Negative Information Revelation: Informed Sales Meet Short Sales

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ABSTRACT

Existing literature concludes that binding short-sale constraints limit the revelation of negative information but overlooks negative information in informed sales. Our study, based on data on informed institutional and illegal insider sales, reveals that informed sales can significantly weaken the impact of short-sale constraints. We provide evidence of a lead-lag information transmission mechanism, with informed sales unidirectionally leading short-sales, other institutional sales, and the stringency of short-sale constraints. These findings are supported by a rational expectations equilibrium model. Our analysis underscores the undervalued role of informed sales in understanding overpricing and market bubbles.

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1 Introduction

Short selling in practice is often constrained and costly for most investors. Constraints/costs include limits on the number of shares that can be shorted, significant borrowing fees, the risk of involuntary covering due to stock loan recalls, and the potential for short squeezes. These limitations and costs are collectively known as short-sale constraints. The existing literature emphasizes the impact of these constraints, highlighting that they restrict negative information revelation (e.g., Diamond and Verrecchia (1987), Hong and Stein (2003)), simply because short-sale constraints prevent short sellers from trading to the full extent to reveal their information.[1] Empirical evidence seems to support this conclusion, with studies showing that more stringent short-sale constraints predict lower future returns across international markets and various asset classes.[2] This conclusion is widely accepted and used to explain market inefficiencies, such as overpricing and market bubbles.[3]

However, by focusing primarily on short sales, the existing literature has largely overlooked the valuable information conveyed by informed sales and the economic importance of such sales. Additionally, while the empirical evidence of lower future returns with stricter short-sale constraints aligns with the conclusion, it does not necessarily validate it itself. In contrast, our rational expectations equilibrium model and empirical analysis underscore the significance of institutional sales in revealing negative information and comprehending market inefficiencies, such as overpricing and market bubbles. They also demonstrate that short-sale constraints stringency and future returns can be negatively correlated even when short sellers do not have any private information.

Intuitively, active investors who sell but do not short sell may acquire more precise infor-

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[1]See also Hong, Scheinkman, and Xiong (2006), Blocher, Reed, and VanWesep (2013).

[2]See, e.g., Figlewski (1981), Senchack and Starks (1993), Jones and Lamont (2002), Ofek and Richardson (2003), Asquith, Pathak, and Ritter (2005), Sorescu, Boehme, and Danielson (2006), Porras Prado, Saffi, and Sturgess (2016), Patatoukas, Sloan, and Wang (2022), Ramachandran and Tayal (2021), and Boehmer, Huszár, Wang, Zhang, and Zhang (2022).

[3]See, e.g., Pontiff (1996), Hong, Lim, and Stein (2000), Geczy, Musto, and Reed (2002), Diether, Malloy, and Scherbina (2002), Ofek and Richardson (2003), Hong and Stein (2003), Scheinkman and Xiong (2003), Nagel (2005), Bai, Chang, and Wang (2006), Hirshleifer, Teoh, and Yu (2011), Stambaugh, Yu, and Yuan (2012, 2015), Patatoukas et al. (2022), Dong, Li, Rapach, and Zhou (2022).

mation due to a higher stake at risk or lower information acquisition cost. Considering the information contained in these informed sales, short-sale constraints do not significantly impede negative information revelation. To empirically evaluate this notion, we find that the stringency of short-sale constraints predicts lower average returns (negative predictability), as documented in existing literature. However, when we condition on large informed institutional sales, this negative predictability weakens significantly or disappears entirely, indicating the weakening effect of informed sales. We propose and support an information transmission mechanism where a small group of informed sellers can reveal and incorporate negative information, irrespective of short-sale constraints. Our rational expectations model further substantiates these empirical findings and the hypothesized mechanism. Additionally, we observe similar empirical results at the aggregate market level. In contrast to prevailing literature, our study highlights the potential significance of informed sales in revealing negative information.

Specifically, over the period of 1981-2018, we conduct cross-sectional regressions to analyze the relationship between monthly stock returns and lagged proxy variables for the stringency of short-sale constraints ($Constraint$), lagged informed institutional sales ($Sale$), and their interaction term. Large hedge fund sales serve as our primary measure for informed institutional sales, consistent with prior research (e.g., Agarwal, Jiang, Tang, and Yang (2013); Jiao, Massa, and Zhang (2016); and Chen, Da, and Huang (2019)). Our findings indicate that higher levels of $Constraint$ and larger $Sale$ both significantly predict lower returns. However, in line with our main intuition, when we condition on larger and presumably more informative institutional sales, the negative predictability associated with $Constraint$ weakens, and in some cases, it disappears or even turns positive. For instance, for stocks in the smallest sales decile, a one-standard-deviation increase in $Constraint$ is linked to a substantial monthly return decrease of 55.8 basis points. In contrast, for stocks in the largest sales decile, the same increase is associated with an economically insignificant decrease of 0.6 basis points. Conversely, when conditioned on high $Constraint$, such as the top decile in short-sale constraint stringency, informed institutional sales still significantly and negatively predict returns. As an alternative

measure, we incorporate non-hedge fund institutional sales in our regression, finding a similar albeit weaker weakening effect on the negative predictability of $Constraint$. Our findings provide complementary evidence to Engelberg, Reed, and Ringgenberg (2012) who find that short sellers' primary advantage lies in analyzing publicly available information rather than acquiring private information.

In addition to the analysis using institutional sales data, we extend our study by incorporating hand-collected insider weekly trading data from Kacperczyk and Pagnotta (2019). This dataset encompasses insider trades based on material and non-public information from the SEC's insider trading litigation files over the period 1995-2015. We find supportive evidence of an even stronger weakening effect. Specifically, when conditioning on informed sales driven by private information, the negative predictability associated with $Constraint$ disappears and can even become positive. These results provide robust and compelling support for our core economic intuition and theoretical framework.

The inclusion of illegal insider trading data complements the above analysis in several key ways. First, it allows us to conduct tests using sales precisely identified as motivated by private information. Such sales can only be indirectly inferred in prior literature, as well as in our hedge fund analysis. Second, it provides sharpest evidence supporting our theory on why short-sale constraints *appear* to negatively predict returns. Indeed, we have access to the actual dates of insider sales and the subsequent public announcements of the negative private information. Therefore, we know the exact date for starting the tests and the total return from the private information. Third, since insiders are prohibited from short selling, we can ascertain that they are exclusively long-only investors. Finally, we can substantially alleviate some endogeneity concerns: (1) the information horizons are short, lasting on average three weeks. In this short horizon, returns are more likely impacted by this private information rather than other market news; and (2) the majority of SEC investigated cases are initiated by whistle blowers, mitigating concerns that these stock events are selectively chosen based on public information.

Two important questions arise: (1) How can small-scale informed sales effectively reveal

negative information and impact asset prices, considering that informed institutions like hedge funds hold a relatively small proportion (less than 5%) of the overall equity market and have limited arbitrage capital? (2) If informed sales have already disclosed negative information, why does the negative predictability of short-sale constraints persist?

Regarding the first question, our findings suggest that the negative information is initially revealed through the sales of highly informed institutions, such as hedge funds, and then transmitted and traded upon by other market participants. Non-hedge funds and short sellers respond to hedge fund sales by increasing their own sales, creating a cascading effect. Collectively, these market participants are significant enough in size to act as marginal investors who influence prices. In this way, the negative information revealed by informed institutional sales permeates the market and leads to price adjustments.

As for the second question, informed sales indicate that expected returns going forward become lower even after an initial price drop. In the meantime, increased short sales and institutional sales reduce the availability of lendable shares and increase short fees, as documented in studies like Kolasinski, Reed, and Ringgenberg (2013), and thus short-sale constraints become more stringent. This correlation results in the negative predictability. We obtain consistent evidence using tests based on both informed institutional sales and illegal insider sales. Our collective results suggest that informed sales take place first and, *only then*, short-sale constraints rise, but stock prices continue dropping until the negative private information becomes public.

Overall, our study provides empirical evidence and insights into the mechanisms through which informed sales reveal negative information and influence market dynamics, shedding light on the role of different market participants and the interplay between informed sales, short-sale constraints, and expected returns.

We next develop a rational expectations equilibrium model to provide economic insights into our empirical findings. Active long-only institutional investors, who hold larger positions than short sellers on average, have a stronger incentive to acquire more precise information. This is especially true when short-sale constraints are more stringent, limiting the potential

benefits short sellers can derive from precise information. Therefore, these institutional investors tend to possess more accurate and high-quality information compared to short sellers. When these institutional investors receive a negative signal indicating lower expected future returns, they respond by selling a portion of their initial position. Importantly, short-sale constraints do not restrict their sales. This selling activity by the institutional investors, along with the equilibrium price adjustment, serves as a signal to other market participants, including short sellers and uninformed active investors, who also adjust their selling behavior accordingly. The increased demand for short sales leads to a tightening of short-sale constraints specifically in states where lower returns are expected. The lower expected returns are a result that a market with noise trading and risk averse investors, private information cannot be completely revealed through trading until it is publicly announced. This explains why there can be a potentially economically significant negative predictability of short-sale constraints in our model, even when these constraints do not impede information revelation *at all*.

Additionally, due to the dominance of information by the institutional investors and their larger population weight, the incremental information that short sellers can reveal beyond what has already been disclosed by the informed sales is economically insignificant. This further reinforces the notion that active long-only institutional investors possess superior and more impactful information compared to short sellers.

Consistent with our empirical findings, the model has three corresponding predictions: 1. the stringency of the short-sale constraints predicts lower future returns; 2. informed institutional sales also predict lower future returns; and 3. conditional on sufficiently large informed institutional sales, the negative predictability of the stringency of the short-sale constraints disappears and can even turn positive. Moreover, all three predictions and the main intuitions remain valid if long-only investors have a lower information acquisition cost such as in the case of illegal insider sales.

In summary, our rational expectations equilibrium model provides theoretical explanations for the dynamics between informed institutional sales, short-sale constraints, and expected

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returns, supporting and enhancing our empirical findings.

Our theory extends to the aggregate market in time series. Prediction 1 implies that the market-wide stringency of short-sale constraints may negatively predict market returns. Previous literature interpreted this as evidence of constraints restricting negative information revelation and causing bubbles even at the market level. However, our theory emphasizes that informed institutional sales are more important for revealing negative information due to their higher incentive and larger size. Consistent with our predictions, we find that both aggregate short-sale constraints and institutional sales negatively predict the market return. Importantly, the negative predictability of constraints becomes insignificant when conditioned on large institutional sales, indicating a weakening effect at the market level.

The main contribution of our paper is to shed light on the significance of informed sales, particularly those made by institutional investors. We demonstrate that these sales play a central role in counteracting the impact of short-sale constraints on information revelation. Unlike generic informed traders in traditional theories, institutions have a larger size, which implies that they *systematically* acquire more precise information. Additionally, institutions have limited ability to conceal their identity, past returns, and trading demand information, allowing other market participants to learn from these public signals and incorporate negative information into prices, thereby reducing overpricing. Our findings underscore the importance of active long-only institutions in mitigating market frictions and call for regulators' attention to the role of informed (institutional) sales and their constraints in shaping market efficiency. These informed sales have been largely overlooked by regulators, but could be centrally important and increasingly so as dedicated professional short sellers are diminishing, suggesting that institutional sales will assume an even greater role in information revelation.[4]

Our empirical analysis contributes to the literature by presenting systematic evidence for the weakening effect of institutional sales and illegal insider sales. We provide insights into the mechanism of information transmission and extend our theoretical implications to the ag-

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[4]See, e.g., "Short Sellers Face End of an Era as Rookies Rule Wall Street," Bloomberg, Jan 29th 2021.

gregate market level. In contrast to the prevailing interpretation in existing literature, which suggests that short-sale constraints impede the revelation of negative information, we offer a novel theory that explains why short-sale constraints can still predict future returns even if they do not significantly restrict negative information revelation. Furthermore, considering the potentially more precise information of some informed institutions and the substantial size of subsequent sales these institutions can lead to, our analysis challenges the notion that short sellers are the only important players in revealing negative information, as previously believed in the literature.

A plethora of studies have examined the role of short selling and short-sale constraints (see Footnotes 1, 2, and 3) in price informativeness and market inefficiency such as overpricing or market bubbles. These studies assume that short-sale constraints create an asymmetry in incorporating good and bad news. For example, the seminal papers by Stambaugh et al. (2012) and Stambaugh et al. (2015) argue that such asymmetry causes overpricing to dominate underpricing in the economy. Recognizing this asymmetry, studies typically focus on short sellers not sellers when studying arbitrage activity/capital for exploiting overpricing (see, e.g., Abreu and Brunnermeier (2002); Hanson and Sunderam (2014)). Complementing this literature, our findings suggest that forces that constrain both sales (e.g., lock up periods and trade suspensions) and short sales may play an important role in generating such asymmetry and its variation. Otherwise, it is puzzling that why institutional sales did not reveal the bulk of the negative information irrespective of whether short sellers participate, given the sheer size difference between sales and short sales.[5]

Overall, our research highlights the importance of understanding the role of both sales and

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[5]As one example, Miller (1977) explains IPOs' positive first-day return and poor long-run performance using short-sale constraints which are relaxed at the expiration of IPO lockup agreements (Ofek and Richardson (2003), Patatoukas et al. (2022)). These studies do not consider the implication that institutional/insider selling is also constrained during the lockup period. Such consideration may also apply to the SPAC-based returns recently reported (e.g., Gahng, Ritter, and Zhang (2023)). As another example, Chu, Hirshleifer, and Ma (2020) show that anomaly return magnitude is smaller among the stocks with exogenously relaxed short-sale constraints than among the control stocks. But there are no high frequency data for them to control for informed sales. Indeed, informed sellers may anticipate the change in the intensity of short selling following such events by acting in a correlated way. When some stocks' $Constraint$ is lowered, sellers may compete with short sellers by selling earlier and sell more.

short sales constraints in shaping market dynamics, providing valuable insights into the asymmetry in incorporating information and its variations.

In contrast to Miller (1977), some theories (e.g., Diamond and Verrecchia (1987)) predict that although short-sale constraints restrict negative information revelation, they have no impact on asset prices, because rational investors fully adjust their beliefs to incorporate the presence of short-sales constraints. Dixon (2020) finds that short-sale constraints always decrease price informativeness and increase adverse selection on the sell side even after taking into account the information in sales. Different from our model and empirical evidence, his study implies that short-sale constraints do not predict lower future returns; In addition, our model predicts that conditional on informed sales, the predictability of short-sale constraints is weakened.

Existing research in finance and accounting has extensively examined the real implications of short sales and short-sale constraints on firms, including their impact on investment decisions, financing choices, corporate governance, financial reporting, disclosure practices, and external auditing.[6] Similarly, a separate body of literature has focused on the effects of fire sales, which are typically perceived as informationless institutional sales.[7] The existing literature has yet to thoroughly examine whether informed sales might have distinct and significant real effects. Our findings highlight the unique and significant role of informed sales in the revelation of negative information. Therefore, our research suggests that investigating the real effects of informed sales could be a fruitful direction for future inquiry.

2 Data and measures

In this section, we describe the data and construction of our institutional sales and short-sale constraints measures, as well as the control variables.

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[6]For example, De Jong, Dutordoir, and Verwijmeren (2011), Massa, Zhang, and Zhang (2015), Grullon, Michenaud, and Weston (2015), Li and Zhang (2015), Fang, Huang, and Karpoff (2016), De Angelis, Grullon, and Michenaud (2017), Hope, Hu, and Zhao (2017), Chang, Lin, and Ma (2019), and Chen, Cheng, Luo, and Yue (2020).

[7]This literature starts from Edmans, Goldstein, and Jiang (2012). See Wardlaw (2020) for a recent review.

2.1 Institutional sales

Our institutional trading measures are based on the 13F data. All institutional investment managers that have investment discretion over $100 million in Section 13(f) securities are required to disclose their quarter-end holdings in these securities. A Form 13F is filed at the "management company" rather than at the "portfolio" or at the individual fund level. The 13F sample includes banks, insurance companies, asset management companies, hedge funds, pension funds, and other non-specified companies.

The extant empirical literature consider hedge funds as the archetypal informed institutions and report that their trades are particularly informative (e.g., Agarwal et al. (2013); Jiao et al. (2016); and Chen et al. (2019)). Following this literature, we use hedge fund sales as our main proxy for informed institutional sales. Additionally, consistent with our model, most of the time, aggregate hedge funds do not completely liquidate their long positions. Notwithstanding, we also examine non-hedge fund sales for robustness checks.

Our institutional sales measure is the negative relative change in institutional holdings $-\Delta IH$, where $-\Delta IH \geq 0$. ΔIH is defined as the percentage change of the current-quarter institutional holdings of a stock relative to the stock's average institutional holdings over the past four quarters.[8] We require $-\Delta IH \geq 0$ (henceforth referred to as the sales sample), because our goal is to examine the relation between negative information revelation and sales. For the ease of interpreting the sales magnitudes, we convert institutional sales into a $Sale$ ranking score with 0 (1) corresponding to the smallest (largest) sales decile of stocks.

Our motivation for using the relative change in holdings is as follows. We need an institutional trading measure that focuses on the active portfolio choice decisions made by informed institutional managers. However, passive trades such as uninformed, flow-induced and benchmark tracking ones are arguably the most frequent type of trades, especially on the sell side (see., e.g., Chan and Lakonishok (1993); Puckett and Yan (2011); Lou (2012)). For these passive

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[8]We obtain similar results using an alternative ΔIH defined as the percentage change of the current-quarter institutional holdings of a stock relative to the last quarter's holdings. Shares are split adjusted. For firms with zero institutional holdings at the beginning of the quarter, the values of ΔIH are set to missing.

trades, they proportionally scale up or down their existing holdings to rebalance (see, e.g., Coval and Stafford (2007); Frazzini and Lamont (2008); Edmans et al. (2012); Lou (2012)) and therefore ΔIH will be the same across stocks.[9] It follows that any cross-stock difference in ΔIH must arise from the fact that managers make active decisions to deviate from the existing portfolio weights.

