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Investor Attention and Insider Trading

Sattar Mansi
Virginia Tech Pamplin College of Business
smansi@vt.edu

Lin Peng
City University of New York Baruch College Zicklin School of Business
lin.peng@baruch.cuny.edu (corresponding author)

Jianping Qi
University of South Florida Muma College of Business
jqi@usf.edu

Han Shi
Louisiana State University Shreveport School of Business
han.shi@lsus.edu

Abstract

We identify a new mechanism of opportunistic insider trading linked to attention-driven mispricing. Insiders are more likely to sell their company's stock during periods of heightened retail attention and more inclined to buy when attention diminishes. The results are particularly pronounced for lottery-type stocks and firms with substantial retail ownership. We demonstrate that our findings—which relate to indicators of mispricing, retail order imbalances, and Robinhood herding episodes—extend to seasoned equity issuances and cannot be solely explained by firm fundamentals. Attention-based insider trading is less likely to result in SEC enforcement actions and persists across different regulatory regimes.

I. Introduction

It is well established that company insiders realize significant abnormal profits by trading their own company's stock.[1] The previous literature has mostly focused on cases involving material information about firm fundamentals as the insiders'

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[1]See, for examples, Lorie and Niederhoffer (1968), Jaffe (1974), Finnerty (1976), Seyhun ((1986), (1992), (1998)), Bettis, Vickrey, and Vickrey (1997), Aboody and Lev (2000), Lakonishok and Lee (2001), Jeng, Metrick, and Zeckhauser (2003), Frankel and Li (2004), Cheng and Lo (2006), Huddart and Ke (2007), Brochet (2010), Agrawal and Nasser (2012), Bonaime and Ryngaert (2013), Kedia and Zhou (2014), Agrawal and Cooper (2015), Hillier, Korczak, and Korczak (2015), Ahern (2017), Ali and Hirshleifer (2017), and Lowry, Rossi, and Zhu (2019). While earlier studies document abnormal returns following insider purchases, Cohen, Malloy, and Pomorski (2012), Alldredge and Cicero (2015), and Biggerstaff, Cicero, and Wintoki (2020) provide strong evidence of informed stock sales by company insiders. In addition, Akbas, Jiang, and Koch (2020) show that the trades of short-horizon insiders tend to be more informed than the trades of long-horizon insiders.

source of advantage. These cases are often subject to significant regulatory and corporate restrictions. However, the recent arrival of fintech brokerage platforms and social media sites such as Reddit has stimulated rising stock market participation by retail investors, who are susceptible to behavioral biases and the influence of social media (e.g., Barber, Huang, and Odean (2022)). These new developments raise important questions about the extent to which corporate insiders trade to benefit from mispricing opportunities driven by retail investor interest in the stock and what regulators should do about the exploitation.

In this article, we provide insights into the above questions by investigating a new type of insider trading associated with investor attention and discussing the policy implications. Our article is motivated by studies demonstrating that heightened retail investor attention leads to excessive net buying, which in turn triggers a temporary stock price increase that subsequently reverts (see, e.g., Barber and Odean (2008), Pedersen (2022)). We therefore hypothesize that company insiders trade the company's stocks to take advantage of the mispricing generated by retail investors.

In our empirical analysis, we first establish that a portfolio strategy of insider trading, when conditioned on retail attention, exhibits return characteristics that are distinctly different from those associated with conventional insider trading, featuring significantly higher, yet more transient, returns. Furthermore, we demonstrate that the link between attention and insider trading is more pronounced for lottery-type stocks and firms with high retail ownership. This connection is also associated with indicators of mispricing, imbalances in retail order flows, and patterns of herding behavior among Robinhood investors. Additionally, we examine how this form of trading correlates with the intensity of the SEC's insider trading enforcement actions and discuss the unique challenges it presents to policymakers.

We measure opportunistic insider trading following Cohen, Malloy, and Pomorski (2012) and proxy for the amount of retail attention to a stock with abnormal Google searches of the stock (ABSVI). We first show that the negative relationship between insider sales and future stock returns is more pronounced when the sales coincide with months of greater retail attention than when they coincide with lower retail attention. On the other hand, the positive relationship between insider buys and future stock returns is stronger when retail attention is low than when retail attention is high.

The pattern is consistent with the evidence that high retail attention tends to be associated with overvaluation (see, e.g., Barber and Odean (2008), Da, Engelberg, and Gao (2011), and Barber et al. (2022)). Our finding is also economically significant—an insider-trading portfolio strategy conditioned on attention generates a monthly abnormal return of 115.4 to 136.7 basis points, which is 42.2 to 50.3 basis points higher than the returns of an unconditional strategy.

Importantly, the returns to the attention-based strategy peak at the 1-month horizon and dissipate within 12 months, a pattern that is distinctly different from that of the unconditional strategy, which persists for up to a year (Cohen et al. (2012)). The sharp contrast suggests that attention-based insider trading is likely due to temporary misvaluation and is very different from trading based on material insider information about firm fundamentals analyzed in previous studies.

We then show that insiders do indeed trade in a way that takes advantage of this opportunity. We find that rising retail attention is associated with significant increases in both the likelihood and size of insider sales. In contrast, retail attention significantly reduces the likelihood and size of insider purchases. Economically, a 1-standard-deviation increase in log(ABSVI) increases the probability of insider sales by 4.94 percentage points, which is 10.28% of the variable's standard deviation, and the average sale amount by 4,502 shares. On the other hand, the same increase in log(ABSVI) reduces the insider purchase probability by 4.05 percentage points and the purchase amount by 7,147 shares. We further show that attention-based insider sales are more pronounced for firms with higher retail ownership and for lottery stocks, which tend to attract more attention from retail investors and are overvalued (Kumar (2009), Bali, Cakici, and Whitelaw (2011)). The results are consistent with insiders actively trading to take advantage of mispricing opportunities driven by high retail investor attention.

Turning to policy implications, we investigate the relation between insiders' propensity to engage in attention-based trading and the intensity of SEC enforcement actions. We first show that attention-based insider trading is considerably less sensitive to insider trading enforcement actions of the SEC, compared to the unconditional measures of insider trading. One explanation is that such trades are less likely to be investigated by the SEC because the trades rely on retail sentiment rather than on material private information about the firm.

We conduct insider-level analysis and provide evidence in support of this explanation. While unconditional insider sales significantly increase the likelihood of SEC enforcement actions, the relationship is substantially weaker for attention-based insider sales. The results suggest that attention-based insider sales face a lower risk of SEC enforcement actions.

While the evidence presented so far is consistent with insiders trading to exploit attention-driven mispricing, a possible alternative explanation is that periods with high retail attention also exhibit high levels of noise trading, which enables insiders with private information to better camouflage their trades (see, e.g., Kyle (1985)). This alternative mechanism would explain why insiders are more likely to sell during periods of high retail attention but would not explain our finding that insiders are more likely to purchase stocks when retail attention is low.

We provide direct evidence that high retail investor attention is associated with overvaluation by utilizing measures that more directly capture mispricing and retail sentiment. First, we utilize two direct measures of mispricing following Stambaugh, Yu, and Yuan (2012) and Cong, George, and Wang (2023). We find that stocks classified as overvalued also exhibit higher levels of ABSVI compared to those classified as undervalued and that the mispricing mechanism contributes to the explanatory power of ABSVI on insider trading.

We next demonstrate that retail sentiment plays a role in mediating the link between attention and insider trading by examining retail order imbalances (OIB), as measured by the methodology of Boehmer, Jones, and Zhang (2021). The results indicate that a high value of OIB strengthens the positive association between retail attention and insider sales while further discouraging insider purchases. This finding is consistent with the explanation that retail sentiment acts as a channel through which investor attention influences insider trading.

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Our second proxy for investor sentiment is based on the herding behavior of investors on the Robinhood trading platform. Barber et al. (2022) demonstrate that Robinhood users are more inclined to engage in attention-driven buying and to herd into certain stocks, compared to other retail investors.

We follow Barber et al. (2022) and classify firm-month observations into Buy Herding, Sell Herding, and Neutral months, based on whether a stock has a sharp increase or decrease in the number of Robinhood investors. We find that the levels of ABSVI and insider sales are the highest during Buy Herding months, and the lowest during Sell Herding months. In contrast, insider purchases are significantly higher during Robinhood's Sell Herding months than Buy Herding or Neutral months. These findings indicate that insiders trade against Robinhood investors, selling more during periods of sharp increases in the number of such investors, and buying more when they herd to sell the stock. The evidence supports our narrative that insiders exploit mispricing arising from intensive buying or selling pressure from naive retail investors.

In an additional analysis, we explore whether the relation between retail attention and insider trading is associated with stock and firm characteristics. We find that the relationship is stronger for firms subject to weaker corporate governance, firms with low corporate social responsibility scores, and less reputable firms.

One concern about our analysis is that the relation between retail investor attention and insider trading may be driven by insiders' private information related to firm fundamentals, or news events that affect both insider trading and retail attention. We address this concern in several ways and our results are robust to the additional tests.[2] We also consider different regulatory regimes. The first corresponds to a period of the more laissez-faire Republican Bush administration, and the second to that of the Democratic Obama administration during which more active SEC enforcement actions took place. We show that the attention–insider trading relation remains robust across both regimes. We conduct another robustness check by excluding all Rule 10b5-1 trades from our sample. To the extent that it is difficult for insiders to predict future retail attention and sentiment, the prescheduled 10b5-1 trades are less likely to be opportunistic trades intended to exploit attention-driven mispricing. Our results remain robust.

Finally, we ask whether attention-related mispricing influences corporate policies by examining the likelihood of seasoned equity offerings (SEOs). The SEO decision is associated with perceived overvaluation (Khan, Kogan, and

[2]First, Ben-Rephael, Da, and Israelsen (2017) show that institutional investor attention strongly responds to fundamental news. As in their study, we account for fundamental news using Bloomberg Terminal activities to measure changes in the attention of institutional investors. We show that our results remain robust after this control. Second, we obtain data on firm-level news from RavenPack and show that it does not affect our results. Third, we decompose retail attention into two components: one that can be explained by fundamental factors and the other that is unrelated to the fundamentals. We show that our results are driven mostly by the nonfundamental component. Fourth, we exclude insider trades prior to earnings announcements or the releases of negative 8-K filings on Fridays and find our main results to be robust. This alleviates the concern that the results are driven by insiders' private information or their strategic disclosure of material information. Fifth, we exploit exogenous variations in retail investor attention and perform an instrumental variable analysis to show that the effect of retail attention on insider trading is causal and that our main results are robust.

