,\xi_1<0}+b_{-+}\mathbb{I}_{\zeta_1<0,\xi_1>0}+b_{--}\mathbb{I}_{\zeta_1<0,\xi_1<0}+\epsilon$. Panel A corresponds to the results derived from the NLI benchmark of the model and Panel B corresponds to the AI benchmark. The primitive parameters are as follows: for the two top graphs $\sigma_v^2/\sigma_w^2=1$ and $n=3$ while σ_v^2/σ_u^2 changes from 4 down to 0.25; for the two middle graphs $\sigma_v^2/\sigma_u^2=1$ and $n=3$ while σ_v^2/σ_w^2 changes from 4 down to 0.25; for the two bottom graphs $\sigma_v^2/\sigma_u^2=1$ and $\sigma_v^2/\sigma_w^2=1$ while n changes from 3 to 20. The rest of the parameters in the models are computed numerically by solving the system of equations (6) and (8) for the NLI and AI benchmark, respectively.

FIGURE A3

Expected demand of the insider conditional on signs of innovations.

Panel A: NLI benchmark *Panel B: AI benchmark*



This figure plots the conditional expectations of insider's demand ζ_1 conditional on signs of fundamental innovations v_1 and v_2. Panel A corresponds to the NLI benchmark of the model and Panel B corresponds to the AI benchmark. The primitive parameters are as follows: for the two top graphs σ_v^2/σ_w^2=1 and n=3 while σ_v^2/σ_u^2 changes from 4 down to 0.25; for the two middle graphs σ_v^2/σ_u^2=1 and n=3 while σ_v^2/σ_w^2 changes from 4 down to 0.25; for the two bottom graphs σ_v^2/σ_u^2=1 and σ_v^2/σ_w^2=1 while n changes from 3 to 20. The rest of the parameters in the models are computed numerically by solving the system of equations (6) and (8) for the NLI and AI benchmark, respectively.