We identify hedge funds using the classification in Agarwal et al. (2013) which combines the information in the 13F institutional holdings data and hedge fund name information from a union of five major commercial hedge fund databases to identify the hedge funds in 13F. A 13F-filing institution is classified as a hedge fund if its major business is sponsoring/managing hedge funds according to the information revealed from a range of sources, including the institution's own websites, SEC filings, industry directories and publications, and news article searches. Our final sample consists of 1,565 unique hedge funds and 6,680 non-hedge funds.

For tests based on 13F institutional sales, the stock sample includes all stocks listed on NYSE, AMEX, and NASDAQ over the period from January 1981 to December 2018.

2.2 Illegal insider sales

Our illegal insider sales data are from a hand-collected illegal insider trading dataset in Kacperczyk and Pagnotta (2019). Kacperczyk and Pagnotta (2019) identify 5,000 options and equity market trades based on material and non-public information in SEC's insider trading litigation files. The files include all the available civil complaint files available on the SEC website and filed cases from the U.S. District Court spanning the period 1995-2015. These insiders include officers, directors, large shareholders who have low information acquisition costs relative to outsiders. The data allow to accurately identify informed trades including the actual dates

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[9]To see this intuition, consider a fund portfolio consisting of Stocks A and B. Their weights in the portfolio are determined by their respective market values $P_A \times \overline{Shares_A}$ and $P_B \times \overline{Shares_B}$, where P and Shares are the price and shares held in the existing portfolio. F dollars of flows induce the managers to trade $\Delta Shares_A$ and $\Delta Shares_B$ of Stocks A and B. If the flows are proportionally allocated according to the market value weight of A and B in the portfolio, then $\frac{P_A \times \Delta Shares_A}{P_B \times \Delta Shares_B} = \frac{F \times [\frac{P_A \times \overline{Shares_A}}{PortfolioValue}]}{F \times [\frac{P_B \times \overline{Shares_B}}{PortfolioValue}]}$. After rearranging, we obtain $\frac{\Delta Shares_A}{Shares_A} = \frac{\Delta Shares_B}{Shares_B}$. This means the relative change in holdings of A and B should be the same, i.e., $\Delta IH_A = \Delta IH_B$.

on which insiders trade and the dates when the underlying private information is publicly announced. Moreover, most SEC investigated cases are based on external referrals (i.e., whistle blowers) rather than based on the SEC's screening of publicly available market signals such as abnormal trading volume, volatility, or liquidity metrics. This alleviates the concern that these stock-events are selected based on public information. Due to the data availability of Markit, for high-frequency tests, the sample period is from January 2002 to December 2015. After merging with the Markit and other data, the resulting sample consists of 252 firm-day stock sales and involves 89 firms.

2.3 Stringency of short-sale constraints

We need an appropriate measure to capture the notion of the stringency of short-sale constraints, henceforth referred to as $Constraint$.

For low-frequency (monthly) tests, realized shorting demand is proxied by short interest (SI), defined as the ratio of shares sold short to total shares outstanding (see, e.g., Figlewski (1981)). The former (latter, resp.) is obtained from COMPUSTAT and NASDAQ (CRSP, resp.). Before 2002, short interest data for most NASDAQ stocks are not available in COMPUSTAT. We obtain them from NASDAQ instead of COMPUSTAT. We compute the average monthly SI over a quarter as the measure of SI for that quarter. Following the literature (Asquith et al. (2005); Nagel (2005); Porras Prado et al. (2016)), the supply of shares for a stock is proxied by its institutional ownership ratio (IO), defined as its shares held by 13F institutions at a quarter end divided by its total outstanding shares.[10] Since our main informed institutional sale measure is based on hedge funds' holdings, we use only non-hedge funds' IO as the share supply proxy.[11] Our main measure of $Constraint$ is SIO, defined as $\frac{SI}{IO}$. When the supply IO is low, the share borrowing fee tends to be high, and thus $\frac{1}{IO}$ proxies for share lending fee per share. Then the ratio SIO represents $Realized Demand \times Lending Fee Per Share$, and is thus a measure of the

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[10]Following Cremers and Nair (2005), the quarterly institutional ownership is set to zero if it is missing.

[11]Our results are robust regardless of whether we remove hedge fund holdings from IO.

total realized short sale costs. Because the more stringent the short-sale constraints, the higher the total realized short-sale costs, the ratio SIO is also a measure of the stringency of the short-sale constraints. This measure is used as the main constraint measure in the recent empirical literature (see, e.g., Asquith et al. (2005) and Ramachandran and Tayal (2021)). It is also closely related to our measure of the short-sale constraint stringency in our model.[12] Boehmer et al. (2022) shows that the short selling measure based on the notion of supply/demand obtains the most robust predictive power for future stock returns in global capital market.

In our robustness checks, we also consider several other proxies for $Constraint$. They include ΔSIO, which measures the change in SIO; the inverse of institutional ownership ratio $\frac{1}{IO}$ (e.g., Nagel (2005)); and the inverse of change in breadth of mutual fund ownership $\frac{1}{DBreadth}$ (Chen, Hong, and Stein (2002); Choi, Jin, and Yan (2013)).

For higher frequency (weekly) tests, our main measure for $Constraint$ is based on the same intuition as that for the low frequency tests. We obtain short selling data from the proprietary security lending database from IHS Markit, which has been used in several recent studies (Saffi and Sigurdsson (2011); Aggarwal, Saffi, and Sturgess (2015); Beneish, Lee, and Nichols (2015); Prado (2015)). Markit sources their data from several custodians and prime brokers. Beneish et al. (2015) report that Markit covers a majority of the tradable equities in the NYSE, AMEX, and NASDAQ (more than 78.3% by market cap), and that the stocks covered tend to be larger than those not covered. We obtain weekly information on the utilization of lendable supply and lending fees, which are available starting from year 2002. $Utilization$ is measured as value on loan (a measure of demand) divided by the total lendable value (a measure of supply). To the extent that SI and IO are valid proxies for, respectively, shorting demand and shorting supply, the $Utilization$ measure closely matches the SIO measure in our low frequency tests. Beneish

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[12]Lending fee per share alone is not a good measure of the constraint stringency, because a stringency measure should take into account the demand. Given a fee per share, the higher the demand, the more stringent the short-sale constraint. This is why we use SIO instead of $1/IO$ as our main measure of stringency. Furthermore, since IO is approximately proportional to short selling quantity in equilibrium, as IO decreases, lending fee per share as measured by $\frac{1}{IO}$ increases at an increasing rate. Therefore, $\frac{1}{IO}$ also reflects the notion of convex short-sale costs assumed in the theory part of the paper. Finally, the measure has an added advantage of being based on data that are publicly available over a long sample period, starting as early as 1981.

et al. (2015) find that $Utilization$ is highly correlated with the difficulty of borrowing in the equity lending market.

For robustness, we also consider the simple average fee (SAF) per share as an alternative high-frequency proxy for $Constraint$. Relative to $Utilization$, a drawback of the short costs per share measure is that we lose approximately 56% of the illegal insider sale events.

2.4 Control variables and other data

We obtain monthly and weekly stock market data from CRSP and accounting data from COM-PUSTAT. We remove stocks with price lower than \$5. In all regressions, we control for firm size, measured by the natural logarithm of firm market capitalization; book-to-market ratio; past-month ($t-1$) stock return, and momentum returns measured as the cumulative returns from month $t-12$ to month $t-2$. To mitigate the impact of outliers, we further winsorize all control variables at the 1% and 99% levels.

2.5 Summary statistics

Table I presents the summary statistics of our main variables for the hedge fund sales sample. Appendix Table A.I presents the summary statistics for the full sample. Comparing across the two tables reveals that the sales sample is about half the size of the full sample in terms of the number of observations. The SIO in the sales sample is slightly higher than the full sample in its mean (10% vs. 9%). For the sales sample, consistent with the conventional wisdom of hedge funds being more active and aggressive, average hedge fund sales are 47% with a standard deviation of 36%, while average non-hedge fund sales are 16% with a standard deviation of 23%. In contrast, in the full sample where we do not require sales≥0, hedge fund (non-hedge fund) sales are -50% (-12%). This negative number is consistent with the fact that institutions on average need to buy stocks due to many reasons such as fund flows being positive on average. The control variables in the two samples are not materially different.

The average position size of long institutions, as measured by the IO of all institutions, is

Table I: Summary Statistics

This table reports the summary statistics for the main variables used in the paper for the sales sample where we require hedge fund sale≥0. SIO is defined as short interest SI (defined as the ratio of shares sold short to total shares outstanding at a quarter end) to institutional ownership IO (defined as the ratio of ownership by institutions at a quarter end relative to total outstanding shares) for each firm every quarter. We use only non-hedge fund IO for computing SIO. Hedge fund (Non-hedge fund) sales is the negative percentage change of the current-quarter shares held -ΔIH from hedge funds (Non-hedge funds) relative to its average over the past four quarters, where we require -ΔIH≥0. Control variables include log of market capitalization (size), book-to-market ratio (B/M), past one-month return (Reversal), and momentum return (Mom12m) measured as the cumulative return from month t-12 to month t-2. Number of observations, Mean, standard deviation, median, the first and third quartiles (P25 and P75), skewness, and kurtosis of the firm-month observations for each variable are reported. The sample period is January 1981 through December 2018.

	N	Mean	Std. Dev.	P25	Median	P75	Skewness	Kurtosis
SIO	627,569	0.102	0.271	0.007	0.030	0.084	5.559	36.206
SI	627,569	0.031	0.050	0.002	0.013	0.038	4.525	47.160
HF Sales	627,569	0.469	0.361	0.145	0.368	0.868	0.368	1.611
Non-HF Sales	632,620	0.159	0.229	0.024	0.069	0.18	2.375	8.244
IO All	627,569	0.48	0.269	0.258	0.477	0.698	0.042	1.972
Size	627,569	13.363	1.754	12.079	13.276	14.554	0.195	2.571
B/M	627,569	0.581	0.443	0.287	0.499	0.773	1.841	10.272
Reversal	627,569	0.014	0.124	-0.05	0.009	0.07	0.643	6.324
Mom12m	627,569	0.147	0.466	-0.125	0.088	0.322	1.775	9.022

around 50%, whereas that of the short sellers, as measured by the SI, is around 3% in both samples. Some institutions may have passive funds. We can not separate passive from active funds within a fund family using the 13f data. However, using the Morningstar data, we find that the ratio of total net assets of index funds to total equity funds is 11% on average in the sample period. Therefore, if this ratio is applicable to other types of funds, then the long position size of active funds in 13f would be 44.5%$(= 50\% \times (1 - 0.11))$. Likewise, not all SI is information-motivated. Many short sellers establish short positions for hedging purposes. Therefore, the information-motivated short interest is likely to be smaller than 3%. Taken together, these considerations suggest that the average position size of the long active funds is much larger than that of active short sellers, which motivates our empirical tests and theory.

3   Informed institutional sales, stringency of short-sale constraints, and cross-sectional return predictability

In this section, we focus on the role of informed institutional large sales. Specifically, we examine whether informed institutional large sales significantly weaken the cross-sectional negative return predictability of the stringency of short-sale constraints measured by $Constraint$. We first examine the most likely informed institutions—hedge funds. We then examine all other institutions—non-hedge funds. Although non-hedge funds maybe less informed than hedge funds, they still have the advantage of being much bigger than short sellers.

In Table II, we focus on our informed institutional sales proxy—hedge fund sales—and the $Contraint$ measure SIO. We use panel regressions of returns on lagged independent variables with month fixed effects and controls. Standard errors are double-clustered by firm and month. We make sure that the timing of $Constraint$ is consistent with the quarterly institutional sales measure as follows: We first average $Constraint$ over a quarter and assign its quarterly average to each month in the quarter; Correspondingly, the institutional sales value of a quarter is assigned to every month in the quarter; We then regress $Return_{i,t}$ on $Constraint_{i,t-3}$, $Sale_{i,t-3}$,

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and/or $Constraint_{i,t-3} \times Sale_{i,t-3}$. This ensures that we use the prior quarter $Constraint$ or $Sale$ to predict returns. We standardize $Constraint$ for the ease of interpreting its economic magnitude.

In Column (1), we first regress $Return_{i,t}$ on $SIO_{i,t-3}$ only. The result shows that SIO negatively predicts returns with statistical significance at the 1% level, consistent with the findings in the existing literature. This result is commonly interpreted as suggesting that the stringency of short-sale constraints significantly restrict negative information revelation and thus stock prices tend to drop over time as the remaining negative information gets gradually revealed to the market. As we will show later in our theory (see Prediction 1), this result is also consistent with our model where the stringency of short-sale constraints does not restrict negative information revelation, but short-sale constraints become more stringent when expected returns drop.

We then examine the informativeness of our informed institutional sales measure by regressing $Return_{i,t}$ on $Sale_{i,t-3}$ only. Column (2) shows that $Sale$ also significantly negatively predicts returns. Moving from the smallest sales decile ($Sale = 0$) to the largest sales decile ($Sale = 1$) predicts a 41.1-bp ($t = -4.23$) lower return. This evidence suggests that larger informed institutional sales are likely more informative of the greater extent of negative information.

Next, we test Prediction 3 by including both $SIO_{i,t-3}$, $Sale_{i,t-3}$, and their interaction $SIO_{i,t-3} \times Sale_{i,t-3}$ in the regression. We expect a positive coefficient estimate on the interaction term. Column (3) shows that this is indeed the case, suggesting that the negative return predictability of SIO significantly weakens as the relative size of the institutional sales increase. When sales are in their smallest decile ($Sale = 0$), the coefficient estimate on SIO is -0.558 ($t = -3.47$), indicating that a 1-STD increase in SIO predicts a 55.8-bp lower return next month. Therefore, the negative return predictability of the stringency of short-sale constraints is strong in the absence of large sales. The positive coefficient estimate on $SIO \times Sale$ captures a weakening effect of $Sale$ on SIO: as $Sale$ increases, the total return predictability of SIO (the coefficient estimates

Table II: Stringency of Short-Sale Constraints and Informed Institutional Sales

This table reports the results from the panel regressions of the monthly stock Return (i,t) on the last-quarter hedge fund Sale (i,t-3), Constraint (i, t-3), and their interaction term. Constraint=standardized SIO. Definition of SIO and hedge fund sales are detailed in Table I. Hedge fund sales are converted into a Sale score with 1 (0) corresponding to the largest (smallest) decile of hedge fund sales. Month fixed effects and firm-level controls depicted in Table I are included. T-statistics are reported in the bracket, and are based on standard errors clustered by firm and month. The sample period is January 1981 through December 2018. *, **, and *** indicate that the coefficients are statistically significant at the 10%, 5%, and 1% level, respectively. Gray shade highlights the results of interest, and bold coefficients indicate the significant results of interest.

Dependent Variable	Return (i,t) (%)		
	Constraint=SIO		
	(1)	(2)	(3)
Constraint (i,t-3)	-0.182***		-0.558***
	[-4.67]		[-3.47]
Sale (i,t-3)		-0.411***	-0.673***
		[-4.23]	[-4.17]
Contraint (i,t-3) × Sale (i,t-3)			**0.552*****
			[2.69]
Size (i,t-1)	0.014	0.007	0.004
	[0.38]	[0.21]	[0.11]
B/M (i,t-1)	0.490***	0.501***	0.484***
	[3.05]	[3.11]	[3.02]
Reversal (i,t-1)	-1.39	-1.386	-1.383
	[-1.38]	[-1.38]	[-1.38]
Mom12m (i,t-1)	0.764***	0.757**	0.761**
	[2.60]	[2.57]	[2.58]
Observations	627,569	627,569	627,569
Adj R^2	0.156	0.156	0.156
Constraint + Constraint × [Sale=Top decile]			-0.006
			[-0.11]

on the terms containing *SIO*) becomes less negative. In particular, it indicates that when sales are in their largest decile (*Sale* = 1), the negative return predictability of *SIO* shrinks by 55.2 bps (t = 2.69). Combining these two numbers, we obtain that a 1-STD increase in *SIO* predicts merely a 0.6-bp (= 55.2 − 55.8) lower return, which suggests economic insignificance. In the bottom row of Column (3), a test on the significance of the sum of the coefficients on the *SIO* and *SIO* × *Sale* terms conditional on *Sale* = 1 indicates that the sum is also statistically insignificant. In contrast, when the value of *Constraint* reaches its top decile, the coefficient estimates on the *SIO* and *SIO* × *Sale* terms imply that the sum of coefficients on *Sale* is -0.278 with t = −2.88 (untabulated). This suggests that when the stringency of short-sale constraints is high, informed institutional sales can still significantly negatively predict returns.

Overall, the results in Table II suggest that, conditional on large informed institutional sales, the stringency of short-sale constraints no longer negatively predicts returns. This implies that short-sale constraints may not significantly restrict negative information revelation in the presence of large informed institutional sales.

We also check robustness by repeating the tests in Table II using alternative measures of stringency of short-sale constraints or institutional sales. In Appendix Table A.II, we use three alternative *Constraint* measures: (1) the inverse of institutional ownership ratio ($\frac{1}{IO}$)(Nagel (2005)), which focuses on the quantity of short supply; (2) ΔSIO—the relative change in *SIO*, which is less persistent and thus may potentially capture faster-moving information flows than *SIO*; and (3) the inverse of change in breadth of mutual fund ownership $\frac{1}{DBreadth}$ (Chen et al. (2002); Choi et al. (2013)), which is a valuation indicator reflecting the change in the number of investors who hold pessimistic valuations and remain on the sidelines.[13] We find a similar weakening effect. In particular, the bottom row of Column (3) indicates that the negative return predictability of *Constraint* is completely eliminated and even turns positive, conditional on large informed institutional sales.

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[13]We shift ΔSIO to be greater than or equal to zero so that similar to *SIO*, zero ΔSIO can be interpreted as the lowest level of stringency in short-sale constraints. We shift *DBreadth* in a similar fashion so that $\frac{1}{DBreadth}$ is a monotone transformation of *DBreadth*.

Last, in Appendix Table A.III, we replace hedge fund sales with non-hedge fund sales. We again find a similar, albeit weaker, weakening effect.[14] This result suggests that although hedge fund sales provide a better setting for testing our theory, non-hedge fund institutional sales can also significantly weaken the negative return predictability of $Constraint$. Therefore, the sales of *all* active institutions can help reveal negative information, albeit to varying extents. We will shed light on the information transmission mechanism in Section 5.