Serafeim (2012)), and a substantial number of SEOs are announced and issued overnight (Gustafson (2018)). We find that firms are indeed more likely to conduct SEOs following periods of high retail attention. Together, our evidence suggests that insiders take advantage of attention-driven mispricing by trading on their own accounts, and their firm by timing its seasoned equity issuances.

Our article contributes to the insider-trading literature by identifying an important component of opportunistic trading in which insiders exploit the behavioral biases of retail investors. Our article complements Alldredge and Cicero (2015) who show that insiders trade on public information about their customers when investors are inattentive. Relatedly, Niessner (2015) finds that managers strategically disclose negative news on Fridays, when investors are likely inattentive and benefit by selling ahead of the news. While these papers focus on insider sales that take advantage of inattentive investors, we find that insiders make significant profits by selling when investor attention is excessive and that both attention-based buys and sells are profitable.

Our finding that attention-based insider sales face a lower risk of SEC enforcement actions suggests that increases in SEC actions may have little impact on insiders' exploitation of retail investors. This finding contrasts sharply with Cohen et al.'s (2012) finding that more intense SEC enforcement activity reduces insider sales. The striking contrast raises important policy questions regarding whether and how regulators should address attention-based insider trading in an era marked by increasing retail participation in speculative stocks, fueled by attention propagated through social media platforms and enabled by zero-commission fintech brokerage firms (Barber et al. (2022)).

Our article also contributes to the literature on investor attention. Most existing studies focus on asset pricing implications, showing that inadequate attention is associated with underreaction to information whereas excessive attention triggers overvaluation.[3] A growing literature finds that investor attention also has important implications for corporate finance. Daniel, Hirshleifer, and Teoh (2002) find that firms exploit inattentive investors by issuing overvalued equity shares. Kempf, Manconi, and Spalt (2017) show that investor attention influences corporate investment and executive compensation. Iliev, Kalodimos, and Lowry (2021) find that investor attention is associated with monitoring by sophisticated investors.[4] Our article adds to this literature by showing that insiders strategically trade on mispricing related to retail attention.

[3]For examples of studies on investor inattention and underreaction to information, see Huberman and Regev (2001), Peng (2005), DellaVigna and Pollet (2009), Hirshleifer, Lim, and Teoh (2009), Hirshleifer, Hsu, and Li (2013), Ben-Rephael, Da, and Israelsen (2017), Hirshleifer and Sheng (2022), and Liu, Peng, and Tang (2023). For examples of papers showing that excessive attention drives overvaluation, see Peng and Xiong (2006), Barber and Odean (2008), Da, Engelberg, and Gao (2011), and Barber, Huang, Odean, and Schwarz (2022).

[4]More broadly, an important empirical behavioral literature studies the effect of market misvaluation on firm policies such as financing and investment (D'mello and Shroff (2000), Graham and Harvey (2001), Baker, Stein, and Wurgler (2003), Polk and Sapienza (2009), Bakke and Whited (2010), Jenter, Lewellen, and Warner (2011), Dong, Hirshleifer, and Teoh (2012), and Warusawitharana and Whited (2016)). See also Eckbo, Masulis, and Norli (2007) and Baker and Wurgler (2013) for reviews. Relatedly, Dessaint, Foucault, Frésard, and Matray (2019) show that nonfundamental shocks to stock prices affect real investment decisions by firms.

Another strand of literature concerns strategic trading behavior. In classical finance theory, sophisticated investors profit by trading against unsophisticated investors or those who are subject to liquidity shocks (e.g., Kyle (1985), Lakonishok, Shleifer, and Vishny (1994)).[5] To the best of our knowledge, our article is the first to document strategic trading behavior by insiders taking advantage of mispricing caused by naïve retail traders. One unique aspect of corporate insiders is their access to material nonpublic information and a deeper understanding of their firm's operations and business dynamics as well as the implications of both public and nonpublic information. Therefore, insiders are in a unique position to exploit anomalies created by naïve investors, in a way that is fundamentally different from other market participants, even those who are well-informed. However, insiders' unique role as agents with fiduciary duties to shareholders also carries significant regulatory implications for their trading activities.

II. Data and Key Variables

Our sample consists of all common stocks (SHRCD = 10 and 11) traded on the NYSE, Amex, Nasdaq, and Arca exchanges (EXCHCD = 1, 2, 3, and 4) for the period of July 2004 to Dec. 2021.[6]

We obtain insider trading data from the Thomson Reuters Insider Database, which includes all equity-related transactions filed by insiders with the SEC via Forms 3, 4, and 5. We follow Cohen et al. (2012) and consider opportunistic (nonroutine) open-market purchases and sales by company insiders.[7] Following Alldredge and Cicero (2015), we aggregate all insiders' net trades (sales and purchases) for a given firm and a given month and conduct our main analyses at the firm-month level. We label a firm-month observation as an "insider purchase" if the sum of insider purchases is greater than 0, and as an "insider sell" if the sum of insider sales is greater than 0.[8] We supplement the firm-level analysis with additional analyses at the insider level.

[5]A significant obstacle in the empirical analysis of arbitrage activity is the scarcity of data regarding the actions of arbitrageurs. The availability of recent data on hedge fund holdings and short-selling data has enabled empirical studies to investigate arbitrage trading (e.g., Brunnermeier and Nagel (2004), Boehmer, Jones, and Zhang (2008), Griffin and Xu (2009), Hanson and Sunderam (2014), Edelen, Ince, and Kadlec (2016), Cao, Chen, Goetzmann, and Liang (2018), Chen, Da, and Huang (2019), and Hwang, Liu, and Xu (2019)).

[6]We exclude stocks with a price of less than \$5 or a market capitalization of less than \$100 million. We retain only transactions verified by Thomson Reuters based on a cleanse code of R, H, L, C, or Y. We also exclude observations for which transaction prices are either more than 3 times or less than one-third of the same-day closing price because they likely result from data errors. We then exclude routine trades that satisfy at least one of the following two conditions: i) they are executed by an insider who made a similar trade in the same month of the year for the last 3 years, and ii) they are related to an insider's stock option transactions.

[7]Form 3 includes all insiders registering equity securities with the SEC for the first time. Form 4 documents any transactions involving ownership changes, which must be reported within 2 business days. Form 5 reports any missing Form 4 transactions from those insiders who are eligible for deferred reporting.

[8]We omit observations that correspond to both an insider net sale and an insider net purchase as in Alldredge and Cicero (2015).

Our measure of investor attention follows Da et al. (2011), who use the Google Trends search volume index (SVI) on a stock to proxy for retail investor attention to the stock. We download weekly SVI data based on a stock's ticker symbol and construct a monthly SVI as the average weekly SVI for a month.[9] We define a stock's abnormal search volume index (ABSVI) as the ratio of the monthly SVI to the median SVI over the previous 6 months.

The coverage of Google Trends is tilted toward large firms with frequent searches, and the SVI variable is often missing for firms that are searched less frequently. To maintain a cross-sectional coverage of our sample, we include firm-month observations with nonmissing SVI data and those for which SVI is missing. We consider two types of attention measures, a qualitative and a quantitative measure. For the qualitative measure, we construct an Attention subsample that contains all firm-month observations with nonmissing SVI and a Nonattention subsample that covers observations with missing SVI. Since the SVI information is available only for firms that have been the subject of a substantial number of Google searches over a given period, the observations in the Attention subsample correspond to higher levels of retail investor attention than those in the Nonattention subsample. Within the Attention subsample, we also use the continuous ABSVI variable as a quantitative measure of attention.

Stock prices, returns, and trading volume are from CRSP, and financial statement information is from the merged CRSP-Compustat database. As in Cohen et al. (2012) and Alldredge and Cicero (2015), abnormal stock returns are size-adjusted based on NYSE breakpoints. We also examine excess return (Exret), defined as stock return minus the risk-free rate. Institutional holdings data are from the Thompson Reuters Institutional Holdings (13F). All variables are winsorized at 1% and 99% to minimize the effects of outliers. The Appendix provides a list of variables used and their definitions.

Combining the SVI and insider trading data with the information on stock returns and firm characteristics, we obtain a final sample of 128,211 firm-month observations from July 2004 to Dec. 2021. The Attention subsample contains 64,818 net sale months (4,558 unique firms) and 25,803 net purchase months (4,041 unique firms). The Nonattention subsample has 27,448 net sale months (3,757 unique firms) and 10,142 net purchase months (2,844 unique firms).

Table 1 presents summary statistics for firm-month observations. Panel A compares our Attention subsample to the full sample. Firms in the Attention subsample tend to be larger, consistent with Google's coverage of larger firms. However, the monthly mean and median numbers of insider trades are similar, suggesting that insider trading activities are comparable between the Attention

[9]The SVI is a relative search popularity score between 0 and 100, measured by the number of searches for a particular term relative to the total number of searches in a specific geographic area for a given period. We exclude ambiguous ticker symbols such as A, AUTO, ALL, B, BABY, BED, DNA, GPS, GAS, and GOLF because they could be associated with things unrelated to a stock. There are instances in which weekly SVI data near the end of a calendar month encompass the beginning days of the next month. In such instances, we prorate the weekly SVI based on the number of days in that month. Google search data are also used to capture retail attention in Ginsberg, Mohebbi, Patel, Brammer, Smolinski, and Brilliant (2009), Choi and Varian (2012), Drake, Roulstone, and Thornock (2012), Andrei and Hasler (2015), and Ben-Rephael et al. (2017).

TABLE 1

Summary Statistics

Table 1 reports the summary statistics of firm-month observations for opportunistic insider trades from July 2004 to Dec. 2021. Panel A compares the Attention subsample with the full sample. Panel B focuses on the Attention subsample. ABSVI is the abnormal Google search volume index on a stock's ticker symbol. Size is based on the previous year-end market value (in millions of dollars). BM is the previous year-end book-to-market equity value ratio. No. of trades and No. of traders are the number of opportunistic insider trades and the number of opportunistic insider traders per firm-month, respectively. No. of firms is the average number of firms per month.