4 Illegal insider sales, stringency of short-sale constraints, and cross-sectional return predictability

In the above analysis, we assume that larger institutional sales such as those by hedge funds are more informative. This identification of informed sales is clearly not perfect. We next test the same weakening effect using illegal insider sales which are most likely motivated by private information.[15] The occurrence of illegal insider sales is rare. However, this analysis is important because it provides a clean setting to tease out the effect of *informed* sales, which is the key for our analysis.

4.1 Illegal insider sales and pricing of negative private information

We first show that the illegal insider sales help precisely identify material negative information. We define the event week as the five-trading-day window where an illegal insider sale occurred for stock i on the first day of the window. We require the private material information relevant to the insider sales not to be announced within the illegal insider sales week. This ensures that the signal is a private signal during the insider trading week. For exposition simplicity, we refer

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[14]A 1-STD increase in SIO predicts a 67.0-bp lower monthly return conditional on small non-hedge fund sales vs.11.9-bp lower monthly return conditional on large non-hedge fund sales. Thus, increasing from small to large sales weakens the return predictability of SIO by 82%, with the remaining predictability economically small.

[15]This corresponds to the case in our theory where L investors (illegal insiders here) have lower information acquisition costs than S investors in our theory introduced later, which will yield the same predictions as the setting based on L investors having a larger stake at risk.
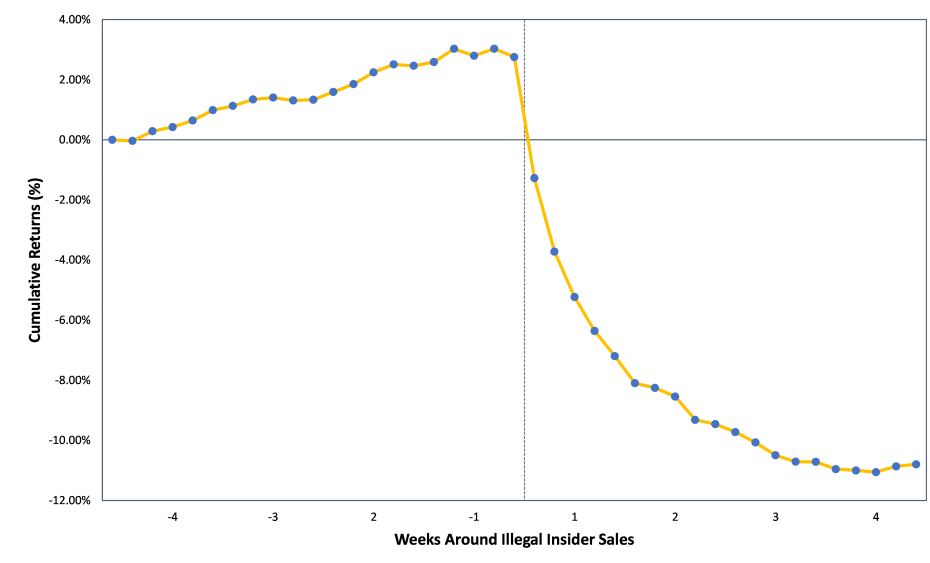
Figure I: Cumulative returns of eight weeks around the illegal insider sales. This figure presents the cumulative weekly returns of illegal insider sales over the period of January 2002 to December 2015.

to the event week as week 1 and the week before the event week as week -1 to highlight the fact that illegal insiders trade on the information sometime between week -1 and 1. Figure I plots the average cumulative return across the stocks involved in the insider cases each day over the four-week window around the event week. It shows that the cumulative return starts dropping dramatically during the event week (week 1) and the subsequent week (week 2), and reaches the bottom around week 4. The total decline in price from the event day to its lowest level is around -11%. In contrast, for the four weeks before the event, price goes up. The results suggest that the illegal insider sale setting provides a clean setting for precisely identifying private information-motivated trades and the price movements associated with such private information.

4.2   Weekly return predictability and a difference-in-difference (DiD) test

We then show that when we can unequivocally condition on private information-motivated informed sales, we obtain stronger evidence that the negative return predictability of the strin-

gency of short-sale constraints weakens even more.

We first verify that the $Constraint$ measures negatively predict returns at the weekly frequency. In Appendix Table A.IV, we regress weekly stock returns on lagged weekly $Utilization$ or the short costs measure with week fixed effects and controls. The results show that a 1-STD increase of $Utilization$ predicts a 6-bp lower return in the subsequent week. Short costs display a similar return predictability.

We then use a DiD framework to test whether the negative return predictability of $Constraint$ for the treatment firms is significantly weaker than that for the control firms *only* when we condition on the illegal insider sales event.

Specifically, for each treatment firm, we identify a set of control firms that do not experience illegal insider sales, using a one-to-ten nearest neighbor propensity score matching with replacement. We match firms based on stock price, size, book-to-market ratio, past-month returns, momentum returns, and return volatility measured at the week prior to the insider sale event. We then run the following weekly regression with week fixed effects over the four-week event window between week -3 and week 1:

$$Ret_{i,t+1} = \alpha + \beta_1 Constraint_{i,t} + \beta_2 Event_t + \beta_3 IllegalInsider_{i,t} + \beta_4 IllegalInsider_{i,t} \times Event_t$$
$$+ \beta_5 Constraint_{i,t} \times Event_t + \beta_6 Constraint_{i,t} \times IllegalInsider_{i,t}$$
$$+ \beta_7 Constraint_{i,t} \times Event_t \times IllegalInsider_{i,t} + \gamma Controls + \varepsilon_{i,t}, \qquad (1)$$

where the $Constraint_{i,t}$ measure is standardized; $IllegalInsider_{i,t}$ is a dummy variable that equals one for treatment firms and zero for control firms; $Ret_{i,t+1}$ is the return of stock i in week t+1; $Event_t$ is a dummy variable that equals one for the event week (week 1), and zero for the three weeks before; Controls include the same controls as in Table II.

Two parameters are of particular interest. The first one is β_7 on the term $Constraint_{i,t} \times Event_t \times IllegalInsider_{i,t}$. We expect it to be positive, which means that conditional on the illegal insider sales event, the negative return predictability of $Constraint$ in treated stocks is

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weakened relative to that in control stocks. The second parameter of interest is the sum $\beta_1 + \beta_5 + \beta_6 + \beta_7$, which measures the total return predictability of the event-week $Constraint$, conditional on $IllegalInsider_{i,t} = 1$. Recall that in Prediction 3, conditioning on large sales is only one identification method for empiricists to test our theory. Conditioning on $IllegalInsider_{i,t} = 1$ can serve as an alternative identification method because for the firms experiencing illegal insider sales, the disparity in informativeness between illegal insiders and short sellers is likely to be also large. Therefore, consistent with the weakening effect in Section 3, we expect the sum to be zero or even positive.

Panel A of Table III reports the quality of the propensity score matching. The panel shows that none of the characteristics of treated stocks are statistically different from those of control stocks, alleviating the concerns that treated stocks are different from control stocks along important dimensions of firm characteristics.

Panel B of Table III presents the results using $Utilization$ as the $Constraint$ measure. We first note that the point estimate of β_4 on the term $IllegalInsider_{i,t} \times Event_t$ is significantly negative, indicating that, the event-week $IllegalInsider$ dummy can significantly negatively predict the subsequent-week return. This is consistent with the fact that the illegal insiders can precisely identify negative information.

We then turn to our parameters of interest. The point estimate for β_7 is significantly positive at the 5% level, supporting that illegal insider sales weaken the negative predictability of $Constraint$. The sum of the point estimates $\beta_1 + \beta_5$ on the terms $Constraint_{i,t}$ and $Constraint_{i,t} \times Event_t$ is negative and significant in a joint test, indicating that the negative predictability of the event-week $Constraint$ is significant when we do not condition on illegal insider sales. The magnitude of the weakening effect β_7 is substantially larger than that of $Constraint$'s negative predictability $\beta_1 + \beta_5$. Furthermore, β_6 on the term $Constraint_{i,t} \times IllegalInsider$ is insignificant, suggesting that absent the illegal insider sales event, there would be no difference in the return predictability of $Constraint$ between treatment and control firms. As a result, the bottom row shows that the sum $\beta_1 + \beta_5 + \beta_6 + \beta_7$ is significantly positive. Therefore, conditional on

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illegal insider sales, the negative predictability of $Constraint$ for the treatment firms significantly weakens relative to that for the control firms; In fact, the predictability not only weakens but also completely reverses its sign to be positive.

To assess the plausibility of the parallel trend assumption that is crucial for the DiD approach, we visually check the difference in the negative predictability of $Constraint$ between treatment and control firms week by week around the event window. Since the illegal insider sales only happen in week 1, the negative predictability of $Constraint$ for treatment firms is expected to be weakened relative to that for control firms only during the couple of weeks post the insider sales, as the information related to the illegal insider sales is completely priced in around week 4 (see Figure I). Specifically, for each week t, we run a cross-sectional regression of $Ret_{i,t+1}$ on $Constraint_{i,t}$, $IllegalInsider_{i,t}$, $Constraint_{i,t} \times IllegalInsider_{i,t}$, and controls, where $t = -3, -2, ..., 3$. Figure II plots the time series of the point estimate for the coefficient on $Constraint_{i,t} \times IllegalInsider_{i,t}$. The point estimate quantifies the difference in the return predictability of $Constraint$ between the treatment and control firms in each week. Economically, it captures the difference in the predicted returns between treatment and control firms for a 1-STD increase in $Constraint$. We do not observe any significantly different pre-trend in this predictability between the treatment and control firms over the three weeks prior to the illegal insider sales. The point estimate is around zero from week -3 to week -1. It then increases to a significantly positive 2% in week 1, suggesting that illegal insider sales weaken $Constraint$'s negative return predictability in treatment firms by a weekly return of 2% relative to that in control firms. This weakening effect then dissipates in week 2 and reverses back to zero in week 3. In other words, there is no difference between the treatment and control firms in the ability of their week-3 $Constraint$ to predict their week-4 returns.

In terms of economic magnitude, $\beta_7 = 2.252$, $\beta_1 + \beta_5 = -0.548$, and $\beta_1 + \beta_5 + \beta_6 + \beta_7 = 1.751$. These numbers imply that a 1-STD increase in the event-week $Constraint$ would have predicted a 54.8-bp lower return in the subsequent week without conditioning on illegal insider sales; however, conditional on such sales, it predicts a 175.1-bp *higher* return.

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Table III: Illegal Insider Sales

This table reports the differences-in-difference (DiD) tests on the effect of illegal insider sales on the return predictability of *Constraint*. Constraint=standardized Utilization in Column (1). Constraint (i,t) is the weekly average of daily ratio of value on loan to total lendable value over week t obtained from Markit. Event is a dummy that equals one if a firm-week observation is in the illegal insider sale week (week 1) and zero if it is in the three weeks before the insider sales (week -3, -2, and -1). IllegalInsider is a dummy that equals one for treatment firms (firms with illegal insider sales) and zero for control firms (firms without illegal insider sales). We match the treatment firms with control firms using one-to-ten nearest neighbor propensity score matching, with replacement. Panel A reports the validity of the propensity score matching by comparing the matched characteristics between the treatment and control groups in the pre-treatment week. Panel B reports the DiD results. We require the information relevant to the insider sales not be announced within a week window around the sales. Week fixed effects and firm-level controls depicted in Table I are included. *T*-statistics are reported in the bracket, and are based on standard errors clustered by firm and week. The sample period is January 2002 through December 2015. *, **, and *** indicate that the coefficients are statistically significant at the 10%, 5%, and 1% level, respectively. Gray shade highlights the results of interest, and bold coefficients indicate the significant results of interest.

Panel A: Post-match Comparison

	Treatment Group	Control Group	Difference (ttest)
Utilization	2.827	2.879	[-0.36]
Price	28.092	27.933	[0.70]
Size	21.412	21.39	[0.10]
B/M	0.346	0.339	[0.20]
Reversal	0.004	0.003	[0.11]
Mom12m	0.062	0.092	[0.50]
RetVol	0.03	0.029	[0.03]

Panel B: DiD Analysis	
Dependent Variable	Ret (i,t+1) (%)
Event Window [-3,1]	
Constraint (i,t)	-0.146
	[-0.86]
IllegalInsider (i,t) × Event (i,t)	-9.855***
	[-3.57]
Constraint (i,t) × Event (i,t)	-0.402**
	[-2.36]
Constraint (i,t) × IllegalInsider (i,t)	0.049
	[0.12]
Constraint (i,t) × Event (i,t) × IllegalInsider (i,t)	**2.252****
	[2.23]
Other regressors: Event, IllegalInsider, Size, B/M, Reversal, Mom12m	
Observations	5,353
Adj R^2	0.267
Constraint (i,t) + Constraint (i,t) × Event (i,t) + Constraint × [IllegalInsider =1] + Constraint × [IllegalInsider =1] × Event	**1.751***
	[1.76]

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Because the illegal insider sales in week 1 and the return in week 2 are most likely due to insiders' negative private information identified in SEC's insider trading investigation, the strong weakening effect over this short time window when the private information matters for pricing is unlikely to be caused by almost any omitted variables. Put another way, it is unlikely for omitted variables to cause the weakening effect only in this short time window but not in other adjacent weeks.

4.3 Further endogeneity and robustness checks

We conduct several additional tests to further address the endogeneity concerns of the weakening effect and check robustness.

First, we analyze the lead-lag relation between $Constraint$ and illegal insider sales to rule out that firms with more stringent short-sale constraints are more likely to have the illegal insider sales. We present the results in Section 5.3 and find that it is the illegal insider sales that lead $Constraint$, and not the reverse.

Second, we check the robustness of our DiD test results to short-sale costs as the $Constraint$ measure. Appendix Table A.V shows that the results based on short-sale costs are in line with those in Table III.

Lastly, we evaluate whether our DiD test results are robust to longer gaps between the illegal insider sales and the news announcement. Recall that in Table III, we require that the information that insiders possess cannot be announced within the illegal insider sales week. In Appendix Table A.VI, we use two alternative requirements: (1) $Gap > 7$ trading days; (2) $Gap > 10$ trading days. These requirements further delay the time when the information can become public to the point that the information is not announced in the period when return is measured (i.e., $Gap > 10$). The results show that there is still a significant weakening effect and that the return predictability of $Constraint$ is positive conditional on illegal insider sales. Additionally, the point estimate of β_4 on $IllegalInsider_i \times Event_t$ is significantly negative, even when $Gap > 10$. This result suggests that insiders may have partially revealed the private infor-

Utilization

Coefficient (%)

Treated-Control
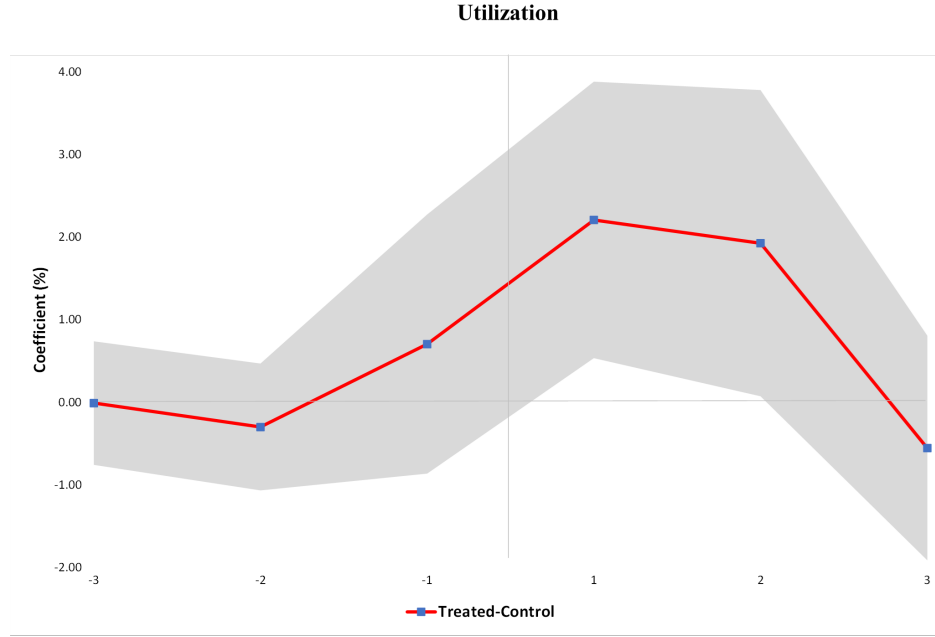
Figure II: Return predictability of stringency of short-sale constraints surrounding illegal insider sales. This figure shows the point estimates and confidence intervals of β_3 in the following regression with week fixed effects: $Ret_{i,t+1} = \alpha + \beta_1 Constraint_{i,t} + \beta_2 IllegalInsider_{i,t} + \beta_3 Constraint_{i,t} \times IllegalInsider_{i,t} + Controls_{i,t} + \varepsilon_{i,t}$, where β_3 captures the differences in the return predictability of Constraint (=Utilization) between treatment firms and control firms surrounding weeks of illegal insider sales over the period of January 2002 to December 2015. Controls include previous-month log market capitalization (Size (i,t)), book-to-market ratio (B/M (i,t)), past-month return (Reversal (i,t)), momentum return (MOM12m (i,t)) measured as the cumulative return from month t-12 to month t-1 included.

mation into prices even before the information becomes public, consistent with the discussion in Section 5 that other market participants gradually learn about such information.

Overall, the results using the illegal insider sales offer the strongest support for our theory to be introduced later. This is because informed sales and the timing of when the private information matters are almost precisely identified, and in addition, as in our model, the negative information of these illegal insider sellers almost surely dominates that of short sellers.

5 Information transmission mechanism

Given that hedge funds hold less than 5% of the equity market and have limited arbitrage capital, how can the sales of informed institutions like hedge funds "reveal" negative information to the market and drive down asset prices? In addition, how can the stringency of short-sale constraints predict lower returns if informed institutional sales have already revealed negative information? In this section, we aim to address these two questions.