Panel A. Attention Subsample Versus Full Sample

	Attention Sample		Full Sample	
	Mean	Median	Mean	Median
SIZE	7,509.38	1,231.07	6,998.35	1,194.86
BM	0.54	0.46	0.54	0.45
No. of trades	2.56	2.00	2.60	2.00
No. of traders	1.59	1.00	1.60	1.00
No. of firms	721	745	983	1,025

Panel B. Mean Value for the Attention Subsample

	Insider Net Sale Months	Insider Net Purchase Months	Diff.	*p*-Value
ABSVI	1.05	0.98	0.07	<0.00
SIZE	8321.97	5241.79	3,080.18	<0.00
BM	0.50	0.64	−0.13	<0.00
No. of trades	2.57	2.54	0.03	0.03
No. of traders	1.58	1.60	−0.02	0.07
No. of firms	480	247	233	–

subsample and the full sample. Panel B focuses on the Attention subsample and shows that the average ABSVI is 1.05 for insider sales and 0.98 for insider purchases. The ABSVI difference of 0.07 is statistically significant (t-stat. = 22.41), suggesting that abnormal insider sales are associated with a higher level of abnormal retail investor attention than abnormal insider purchases.[10]

III. Retail Attention and the Returns Following Insider Trades

In this section, we investigate whether retail attention is related to the profitability of insider trading. Our key hypothesis is that insider trading is more profitable during periods of high retail attention on the stock. This hypothesis is motivated by Barber and Odean (2008), who find that attention-triggered buying by retail investors exerts upward price pressure and results in a (temporary) rise in the stock price. We test our hypothesis first by analyzing stock returns following months of net insider sales or purchases. We then assess the magnitude of profitability of insider trading using hypothetical long-short portfolios that mimic insider trades.

[10]We also report in Table 1 in the Supplementary Material firm-month observations across the Fama–French 17 industries for both Attention and Nonattention subsamples. Panel A shows that the industry distribution is similar between the two subsamples, except for the machinery and business equipment and financial institution industries. Panel B presents the average monthly ABSVI for insider purchase and insider sale months by each industry. Consistent with Panel B of Table 1, ABSVI is larger for months with net insider sales than net insider purchases for all industries. This suggests that insiders are more likely to sell than buy when retail investor attention is high. The ABSVI differences are significant for 13 of the 17 industries, and the cross-industry average is 0.070 and highly significant. Our results remain robust if we exclude financial firms.

A. Univariate Analysis

We first present a univariate analysis of the relationship between retail investor attention and stock returns following net insider sales or net insider purchases. Column 1 in Panel A of Table 2 reports monthly abnormal returns (CAR) following the insider sale month for both Attention and Nonattention subsamples. Consistent with previous studies (e.g., Cohen et al. (2012)), the average CAR following insider sales months is significantly negative. More important, following the sale months, the average CAR is −66.8 basis points per month for the Attention subsample and only −45.6 basis points for the Nonattention subsample. Their difference is a significant −21.2 basis points per month (t-stat. = −2.25). The results suggest that insider sales during times of high retail attention are followed by substantially higher returns, compared to sales during low attention periods.

Column 1 in Panel B of Table 2 presents monthly abnormal returns following insider purchases. Consistent with Cohen et al. (2012), average abnormal returns following insider purchases are generally positive. However, the average abnormal return after insider purchases is significantly lower for the Attention subsample than for the Nonattention subsample, indicating that insider purchases are more profitable following months of lower retail investor attention. The average size-adjusted CAR following the insider purchase month is 111.6 basis points for the

TABLE 2

Monthly Stock Returns Following Insider Trades

Table 2 reports the 1-month abnormal returns (CAR) following the months of net insider sales (Panel A) and net insider purchases (Panel B). CAR is the NYSE size decile portfolio-adjusted return. Columns 1–4 report results for net insider sales and net insider purchases by all insiders, top-level officers (CEO, CFO, COO, and board chair), (other) inside directors, and outside directors, respectively. The Attention and Nonattention subsamples correspond to firm-month observations for which the Google search volume index (SVI) is nonmissing and missing, respectively. Standard errors (in parentheses) are clustered by firm and month. We report the CAR difference between the Attention and the Nonattention subsample. *, **, and *** denote significance at the 1%, 5%, and 10% levels, respectively.

Abnormal Returns	All Insiders	Top-Level Officers	Inside Directors	Outside Directors
	1	2	3	4
Panel A. Returns Following Net Insider Sales				
Attention Sample				
CAR(%)	−0.668*	−0.936*	−0.768*	−0.583*
	(0.034)	(0.069)	(0.052)	(0.045)
No. of obs.	64,818	18,475	30,531	35,171
Nonattention Sample				
CAR(%)	−0.456*	−0.715*	−0.444*	−0.325**
	(0.104)	(0.155)	(0.146)	(0.148)
No. of obs.	27,448	7,927	12,901	14,194
CAR(%) diff	−0.212**	−0.221***	−0.324**	−0.258**
(attention–nonattention)	(0.094)	(0.131)	(0.131)	(0.132)
Panel B. Returns Following Net Insider Purchases				
Attention Sample				
CAR(%)	0.911*	1.049*	0.829*	1.122*
	(0.059)	(0.115)	(0.069)	(0.129)
No. of obs.	25,803	6,625	13,759	8,719
Nonattention Sample				
CAR(%)	1.116*	1.356*	0.974*	1.327*
	(0.109)	(0.117)	(0.103)	(0.118)
No. of obs.	10,142	2,923	7,277	2,281
CAR(%) diff	−0.205**	−0.307*	−0.145***	−0.205**
(attention–nonattention)	(0.101)	(0.107)	(0.081)	(0.103)

Nonattention subsample and 91.1 basis points for the Attention subsample. The difference of −20.5 basis points is statistically significant (t-stat. = −2.41), suggesting that insider buys are associated with higher subsequent returns during low attention periods than during high attention times.

We further examine the profitability of insider trades by three classifications of insider types: top-level officers, (other) inside directors, and outside directors.[11] Columns 2–4 in Table 2 show that our findings are largely robust across the three types of insiders. Overall, the univariate results in Table 2 are consistent with the hypothesis that high retail attention increases the profitability of insider sales and decreases that of purchases.

B. Regression Analysis

Our analysis thus far has focused on examining returns following months of insider sales or purchases separately. In the next step, we combine firm-month observations with insider sales and purchases and perform the following panel regression analysis on this pooled sample:

$$\text{(1)} \qquad \text{Exret}_{i,t+1} = \alpha + \beta_1 \cdot I_{i,t} + \beta_2 \text{Attention}_{i,t} + \beta_3 \text{Attention}_{i,t} \cdot I_{i,t} + \gamma \cdot X_{i,t} + \varepsilon_{i,t},$$

where Exret is the excess returns. Attention is either Att, an indicator variable that equals 1 if Google SVI is nonmissing, and 0 otherwise, or log(ABSVI). I equals 1 if the firm-month observation corresponds to a net insider sales month, and 0 to a net insider purchase month. X represents a vector of control variables: firm size, book-to-market ratio, advertising to sales ratio, number of analysts covering the stock, the stock's price, turnover, past returns, and the CRSP value-weighted market return. Firm fixed effects are included for all specifications, and t-statistics (reported in parentheses) are computed with 2-way clustered standard errors by firm and month. The variable of interest is Attention $\cdot I$, which captures the effect of attention on modulating the return predictability of insider sales relative to insider purchases.

Table 3 presents our panel regression analysis of stock returns following net insider sales. Columns 1–2 report results for the full sample, which includes both Attention and Nonattention subsamples, and use the indicator variable ATT to capture investor attention. Column 1 shows a statistically significant coefficient of −0.657 for $I_{i,t}$, consistent with the previous finding that opportunistic insider sales tend to be followed by lower stock returns. More important, column 2 shows that the coefficient of Attention $\cdot I$ is a highly significant −0.682 (t-stat. = −2.93). This result indicates that insider sales during a high-attention month are followed by a lower return of 73.7 (= 68.2 + 5.5) basis points, compared to sales during a normal month, suggesting that a significant part of return predictability of insider sales is associated with retail attention.

[11]These classifications follow Cohen et al. (2012). The top-officers type consists of a firm's chief executive officer, chief financial officer, chief operating officer, and chair of the board (role classification codes, CEO, CFO, COO, and CB). The inside-directors type refers to nonindependent directors who are not top-level officers but have an employment contract or a beneficial interest of more than 10% with the firm. The outside-directors type contains all insiders who are not included in the other two types.

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TABLE 3

Regression Analysis: Investor Attention and Stock Returns Following Insider Trades

Table 3 presents results from the following monthly panel regression for the sample of firm-month observations with insider trading:

$$\text{Exret}_{i,t+1} = \alpha + \beta_1 \cdot I_{i,t} + \beta_2 \text{Attention}_{i,t} + \beta_3 \text{Attention}_{i,t} \cdot I_{i,t} + \gamma \cdot X_{i,t} + \varepsilon_{i,t},$$

where Exret is the excess returns. Attention is either Att, an indicator variable that equals 1 if Google SVI is nonmissing, and 0 otherwise, or log(ABSVI), the natural logarithm of abnormal Google volume on a stock. I equals 1 if the firm-month observation corresponds to a net insider sales month, and 0 if it corresponds to a net insider purchase month. X represents a vector of the following control variables: log(SIZE) is the natural logarithm of the previous year-end market value of a firm. log(BM) is the natural logarithm of the previous year-end book-to-market equity value ratio. Adv/Sales is the previous year-end ratio of advertising expense to sales. log(Price) is the natural logarithm of the previous year-end stock price. log(Turnover) is the natural logarithm of average monthly turnover in the previous year, where the monthly turnover is the month's trading volume scaled by the number of shares outstanding. $\text{Ret}_{m,t+1}$ is the value-weighted market return. $\text{CAR}_{t-3,t-1}$ is the firm's 3-month market-adjusted return from months $t-3$ to $t-1$. $\text{CAR}_{t-12,t-1}$ is the firm's 1-year market-adjusted return from months $t-12$ to $t-1$. log(ABSVI Duration) is the natural logarithm of the number of months between the trading month and the month of first valid ABSVI. Anews is the natural logarithm of the ratio of 1 plus the number of news articles published on the Dow Jones newswire during month t to that in the previous month. log(ABDMR) is the natural logarithm of ABDMR, where ABDMR is the ratio of the monthly average of Bloomberg's daily maximum readership score (DMR) to its prior month value. log(Analysts) is the natural logarithm of the number of analysts covering the firm. Columns 1–2 use the full sample and columns 3–6 use the Attention subsample. Two-way clustered standard errors at the firm and month level are in parentheses. *, **, and *** denote significance at the 1%, 5%, and 10% levels, respectively.