5.1 A lead-lag mechanism

Institutional holdings at the end of a quarter are required to be disclosed within 45 days after the quarter end. Many websites and social media regularly track the trades of the hedge fund sector or star hedge/mutual fund managers (see, e.g., seeking alpha, hedgefundfollow.com, gurufocus.com, and Wallethub). Star fund managers or, more generally, informed institutional traders in a particular stock can be determined by tracking the past returns of the managers or the stock. Such return information is largely publicly available, unlike an anonymous informed trader. Hedge fund order flow information can be leaked through investment banks (see, e.g., the Archegos event, 2021). Aggregate institutional order flows are also recorded by custodian banks like StateStreet (see, e.g., Froot, O'connell, and Seasholes (2001)).

After identifying informed institutional sales, other institutions may follow by selling the same stocks. For institutions that can both lend shares and act on negative information by

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selling, evidence suggests that they sell the shares directly (Evans, Ferreira, and Porras Prado (2017)) and reduce lendable shares (Li, MacKinlay, and Ye (2021)). Furthermore, recent studies show that high-frequency public signals (e.g., volume, returns, liquidity, and volatility) can help identify informed trading (e.g., Bogousslavsky, Fos, and Muravyev (2021)), including the high-frequency illegal insider trading studied in Section 4 (e.g., Kacperczyk and Pagnotta (2019)). This means that quant funds could also follow the traces of informed institutional sales. Taken together, the information in informed institutional sales can be gradually learned by other institutions over time.

In addition, short sellers may also learn from stock price declines and informed institutional sales. Observation of such information and the ensuing shorting demand increase and/or lendable share supply decrease may also induce brokers to increase short selling fees per share (see, e.g., Kolasinski, Reed, and Ringgenberg (2013)).

Note that, as will be demonstrated in our model, regardless of whether short sellers will be constrained by short-sale constraints, all active long institutions alone can reveal the vast majority of the information that can be revealed. The intuition is that consistent with empirical observations, non-hedge funds are on average much bigger than short sellers, thus more likely being the marginal investors. Therefore, institutional sales are likely to be centrally important in pricing in the negative information. With them already impounding negative information, it is difficult for a small quantity of short sales to further move the needle in the financial market.

Separately, one might argue that hedge funds can do short selling after selling all their long positions. However, this still means that selling would lead short selling. For the general public including non-hedge funds, they can only observe hedge-fund selling from the publicly disclosed holdings data, but not hedge-fund short selling. It is therefore more direct for hedge fund sales than their short sales to reveal the negative information to non-hedge funds and the general public.

Accordingly, we conjecture a lead-lag mechanism at work. Specifically, after observing a piece of negative information, a small group of informed institutions like hedge funds reveal

it first through selling. Then, the information is priced in due to the subsequent sequential learning of other market participants through trading. Given the sheer size of the holdings of institutions like non-hedge funds, these institutions are likely to be more important in affecting prices than short sellers. Therefore, all active long institutions can participate in pricing in the negative information with or without the participation of short sellers. This conjecture suggests that informed institutional sales should lead the sales of other institutions and the stringency of short-sale constraints (in terms of both short demand and supply). Furthermore, hedge fund and non-hedge fund sales and *Constraint* all negatively predict returns, and short sales and short-sales constraints increase following more negative returns. In the following two subsections, we provide evidence consistent with this lead-lag mechanism conjecture.
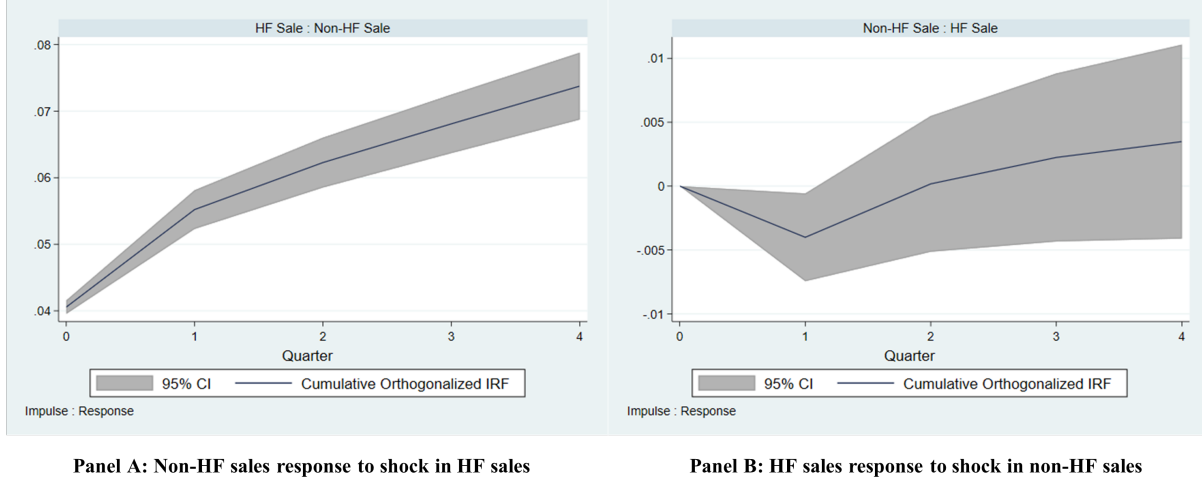
5.2 How can informed institutional sales impound negative information into prices?

We first examine the lead-lag relation between hedge fund sales and non-hedge fund sales in a vector autoregression (VAR) analysis and plot these relationships using impulse response functions. This investigation helps us understand how informed institutional sales, which may be a small portion of all institutions' sales, are able to impound information into price.

Figure III, Panel A shows the cumulative response of non-hedge funds sales over a horizon of four quarters to a 1-STD shock in hedge fund sales. The plot shows that non-hedge fund sales significantly positively respond to past hedge fund sales in all four quarters. The strongest response is in the first quarter, which accounts for 60% of the total responses over the four quarters. In contrast, as shown in Panel B hedge fund sales display little response to non-hedge fund sales. The only statistically significant response is in the first quarter. It is, however, in the wrong direction, suggesting that hedge fund sales decrease after non-hedge fund sales increase. The magnitude of the response is economically not meaningful either with a 1-STD increase in non-hedge fund sales resulting in a 0.005-STD decrease in hedge fund sales.

In Table A.VII in the Appendix, we report the long horizon return predictability of hedge fund

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Panel A: Non-HF sales response to shock in HF sales   **Panel B: HF sales response to shock in non-HF sales**

Figure III: Cumulative impulse response of hedge fund sales and non-hedge fund sales. This figure reports the cumulative impulse response of hedge fund sales and non-hedge fund sales using the following panel VAR with four lags of each dependent variable:

$NonHF\ sales_{i,t} = \alpha + \sum_{j=1}^{4} \beta_{1,j} NonHF\ sales_{i,t-j} + \sum_{j=1}^{4} \delta_{1,j} HF\ sales_{i,t-j} + \varepsilon_{i,t}$,

$HF\ sales_{i,t} = \alpha + \sum_{j=1}^{4} \beta_{2,j} NonHF\ sales_{i,t-j} + \sum_{j=1}^{4} \delta_{2,j} HF\ sales_{i,t-j} + \varepsilon_{i,t}$.

Panel A depicts the cumulative response of non-hedge fund sales to a shock in hedge fund sales and Panel B depicts the cumulative response of hedge fund sales to a shock in non-hedge fund sales. Standard errors and confidence interval of the impulse response are estimated via 200 simulations. The sample period is from January 1981 to December 2018.

sales by regressing future quarterly returns on lagged hedge fund sales for up to four quarters in the future. The point estimates are significantly negative for all four quarterly returns and dissipate over time. The magnitude of the point estimate for the first quarter is considerably larger than that for the other three quarters, as well as for the monthly return regression in Table II, Panel A, Column (2). In contrast, the point estimate for the fourth quarter is close to be statistically insignificant. These results support that negative information is gradually impounded into prices. The results also rule out that the pricing effect of hedge fund sales is due to fire sales or temporary price pressure as such story would have predicted a return reversal.

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Overall, our results support that the negative information in the informed institutional sales gets gradually reflected in prices through a lead-lag mechanism where other institutions sell following the informed institutional sales. In addition, as we will show in the next subsection, short-sale constraints become more stringent following informed institutional sales. Given the tighter restriction on short sellers, their importance in pricing in negative information becomes even smaller following large institutions sales. In contrast, short-sale constraints do not restrict sales, and thus do not restrict negative information revelation through institutional sales. Furthermore, as we show in Section 2.5, the aggregate position size of active institutions is much larger than that of short sellers. Therefore, institutional sales can be potentially a much more important force in pricing in negative information than short sales.

5.3 How can the stringency of short-sale constraints predict returns?

We then examine the lead-lag relation between informed institutional sales and the stringency of short-sale constraints.

5.3.1 Low-frequency evidence

Column (1) ((2)) of Table IV reports the results of the panel regressions of SIO (hedge fund sales $Sale$) on lagged SIO and lagged hedge fund sales with quarter fixed effects. Column (1) shows that SIO positively responds to past hedge fund sales, whereas Column (2) suggests that hedge fund sales do not significantly respond to past SIO. The lead-lag relationships suggest that high hedge fund sales tend to lead to high SIO, but not vice versa.[16]

We then break down SIO into the SI and $\frac{1}{IO}$ components, which proxy for shorting demand and supply (or fees per share) respectively. We study the lead-lag relationships of each component with hedge fund sales. Columns (3) and (4) show that hedge fund sales significantly positively lead short sales SI, whereas short sales significantly negatively predict hedge fund

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[16]In untabulated results, we examine the lead-lag relation between hedge fund sales and ΔSIO, which may capture faster moving information flows than SIO. We find that hedge fund sales also lead ΔSIO but not vice versa.

Table IV: Quarterly Lead-Lag Relation of Stringency of Short-Sale Constraints and Informed Institutional Sales

This table reports the quarterly lead-lag relation of stringency of short-sale constraints and informed institutional sales. Column (1) ((3) or (5)) reports the results from the panel regressions of the quarterly SIO (i,t) (SI (i,t) or 1/IO (i,t)) on the last-quarter SIO (i,t-3) (SI (i,t) or 1/IO (i,t)) and hedge fund sales (i,t-3), and Column (2) ((4) or (6)) reports the quarterly hedge fund sales (i,t) on the last-quarter SIO (i,t-3) (SI (i,t) or 1/IO (i,t)) and hedge fund sales (i,t-3). Definitions of SIO, SI, IO, and hedge fund sales are detailed in Table I. We further standardize SIO. T-statistics are reported in the bracket, and are based on standard errors clustered by firm and quarter. The sample period is January 1981 through December 2018. *, **, and *** indicate that the coefficients are statistically significant at the 10%, 5%, and 1% level, respectively. Gray shade highlights the results of interest, and bold coefficients indicate the significant results of interest.

Dependent Variable	Constraint=SIO		Constraint=SI		Constraint=1/IO		Ret and Constraint	
	(1) SIO (i,t)	(2) HF Sales (i,t)	(3) SI (i,t)	(4) HF Sales (i,t)	(5) 1/IO (i,t)	(6) HF Sales (i,t)	(7) SIO (i,t)	(8) SI (i,t)
SIO (i,t-3)	0.683***	-0.015						0.691***
	[14.41]	[-0.73]						[14.01]
SI (i,t-3)			0.663***	-0.009***			0.667***	
			[97.74]	[-3.84]			[77.75]	
1/IO (i,t-3)					33.937***	0.007		
					[4.21]	[0.46]		
HF Sales (i,t-3)	0.090***	0.354***	0.098***	0.345***	2.963***	0.343***	0.081***	0.091***
	[3.54]	[16.65]	[8.50]	[12.22]	[3.24]	[13.67]	[6.53]	[3.77]
Ret3m (i,t-3)<0							-0.023***	-0.036***
							[-4.03]	[-5.30]
Observations	207,569	200,831	207,569	200,831	207,569	200,831	102,260	103,593
Adj R²	0.546	0.042	0.58	0.042	0.125	0.042	0.581	0.561

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sales. This result suggests that hedge fund sellers not only lead short sales, they also start reducing their sales after short sellers start increasing their short sales. Columns (5) and (6) show that hedge fund sales also significantly positively lead supply (or fees per share) $\frac{1}{IO}$, whereas $\frac{1}{IO}$ do not significantly predict hedge fund sales. These results suggest that hedge fund sales lead lower short supply (or higher short fees per share) rather than the other way around. Note that the IO in SIO is the ownership of non-hedge funds and that hedge fund sales lead non-hedge fund sales, as documented in the last subsection. Therefore, our results suggest that the decline in short supply IO following hedge fund sales is related to non-hedge fund selling their lendable shares following hedge fund sales.

Finally, Columns (7) and (8) show that more negative recent quarterly returns predict significantly higher short sales and SIO. This finding suggests that short sellers learn about the negative information from market price declines and short more, which leads to more stringent short-sale constraints.

5.3.2 High-frequency evidence

We then examine the lead-lag relation between clearly identified private information-motivated sales —illegal insider sales—and the stringency of short-sale constraints at the weekly frequency. A unique aspect of the illegal insider setting is that we know the precise timing of the private negative information. This alternative analysis allows us to present more compelling evidence that the return predictability of the stringency of short-sale constraint appears because the stringency rises after the informed sales and the expected return is lower given the negative information.

First, we examine whether informed insiders sell first and then short-sale constraints tighten subsequently. Table V, Column (1) reports the results of the panel regressions of $Constraint$ in week t+1 on its lag in week t and the $IllegalInsider$ dummy in week t with week fixed effects, where week t is the event week. The results show that illegal insider sales in the event week lead significantly higher $Constraint$ in the subsequent week. In contrast, Column (2) reports the

results of the probit regression of the $IllegalInsider$ dummy in event week t on $Constraint$ in week t-1.[17] The result shows that $Constraint$ in week t-1 is not significantly related to the illegal insider dummy in the event week. These results suggest that the illegal insider sales in treatment firms lead to higher subsequent $Constraint$ in treatment firms, whereas there is no difference in $Constraint$ between treatment and control firms before the insider sales event. We further verify that the firms with illegal insider sales are ranked around 70% in size and 36% in $Utilization$ on average across the cross section of all stocks before the event. This result suggests that treatment firms are medium to large firms with relatively lax short-sale constraints to begin with.

Taken together, the results rule out the possibility that higher $Constraint$ in treatment firms prevents short sellers from revealing the negative information before illegal insider sales. They also further alleviate the endogeneity concern that firms with more stringent short-sale constraints are more likely to have the illegal insider sales.

Next, the precise timing of when the private information matters for pricing sheds light on why the stringency of short-sale constraints appears to predict returns. Recall that Figure I shows that the treatment firm returns are negative from week 1 to week 4. Therefore, the higher $Constraint$ in treatment firms in week 2 appears to predict lower returns in these firms in week 3 because $Constraint$ in treatment firms increases following informed insider sales but before the negative information is publicly announced.

Overall, the findings in this section support that informed institutions such as hedge funds can incorporate negative information into stock prices with the assistance of other institutions. Furthermore, we provide evidence consistent with a learning mechanism where short sellers learn about the negative information (i.e., the lower future expected return) through stock prices, short more, and $Constraint$ becomes more stringent. However, stock prices may continue to go down before the information is eventually publicly announced. As will be shown in theory, such further decline in prices need not be due to inefficient pricing. Instead, it can

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[17]We use the probit regression to account for the fact that $IllegalInsider$ is a dummy variable.

Table V: Weekly Lead-lag Relation of Stringency of Short-Sale Constraints and Private Information-Motivated Sales

This table reports the weekly lead-lag relation of Constraint and illegal insider sales. t is the event week and t-1 (t+1) is the week before (after) the event week. Constraint= standardized Utilization. Column (1) reports the results from the panel regression of post-event week Constraint (i,t+1) on the event-week Constraint (i,t) and IllegalInsider (i,t) dummy. Column (2) reports the results from the probit regression of the event-week IllegalInsider (i,t) dummy on the before-event week Constraint (i,t-1). Utilization (i,t) is the weekly average of daily ratio of value on loan to total lendable value obtained from Markit. Standardized Utilization is used in the regressions. IllegalInsider (i,t) is a dummy that equals one for treatment firms (firms with illegal insider sales) and zero for control firms (firms without illegal insider sales) in the event week. Week fixed effects are included. T-statistics are reported in the bracket, and are based on standard errors clustered by firm and week. The sample period is January 2002 through December 2015. *, **, and *** indicate that the coefficients are statistically significant at the 10%, 5%, and 1% level, respectively. Gray shade highlights the results of interest, and bold coefficients indicate the significant results of interest.

	Constraint=Utilization	
Dependent Variable	(1) Constraint (i,t+1)	(2) IllegalInsider (i,t)
IllegalInsider (i,t)	**0.048****	
	[2.05]	
Constraint (i,t)	0.890***	
	[160.70]	
Constraint (i,t-1)		-0.015
		[-0.17]
Observations	1,077	1,112
Adj R^2	0.969	0.000

be due to the fact that the negative information cannot be fully revealed through trading alone even in an efficient market, due to noise trading and risk aversion of informed sellers. As a result, $Constraint$ negatively predicts returns.

6 The model

To help understand the economics behind the empirical results of our paper, in this section, we present a rational expectations equilibrium model.

In a one-period setting with trading dates 0 and 1, a continuum of active investors with a total population mass of 1 can trade a risk-free asset and a risky asset ("stock") on date 0 to maximize their expected constant absolute risk aversion (CARA) utility from the terminal wealth on date 1. There is a zero net supply of the risk-free asset, which also serves as the numeraire, and thus the risk-free interest rate is normalized to 0. The total supply of the stock is $\bar{\theta} > 0$ shares and the date 1 payoff of each share is $V = \bar{V} + F + \varepsilon$, where $\bar{V}$ is a constant, F and ε are independently normally distributed with $F \sim \mathbf{N}(0, 1/\tau_F)$, $\varepsilon \sim \mathbf{N}(0, 1/\tau_\varepsilon)$, $\tau_F > 0$ and $\tau_\varepsilon > 0$ being constants. The stringency of short-sale constraints can manifest itself in the form of greater short-sale costs or tighter limits on the number of shares that can be shorted.[18] For tractability and without loss of main insights, we use short-sale costs to represent the stringency of short-sale constraints.

There are a continuum of investors that fall into three types: a mass $\omega \in [0,1]$ of active traders are labeled as long institutional investors ("L" investors) who tend to hold a long position, a mass $1 - \omega$ of active investors are labeled as short selling investors ("S" investors) who tend to hold a short position, and a mass 1 of passive investors who submit an exogenous trade $z \sim \mathbf{N}(0, 1/\tau_z)$ for liquidity reasons. Although most of the time, L investors hold a long position and S investors hold a short one, they can choose to do the opposite if their information justifies. L investors represent the vast majority of active institutional investors who rarely short sell and S investors represent short sellers. Indeed, empirically, most institutional investors such as mutual funds only hold long positions (e.g., An, Huang, Lou, and Shi (2021)). Even for hedge funds, their positive market beta of 0.45 in our sample suggests that on average they also hold

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[18]As the costs increase, the number of shares that investors choose to short sell decreases, and thus having the same qualitative effect as a tighter limit on the number of shares that can be short. More generally, the costs can be interpreted as implicit or explicit costs related to short selling, such as stock borrowing costs, recall risk, and short squeezes.

long positions. These long institutional investors' aggregate wealth under management is usually much larger than that of short sellers. Since risk aversion tends to decrease with wealth, we assume that L investors are less risk averse than S investors.[19] As a result, L investors on average hold a larger stock position than S investors in our model. Accordingly, we assume that L investors initially hold a large long position $\bar{\theta}_L >> 0$ in the stock, but short sellers initially do not hold any shares of the stock, $\bar{\theta}_S = 0$. This is consistent with our empirical finding that for an average stock, the aggregate long institutional investor owns 50% of its total shares outstanding, whereas short sellers merely establish an aggregate short position of about 3% (see Section 2.5).[20]

Just before time 0, both L investors and S investors can choose whether to observe the component F of the stock payoff V by paying a cost c of information acquisition.[21] While we interpret observing F as acquiring private information, it can also be interpreted as acquiring greater processing capability of public information. Let λ_L (λ_S, respectively) denote the endogenous fraction of L (S, respectively) investors who pay c to observe F.[22]

We first solve for the equilibrium stock price P at time 0 taking investors' information acquisition decisions before time 0 as given. For $i \in \{L, S\}$, type i investors choose an optimal stock position θ_i to maximize the expected exponential utility function from the terminal wealth at time $t = 1$. More specifically, L investors choose θ_L to maximize

$$E[-e^{-\delta_L W_L}|I_L], \tag{2}$$

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[19]See Section 6.1 for a detailed discussion of this assumption.

[20]In this paper, we take investor heterogeneity as given, but endogenizing the heterogeneity would unlikely change the main results. For example, the initial position is exogenously given, but one can extend the model to include date -1 where every active trader has the same initial endowment and the same prior, and chooses endogenously date 0 position. The investor with a lower risk aversion will on average choose a larger position, which is what we assume here.

[21]Our main results still hold even when the information acquisition cost of short sellers is lower than that of L investors as long as it is not too low.

[22]Although for simplicity the model assumes a single risky asset, we can extend it to the case with multiple, independent stocks with the same conclusions because of the CARA preferences. Thus our model has cross-sectional implications for empirical tests.

subject to the budget constraint

$$W_L = \bar{\theta}_L P + \theta_L(V - P) - \frac{1}{2}k_L(\bar{\theta}_L - \theta_L)^2, \tag{3}$$

where $\delta_L > 0$ is L investors' absolute risk aversion parameter, k_L is the quadratic trading cost coefficient,[23] and I_L is L investors' information set. If an investor pays c to observes F, his information set is $\{F, P\}$, otherwise, her information set is $\{P\}$.

Type S investors choose θ_S to maximize

$$E[-e^{-\delta_S W_S}|I_S], \tag{4}$$

subject to the budget constraint

$$W_S = \theta_S(V - P) - \frac{1}{2}k_S(\theta_S^-)^2, \tag{5}$$

where $\delta_S > \delta_L$ is S investors' absolute risk aversion parameter, $k_S < k_L$ is the quadratic short-sale cost coefficient, and the function $X^- = \max(0, -X)$. Unlike L investors, S investors pay trading costs only when they short and their short-sale costs per share are lower than those of L investors.[24] The higher cost coefficient k_L for L investors is in line with the fact that their trade sizes are typically larger than those of short sellers. By assuming that L investors also pay trading costs when they buy and they pay higher costs when they short sell, we bias against us finding that L investors acquire more precise information than S investors.

The total realized short-sale costs $\frac{1}{2}k_S(\theta_S^-)^2$ paid by short sellers qualitatively capture the stringency of short-sale constraints. The higher the costs the short sellers pay, the less they are willing to short sell, and thus qualitatively similar to facing more stringent short-sale con-

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[23]The empirical literature generally finds trading costs to be convex (e.g., Engle, Ferstenberg, and Russell (2012), Lillo, Farmer, and Mantegna (2003)), with some researchers actually estimating quadratic trading costs (e.g., Breen, Hodrick, and Korajczyk (2002)).

[24]For simplicity, we assume the short-sale costs paid by active investors go to the passive investors with long positions who lend the shares.

straints. Furthermore, the total realized short-sale costs $\frac{1}{2} k_S (\theta_S^-)^2$ increases at an increasing rate with shorting demand, which is consistent with what we find in data.[25]

Let $\theta_{i,I}^*$ ($\theta_{i,U}^*$, respectively) be the equilibrium positions of type i active investors who observe (do not observe, respectively) F. The equilibrium price P^* is set to clear the market:

$$\omega \lambda_{L,I}(\theta_{L,I}^* - \bar{\theta}_L) + \omega(1 - \lambda_{L,I})(\theta_{L,U}^* - \bar{\theta}_L) + (1-\omega)\lambda_{S,I}\theta_{S,I}^* + (1-\omega)(1 - \lambda_{S,I})\theta_{S,U}^* + z = 0, \quad (6)$$

where the left hand side of the equation represents the aggregate net trade from the market participants.

If an investor pays c to observes F, the conditional mean and variance of the stock payoff are:

$$\mathrm{E}[V|F] = \bar{V} + F, \quad \mathrm{Var}[V|F] = 1/\tau_\varepsilon. \quad (7)$$

If an investor does not pay, the investor will infer part of the private information from observing the equilibrium price.

6.1 Discussions of main assumptions

The key driving force of our main result is that L investors have greater incentives of acquiring information than S investors. One possible reason leading to such greater incentives is that as previously stated, long active institutions have much larger wealth and the empirical evidence suggests L investors on average hold larger positions (see Section 2.5). Thus, L investors have a greater stake at risk than S investors. There are at least two ways to generate such larger positions in a model: 1. Assuming that L investors are less risk averse than S investors; 2. Assuming that a short position is riskier than a long position of the same size *cetaris paribus*.

In the model, we adopt the first assumption for simplicity. However, one can impose the second assumption to obtain the same qualitative results. The extra risk of shorting may come

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[25]The degree of this interaction effect could be further captured by changing k_S which may also increase with shorting demand.

from the fact that contrary to a long position, a short position has a limited upside gain, but may suffer an unlimited loss. Such extra risk may also come from the uncertain short-selling fees over time or short squeeze or forced premature short covering by lenders, consistent with empirical evidence (e.g., Engelberg, Reed, and Ringgenberg (2018); Blocher, Dong, Ringgenberg, and Savor (2021)).[26] Consequently, it is reasonable to assume that the conditional variance of the period-end return, considering the potential for short squeeze and premature short covering, is higher for determining an optimal short position compared to an optimal long position. Because what matters for the position size of an short seller is the product of the risk aversion coefficient and the conditional variance, it can be shown that assuming a greater conditional variance for a short position but keeping the risk aversion coefficient the same across L investors and S investors is equivalent to assuming a greater risk aversion coefficient for the short sellers but keeping the conditional variance the same across a short position and a long position. Both approaches result in a smaller short position.

Another potential explanation for certain L investors having stronger incentives to acquire information is the possibility of lower information acquisition costs. If L investors were to have lower information acquisition costs while maintaining the same risk aversion coefficients as S investors, our model would yield the same qualitative results. One extreme example of such L investors is insiders whose information acquisition costs are virtually zero. Their information clearly dominates that of outsiders (including the short sellers). Because short sellers do not have such information to reveal, short-sale constraints do not restrict the revelation of such information.

In the model, we assume that S investors can only acquire the same information as L investors by paying the same cost. This is for expositional simplicity only. The model can be extended to one with multiple private signals which active investors (both L and S investors)

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[26]One may argue that if short selling is riskier than buying a risky asset, then it must be that short sellers are less risk averse than long institutional investors, and thus contradicts the first assumption. This is not necessarily true, however, because on average the position held by short sellers is much smaller than that by long institutional investors and thus the total risk exposure of short sellers can still be much smaller. Therefore, we elect to use the risk aversion assumption in our main results instead of the risk assumption.

can choose which signals to observe by paying a cost. By the same intuition (to be explained below), as long as L investors in the aggregate are much larger than short sellers and their information acquisition cost for each signal is not much greater than that of S investors, then the information revelation by short sellers is still very limited.

Moreover, in the model we assume that all L investors are active. This is for expositional convenience only. It is clear that the introduction of passive L investors would not change the main results. After all, in some cases of the model, as will be shown below, some L investors already choose to be passive (i.e., do not acquire private information). This is consistent with the lead-lag mechanism we discussed in the empirical part (Section 5), where less informed non-hedge funds and short sellers can learn from stock prices, holdings, and trades of other investors.

6.2 The equilibrium

It can be shown that observing price P is equivalent to observing the following signal with noise:

$$S_p(\lambda_{L,I}^*, \lambda_{S,I}^*) := F + c_z(\lambda_{L,I}^*, \lambda_{S,I}^*)z,$$

where coefficient c_z is defined in equation (B-1) in Appendix B. The conditional mean and variance of the stock payoff on observing the equilibrium price are respectively:

$$\mathrm{E}[V|S_p(\lambda_{L,I}^*, \lambda_{S,I}^*)] = \bar{V} + \frac{\tau_z}{c_z(\lambda_{L,I}^*, \lambda_{S,I}^*)^2\tau_F + \tau_z} S_p(\lambda_{L,I}^*, \lambda_{S,I}^*),$$

$$\mathrm{Var}[V|S_p(\lambda_{L,I}^*, \lambda_{S,I}^*))] = \frac{\tau_z + c_z(\lambda_{L,I}^*, \lambda_{S,I}^*)^2(\tau_\varepsilon + \tau_F)}{\left(\tau_z + c_z(\lambda_{L,I}^*, \lambda_{S,I}^*)^2\tau_F\right)\tau_\varepsilon}. \tag{8}$$

Define endogenous parameters

$$c_1 := \frac{1}{\delta_L}\ln\frac{\mathrm{E}[U_{L,S_p(0,0)}(P_1)]}{\mathrm{E}[U_{L,F}(P_1)]}, \quad c_2 := \frac{1}{\delta_L}\ln\frac{\mathrm{E}[U_{L,S_p(1,0)}(P_3)]}{\mathrm{E}[U_{L,F}(P_3)]},$$

$$c_3 := \frac{1}{\delta_S}\ln\frac{\mathrm{E}[U_{S,S_p(1,0)}(P_3)]}{\mathrm{E}[U_{S,F}(P_3)]}, \quad c_4 := \frac{1}{\delta_S}\ln\frac{\mathrm{E}[U_{S,S_p(1,1)}(P_5)]}{\mathrm{E}[U_{S,F}(P_5)]}, \tag{9}$$

where traders' expected utility functions $E[U_{L,S_p(\cdot)}(P)], E[U_{S,S_p(\cdot)}(P)], E[U_{L,F}(P)]$, and $E[U_{S,F}(P)]$ are presented in equation (B-1) in Appendix B. Define function $f(z, \lambda_{L,I}^*)$ and coefficients $b_1, b_2, b_3, b_5, z_1, z_2, z_3$, and z_5 as in equation (B-1) in Appendix B. We next present our main theoretical results in the following theorem.

Theorem 1 (The Equilibrium). *Assume*

$$\delta_S > \frac{\ln E[U_{S,S_p(0,0)}(P_1)] - \ln E[U_{S,F}(P_1)]}{\ln E[U_{L,S_p(1,0)}(P_3)] - \ln E[U_{L,F}(P_3)]} \delta_L, \tag{10}$$

where P_1 and P_3 are as defined in equations (11) and (12) below. There are five cases in the equilibrium.

(i) If $c \geq c_1$, then $\lambda_{L,I}^* = \lambda_{S,I}^* = 0$, and the equilibrium price and trading quantities are

$$P_1 = \bar{V} + b_1(z - z_1), \tag{11}$$

$$\theta_{L,U} = \frac{E[V] - P_1 + k_L \bar{\theta}_L}{k_L + \delta_L \text{Var}[V]}, \quad \theta_{S,U} = \frac{E[V] - P_1}{k_S 1_{\{z > z_1\}} + \delta_S \text{Var}[V]}.$$

(ii) If $c_2 < c < c_1$, then $0 < \lambda_{L,I}^* < 1$, $\lambda_{S,I}^* = 0$, and the equilibrium price and trading quantities are

$$P_2 = \frac{\omega \lambda_{L,I}^* b_2}{k_L + \delta_L \text{Var}[V|F]} E[V|F] + \left(1 - \frac{\omega \lambda_{L,I}^* b_2}{k_L + \delta_L \text{Var}[V|F]}\right) E[V|S_p(\lambda_{L,I}^*, 0)] + b_2(z - z_2),$$

$$\theta_{L,I} = \frac{E[V|F] - P_2 + k_L \bar{\theta}_L}{k_L + \delta_L \text{Var}[V|F]}, \quad \theta_{L,U} = \frac{E[V|S_p(\lambda_{L,I}^*, 0)] - P_2 + k_L \bar{\theta}_L}{k_L + \delta_L \text{Var}[V|S_p(\lambda_{L,I}^*, 0)]}, \quad \theta_{S,U} = \frac{E[V|S_p(\lambda_{L,I}^*, 0)] - P_2}{k_S 1_{\{F > f(z, \lambda_{L,I}^*)\}} + \delta_S \text{Var}[V|S_p(\lambda_{L,I}^*, 0)]}.$$

(iii) If $c_3 \leq c \leq c_2$, then $\lambda_{L,I}^* = 1$, $\lambda_{S,I}^* = 0$, and the equilibrium price and trading quantities are

$$P_3 = \frac{\omega b_3}{k_L + \delta_L \text{Var}[V|F]} E[V|F] + \left(1 - \frac{\omega b_3}{k_L + \delta_L \text{Var}[V|F]}\right) E[V|S_p(1,0)] + b_3(z - z_3), \tag{12}$$

$$\theta_{L,I} = \frac{E[V|F] - P_3 + k_L \bar{\theta}_L}{k_L + \delta_L \text{Var}[V|F]}, \quad \theta_{S,U} = \frac{E[V|S_p(1,0)] - P_3}{k_S 1_{\{F > f(z,1)\}} + \delta_S \text{Var}[V|S_p(1,0)]}.$$

(iv) If $c_4 < c < c_3$, then $\lambda_{L,I}^* = 1$, $0 < \lambda_{S,I}^* < 1$, and the equilibrium price can be solved numeri-

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cally.[27]

(v) If $c \leq c_4$, then $\lambda^*_{L,I} = 1$, $\lambda^*_{S,I} = 1$, and the equilibrium price and trading quantities are

$$P_5 = E[V|F] + b_5(z - z_5), \quad \theta_{L,I} = \frac{E[V|F] - P_5 + k_L \bar{\theta}_L}{k_L + \delta_L \text{Var}[V|F]}, \quad \theta_{S,I} = \frac{E[V|F] - P_5}{k_S 1_{\{z > z_5\}} + \delta_S \text{Var}[V|F]}. \tag{13}$$

Theorem 1 states the following intuitive information acquisition pattern: When the acquisition cost is sufficiently high, no investor acquires information (Case (i)); when the acquisition cost is sufficiently low, all active investors acquire information (Case (v)); when the acquisition cost is in between, some active investors acquire information (Cases (ii)-(iv)). More importantly, Theorem 1 shows that whenever S investors acquire information, all L investors would have acquired information, and that even when S investors do so, they do *not* acquire better information than L investors. This implies that the information acquired by L investors always dominates that acquired by S investors, regardless of the information acquisition cost level (weak domination in Case (v) and strict domination in other cases). For example, in Cases (ii) and (iii), S investors choose not to observe private information while the L investors do. Intuitively, because L investors expect to have a larger position in the stock than S investors, they have a greater stake at risk and thus it benefits them more to acquire more precise information as long as their trading costs are not too high relative to those of S investors.

We next illustrate the results using the following parameter values: $\tau_\varepsilon = 0.5, \tau_F = 0.4, \tau_z = 0.5, \delta_L = 0.1, \delta_S = 0.5, \omega = 0.1, \bar{\theta} = 1, \bar{\theta}_L = \bar{\theta}/\omega, \bar{V} = 1, k_L = 0.1, k_S = 0.05$. In this example, the endogenous parameter $c_1 = 3.03, c_2 = 2.75, c_3 = 0.73$, and $c_4 = 0.36$. Assumption (10) is satisfied:

$$\frac{1}{\delta_S} \ln \frac{E[U_{S,Sp(0,0)}(P_1)]}{E[U_{S,F}(P_1)]} = 0.36 < c_2 := \frac{1}{\delta_L} \ln \frac{E[U_{L,Sp(1,0)}(P_3)]}{E[U_{L,F}(P_3)]} = 2.75.$$

This condition ensures that no short seller would pay the information acquisition cost to ob-

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[27]In the absence of trading costs (i.e., $k_L = k_S = 0$), we have $\lambda^*_{L,I} = \delta_L/(\omega\tau_\varepsilon)(\tau_\varepsilon + \tau_F(1 - e^{2\delta_L c}))^{1/2}((e^{2\delta_L c} - 1)\tau_z)^{-1/2}$ in Case (ii) and $\lambda^*_{S,I} = \delta_S/((1 - \omega)\tau_\varepsilon)(\tau_\varepsilon + \tau_F(1 - e^{2\delta_S c}))^{1/2}((e^{2\delta_S c} - 1)\tau_z)^{-1/2} - \omega\delta_S/((1 - \omega)\delta_L)$ in Case (iv).
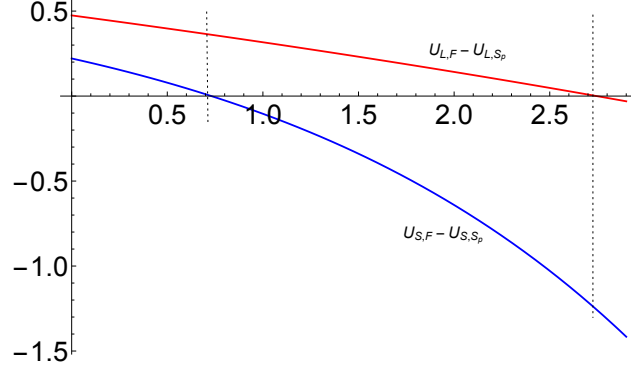
Figure IV: The expected utility difference between long investors (resp. short sellers) who observe F and those who do not observe F, $\mathrm{E}[U_{L,F}(P_3)] - \mathrm{E}[U_{L,S_p(1,0)}(P_3)]$ (resp. $\mathrm{E}[U_{L,F}(P_3)] - \mathrm{E}[U_{L,S_p(1,0)}(P_3)]$) for $\lambda_L^* = 1$ and $\lambda_S^* = 0$. The parameter values are $\tau_\varepsilon = 0.5, \tau_F = 0.4, \tau_z = 0.5, \delta_L = 0.1, \delta_S = 0.5, \omega = 0.1, \bar{\theta} = 1, \bar{\theta}_L = \bar{\theta}/\omega, \bar{V} = 1, k_L = 0.1, k_S = 0.05$. The endogenous parameter value $c_3 = 0.73$, and $c_2 = 2.75$.

serve private signal F before all L investors have paid and observed F. Intuitively, if some L investors have greater incentives (e.g., for investors who are expected to have a larger position) or lower costs (e.g., for insiders) to acquire information than S investors, they will acquire more precise information than S investors.