	Full Sample		Attention Subsample		
$\text{Exret}_{i,t+1}$ (%)	1	2	3	4	5
$I_{i,t}$	−0.657* (0.083)	−0.525** (0.223)	−0.685* (0.099)	−0.552* (0.199)	−0.566* (0.204)
$\text{Att}_{i,t}$		−0.055 (0.224)			
$\text{Att}_{i,t} \times I_{i,t}$		−0.682* (0.233)			
$\log(\text{ABSVI})_{i,t}$			−1.214*** (0.687)	−1.648** (0.691)	−1.223*** (0.724)
$\log(\text{ABSVI})_{i,t} \times I_{i,t}$			−0.371*** (0.195)	−0.268** (0.132)	−0.763** (0.336)
$\log(\text{ABDMR})_{i,t}$				0.220*** (0.119)	0.228*** (0.135)
$\log(\text{ABDMR})_{i,t} \times I_{i,t}$				0.191** (0.091)	0.194** (0.083)
$\text{Anews}_{i,t}$					0.070 (0.149)
$\log(\text{ABSVI\_Duration})_{i,t}$					0.587** (0.260)
log(Analysts)					0.054 (0.104)
log(Size)	−1.480* (0.116)	−1.487* (0.116)	−1.681* (0.143)	−2.078* (0.285)	−2.101* (0.295)
log(BM)	−0.182*** (0.095)	−0.183*** (0.095)	−0.303* (0.116)	−0.612* (0.204)	−0.587* (0.213)
Adv/Sales	−1.153 (3.608)	−1.255 (3.609)	−1.687 (4.505)	−3.201 (3.63)	−6.745 (8.844)
log(Price)	−0.376* (0.127)	−0.381* (0.126)	−0.309** (0.154)	−0.559*** (0.299)	−0.413 (0.307)
log(Turnover)	−0.482* (0.086)	−0.482* (0.086)	−0.611* (0.103)	−1.133* (0.244)	−1.051* (0.258)
$\text{Ret}_{m,t+1}$	117.114* (0.877)	117.151* (0.877)	118.190* (1.078)	120.599* (1.872)	120.354* (1.921)
$\text{CAR}_{i,t-3,t-1}$	−0.747* (0.236)	−0.755* (0.236)	−1.088* (0.286)	−0.957*** (0.511)	−0.624 (0.525)
$\text{CAR}_{i,t-12,t-1}$	−0.667* (0.098)	−0.666* (0.097)	−0.734* (0.120)	−0.885* (0.206)	−0.890* (0.214)
Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
No. of obs.	128,211	128,211	90,621	27,504	25,911
R^2	0.209	0.214	0.246	0.221	0.226

Columns 3–5 present results for the Attention subsample, for which we use the continuous variable log(ABSVI) to capture variations in retail attention. In column 3, the coefficient on $\log(\text{ABSVI}) \cdot I$ is a statistically significant -0.371. Economically, it indicates that a 1-standard-deviation increase in log(ABSVI) is associated with an incremental return reduction of 40 basis points in the following month. Our results strongly support the hypothesis that insiders generate substantial profits when selling their firm shares during periods of high retail attention.

One concern is that the observed relation between retail attention and insider trading profits may be driven by unobservable fundamental information flows. We address this concern by further controlling the attention of institutional investors who are more attuned to the arrival of fundamental information. Following Ben-Rephael et al. (2017), we use Bloomberg Terminal's daily maximum readership score (DMR), available from 2010 to proxy for institutional investor attention.[12] We construct a monthly DMR measure as the averages of daily DMR and define abnormal institutional investor attention, log(ABDMR), as the natural logarithm of the change in the monthly DMR. To the extent that log(ABDMR) captures attention associated with fundamental information, controlling for log(ABDMR) alleviates the concern that our results are driven by fundamental information flows.

Column 4 of Table 3 reports results after controlling for log(ABDMR) and its interaction with *I*. The coefficients on log(ABDMR) and the corresponding interaction term are both positive and significant, consistent with the finding in Ben-Rephael et al. (2021) that information consumption by institutional investors is associated with a return premium. Notably, the coefficient on $\log(\text{ABSVI}) \times I$ remains robust at -0.268. The distinctly different coefficients on retail attention and institutional attention variables suggest that fundamental information is unlikely to generate the result that we observe.

To control for firm-specific news, we repeat the same analysis while including a news variable. We obtain news data from RavenPack and define Anews, the news variable, as the natural logarithm of the ratio of 1 plus the number of news articles about a firm during a month over the previous month. Column 5 presents the results. The coefficients on $\log(\text{ABSVI}) \times I$ remain negative and significant. In comparison, the coefficient on Anews is insignificant, suggesting that firm-specific news is unlikely to drive our results.[13]

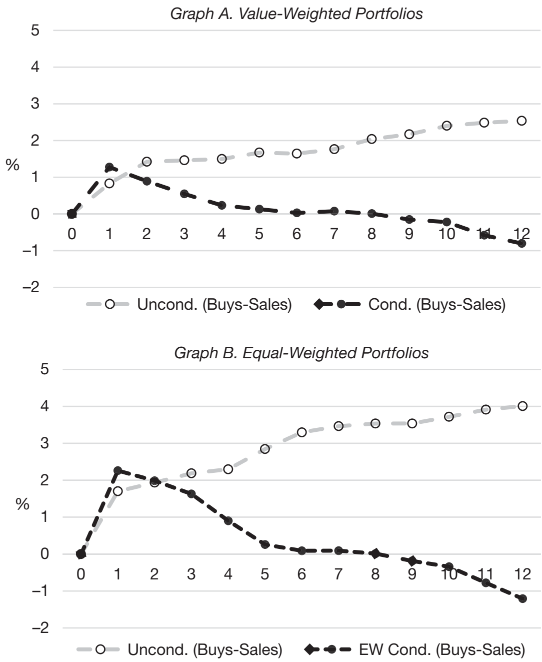
[12] Bloomberg Terminal reports hourly user activities on a stock (including searches and readership) relative to the activities for the same stock during the previous 30 days. The daily DMR score equals 0, 1, 2, 3, and 4 if the maximum of hourly user activities on a stock during the day is, respectively, less than 80%, 80% to 90%, 90% to 94%, 94% to 96%, and greater than 96% of the past distribution for the stock.

[13] We include two additional control variables. log(ABSVI Duration) is the natural logarithm of the number of months with nonmissing ABSVI as of the insider trade month. An extended period of high attention can impose a substantial risk on the arbitrageurs, resulting in sustained overvaluation or even further increases in valuation in the short term before the eventual reversal (De Long, Shleifer, Summers, and Waldmann (1990)). log(Analysts) is the natural logarithm of the number of analysts covering a stock, which is a variable widely used to capture the availability of public information about the stock. A firm with more analyst coverage is typically associated with a more informative stock price that is less susceptible to the influence of retail investors. The coefficient on log(ABSVI Duration) is positive and significant, suggesting that a prolonged period of high retail attention reduces the profits of insider sales. This finding is consistent with the noise trading risk that attention-based insider trades face.

FIGURE 1

Returns to the ABSVI Versus Non-ABSVI Trades, Event-Time Returns

Figure 1 shows the event-time returns to the portfolios that follow the trades from July 2004 to Dec. 2021. They present the differences in unconditional and conditional portfolio performances based on the ABSVI over 12 months following the portfolio formation.



The economic magnitude of the return predictability of attention-related insider trading can be assessed by comparing the return patterns of two long-short trading strategies, with and without conditioning on retail attention.[14] Table 2 in the Supplementary Material reports monthly average raw returns and risk-adjusted alphas for both. The results confirm that insiders can potentially generate substantially more trading profits by exploiting retail attention. This conditional strategy generates significantly higher abnormal returns, with the risk-adjusted alphas ranging from 115.4 to 136.7 basis points per month for the value-weighted portfolios, substantially higher than the 73.2 to 89.7 basis points level for the unconditional strategy.

How persistent is the impact of retail attention on insider trading profits? Da et al. (2011) find that attention-driven overvaluation starts to reverse 4 weeks after the high-attention week, and the reversals last up to a year. In Figure 1, we present the performances of the conditional and unconditional mimicking portfolios over

[14]The first portfolio longs a stock if the firm-month observation corresponds to net insider buying and shorts the stock if the observation corresponds to net insider selling. The second is a conditional portfolio strategy that longs a stock if the firm-month observation corresponds to net insider buying and if ABSVI > 1 and shorts a stock if the observation corresponds to net insider selling and if ABSVI < 1. At the end of each month, we rebalance the conditional and unconditional portfolios and report the corresponding abnormal returns for the subsequent month.

time. It shows that the returns of unconditional insider trades are persistent, consistent with the pattern documented in Cohen et al. (2012). In sharp contrast, the returns on the conditional portfolio are higher for month 1, start to diminish in month 2, and completely reverse by around month 6.[15] The distinctively different patterns in the returns of the conditional and unconditional portfolios highlight that attention-driven insider trading captures a new channel through which insiders benefit from mispricing.

IV. Retail Attention and Insider Trading

We have established that the stock returns following insider trades are strongly associated with retail attention. In this section, we address the question of whether insiders trade in a way to take advantage of the mispricing opportunities associated with retail attention. To this end, we explore the relation between retail attention and the likelihood and quantity of insider sales or purchases.

A. Baseline Results

We begin by analyzing the relation between investor attention and the probability and magnitudes of insider trades. We model the probability of insider sales for a given firm-month with a Probit model, in which the dependent variable is a Sale indicator that equals 1 for a net insider sale month, and 0 otherwise. Likewise, we define a Purchase indicator that equals 1 for a net insider purchase month. To capture the quantity of insider trades for a given firm-month, we define the Shares Sold and Shares Purchased variables as the number of shares (in thousands) sold and bought by insiders, respectively. We use a Tobit model for trade sizes. The key independent variable is the contemporaneous log(ABSVI). We control for a comprehensive list of lagged firm characteristics that may influence insider trading (Cohen et al. (2012), Lou (2014), and Alldredge and Cicero (2015)).[16] We report standard errors based on firm and month 2-way clustering.[17]

In Table 4, columns 1–4 report the baseline results on insider sales, and columns 5–8 on insider purchases. More specifically, columns 1–2 and 5–6 present Probit regressions with the Sale or Purchase indicator as the dependent variable.