If $c > c_1$, then no investor pays c to observe F, and $\lambda_{L,I}^* = \lambda_{S,I}^* = 0$ (Case (i)). If $c_2 < c < c_1$, then $0 < \lambda_{L,I}^* < 1$, $\lambda_{S,I}^* = 0$, and the unique endogenous fraction of L investors can be solved numerically. For example, if $c = 2.8$, then, $\lambda_{L,I}^* = 0.89$. If $c_3 \le c \le c_2$, then $\lambda_{L,I}^* = 1$, $\lambda_{S,I}^* = 0$, implying all L investors pay to observe the private signal F, no S investors pay to observe F. This case is the focus of this paper and is illustrated in Figures IV. If $c_4 < c < c_3$, then $\lambda_{L,I}^* = 1$, $0 < \lambda_{S,I}^* < 1$, we don't have a closed form solution for this case, because the rational Bayesian updating involves solving for truncated normal distributions. If $c \le c_4$, then $\lambda_{L,I}^* = 1$ and $\lambda_{S,I}^* = 1$, implying all active investors pay to observe the private signal F.

Our model, like most rational expectations models, abstract away the dynamic evolution of market prices on a given date and assumes that the equilibrium price that equalizes the de-

mand and supply is reached instantly after a signal F is observed. Like other rational expectations models, one can view heuristically the following process of reaching an equilibrium: After the informed trade, the market price changes, other uninformed investors learn from the new market price and trade accordingly, which further changes the market price, and given the new price, the informed trade more. This iterative process continues until the price equalizes demand and supply. This process is consistent with the lead-lag mechanism found in our empirical analysis.

A measure of how much information is revealed to the market is the price informativeness represented by the variance of the stock payoff conditional on the market price, as shown in Equation (8). The lower this conditional variance, the more information revealed by market participants. Accordingly, we use its increase due to more stringent short-sale constraints to gauge the information revelation restrictiveness of the constraints.

For Cases (i)-(iii) where S investors do not acquire private information (i.e., $\lambda_{S,I}^* = 0$), it is clear from Equation (8) and Equation (B-1) in Appendix B that short-sale constraints do not affect the conditional variance and thus do not restrict information revelation.

For Cases (iv)-(v) where S investors acquire private information and short sell, as k_S increases, c_z (defined in Equation (B-1)) increases, and thus the conditional variance increases. In these two cases, short-sale constraints do reduce information revelation even though S investors do not have extra information compared to L investors. This is because L investors are risk averse and there is a trading cost, they trade a limited amount and thus in the presence of liquidity trades, their information is not fully revealed. As a result, an informed S investor's trade helps reveal more of the (same) information. Nevertheless, it is important to note that the contribution of short sellers to information revelation is likely to be economically insignificant. To illustrate this point, we examine two scenarios. The first and most realistic scenario is that there are much more L investors than S investors (i.e., ω is close to 1). Indeed, consistent with our earlier summary statistics, only 9% of the active investors are short sellers, i.e., $\omega = 0.91$. To show the robustness, we also consider an extreme scenario where 50% of the active investors are

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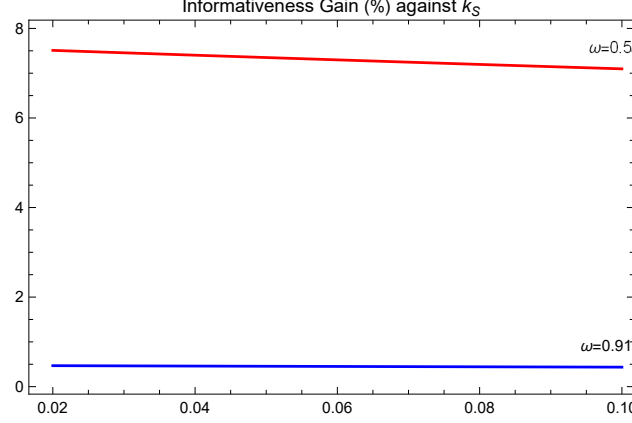
Figure V: The percentage gain in the informativeness from the information revealed by short sellers against the short-sale cost coefficient k_S. The parameter values are $\tau_\varepsilon = 0.5, \tau_F = 0.4, \tau_z = 0.005, \delta_L = 0.1, \delta_S = 0.5, \bar{\theta} = 1, \bar{\theta}_L = \bar{\theta}/\omega, \bar{V} = 10$, and $k_L = 0.1$.

short sellers, i.e., $\omega = 0.5$. We plot the percentage gain in the price informativeness (measured by the decrease in the conditional variance) from the information revealed by short-sellers in Case (v) (where all S investors acquire information) against the short-sale cost coefficient k_S in Figure V for these two mass levels of the L investors: $\omega = 0.91$ and $\omega = 0.5$. Figure V shows that the gain is a tiny 0.5% when $\omega = 0.91$ and only about 7% even when $\omega = 0.5$, i.e., L investors can reveal respectively 99.5% and 93% of the information that can be revealed in these two scenarios. These findings suggest that the additional information revealed by short sellers is indeed negligible and likely lacks economic significance. In addition, if liquidity trades are less volatile (τ_z is large) or the risk bearing capacity of the S investors is small (δ_S is large), the effect of short-sale constraints on information revelation is even smaller.

Intuitively, even when no short sellers trade to reveal any information (e.g., $k_S = \infty$), L investors can reveal some of the information F through selling and the information in the market gets close to what short sellers would reveal, even if they were able to trade without any constraints (i.e., $k_S = 0$). Therefore, it is difficult to significantly *further* reduce the conditional variance by short selling.

In summary, the results in Theorem 1 suggests that due to L investors acquiring superior information compared to S investors and their trades already revealing a portion of this information, the additional information that S investors can reveal is likely economically insignificant. This conclusion is a result of the joint effect of the information dominance of L investors and their relatively larger size (determined by θ_L and ω). Combining this conclusion with the lead-lag mechanism we empirically observe in Section 5, our study suggests that institutional sales are likely to play an important role in pricing in negative information, which were under-appreciated in the prior literature.

6.3 Model implications

Theorem 1 implies that L investors optimally acquire more precise private information than S investors. The information revealed from the sell orders of L investors at least weakly dominates S investors' information. In addition, the population of short sellers is much smaller than L investors. As a result, the stringency of short-sale constraints does not significantly prevent negative information from being revealed. Yet, the stringency of short-sale constraints may still "predict" lower average returns. This is because short-sale constraints are more likely to be binding (or short sellers are more willing to pay higher short-sale costs) when the stock return is foreseen *by all active investors* to be low. More specifically, the realized return at time 1, $V - P$ or $(V - P)/P$, depends on the realizations of F and z. In the states (represented by (F, z)) where the information revealed by the market price is more negative and thus the expected return going forward is more negative, S investors short sell more and pay greater short-sale costs. Note that the expected return becomes lower not because there is any inefficient pricing. Instead, the lower expected returns are a result that in a market with noise trading and risk averse investors, private information cannot be completely revealed through trading until it is publicly announced later. Therefore, consistent with empirical findings in the literature, the first prediction of our model is:

Prediction 1: The date 0 stringency of the short-sale constraints is negatively correlated with the return from date 0 to date 1.

To illustrate this prediction, we simulate the model in Case (iii) where all L investors acquire information and none of S investors do, with 100,000 samples from the distributions of the three random variables F, ε, and z for each value of k_S equally spaced between 0.03 and 0.08, a total sample size of 600,000. Allowing the short-sale cost coefficient k_S to vary, we capture the variation of the different short-sale cost levels in data. We plot the simple OLS regression line of the realized returns against the total realized short-sale costs, a measure of the stringency of the short-sale constraints, in Figure VI.[28] Consistent with Prediction 1, Figure VI suggests that when the stringency of short-sale constraints increases, the future realized returns tend to decrease, resulting in a negative correlation between the stringency of short-sale constraints and future realized stock returns, as predicted by the model and found in the existing literature.

Because Figure VI is generated for Case (iii) where none of S investors acquire any private information, S investors have no private information to reveal and thus short-sale constraints cannot restrict information revelation. Still, we find the negative predictability in Figure VI. This suggests that the finding of a negative predictability of short-sale constraints does not necessarily imply that short-sale constraints significantly restrict negative information revelation, as commonly interpreted in the existing literature. Intuitively, this predictability in our model is simply because a negative signal F implies that the expected return from date 0 to date 1 is negative given the equilibrium price P on date 0 (see Equation (B-2)),[29] and thus S investors tend to short sell more, making short-sale constraints more stringent. In terms of the time line, after receiving a negative signal L investors sell due to the lower expected return, short sellers then partially infer the states from the market price decline and short sell, making short-sale

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[28]As in the existing literature with CARA preferences, equilibrium prices can be negative. In Figures VI and VII and Table VI, we compute the simple percentage returns using only samples where prices are positive. When the unconditional expected return is high, it is with high probability that the equilibrium prices are positive.

[29]As an example, suppose the stock price was $10 before the negative signal was received. After trading following the signal, the equilibrium price on date 0 goes down to $8. The expected return from $8 on date 0 to date 1 is still negative (e.g., expected to go down further to $7). This shows why short sellers are willing to short sell even after the price has already dropped to $8 from $10.

$\dfrac{V-P}{P}$ **against** $\dfrac{1}{2}k_S\theta_{S,U}^2$
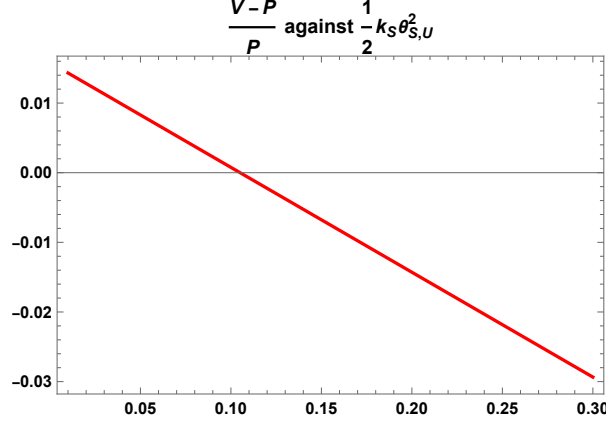
Figure VI: The realized returns against the stringency of short-sale constraints (short-sale costs paid by the short sellers) in Case (iii) from a random sample size of 1 million. The parameter values are $\tau_\varepsilon = 0.5, \tau_F = 0.4, \tau_z = 0.005, \delta_L = 0.1, \delta_S = 0.5, \omega = 0.1, \bar{\theta} = 1, \bar{\theta}_L = \bar{\theta}/\omega, \bar{V} = 10,\ k_S = 0.03, 0.04, ..., 0.08$, and $k_L = 0.1$.

constraints more stringent, and then on average the anticipated lower returns are realized.

Turning to L investors, we note that the more negative the signals observed by L investors, the lower the future returns, and thus these L investors will sell more shares. This leads to our second prediction:

Prediction 2: The date 0 percentage of L investors' sales $(\bar{\theta}_L - \theta_{L,I})/\bar{\theta}_L$ is negatively correlated with the return from date 0 to date 1.

To illustrate this prediction, we use the same sample used for generating Figure VI to plot the simple OLS regression line of the realized returns against the percentage of L investors' sales together with realized returns in Figure VII. Consistent with Prediction 2, the return tends to decrease as the percentage of sales increases.[30]

Predictions 1 and 2 imply that both the stringency of short-sale constraints and the percentage sales of L investors predict lower future returns. A natural question is whether the stringency

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[30]It is worth noting that Predictions 1 and 2 can be analytically shown using Equation (B-2) and Theorem 1 in all cases except Case (iv). For example, consider Case (v) with a negative expected return $E[V|F] - P$. By Equation (B-2), we have the realized short-sale costs are equal to

$$\frac{1}{2}k_S(\theta_{S,I}^*)^2 = \frac{1}{2}k_S\left(\frac{E[V|F] - P}{k_S 1_{\{\theta_{S,I}^* < 0\}} + \delta_S \text{Var}[V|F]}\right)^2$$

of short-sale constraints or the percentage of L investors' sales is more informative about future returns. Theorem 1 shows that the information acquired by L investors dominates that of S investors. This information dominance and the much larger size of the L investors imply that short-sale constraints do not significantly, if at all, restrict negative information revelation. In addition, Equations (7) and (8) imply that when L investors submit a larger sell order (after receiving a more negative signal F), they reveal more information and S investors' overestimation of the true expected return is greater, and thus the negative predictability of the stringency of the short-sale constraints is weaker. Intuitively, S investors cannot precisely observe the true fundamental signal from public information. Their conditional valuation of the stock will thus tend to shrink all signals towards the signals' unconditional mean 0. Thus, the more negative the signal, the more S investors will overestimate the true value of the stock compared to L investors who observe the negative signal. Therefore, our model has the following prediction:

Prediction 3: Conditional on the percentage sale of L investors $(\bar{\theta}_L - \theta_{L,I})/\bar{\theta}_L$ being sufficiently large, the stringency of the short-sale constraints no longer predicts lower future returns.

Our model implies that short-sale constraints do not significantly restrict negative information revelation especially when the percentage sale of the long-only investors is large.[31] In some cases (Cases ii and iii), S investors do not possess any private information and only learn from the equilibrium market price, consistent with the main finding of Engelberg et al. (2012).[32] Be-

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and the percentage of L investors' sales

$$\frac{\bar{\theta}_L - \theta_{L,I}^*}{\bar{\theta}_L} = \frac{-(\mathrm{E}[V|F] - P) + \delta_L \mathrm{Var}[V|F]\bar{\theta}_L}{k_L + \delta_L \mathrm{Var}[V|F]}.$$

By Equation (13), both the realized short-sale costs and the percentage of L investors' sales increase in z (conditional on short sellers shorting). Because the realized return $\frac{V-P}{P}$ decreases in z, and z is independent of ε and F, the return is negatively correlated with both the realized short-sale costs and the percentage of L investors' sales, implying Predictions 1 and 2. Case (i) is similar. It can be shown that for Cases (ii) and (iii), both the realized short-sale costs and the percentage of L investors' sales will increase with F and z, while the return decrease in F and z, so implying the same results.

[31]Although short-sale constraints do not affect information revelation in these cases, they may affect information acquisition ex ante in some situations. It can be shown that as the short-sale costs increase, the information acquisition cost threshold c_3 below which some short sellers acquire information decreases. In this sense, short-sale frictions can (but not always) reduce the incentives of short sellers for acquiring information.

[32]This learning mechanism suggests that if we had an alternative model where L investors acquire information and immediately trade, short sellers learn from the market price and trade in the next period, then we would have another prediction: The information of the short sellers lags that of the L investors.

$$\frac{V-P}{P} \text{ against } \frac{\bar{\theta}_L - \theta_{L,I}}{\bar{\theta}_L}$$
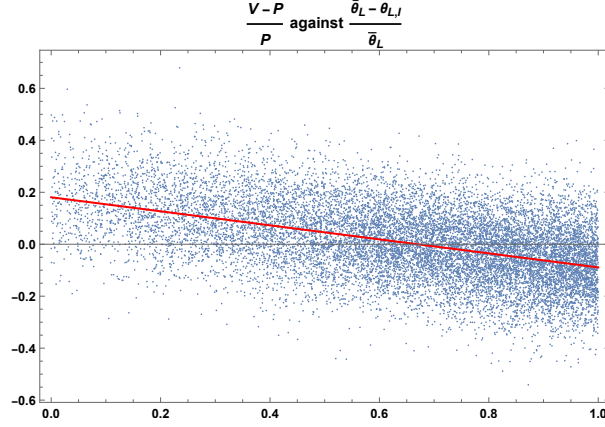
Figure VII: Return against the percentage sale of the long investors $((\bar{\theta}_L - \theta_{L,I})/\bar{\theta}_L)$ from a random sample size of 1 million. The parameter values are The parameter values are $\tau_\varepsilon = 0.5, \tau_F = 0.4, \tau_z = 0.005, \delta_L = 0.1, \delta_S = 0.5, \omega = 0.1, \bar{\theta} = 1, \bar{\theta}_L = \bar{\theta}/\omega, \bar{V} = 10, k_S = 0.03, 0.04, ..., 0.08$, and $k_L = 0.1$.

cause the overestimation of short sellers increases with the percentage sale of L investors, our model also predicts that the predictability of the stringency of the short-sale constraints may even turn positive, conditional on large sales of L investors.

To show that these predictions are valid in our model, we simulate the model with 100,000 samples of the three random variables F, ε and z for each value of k_S equally spaced between 0.03 and 0.08.[33] For the sample where the equilibrium price is positive, S investors short, and L investors sell but do not short sell. We normalize L investors' sale to be between 0 and 1 by dividing the sales by the maximum of the simulated sales. Thus, we define the scaled sale of L investors as

$$ScaledSale_i := \frac{(\bar{\theta}_L - \theta_{L,I,i})/\bar{\theta}_L}{\max\{(\bar{\theta}_L - \theta_{L,I,i})/\bar{\theta}_L\}}, \quad \text{for } i = 1, 2, ..., 600,000.$$

We then conduct the following regressions:

1. Model A: regress the return $\frac{V-P}{P}$ on the total realized short-sale costs $SSCosts$;

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[33] In Figure VI, Figure VII, and Table VI, we use the same set of parameter values as those in the above numerical example and Figure IV, except that $\tau_z = 0.005$. We use a higher precision $\tau_z = 0.5$ in the above numerical example and Figure IV to make the numerical and graphical illustration clearer.

2. Model B: regress the return $\frac{V-P}{P}$ on the scaled sale of L investors $ScaledSale$;

3. Model C: regress the return $\frac{V-P}{P}$ on $SSCosts$, $ScaledSale$, and the interaction term $ScaledSale \times SSCosts$.[34]

We report the regression results in Table VI.[35] Consistent with Predictions 1 and 2, Models A and B show that both $SSCosts$ and $ScaledSale$ predicts lower returns. In Model C, the total return predictability of $SSCosts$ is measured by -0.125+0.180*$ScaledSale$. This number increases with $ScaledSale$. It reaches zero and turns positive when $ScaledSale \geq 0.7$, i.e., when L investors' sale is in its largest 30 percentile. Therefore, the return predictability of $SSCosts$ weakens with $ScaledSale$. Conditional on sufficiently large $ScaledSale$, $SSCosts$ no longer predicts lower returns.

We note that using sufficiently large sales is only one identification method to detect strong disparity in informativeness between L and S investors. If an econometrician can identify truly private information-based sales with sufficiently high precision, then conditional on such sales, the stringency of short-sale constraints also no longer predicts lower future returns. We present such a setting based on illegal insider trading in Section 4.

In summary, in contrast to the key assumption in the existing literature, our model implies that, short-sale constraints may not prevent negative information from being revealed to the market, because more precise information may be inferred from the sales of long institutional investors who sell but do not short sell and are thus not affected by the short-sale constraints. The empirical finding of the negative predictability of short-sale constraints might not be because the short-sale constraints prevent negative information revelation. Instead, it is because the states where short sellers are willing to borrow shares at high fees or where the short-sale constraints bind more are the states where the conditional expected returns are low based on

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[34]We ran similar regressions with a dummy variable $ScaledSaleDummy_i$ defined as 1 if $ScaledSale_i > 0.7$ and 0 if $ScaledSale_i < 0.3$ to classify large sales, and with different cut off points for large sales. We obtain similar results.

[35]The high t-statistics values for some coefficients indicate that the noise is small for the given parameter values. Increasing the noise in the liquidity trades would decrease the t-statistics values, but the corresponding coefficients would still be highly significant.

Table VI: Short-sale Costs (the stringency of short-sale constraints) and Institutional Sales

We simulate the model with 100,000 samples for the three random variables F, ε, and z with 6 different values of k_S equally spaced between 0.03 and 0.08, so the total sample size is 600,000. For the subsample where the equilibrium price is positive, the short sellers short and the long investors sell but still keep a long position, we run the following regressions:

Model A : $R_i = a + b * SSCosts_i + u_i,$

Model B : $R_i = a + b * ScaledSale_i + v_i,$

Model C : $R_i = a + b * SSCosts_i + c * ScaledSale_i + d * SSCosts_i * ScaledSale_i + z_i,$

where R_i is the stock return, $SSCosts_i$ are the short-sale costs, $\frac{1}{2} k_S (\theta_S^-)^2$, $ScaledSale_i$ is the scaled-sale variable for the long-only investors, and u_i, v_i, and z_i are the error terms.

| | Coefficients | | | | | |
| | Model A | | Model B | | Model C | |
Variable	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
$SSCosts$	-0.150	(-12.280)	.	.	-0.125	(-2.960)
$ScaledSale$	.	.	-0.274	(-66.999)	-0.283	(-59.211)
$SSCosts \times ScaledSale$	.	.	.	.	0.180	(3.392)

the negative information that has already been revealed through the sell (*not* short-sell) orders of long institutional investors.

7   Market return predictability

Clearly, the single stock in our model can be reinterpreted as the market index, and thus its predictions still hold at the market portfolio level, if other forces in the data are not strong enough to counteract the mechanism in our model. For example, the model predicts that the market-wide stringency of short-sale constraints negatively predict the market return. This negative predictability could be viewed by the existing literature as evidence that short-sale constraints restrict market-wide negative information revelation, thus leading to market bubbles. However,

our theory suggests that informed institutional sales are likely the much more important force than short sales in revealing negative information because of their much larger size and higher incentive to learn about market-wide negative information than short sellers.

We next test our theory predictions at the market level. To be comparable with Table III, we compute market-wide SIO and $Sale$ as follows: For SIO, we first average SI in each month t across all stocks, and then detrend the aggregate SI following Rapach, Ringgenberg, and Zhou (2016). Similarly, we compute the aggregate IO and detrend it. To avoid that detrending IO changes the monotonicity of SIO, we shift the detrended IO to be greater than or equal to zero. We standardize the resulting SIO and shift it to be greater than or equal to zero so that $SIO = 0$ has the same interpretation of being the lowest level of stringency of short-sale constraints as in Table III. For $Sale$, we first average hedge fund sales across stocks and then detrend the aggregate hedge fund sales measure. We transform the detrended measure into a score between 0 and 1 by ranking the measure in the time series into deciles and then scale the ranks into a score between 0 and 1.

Table VII: Market-Level Stringency of Short-Sale Constraints and Informed Institutional Sales

This table reports the results from the market-level OLS regressions of the S&P 500 index return on the last-quarter SIO (i,t-3) and hedge fund Sale (i,t-3), and their interaction term. The dependent variable is the cumulative 1-month, 3-month, and 6-month index return in Panel A, B, and C respectively. Definitions of firm-level short interest (SI), non-hedge fund IO, and hedge fund sales are detailed in Table I. Each quarter, we aggregate SI, non-hedge fund IO, and hedge fund sales into the market level by averaging across all stocks in the cross-section and are then detrended. We shift the detrended market-level non-hedge fund IO to be bounded above zero, and then standardize the resulting market-level SIO and shift it to be bounded above zero. Market-level hedge fund sales are converted into a Sale score with 1 (0) corresponding to the largest (smallest) decile of hedge fund sales in the time series. Heteroskedasticity- and autocorrelation-robust t-statistics are reported in the bracket. The sample period is January 1981 through December 2018. *, **, and *** indicate that the coefficients are statistically significant with a two-sided test at the 10%, 5%, and 1% level, respectively. Gray shade highlights the significant results of interest.

Dependent Variable	S&P 500 Index Return (%)								
	Panel A: Return (i,t+1) (%)			Panel B: Return (i,t+3)			Panel C: Return (i,t,t+6)		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
SIO (i,t-3)	-0.514**	-0.713***	-0.672***	-0.988*	-1.385**	-1.296***	-1.143	-2.055**	-1.913**
	[-2.07]	[-2.60]	[-2.63]	[-1.92]	[-2.58]	[-2.74]	[-1.58]	[-2.23]	[-2.57]
Sale (i,t-3)		-0.412*	-1.313***		-0.820**	-2.648***		-1.301**	-4.131***
		[-1.88]	[-2.97]		[-2.24]	[-3.64]		[-2.28]	[-3.69]
SIO (i,t-3) × Sale (i,t-3)			0.330**			0.669***			1.037***
			[2.58]			[2.94]			[2.90]
Observations	452	452	452	450	450	450	447	447	447
Adj R²	0.012	0.017	0.030	0.024	0.035	0.062	0.033	0.054	0.099
SIO + SIO × [Sale=Top decile]			-0.342			-0.627			-0.877
			[-1.38]			[-1.34]			[-1.11]

In Column (1) of Panels A—C in Table VII, we regress the future market returns of one, three, and six months on SIO, respectively. In Column (2), we do the same for $Sale$. Columns (1) and (2) show that both SIO and $Sale$ can significantly negatively predict market returns of different horizons.[36] Column (2) shows that a 1-STD increase in SIO predicts a 71-, 139-, and 206-bp lower market returns in the subsequent one, three, and six months, respectively, which are substantial. Large informed institutional sales are also particularly informative about negative market-wide information. Indeed, when sales are in their largest decile ($Sale$ = 1), market returns are lower by 41-, 82-, and 130-bp over the subsequent one, three, and six months, respectively. In Column (3), we include the interaction term $SIO \times Sale$. The coefficient estimates on the interaction term are significantly positive. The last row of Column (3) shows that conditional on large sales ($Sale$ = 1), SIO's negative market return predictability is statistically insignificant across all horizons.

Overall, even at the market level, short-sale constraints and informed institutional sales can negatively predict market returns, consistent with Predictions 1 and 2. But, informed institutional sales weaken the negative return predictability of short-sale constraints, and sufficiently large informed institutional sales can even render such predictability insignificant, consistent with Prediction 3.

8 Conclusion

Existing literature concludes that binding short-sale constraints restrict the revelation of negative information. However it largely overlooks negative information in informed sales. Our study, based on data on informed institutional and illegal insider sales, show that informed sales can significantly weaken the impact of short-sale constraints. We provide evidence of a lead-lag information transmission mechanism, with informed sales unidirectionally leading

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[36]Rapach et al. (2016) show that market-wide short interest (SI) is arguably the strongest known predictor of aggregate stock market returns. Since short interests and the stringency of short-sale constraints are jointly determined in equilibrium, the predictability of SIO is consistent with their findings. Notwithstanding, Rapach et al. (2016) use a one-sided test. We instead use two-sided tests, which is more stringent.

short-sales, other institutional sales, and the stringency of short-sale constraints. These find-ings are also supported by a rational expectations equilibrium model. Our analysis underscores the undervalued role of informed sales in understanding overpricing and market bubbles.

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Appendices

Appendix A   Tables

Table A.I: Full Sample Summary Statistics

This table reports the summary statistics for the main variables used in the paper for the full sample where we do not require hedge fund sales≥0. SIO is defined as short interest SI (defined as the ratio of shares sold short to total shares outstanding at a quarter end) to institutional ownership IO (defined as the ratio of ownership by institutions at a quarter end relative to total outstanding shares) for each firm every quarter. We use only non-hedge fund IO for computing SIO. Hedge fund (Non-hedge fund) sales is the negative percentage change of the current-quarter shares held -ΔIH from hedge funds (Non-hedge funds) relative to its average over the past four quarters, where we do not require -ΔIH≥0. Control variables include log of market capitalization (size), book-to-market ratio (B/M), past one-month return (Reversal), and momentum return (Mom12m) measured as the cumulative return from month t-12 to month t-2. Number of observations, Mean, standard deviation, median, the first and third quartiles (P25 and P75), skewness, and kurtosis of the firm-month observations for each variable are reported. The sample period is January 1981 through December 2018.

	N	Mean	Std. Dev.	P25	Median	P75	Skewness	Kurtosis
SIO	1,276,951	0.094	0.232	0.008	0.032	0.087	6.106	45.571
SI	1,276,951	0.032	0.046	0.003	0.014	0.040	2.582	10.815
HF Sales	1,276,951	-0.502	2.320	-0.489	-0.016	0.348	-5.320	36.723
Non-HF Sales	1,276,951	-0.124	0.518	-0.147	-0.027	0.029	-6.414	65.092
IO All	1,276,951	0.501	0.261	0.289	0.503	0.711	-0.003	2.011
Size	1,276,951	13.408	1.730	12.150	13.317	14.577	0.201	2.586
B/M	1,276,951	0.577	0.445	0.286	0.495	0.765	1.938	10.975
Reversal	1,276,951	0.016	0.124	-0.048	0.010	0.071	0.638	6.283
Mom12m	1,276,951	0.191	0.507	-0.101	0.112	0.361	1.832	8.527

Table A.II: Alternative Measures of Stringency of Short Constraints

This table reports the results from the panel regressions of the monthly stock Return (i,t) on the last-quarter hedge fund Sale (i,t-3), Constraint (i, t-3), and their interaction term. Constraint=standardized 1/IO (ΔSIO and $\frac{1}{Dbreadth}$) in Panel A (B and C). IO is defined as the non-hedge fund institutional ownership. ΔSIO is defined as the relative change in SIO. We further shift ΔSIO so that is greater than or equal to zero. Dbreadth is defined as the quarterly change in breadth of mutual fund ownership. We shift Dbreadth to be greater than or equal to zero so that $\frac{1}{Dbreadth}$ is a monotone transformation of Dbreadth. Definition of hedge fund sales are detailed in Table I. Hedge fund sales are converted into a Sale score with 1 (0) corresponding to the largest (smallest) decile of hedge fund sales. Month fixed effects and firm-level controls depicted in Table I are included. Constant terms are omitted. T-statistics are reported in the bracket, and are based on standard errors clustered by firm and month. The sample period is January 1981 through December 2018. *, **, and *** indicate that the coefficients are statistically significant at the 10%, 5%, and 1% level, respectively. Gray shade highlights the results of interest, and bold coefficients indicate the significant results of interest.

	Panel A: Constraint=1/IO			Panel B: Constraint= Δ SIO			Panel C: Constraint= $\frac{1}{Dbreadth}$		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Constraint(i,t-3)	-0.065*		-0.708**	-0.016		-0.197***	-0.01		-0.088**
	[-1.81]		[-2.48]	[-0.65]		[-2.94]	[-0.46]		[-2.16]
Sale (i,t-3)		-0.437***	-0.437***		-0.394***	-0.449***		-0.389***	-0.407***
		[-4.54]	[-4.54]		[-3.95]	[-4.53]		[-3.84]	[-3.99]
Constraint(i,t-3) × Sale (i,t-3)			**0.830***			**0.280***			**0.190***
			[2.34]			**[2.95]**			**[2.74]**
Observations	623,619	623,619	623,619	574,343	574,343	574,343	529,694	529,694	529,694
Adj R^2	0.156	0.156	0.156	0.154	0.154	0.154	0.156	0.156	0.156
Constraint + Constraint× [Sale=Top decile]			0.122			**0.084**			**0.102**
			[1.52]			**[2.08]**			**[2.54]**

Table A.III: Stringency of Short-Sale Constraints and Non-Hedge Fund Sales

This table reports the results from the panel regressions of the monthly stock Return (i,t) on the last-quarter non-hedge fund Sale (i,t-3), SIO (i,t-3), and their interaction term. Definition of SIO and non-hedge fund sales are detailed in Table I. We further standardize SIO. Non-hedge fund sales are converted into a Sale score with 1 (0) corresponding to the largest (smallest) decile of non-hedge fund sales. Month fixed effects and firm-level controls depicted in Table I are included. Constant terms are omitted. *T*-statistics are reported in the bracket, and are based on standard errors clustered by firm and month. The sample period is January 1981 through December 2018. *, **, and *** indicate that the coefficients are statistically significant at the 10%, 5%, and 1% level, respectively. Gray shade highlights the results of interest, and bold coefficients indicate the significant results of interest.

Dependent Variable	Return (i,t) (%)		
	(1)	(2)	(3)
SIO (i,t-3)	-0.238***		-0.670***
	[-5.98]		[-4.02]
Sale (i,t-3)		-0.723***	-0.887***
		[-5.00]	[-4.85]
SIO (i,t-3) × Sale (i,t-3)			**0.551***
			[3.10]
Size (i,t-1)	0.024	-0.002	-0.004
	[0.75]	[-0.07]	[-0.14]
B/M (i,t-1)	0.449***	0.450***	0.434***
	[3.61]	[3.66]	[3.55]
Reversal (i,t-1)	-2.035**	-1.999**	-1.999**
	[-2.08]	[-2.05]	[-2.05]
Mom12m (i,t-1)	0.901***	0.891***	0.901***
	[3.43]	[3.40]	[3.44]
Observations	632,620	632,620	632,620
Adj R^2	0.12	0.12	0.12
Constraint + Constraint× [Sale=Top decile]			**-0.119***
			[-3.01]

Table A.IV: Weekly Return Predictability of Stringency of Short-Sale Constraints

This table reports the results from the panel regressions of the weekly stock Return (i,t) on the past-week Constraint (t-1). Constraint=standardized Utilization and Short Costs in Columns (1) and (2), respectively. Utilization (i,t-1) is defined as the weekly average of daily ratio of value on loan to total value over week t-1 obtained from Markit. Short Costs (i,t-1) is defined as the weekly average of daily simple average fee (SAF) of stock borrow transactions obtained from Markit. Week fixed effects and firm-level controls depicted in Table I are included. T-statistics are reported in the bracket, and are based on standard errors clustered by firm and week. The sample period is January 2002 through December 2015. *, **, and *** indicate that the coefficients are statistically significant at the 10%, 5%, and 1% level, respectively. Gray shade highlights the results of interest, and bold coefficients indicate the significant results of interest.

Dependent Variable	Return (i,t) (%)	
	(1) Constraint=Utilization	(2) Constraint=Short Costs
Constraint (i,t-1)	**-0.056****	**-0.284***
	[-2.17]	**[-1.92]**
Size (i,t-1)	0.002	0.006
	[0.24]	[0.41]
B/M (i,t-1)	-0.034	-0.048
	[-0.99]	[-1.06]
Reversal (i,t-1)	-0.114	-0.116
	[-0.48]	[-0.41]
Mom12m (i,t-1)	0.037	0.046
	[0.66]	[0.63]
Observations	1,871,378	841,757
Adj R^2	0.207	0.259

Table A.V: DiD Analysis Using Shorting Costs

This table reports the differences-in-difference (DiD) tests on the effect of illegal insider sales on the return predictability of Constraint, where Constraint=standardized Short Costs. Short Costs (i,t-1) is defined as the weekly average of daily simple average fee (SAF) of stock borrow transactions obtained from Markit. Event is a dummy that equals one if a firm-week observation is in the illegal insider sale week (week 1) and zero if it is in the three weeks before the insider sales (week -3, -2, and -1). IllegalInsider is a dummy that equals one for treatment firms (firms with illegal insider sales) and zero for control firms (firms without illegal insider sales). We match the treatment firms with control firms using one-to-ten nearest neighbor propensity score matching, with replacement. Panel A reports the validity of the propensity score matching by comparing the matched characteristics between the treatment and control groups in the pre-treatment week. Panel B reports the DiD results. We require the information relevant to the insider sales not be announced within a week window around the sales. Week fixed effects and firm-level controls depicted in Table I are included. *T*-statistics are reported in the bracket, and are based on standard errors clustered by firm and week. The sample period is January 2002 through December 2015. *, **, and *** indicate that the coefficients are statistically significant at the 10%, 5%, and 1% level, respectively. Gray shade highlights the results of interest, and bold coefficients indicate the significant results of interest.