[15]One possible explanation for the faster price reversal for the conditional portfolio might be that sophisticated outside investors, after observing the publicly available patterns of retail attention, are more apt to mimic the conditional portfolio strategies, and such arbitrage trading in turn accelerates the price corrections. In contrast, the insider trading based on the insiders' private information is relatively harder for the arbitrageurs to discern, and therefore the profitability of such insider trading is likely to be more persistent.

[16]The control variables include log(Size) (the natural logarithm of the previous year-end market value), log(BM) (the natural logarithm of the book-to-market ratio at the end of the previous fiscal year), and Adv/Sales (the advertising expenditure to sales ratio at the end of the previous fiscal year). We also control for Ret (contemporaneous month stock return), Ret_m (contemporaneous CRSP value-weighted market return), log(Price) (the natural logarithm of the previous year-end stock price), log(ABDMR), Anews, and log(Turnover) (the natural logarithm of average monthly turnover in the previous year).

[17]We exclude the firm fixed effects from our nonlinear models. Greene (2003) argues that applying fixed effects to nonlinear models such as Probit and Tobit tends to produce inconsistent and downward-biased standard errors and may overestimate the coefficients.

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TABLE 4

Retail Investor Attention and Insider Trading

Table 4 presents the results of Probit and Tobit regressions that analyze the likelihood and quantity of insider trading. log(ABSVI) is the natural logarithm of ABSVI, which is the abnormal Google search volume index on a stock's ticker symbol. In columns 1–2, the dependent variable is the Sale indicator that equals 1 if a firm-month observation corresponds to net insider sales. In columns 3–4, the dependent variable is the number of shares sold by all insiders (in thousands) for each firm-month observation. In columns 5–6, the dependent variable is the Purchase indicator that equals 1 if a firm-month is a net purchase month. In columns 7–8, the dependent variable is the number of shares bought by all insiders (in thousands) for each firm-month observation. log(ABDMR) is the natural logarithm of ABDMR, the monthly average of Bloomberg's relative daily maximum readership score (DMR). log(SIZE) is the logarithm of a firm's previous year-end market value. Anews is the natural logarithm of the ratio of 1 plus the number of news articles published on the Dow Jones newswire during the month over the previous month. log(BM) is the natural logarithm of the previous year-end book-to-market equity value ratio. Adv/Sales is the previous year-end ratio of advertising expense to sales. Ret_i and Ret_m are the returns of the stock and value-weighted market portfolio, respectively. log(Price) is the natural logarithm of the previous year-end stock price. log(Turnover) is the natural logarithm of average monthly turnover in the previous year, where the monthly turnover is the month's trading volume scaled by the number of shares outstanding. Two-way (firm and month) clustered standard errors at the firm level are in parentheses. *, **, and *** denote significance at the 1%, 5%, and 10% levels, respectively.

	Probit		Tobit		Probit		Tobit	
	Sale Indicator		Shares Sold		Purchase Indicator		Shares Purchased	
	1	2	3	4	5	6	7	8
$\log(\text{ABSVI})_{i,t}$	0.130**	0.157**	10.675*	13.123*	−0.128**	−0.153**	−21.812*	−23.310*
	(0.062)	(0.073)	(4.129)	(4.637)	(0.062)	(0.075)	(6.946)	(7.212)
$\log(\text{ABDMR})_{i,t}$		−0.047*		−8.323*		0.054*		16.533*
		(0.010)		(2.658)		(0.019)		(6.315)
$\text{Anews}_{i,t}$		−0.088		−10.231***		0.096		22.752
		(0.068)		(5.759)		(0.072)		(13.888)
log(Size)	0.064*	0.028*	24.135*	25.029**	−0.065*	−0.029*	−39.608*	−10.713***
	(0.004)	(0.008)	(7.451)	(12.016)	(0.004)	(0.008)	(13.797)	(6.456)
log(BM)	−0.119*	−0.099*	−16.453*	−17.936*	0.120*	0.101*	112.415*	64.569**
	(0.007)	(0.013)	(3.246)	(4.562)	(0.007)	(0.013)	(43.712)	(31.128)
Adv/Sales	0.697*	1.423*	236.709	601.865	−0.699*	−1.463*	−645.544**	−971.097**
	(0.187)	(0.333)	(164.949)	(450.922)	(0.186)	(0.331)	(303.935)	(482.005)
$\text{Ret}_{i,t}$	1.463*	1.770*	241.576**	370.138**	−1.281*	−1.768*	−1157.549*	1053.246**
	(0.046)	(0.098)	(94.640)	(153.656)	(0.136)	(0.098)	(412.387)	(487.878)
$\text{Ret}_{m,t}$	1.252*	2.164*	282.055**	651.386***	−1.444*	−2.195*	−1017.226**	−1194.629**
	(0.136)	(0.296)	(127.180)	(337.852)	(0.046)	(0.294)	(502.353)	(585.884)
log(Price)	0.228*	0.267*	11.430	12.988	−0.226*	−0.257*	−248.904**	−201.403**
	(0.008)	(0.015)	(9.331)	(11.214)	(0.008)	(0.015)	(100.603)	(102.010)
log(Turnover)	0.106*	0.033**	10.424	34.607*	−0.106*	−0.035**	−83.774**	−36.626
	(0.007)	(0.016)	(7.062)	(6.129)	(0.007)	(0.016)	(32.371)	(24.850)
Constant	−1.345*	−0.779*	−644.792*	−843.293**	1.391*	0.800*	450.566**	109.853
	(0.096)	(0.178)	(228.133)	(385.981)	(0.095)	(0.177)	(181.618)	(136.305)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	91,471	27,206	91,471	27,206	91,471	27,206	91,471	27,206
Pseudo R^2	0.110	0.102	0.002	0.001	0.110	0.101	0.013	0.018

Columns 3–4 and 7–8 present Tobit regressions with Shares Sold or Sales Purchased as the dependent variable.

In column 1, the coefficient on log(ABSVI) is a significant 0.130, indicating that insiders are more likely to sell shares during months of high retail attention. In terms of economic significance, a 1-standard-deviation increase in log(ABSVI) increases the probability of insider sales by 4.94 percentage points or 10.28% of the standard deviation. This result is consistent with the hypothesis that insiders actively sell their shares to exploit attention-driven overvaluation.

Column 2 adds the institutional attention and firm-specific news control variables, log(ABDMR) and Anews, to control for fundamental information flows and news that may affect *both* retail and institutional attention. Although only the coefficient of log(ABDMR) is statistically significant, the signs of the coefficients on both variables are negative, suggesting a lower likelihood of insider sales when institutional investors are paying more attention or when firms are experiencing more news coverage. However, even with the additional controls, the coefficient of log(ABSVI) in column 2 remains a significant 0.157, implying an increase of 5.40 percentage points in the probability of insider sales for a 1-standard-deviation increase in log(ABSVI). This result confirms the robustness of the positive relation between retail attention and opportunistic insider sales. Consistent with the finding reported in column 5 in Table 3, increased institutional attention is associated with positive future stock returns and thus reduces the incentive for insider sales. An alternative explanation is that greater institutional attention pertains to institutional investors' closer monitoring of the firm and therefore deters opportunistic insider sales. As before, an increase in firm-specific news coverage (Anews) does not have a significant effect on our results.

Columns 3–4 examine the intensity of insider sales and show that insiders sell more aggressively during months of high retail attention. For example, the log(ABSVI) coefficient in column 4 is a significant 13.123, implying that a 1-standard-deviation increase in log(ABSVI) is associated with insider sales of 4,502 additional shares.

On insider purchases, the results in columns 5–8 show that during periods of high retail attention, insiders are less likely to purchase shares and, when they do purchase, the quantity is significantly smaller. For example, the coefficient of log(ABSVI) in column 5 is negative and significant, at -0.128, implying that a 1-standard-deviation increase in log(ABSVI) decreases the probability of insider purchases by 4.05 percentage points, which is 8.33% of the standard deviation. In terms of the intensity of insider purchases, the negative and significant coefficient on log(ABSVI) in column 8 implies that insiders purchase 7,147 fewer shares for a 1-standard-deviation increase in log(ABSVI).

In columns 2, 4, 6, and 8, we include the institutional attention and firm-specific news variables, log(ABDMR) and Anews. The coefficients on log(ABDMR) are significant but have the opposite signs to those on log(ABSVI). The coefficients on Anews remain largely insignificant. The results are consistent with Ben-Rephael, Da, and Israelsen (2017) and Ben-Rephael et al. (2021) that greater institutional attention is associated with fundamental information flows and predicts positive future returns. More important, our retail attention measure log(ABSVI) remains robust after controlling for institutional attention and firm-specific news. Thus, the association between retail attention and insider trades is unlikely to be driven by omitted fundamental news.[18] Overall, Table 4 shows that

[18]We also directly decompose retail investor attention into fundamental and nonfundamental (sentiment) components by regressing log(ABSVI) on the contemporaneous log(ABDMR) and an extensive list of control variables that are potentially associated with fundamental information. Table 7 in the Supplementary Material reports the regression of insider trades on these two components, showing that the association between retail attention and insider trading that we document is mostly coming from the nonfundamental component. Additionally, we exclude firm-month observations that are associated with earnings announcements and replicate the odd columns of Table 4. Panel A in Table 8 in the Supplementary Material shows that our results are robust. Furthermore, we examine whether our findings are driven by managers systematically disclosing negative information on Fridays when

retail attention is strongly positively associated with both the probability and intensity of insider sales and negatively associated with the likelihood and intensity of insider purchases.

For an additional robustness check, we use an alternative measure of abnormal retail attention to address the concern that Google searches based on a stock's ticker symbols are subject to potential measurement errors. deHaan, Lawrence, and Litjens (2024) propose that the measurement error issue can be dealt with by using the combination of ticker and the word "stock" (TS) when collecting the search data and providing the alternative SVI measure, SVI^{TS}, for Russell 3000 stocks from July 2017 to Dec. 2021.[19] We therefore define $ABSVI^{TS}$ as the abnormal search volume based on the alternative measure and present the findings in Table 3 in the Supplementary Material. Panel A compares the sample distributions between ABSVI and $ABSVI^{TS}$, showing similar distribution characteristics. The correlation between the two measures is 0.635. Panels B and C replicate Tables 3 and 4, replacing ABSVI with $ABSVI^{TS}$. The coefficients remain similar, confirming that our findings are not driven by measurement errors. Furthermore, as noted by deHaan et al. (2024), measurement errors in SVI in the context of time-series analysis tend to attenuate regression estimates. To the extent that we already find strong results using our original measure, the effects that we document should be considered a lower bound of the true effects.

B. Investor Clientele

If insiders trade to take advantage of attention-driven mispricing, we expect the pattern to be stronger for stocks that are more susceptible to the influence of retail investors. In addition, Boone and White (2015) show that greater institutional ownership is associated with more management disclosures, greater analyst followings, and more transparent informational environments, all of which would likely reduce profits for insider trades. Therefore, we expect a stronger relation between retail attention and insider trading for firms with larger retail or lower institutional ownership.

We measure institutional ownership using Form 13F filings. The data set, formerly CDA/Spectrum 34, includes institutional managers with at least \$100 million of assets under management. We measure institutional ownership as the ratio of common shares owned by institutional investors to the total number of shares outstanding. We define an indicator variable, LIO, which equals 1 if a firm's institutional ownership belongs to the lowest quintile, and 0 otherwise. Thus, stocks with the largest retail ownership have an LIO value of 1.

Panel A of Table 5 reports the results of Probit and Tobit regression analyses on the effects of institutional ownership on attention-driven insider trades. The specification is similar to the baseline case in Table 4 but with an additional interaction variable, log(ABSVI) × LIO, the key variable of interest here. Columns 1–2 present

investors are more distracted (Niessner (2015)). We exclude insider sales within 1 and 2 weeks ahead of firms' Friday negative 8-K filings and replicate Table 4 for insider sales. Panel B of Table 8 in the Supplementary Material presents the results and shows that our findings remain robust.

[19]We thank R. Litjens for providing the data, available at: https://github.com/robinlitjens/GoogleTickerStock-SVI/tree/main.

the results for insider sales and show that the coefficients on log(ABSVI) are positive and significant, similar to the baseline case. More important, the coefficients on log(ABSVI) × LIO are also positive and significant, indicating that large retail ownership is associated with more retail attention–driven insider sales. Economically, the coefficient in column 1 implies that for firms with large retail ownership, a 1-standard-deviation increase in log(ABSVI) increases the probability of insider sales by an incremental 4.20 percentage points, and in column 2, it increases insider sales by 3,405 additional shares.

On insider purchases, columns 3–4 in Panel A of Table 5 show that the coefficients on log(ABSVI) and log(ABSVI) × LIO are negative and significant, indicating that high retail attention is associated with a lower likelihood and less intensity of insider purchases, especially for firms with large retail ownership. For such firms, a 1-standard-deviation decrease in log(ABSVI) increases the

TABLE 5

Retail Investor Attention and Insider Trading, Investor Clientele

Table 5 reports insider trading results by investor clientele: stock ownership and lottery-type stocks during the 2004–2021 sample period. Panel A shows the institutional ownership heterogeneities on insider trades. LIO (low institutional ownership) is an indicator variable that equals 1 if the institutional ownership (IO) is in the lowest quintile in the previous quarter, where IO is the percentage of shares owned by institutional investors scaled by common shares outstanding. Panel B shows the average characteristics of lottery type and nonlottery type stocks. Lottery stocks are those with a price lower than the corresponding median value of the sample and volatility and skewness higher than the corresponding median. The Lottery indicator takes a value of 1 if firm *i*'s stock is a lottery stock at the end of month $t-1$. All other variables are defined in Table 4. In columns 1 and 3 of both panels, we run Probit regressions in which the dependent variable is the Sale (Purchase) indicator that equals 1 if a firm-month is a net sale (purchase) month. In columns 2 and 4, we run Tobit regressions in which the dependent variable is the number of shares sold (purchased) by all insiders (in thousands) for each firm-month observation. Two-way (firm and month) clustered standard errors at the firm level are in parentheses. *, **, and *** denote significance at the 1%, 5%, and 10% levels, respectively.

	Insider Sales (Indicator or Shares Sold)		Insider Purchase (Indicator or Shares Purchased)	
	Probit	Tobit	Probit	Tobit
	1	2	3	4
Panel A. By Retail Ownership				
$\log(\text{ABSVI})_{i,t} \times \text{LIO}_{i,t-1}$	0.127*	8.977**	−0.101*	−6.458***
	(0.029)	(4.305)	(0.024)	(3.540)
$\log(\text{ABSVI})_{i,t}$	0.084*	3.567**	−0.085*	−3.647**
	(0.017)	(1.573)	(0.017)	(1.633)
Constant	−1.254*	−657.468*	1.544*	530.644*
	(0.098)	(238.427)	(0.097)	(206.768)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
No. of obs.	91,137	91,137	91,137	91,137
Pseudo R^2	0.110	0.002	0.111	0.003
Panel B. By a Stock's Lottery Features				
$\log(\text{ABSVI})_{i,t} \times \text{Lottery}_{i,t-1}$	0.068**	19.467*	−0.073**	−12.993***
	(0.033)	(7.485)	(0.031)	(7.257)
$\log(\text{ABSVI})_{i,t}$	0.024**	5.707*	−0.021***	−5.095**
	(0.011)	(2.158)	(0.011)	(2.174)
Constant	−1.315*	−637.202*	1.359*	402.504*
	(0.096)	(224.987)	(0.095)	(152.857)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
No. of obs.	91,471	91,471	91,471	91,471
Pseudo R^2	0.110	0.002	0.115	0.004

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probability of insider purchases by 3.90 percentage points and the size of purchases by 2,450 shares. Thus, insiders trade in opposite to the extent of retail attention, especially when their firms have large retail ownership of stock.

Next, we examine how the lottery feature of stock influences the relation between retail attention and insider trading. Kumar (2009) and Bali et al. (2021) show that retail investors are especially attracted to stocks with lottery features, and their demand for such stocks results in overvaluation and low future returns for the stocks. In light of these findings, we expect a stronger relationship between retail attention and insider trading for lottery stocks.

Following Kumar (2009), we identify lottery stocks based on stock price, idiosyncratic volatility, and skewness of daily stock returns.[20] We classify a stock in our sample as a lottery stock if its price is in the bottom half of distribution and its idiosyncratic volatility and skewness are in the top half. We define an indicator variable, Lottery, which equals 1 for a lottery stock, and 0 otherwise.[21]

Panel B of Table 5 presents our Probit and Tobit regression analyses with the key variable of interest being the interaction of log(ABSVI) with the Lottery indicator, log(ABSVI) × Lottery. Columns 1–2 report insider sales. The coefficient of log(ABSVI) is positive and significant, consistent with the baseline results in Table 4. More important, column 1 shows that the coefficient on log(ABSVI) × Lottery is significant and positive at 0.068, implying that for lottery stocks, a 1-standard-deviation increase in log(ABSVI) is associated with an increase of 4.10 percentage points in the probability of insider sales. For nonlottery stocks, the corresponding increase in the probability is only 1.92 percentage points. Thus, lottery stock insiders are more than twice as likely as nonlottery stock insiders to engage in attention-based sales. Regarding the intensity of insider sales, the Tobit regression analysis in column 2 shows that the coefficient on log(ABSVI) × Lottery is also positive and significant. Here, a 1-standard-deviation increase in log(ABSVI) is associated with lottery stock insiders selling 7,653 more shares, an amount that is substantially higher than the sales of 4,164 more shares by nonlottery stock insiders.

On insider purchases, columns 3–4 in Panel B of Table 5 show negative and significant coefficients on log(ABSVI). Here, a 1-standard-deviation increase in log(ABSVI) lowers the probability of insider purchases by 4.57 percentage points for lottery stocks and by only 1.97 percentage points for nonlottery stocks. In terms of the intensity of insider purchases, the same change in log(ABSVI) is associated with 1,533 fewer shares being purchased by lottery stock insiders than by nonlottery stock insiders.

Our evidence shows that the sensitivity of insider trading to retail attention is greater for stocks dominated by retail investors, for which the effect of retail attention on mispricing is more pronounced. In particular, the positive association between retail attention and insider sales is stronger for stocks with large retail

[20]Following Harvey and Siddique (2000) and Ang, Hodrick, Xing, and Zhang (2006), we compute idiosyncratic volatility and skewness for each stock, using its daily return data in the prior 6 months.

[21]Our sample has 2,369 lottery stocks and 6,942 nonlottery stocks. The lottery stocks have an average price of \$7.17, idiosyncratic volatility of 18.84, and idiosyncratic skewness of 2.11. In comparison, the corresponding numbers are \$35.20, 5.13, and 0.32 for the nonlottery stocks.

ownership and with more prominent lottery features while the negative association between retail attention and insider purchases is weaker for the same stocks.

V. SEC Enforcement Actions

Insider trading is subject to significant regulatory and corporate restrictions. A major part of securities regulation in the United States involves enforcement actions by the SEC against illegal insider trading. Many corporations also implement compliance policies to limit questionable insider trades (Lakonishok and Lee (2001)). Furthermore, the SEC is known to scrutinize more insider sales than purchases (Agrawal and Cooper (2015)), suggesting that insiders would be more careful when selling their shares, to reduce the risk of SEC investigations or other enforcement actions.

We investigate the relation between attention-related insider trading and the intensity of SEC enforcement actions. We first examine firm-level insider trading in response to SEC actions. We then consider insider-level analysis and study the likelihood that an insider is subject to SEC insider trading investigations.

Panel A of Table 6 reports the results of firm-level panel regressions, where the dependent variable is the Sale indicator in columns 1–3 and the Shares Sold variable in columns 4–6. To control for unobserved firm characteristics, we use a linear probability model with firm fixed effect. Table 4 in the Supplementary Material reports the results from alternative specifications using Probit and Tobit regressions. ΔSEC Intensity is the natural logarithmic difference between 1 plus the number of SEC enforcement releases against insider trading and 1 plus the median number of SEC insider trading releases over the past 6 months.[22] Columns 1 and 4 show that the coefficients on lagged ΔSEC Intensity are negative and significant, consistent with a deterrent effect of more intense SEC enforcement on opportunistic insider sales (Cohen et al. (2012)). Specifically, columns 1 and 4 imply that a 1-standard-deviation increase in ΔSEC Intensity decreases the probability of insider sales by 1.40 percentage points and the amount of sales by 1,302 shares.