	Panel A: Post-match Comparison		
	Treatment Group	Control Group	Difference (ttest)
Short Costs	0.009	0.01	[-0.24]
Price	27.104	25.8	[0.31]
Size	21.713	21.576	[0.41]
B/M	0.381	0.373	[0.17]
Reversal	0.011	0.005	[0.22]
Mom12m	-0.039	0	[-0.52]
RetVol	0.032	0.034	[-0.42]

Panel B: DiD Analysis

Dependent Variable	Return (i,t+1) (%)
	Event Window [-3,1]
Short Costs (i,t)	-0.305
	[-1.54]
IllegalInsider (i,t) × Event (i,t)	-5.011***
	[-2.80]
Short Costs (i,t) × Event (i,t)	-0.107
	[-0.42]
Short Costs (i,t) × IllegalInsider (i,t)	0.583***
	[2.65]
Short Costs (i,t) × Event (i,t) × IllegalInsider (i,t)	**1.327*****
	[3.63]
Other regressors: *Event, IllegalInsider, Size, B/M, Reversal, Mom12m*	
Observations	2,394
Adj R^2	0.351
Constraint + Constraint × Event	**1.498*****
+ Constraint × [IllegalInsider=1] + Constraint × [IllegalInsider =1] × Event	**[6.31]**

Table A.VI: DiD Analysis with Alternative Gaps between Illegal Insider Sales and News Announcement

This table reports the differences-in-difference (DiD) tests on the effect of illegal insider sales on the return predictability of Constraint using two alternative requirements on the length of the gap between insider sale and the news announcement. Constraint=standardized Utilization. Utilization (i,t) is the weekly average of daily ratio of value on loan to total (active) lendable value over week t obtained from Markit. Event is a dummy that equals one if a firm-week observation is in the illegal insider sale week (week 1) and zero if it is in the three weeks before the insider sales (week -3, -2, and -1). IllegalInsider is a dummy that equals one for treatment firms (firms with illegal insider sales) and zero for control firms (firms without illegal insider sales). We match the treatment firms with control firms using one-to-ten nearest neighbor propensity score matching, with replacement. Panel A reports the validity of the propensity score matching by comparing the matched characteristics between the treatment and control groups in the pre-treatment week. Panel B reports the DiD results. Panel A (B) report the DiD results that require the information relevant to the insider sales not announced within 7 (10) trading days after the insider sales. Week fixed effects and firm-level controls depicted in Table I are included. T-statistics are reported in the bracket, and are based on standard errors clustered by firm and week. The sample period is January 2002 through December 2015. *, **, and *** indicate that the coefficients are statistically significant at the 10%, 5%, and 1% level, respectively. Gray shade highlights the results of interest, and bold coefficients indicate the significant results of interest.

Dependent Variable	Return (i,t+1) (%)	
Gap (Trade, News)	Panel A:>7 days	Panel B: >10 days
Utilization (i,t)	0.317	-0.131
	[1.55]	[-0.53]
IllegalInsider (i,t) × Event (i,t)	-7.911**	-4.098**
	[-2.23]	[-2.09]
Utilization (i,t) × Event (i,t)	0.028	-0.087
	[0.11]	[-0.28]
Utilization (i,t) × IllegalInsider (i,t)	-0.509	-0.146
	[-1.31]	[-0.31]
Utilization (i,t) × Event (i,t) × IllegalInsider (i,t)	**2.404****	**1.614***
	[2.00]	**[1.86]**
Other regressors: *Event, IllegalInsider, Size, B/M, Reversal, Mom12m*		
Observations	3,401	2,614
Adj R^2	0.208	0.245
Constraint + Constraint × Event	**2.240***	1.249
+ Constraint × [IllegalInsider =1] + Constraint × [IllegalInsider =1] × Event	**[1.88]**	[1.62]

Table A.VII: Long-Run Return Predictability of Hedge Fund Sales

This table reports the results from the panel regressions of the long-run stock returns on lagged hedge fund sales. The dependent variables are the quarterly return over month t to t+2, t+3 to t+5, t+6 to t+8, and t+9 to t+11, respectively. Definitions of hedge fund sales is detailed in Table I caption. Hedge fund sales are converted into a Sale score with 1 (0) corresponding to the largest (smallest) decile of hedge fund sales. Month fixed effects and firm-level controls depicted in Table I are included. T-statistics are reported in the bracket, and are based on standard errors clustered by firm and month. The sample period is January 1981 through December 2018. *, **, and *** indicate that the coefficients are statistically significant at the 10%, 5%, and 1% level, respectively. Gray shade highlights the results of interest, and bold coefficients indicate the significant results of interest.

Dependent Variable	(1) Return (i,t,t+2) (%)	(2) Return (i,t+3, t+5) (%)	(3) Return (i,t+6,t+8) (%)	(4) Return (i,t+9,t+11) (%)
Sale (i,t-3)	**-1.163*****	**-0.756*****	**-0.798*****	**-0.494****
	[-4.82]	**[-3.30]**	**[-3.62]**	**[-2.01]**
Size (i,t-1)	0.03	0.042	0.032	0.025
	[0.43]	[0.56]	[0.41]	[0.33]
B/M (i,t-1)	1.330***	1.108***	0.990***	0.894***
	[4.14]	[3.51]	[3.33]	[2.99]
Reversal (i,t-1)	0.458	2.08	2.853**	3.225**
	[0.27]	[1.33]	[2.13]	[2.31]
Mom12m (i,t-1)	1.596***	0.311	-0.767	-0.985**
	[3.22]	[0.60]	[-1.63]	[-2.43]
Observations	619,702	607,193	594,137	581,122
Adj R^2	0.168	0.165	0.163	0.16

Appendix B Proofs

B.1 Proof of Theorem 1

Functions $f(z, \lambda_{L,I}^*)$ and $c_z(\lambda_{L,I}^*, \lambda_{S,I}^*)$ and the endogenous parameters $b_1, b_2, b_3, b_5,\ z_1, z_2, z_3$, and z_5 in Theorem 1 are defined as follows.

$$f(z, \lambda_{L,I}^*) := \frac{\omega \lambda_{L,I}^* \tau_z c_z(\lambda_{L,I}^*, 0) z - \left(c_z(\lambda_{L,I}^*, 0)^2 \tau_F + \tau_z \right) \left(k_L + \delta_L \operatorname{Var}[V|F] \right)(z - z_2)}{c_z(\lambda_{L,I}^*, 0)^2 \omega \lambda_{L,I}^* \tau_F},$$

$$c_z(\lambda_{L,I}^*, \lambda_{S,I}^*) := \left(\frac{\omega \lambda_{L,I}^*}{k_L + \delta_L \operatorname{Var}[V|F]} + \frac{(1-\omega) \lambda_{S,I}^*}{k_S \mathbb{1}_{\{z > z_5\}} + \delta_S \operatorname{Var}[V|F]} \right)^{-1}, \quad b_1 := \left(\frac{\omega}{k_L + \delta_L \operatorname{Var}[V]} + \frac{1-\omega}{k_S \mathbb{1}_{\{z > z_1\}} + \delta_S \operatorname{Var}[V]} \right)^{-1},$$

$$b_2 := \left(\frac{\omega \lambda_{L,I}^*}{k_L + \delta_L \operatorname{Var}[V|F]} + \frac{\omega(1-\lambda_{L,I}^*)}{k_L + \delta_L \operatorname{Var}[V|S_p(\lambda_{L,I}^*, 0)]} + \frac{1-\omega}{k_S \mathbb{1}_{\{F > f(z, \lambda_{L,I}^*)\}} + \delta_S \operatorname{Var}[V|S_p(\lambda_{L,I}^*, 0)]} \right)^{-1},$$

$$b_3 := \left(\frac{\omega}{k_L + \delta_L \operatorname{Var}[V|F]} + \frac{1-\omega}{k_S \mathbb{1}_{\{F > f(z, 1)\}} + \delta_S \operatorname{Var}[V|S_p(1, 0)]} \right)^{-1}, \quad b_5 = c_z(1, 1),$$

$$z_1 := \frac{\omega \delta_L \operatorname{Var}[V] \bar{\theta}_L}{k_L + \delta_L \operatorname{Var}[V]}, \quad z_2 := \frac{\omega \lambda_{L,I}^* \delta_L \operatorname{Var}[V|F] \bar{\theta}_L}{k_L + \delta_L \operatorname{Var}[V|F]} + \frac{\omega(1-\lambda_{L,I}^*) \delta_L \operatorname{Var}[V|S_p(\lambda_{L,I}^*, 0)] \bar{\theta}_L}{k_L + \delta_L \operatorname{Var}[V|S_p(\lambda_{L,I}^*, 0)]},$$

$$z_5 := \frac{\omega \delta_L \operatorname{Var}[V|F] \bar{\theta}_L}{k_L + \delta_L \operatorname{Var}[V|F]} \quad z_3 := z_5.$$

(B-1)

If $\lambda_{L,I}^* = 1$ and $0 < \lambda_{S,I}^* < 1$, we don't have a closed-form solution in this case. We will look at the cases where $\lambda_{S,I}^* = 0$ or $\lambda_{S,I}^* = 1$.

In the presence of short-sale costs, from optimization of the CARA utility function for traders, the optimal positions of traders are

$$\theta_{L,I}^* = \frac{\operatorname{E}[V|F] - P + k_L \bar{\theta}_L}{k_L + \delta_L \operatorname{Var}[V|F]}, \quad \theta_{L,U}^* = \frac{\operatorname{E}[V|P] - P + k_L \bar{\theta}_L}{k_L + \delta_L \operatorname{Var}[V|P]},$$

$$\theta_{S,I}^* = \frac{\operatorname{E}[V|F] - P}{k_S \mathbb{1}_{\{\theta_{S,I} < 0\}} + \delta_S \operatorname{Var}[V|F]}, \quad \theta_{S,U}^* = \frac{\operatorname{E}[V|P] - P}{k_S \mathbb{1}_{\{\theta_{S,U} < 0\}} + \delta_S \operatorname{Var}[V|P]}.$$

(B-2)

Define the signal $S_p(\lambda_{L,I}^*, 0) := F + \frac{k_L \tau_\varepsilon + \delta_L}{\omega \lambda_{L,I}^* \tau_\varepsilon} z$. Before time 0, if all traders choose not to observe F, implying $\lambda_{L,I}^* = \lambda_{S,I}^* = 0$. Substituting equation (B-2) into the market-clearing condition (6) yields the equilibrium price

$$P_1 = \bar{V} + b_1 (z - z_1).$$

(B-3)

Similarly, if $0 < \lambda_{L,I}^* < 1$, and $\lambda_{S,I}^* = 0$, substituting equation (B-2) into the market-clearing condition (6) yields the equilibrium price P_2 as in Theorem 1. If $\lambda_{L,I}^* = 1$, and $\lambda_{S,I}^* = 0$, substituting equation (B-2) into the market-clearing condition (6) yields the equilibrium price P_3 as in Theorem 1. If $\lambda_{L,I}^* = 1$, $\lambda_{S,I}^* = 1$, substituting equation (B-2) into the market-clearing condition (6)

yields the equilibrium price P_5 as in Theorem 1. Define

$$\mathrm{E}[U_{L,F}(P)] := -\mathrm{E}\left[e^{-\frac{(\mathrm{E}[V|F]-P+k_L\bar{\theta}_L)^2}{2(k_L/\delta_L+\mathrm{Var}[V|F])}-\delta_L(\bar{\theta}_L P-\frac{1}{2}k_L\bar{\theta}_L^2)}\right],$$

$$\mathrm{E}[U_{L,S_p(\lambda_{L,I}^*,0)}(P)] := -\mathrm{E}\left[e^{-\frac{(\mathrm{E}[V|S_p(\lambda_{L,I}^*,0)]-P+k_L\bar{\theta}_L)^2}{2(k_L/\delta_L+\mathrm{Var}[V|S_p(\lambda_{L,I}^*,0)])}-\delta_L(\bar{\theta}_L P-\frac{1}{2}k_L\bar{\theta}_L^2)}\right],$$

(B-4)

$$\mathrm{E}[U_{S,F}(P)] := -\mathrm{E}\left[e^{-\frac{(\mathrm{E}[V|F]-P)^2}{2\mathrm{Var}[V|F]}}|\theta_{S,I}\geq 0\right]Prob(\theta_{S,I}\geq 0)$$

$$-\mathrm{E}\left[e^{-\frac{(\mathrm{E}[V|F]-P)^2}{2(k_S/\delta_S+\mathrm{Var}[V|F])}}|\theta_{S,I}<0\right]Prob(\theta_{S,I}<0),$$

(B-5)

$$\mathrm{E}[U_{S,S_p(\lambda_{L,I}^*,\lambda_{S,I}^*)}(P)] := -\mathrm{E}\left[e^{-\frac{(\mathrm{E}[V|S_p(\lambda_{L,I}^*,\lambda_{S,I}^*)]-P)^2}{2\mathrm{Var}[V|S_p(\lambda_{L,I}^*,\lambda_{S,I}^*)]}}|\theta_{S,U}\geq 0\right]Prob(\theta_{S,U}\geq 0)$$

$$-\mathrm{E}\left[e^{-\frac{(\mathrm{E}[V|S_p(\lambda_{L,I}^*,\lambda_{S,I}^*)]-P)^2}{2(k_S/\delta_S+\mathrm{Var}[V|S_p(\lambda_{L,I}^*,\lambda_{S,I}^*)]}}|\theta_{S,U}<0\right]Prob(\theta_{S,U}<0).$$

(B-6)

then the expected utility of an institutional trader who observes F is

$$\mathrm{E}[U(W_L(P))|F] = \mathrm{E}[-e^{-\delta_L W_L(P)}|F] = \mathrm{E}[U_{L,F}(P)]\,e^{\delta_L c}.$$

(B-7)

The expected utility of an institutional trader who does not observe F is

$$\mathrm{E}[U(W_L(P))|S_p(\lambda_{L,I}^*,0)] = \mathrm{E}[-e^{-\delta_L W_L(P)}|S_p(\lambda_{L,I}^*,0)] = \mathrm{E}[U_{L,S_p(\lambda_{L,I}^*,0)}(P)].$$

(B-8)

The expected utility of an short-seller who observes F is

$$\mathrm{E}[U(W_S(P))|F] = \mathrm{E}[-e^{-\delta_S W_S(P)}|F] = \mathrm{E}[U_{S,F}(P)]\,e^{\delta_S c}.$$

(B-9)

The expected utility of an short-seller who does not observe F is

$$\mathrm{E}[U(W_S(P))|S_p(\lambda_{L,I}^*,0)] = \mathrm{E}[-e^{-\delta_S W_S(P)}|S_p(\lambda_{L,I}^*,0)] = \mathrm{E}[U_{S,S_p(\lambda_{L,I}^*,0)}(P)].$$

(B-10)

From equations (B-7)–(B-10), if the information acquisition cost

$$c > c_1 := \max\left\{\frac{1}{\delta_L}\ln\frac{\mathrm{E}[U_{L,S_p(0,0)}(P_1)]}{\mathrm{E}[U_{L,F}(P_1)]}, \frac{1}{\delta_S}\ln\frac{\mathrm{E}[U_{S,S_p(0,0)}(P_1)]}{\mathrm{E}[U_{S,F}(P_1)]}\right\},$$

then neither long investors nor short sellers pay c to observe F, and $\lambda_{L,I}^* = \lambda_{S,I}^* = 0$.

It is straightforward to show that $\mathrm{E}[U_{S,S_p(0,0)}(P)] < \mathrm{E}[U_{S,F}(P)]$ and $\mathrm{E}[U_{S,S_p(0,0)}(P)] < \mathrm{E}[U_{S,F}(P)]$,

i.e., investors are better off knowing F than not for any given price P if the information acqui-

sition cost is zero. This implies that $\frac{\mathrm{E}[U_{S,Sp(0,0)}(P)]}{\mathrm{E}[U_{S,F}(P)]} > 1$ and $\frac{\mathrm{E}[U_{S,Sp(0,0)}(P)]}{\mathrm{E}[U_{S,F}(P)]} > 1$ because the expected utilities are negative. We assume

$$\frac{1}{\delta_S} \ln \frac{\mathrm{E}[U_{S,Sp(0,0)}(P_1)]}{\mathrm{E}[U_{S,F}(P_1)]} < c_2 := \frac{1}{\delta_L} \ln \frac{\mathrm{E}[U_{L,Sp(1,0)}(P_3)]}{\mathrm{E}[U_{L,F}(P_3)]},$$

this is equivalent to the condition that $\delta_S > \frac{\ln \mathrm{E}[U_{S,Sp(0,0)}(P_1)] - \ln \mathrm{E}[U_{S,F}(P_1)]}{\ln \mathrm{E}[U_{L,Sp(1,0)}(P_3)] - \ln \mathrm{E}[U_{L,F}(P_3)]} \delta_L$.

If $c_2 < c < c_1$, then $0 < \lambda_{L,I}^* < 1$, $\lambda_{S,I}^* = 0$, and the unique endogenous fraction of long investors who observe F can be solved numerically. If $c_3 \le c \le c_2$, then $\lambda_{L,I}^* = 1$ and $\lambda_{S,I}^* = 0$. If $c_4 < c < c_3$, then $\lambda_{L,I}^* = 1$, $0 < \lambda_{S,I}^* < 1$, and $\lambda_{S,I}^*$ can be solved numerically. If $c \le c_4$, then $\lambda_{L,I}^* = 1$ and $\lambda_{S,I}^* = 1$.