The key variable of interest is the interaction term log(ABSVI) × ΔSEC Intensity, which captures how attention-based insider trading responds to changes in SEC action intensity. Columns 3 and 6 show that the coefficients on the interaction term are positive and significant, suggesting that the deterrence role of SEC enforcement actions on insider trading is significantly dampened during periods of high investor attention. One reason may be that such sales are less likely to be subject to SEC investigations because they rely more on retail sentiment than on material private information about the firm.

We provide additional evidence for this explanation by regressing the probability that an insider is subject to an SEC investigation on the contemporaneous insider trading variables. The dependent variable, SEC-Investigation, equals 1 if an insider is the target of SEC insider trading enforcement actions, and 0 otherwise. We capture the overall intensity of an insider's opportunistic trading with the Total

[22]The summary statistics for our litigation data are as follows: The average number of SEC cases related to insider trading in a month is 4.9 (median 5.0), with a standard deviation of 2.46 (max = 13, 75th percentile = 6, 25th percentile = 3, min = 0).

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TABLE 6

SEC Enforcement Actions and Opportunistic Insider Trading

Table 6 explores the link between SEC litigation and opportunistic insider trading. Panel A reports the results of firm-level OLS regressions in which the dependent variables are Sale (columns 1–3) and Shares Sold (columns 4–6). ΔSEC Intensity is the natural logarithmic difference between 1 plus the number of SEC enforcement releases against insider trading and 1 plus the median number of SEC insider trading releases over the past 6 months. log(ABSVI) is the natural logarithm of the abnormal Google search volume index on a stock's ticker symbol. Control variables include log(SIZE), log(BM), Adv/Sales, the firm's contemporaneous monthly return ($Ret_{i,t}$), the value-weighted market return ($Ret_{m,t}$), log(Price), and log(Turnover), as defined in Table 4. Panel B reports Logit regressions of SEC investigations following Cohen, Malloy, and Pomorski (2012). The observations are at the insider level, and insider characteristics are constructed based on all trades and sales for each insider. The dependent variable, SEC-Investigation, equals 1 if the insider is subject to SEC enforcement action, and 0 otherwise. The SVI Sales Indicator equals 1 if an insider sells in a month when log(ABSVI) is positive. Total Insider Trades are the total number of trades an insider makes. We further decompose this variable to SVI Trades and Non-SVI Trades, defined as the numbers of insider trades that are related to SVI and unrelated to SVI, respectively. Clustered standard errors by firm and month are in parentheses. *, **, and *** denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Insider Trading Responses to SEC Enforcement Actions

	Sale			log(Shares Sold)		
	1	2	3	4	5	6
ΔSEC_Intensity$_{t-1}$	−0.011***	−0.012**	−0.011	−0.213*	−0.214*	−0.200*
	(0.006)	(0.006)	(0.007)	(0.058)	(0.069)	(0.069)
log(ABSVI)$_{i,t}$		0.032**	0.027**		0.474*	1.816*
		(0.015)	(0.011)		(0.175)	(0.637)
log(ABSVI)$_{i,t}$ × ΔSEC_Intensity$_{t-1}$			0.032**			2.011**
			(0.016)			(0.911)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	129,430	91,471	91,471	129,430	91,471	91,471
R^2	0.351	0.353	0.354	0.341	0.344	0.344

Panel B. The Probability of SEC Investigations, Insider-Level Analysis

	Dependent Variable: SEC-Investigation	
	1	2
SVI Sales	−0.673*	−0.420*
	(0.229)	(0.161)
Total Insider Trades	0.315**	
	(0.157)	
SVI_Trades		0.146
		(0.124)
NON_SVI_Trades		0.294**
		(0.126)
No. of obs.	161,172	161,172
Pseudo R^2	0.019	0.021

Insider Trades variable, defined as the number of opportunistic trades the insider makes in the month. To capture the extent to which insiders engage in attention-driven trading, we define an SVI Sales indicator that equals 1 for observations where an insider is a net seller and when log(ABSVI) is positive, and 0 otherwise. The regression results are reported in Panel B of Table 6 Column 1 shows that the coefficient on the SVI Sales indicator variable is significantly negative, suggesting that attention-related insider sales are less likely to be targeted by the SEC, compared to other types of insider sales.

Next, we decompose total insider trades into two components, SVI Trades and Non_SVI Trades. SVI Trades equals the number of insider trades when log(ABSVI) is positive, and 0 otherwise. Similarly, Non_SVI Trades equals the number of insider trades when log(ABSVI) is negative, and 0 otherwise. Column 2

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presents the results with Total Insider Trades replaced by the decomposed variables. The coefficient on Non_SVI Trades is positive and significant, but the coefficient on SVI Trades is insignificant. The results confirm that while non-SVI-related trades substantially increase the likelihood of an SEC investigation, SVI-related trades do not significantly affect this likelihood.

Together, the results suggest that the current practice of SEC enforcement actions targeting insider trading may not affect insider trading activities that exploit retail attention. Given rising retail investor participation in the stock market and the increasing influence of social media platforms on retail investors, whether or how to regulate attention-based insider trading is an important topic for policy considerations.

VI. Mispricing, Retail Trading, and Robinhood Herding

We have established that insiders are more likely to sell (buy) shares of their own companies when there is high (low) retail attention on the stock. Furthermore, such trades are followed by lower (higher) future stock returns. Additionally, we demonstrate that the sensitivity of insider sales to retail attention is greater for stocks dominated by retail investors and those with more prominent lottery features. In contrast, the negative association between retail attention and insider purchases is weaker for such stocks.

While we interpret this evidence as consistent with insiders trading to exploit attention-driven mispricing, a possible alternative explanation for our findings is that retail attention serves as a proxy for noise trading. It is well established that traders with private information find it advantageous to trade during periods of high levels of noise trading because noise helps camouflage their trades (e.g., Kyle (1985)). If retail attention reflects noise trading, this alternative mechanism could explain our result that insiders are more likely to sell during periods of high retail attention. However, the noise trading-based mechanism would also predict that insiders are more likely to purchase stocks when retail attention is high. Contrary to this prediction, our empirical finding also indicates that insiders are more likely to buy when retail attention is low. Hence the noise trading-based mechanism does not fully explain our findings.

In this section, we provide more direct evidence for the mispricing explanation by utilizing measures that more directly capture mispricing and retail sentiment.

A. Mispricing

We utilize two direct measures of mispricing that have been proposed in previous studies. The first measure, RIM, introduced by Cong et al. (2023), is the ratio of intrinsic firm value based on the Residual-Income-Model to its market price. The second is the Mispricing (MISP) measure of Stambaugh et al. (2012), based on the average percentile rankings of a stock across 11 anomaly variables.[23]

[23]The list of anomalies includes net stock issues, composite equity issues, accruals, net operating assets, asset growth, investment-to-assets, distress, O-score, momentum, gross profitability premium, and return on assets. A ranking of 100 corresponds to maximum overvaluation, while a ranking of zero suggests the highest level of undervaluation. We are grateful to Will Cong for sharing the RIM data. The

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TABLE 7

Retail Attention, Mispricing, and Insider Trading

Table 7 reports the results of retail attention, mispricing, and insider trading. Panel A compares our attention measure and insider trades based on two mispricing measures: RIM and MISP. RIM is defined as a stock's market value divided by its intrinsic value, which is derived based on Cong, George, and Wang (2023). A stock is overvalued (undervalued) if RIM is larger (smaller) than 1. MISP is based on the 11 anomaly variables defined by Stambaugh, Yu, and Yuan (2012), who consider stocks with a higher (lower) value of MISP as more likely to be overvalued (undervalued). We define stocks in the top (bottom) 30 percentiles of MISP ranks to be overvalued (undervalued). ABSVI is the abnormal Google search volume index on a stock's ticker symbol. No. of trades and No. of traders are the number of opportunistic insider trades and the number of opportunistic insider traders per firm-month, respectively. Shares Sold and Shares Purchased are the number of shares insiders sold and purchased (in thousands) in a firm-month. Panel B reports the results of regression analysis. The dependent variable is the Sale or Purchase indicator in columns 1, 3, 5, and 7, and is the number of shares sold or purchased in columns 2, 4, 6, and 8. Control variables include log(Size), log(BM), Adv/Sales, firm contemporaneous return ($Ret_{i,t}$), the value-weighted market return ($Ret_{m,t}$), log(Price), and log(Turnover), as defined in Table 4. Two-way (firm and month) clustered standard errors at the firm level are in parentheses. *, **, and *** denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Relationships Between Retail Attention, Mispricing, and Insider Trades

	RIM (2004/07–2018/08)			MISP (2004/07–2021/12)		
	Overvaluation (RIM > 1)	Undervaluation (RIM < 1)		Overvaluation (Top 30 Percentiles)	Undervaluation (Bottom 30 Percentiles)	
	Mean	Mean	Diff.	Mean	Mean	Diff.
ABSVI	1.089	0.984	0.105*	1.104	0.986	0.118*
No. of trades (Sales)	1.949	1.591	0.358*	1.713	1.464	0.249**
No. of trades (Purchases)	0.458	0.907	−0.449*	1.105	1.446	−0.341*
Shares Sold	81.521	46.533	34.988*	87.861	40.419	47.222**
Shares Purchased	20.874	37.941	−17.067*	18.948	35.333	−16.385**

Panel B. Regression Analysis

	Probit	Tobit	Probit	Tobit	Probit	Tobit	Probit	Tobit
	Sale	Shares Sold	Purchase	Shares Purchased	Sale	Shares Sold	Purchase	Shares Purchased
	1	2	3	4	5	6	7	8
$\log(RIM)_{i,t}$	0.124*	18.732**	−0.118*	−6.869*				
	(0.014)	(8.619)	(0.014)	(2.249)				
$\log(MISP)_{i,t}$					0.082*	16.278**	−0.083*	−7.449*
					(0.004)	(7.347)	(0.004)	(1.307)
$\log(ABSVI)_{i,t}$	0.143***	9.279**	−0.128**	−2.426	0.107***	6.037**	−0.104***	−5.133**
	(0.081)	(4.639)	(0.051)	(8.661)	(0.064)	(3.005)	(0.054)	(2.415)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	43,798	43,798	43,798	43,798	83,398	83,398	83,398	83,398
Pseudo R^2	0.068	0.001	0.068	0.014	0.110	0.002	0.116	0.002

We classify a stock as overvalued when its RIM exceeds one or when it ranks in the top 30 percentile of MISP, and as undervalued when its RIM is below 1 or when it ranks in the bottom 30 percentile of MISP. Panel A of Table 7 presents the average levels of retail attention and insider trading during periods of over- and undervaluation, respectively. The results show that periods of overvaluation are associated with more insider sales and fewer insider purchases, both in terms of the number of trades and the number of shares traded. While this finding is not surprising and aligns with previous studies, it serves as an external validity check, confirming that our mispricing measures correspond to insider trading activities as

MISP mispricing measure can be retrieved from R. F. Stambaugh's website: https://finance.wharton.upenn.edu/~stambaug/.

expected. Additionally, Panel A shows that retail attention tends to be significantly higher during periods of overvaluation, as measured by RIM and MISP, than during periods of undervaluation. This evidence is also consistent with the findings of Barber and Odean (2008), Da, Engelberg, and Gao (2011), and Barber et al. (2022) that high attention is usually associated with overvaluation.

Panel B of Table 7 presents the results of regression analysis. Columns 1, 3, 5, and 7 represent Probit regressions, where the dependent variable is the Sale or Purchase indicator. Columns 2, 4, 6, and 8 represent Tobit regressions, where the dependent variable is Shares Sold or Sales Purchased. The coefficients on log(RIM) and log(MISP) are statistically significant in all specifications, indicating a greater extent of insider sales and a lesser extent of insider purchases during periods of higher overvaluation. The coefficients on log(ABSVI) are attenuated and less significant, compared to the corresponding coefficients in Table 4, suggesting that the mispricing measures capture at least a portion of the explanatory power of ABSVI.

Our results from Tables 4 and 7 are broadly consistent with the explanation that periods of high retail attention tend to be associated with overvaluation and hence more insider selling. However, it is possible that there are cases in which retail attention is directed to salient negative news, resulting in overreaction to negative news and therefore a downward price pressure and undervaluation. In such cases, insiders can take advantage of this undervaluation, and their buying should be followed by higher future returns. To explore this hypothesis, we estimate the following regression:

$$\text{(2)} \qquad \text{Exret}_{i,t+1} = \begin{aligned}[t] &\alpha + \beta_1 \log(\text{ABSVI})_{i,t} \cdot I\_\text{Lowret}_{i,t} + \beta_2 \cdot I\_\text{Buy}_{i,t} \\ &+ \beta_3 \log(\text{ABSVI})_{i,t} + \beta_4 \log(\text{ABSVI})_{i,t} \cdot I\_\text{Buy}_{i,t} \\ &+ \beta_5 \log(\text{ABSVI})_{i,t} \cdot I\_\text{Buy}_{i,t} \cdot I\_\text{Lowret}_{i,t} \\ &+ \beta_6 \log(\text{ABSVI})_{i,t} \cdot I_{\text{Lowret}\,i,t} + \beta_7 I_{\text{Buy}\,i,t} \\ &\cdot I_{Lowret\,i,t} + \gamma \cdot X_{i,t} + \varepsilon_{i,t}, \end{aligned}$$

where I_Buy equals 1 for insider purchase months and 0 for insider sales months, and I_Lowret equals 1 if the month t stock return is below the 1st, 5th, 10th, or 20th percentile of the return distribution, respectively. The coefficient of interest is the triple interaction term: $\log(\text{ABSVI})_{i,t} \cdot I\_\text{Buy}_{i,t} \cdot I\_\text{Lowret}_{i,t}$. A higher value of the triple interaction term indicates that insiders are net buyers during months of large negative returns and high retail attention. A positive coefficient on this term indicates that periods of large price drops, high retail attention, and net insider purchases are followed by higher returns the next month, in support of the hypothesis.

Our results are presented in Table 5 in the Supplementary Material. Columns 1–4 show that the coefficients of the triple interaction term are all positive and larger in magnitude for more extreme negative returns (the lower percentiles of the distribution). Hence, although not significant, the point estimates suggest that while attention is typically associated with overvaluation during normal periods as previous studies document, investor attention may lead to overreactions to rare and sharp price drops. This in turn can create opportunities for insiders to buy shares and profit from the transitory undervaluation. Future work that identifies these unique events and analyzes the psychological foundations of investors' belief formation mechanisms is worth pursuing.

B. Retail Trading

Having established that our retail attention measure is directly related to mispricing and is not merely capturing noise in stock prices, we next turn to how retail sentiment plays a role in mediating the link between attention and insider trading. To this end, our first proxy for retail sentiment is based on retail order imbalances. The existing literature has documented that retail investors' sentiment, as reflected in their demand, can cause stock prices to temporarily deviate from its fundamental value (e.g., Barber, Odean, and Zhu (2009)). Following Boehmer et al. (2021), we use TAQ/ISSM data between 2010 and 2019 to construct retail order imbalance (OIB) measures to proxy for retail sentiment. For each day, we compute the volume-weighted OIBVOL (trade-size-weighted OIBTRD) as the number of shares (trades) that retail investors buy minus sell, divided by the sum of the buy and sell shares (trades). We then calculate the average daily OIBVOL and OIBTRD to obtain monthly measures. A positive OIBVOL or OIBTRD indicates positive retail sentiment as it reflects excessive buying compared to selling, while a negative value indicates negative sentiment.[24]

Panel A of Table 8 presents the average number of shares bought or sold by insiders under different combinations of ABSVI and OIB levels: whether log(ABSVI) is positive or negative, and whether net retail order imbalance (OIB) is positive or negative. The results show that during periods of high investor attention (log(ABSVI) > 0), insiders sell significantly more shares when OIB is positive than when OIB is negative. Thus, the positive association between retail attention and insider sales is largely driven by periods with positive retail sentiment. Similarly, when retail attention is low, insiders purchase fewer shares when retail sentiment is negative, indicating that the negative association between retail attention and insider buying is attributed to periods with negative retail sentiment. These findings suggest that retail sentiment is a channel that mediates the effect of retail attention on insider trading. In comparison, insider sales during low attention months and insider buys during high attention months, which we previously demonstrated to be small, do not depend on retail OIB.

We further investigate how retail attention and retail sentiment interact with each other and influence insider trades with a panel regression analysis and present the results in Panel B of Table 8. The coefficients on the key variable of interest, the interaction of log(ABSVI) with the retail order imbalance measures (OIBVOL or OIBTRD), are highly significant across all specifications. The results are also economically significant. For example, the coefficients in columns 1–2 imply that a 1-standard-deviation increase in OIBVOL increases the probability of insider sales by 1.51 percentage points and the number of shares sold by 4,491, when ABSVI is at its mean value. In columns 5–6, the same increase in OIBVOL

[24]There are 21,031 firm-month observations in this sample that correspond to positive OIBVOL, and 29,810 observations with negative OIBVOL. For OIBTRD, the corresponding numbers are 24,032 and 26,809, respectively.

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TABLE 8

Retail Attention, Retail Order Imbalance, and Insider Trading

Table 8 reports the results of retail attention, retail sentiment, and insider trading. Panel A presents the average number of shares bought or sold by insiders under different combinations of ABSVI and OIB levels: log(ABSVI) positive or negative and OIB positive or negative. log(ABSVI) is the natural logarithm of the abnormal Google search volume index on a stock's ticker symbol. $OIBVOL_{i,t}$ and $OIBTRD_{i,t}$ are the average of daily volume-weighted $OIBVOL_{i,d}$ and trade-size-weighted $OIBTRD_{i,d}$ in month t, where $OIBVOL_{i,d}$ is the number of firm i's shares bought minus the number of its shares sold on day d scaled by the total number of shares traded and $OIBTRD_{i,d}$ is the number of purchases minus the number of sales on stock i on day d scaled by the total number of trades. Panel B reports the results of regression analysis. The dependent variable is the Sale or Purchase Indicator in columns 1, 3, 5, and 7, and is the number of shares sold or purchased in columns 2, 4, 6, and 8. Control variables include log(SIZE), log(BM), Adv/Sales, firm contemporaneous return ($RET_{i,t}$), the value-weighted market return ($RET_{m,t}$), log(PRICE), and log(Turnover), as defined in Table 4. Two-way (firm and month) clustered standard errors at the firm level are in parentheses. *, **, and *** denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Average Insider Trades

	OIB=OIBVOL					
	SHARES_SOLD			SHARES_PURCHASED		
	+OIB	−OIB	Diff.	+OIB	−OIB	Diff.
log(ABSVI) > 0	70.117	43.240	26.877*	24.324	24.710	−0.386
log(ABSVI) < 0	38.989	37.986	1.003	28.974	39.195	−10.221*
	OIB=OIBTRD					
	SHARES_SOLD			SHARES_PURCHASED		
	+OIB	−OIB	Diff.	+OIB	−OIB	Diff.
log(ABSVI) > 0	68.250	44.709	23.541**	23.061	26.240	−3.179
log(ABSVI) < 0	40.032	36.772	3.260	31.974	38.195	−6.221**

Panel B. Regression Analysis

	Probit	Tobit	Probit	Tobit	Probit	Tobit	Probit	Tobit
	Sale	Shares Sold	Sale	Shares Sold	Purchase	Shares Purchased	Purchase	Shares Purchased
	1	2	3	4	5	6	7	8
$\log(ABSVI)_{i,t} \times OIBVOL_{i,t}$	0.155*	13.728***			−0.152*	−16.478**		
	(0.036)	(7.075)			(0.037)	(8.286)		
$\log(ABSVI)_{i,t} \times OIBTRD_{i,t}$			0.361*	23.217*			−0.405*	−28.279**
			(0.071)	(8.310)			(0.090)	(8.526)
$\log(ABSVI)_{i,t}$	0.065***	4.961***	0.061	4.379***	−0.063	−6.417	−0.059***	−4.947
	(0.038)	(2.898)	(0.074)	(2.504)	(0.039)	(4.762)	(0.034)	(5.441)
$OIBVOL_{i,t}$	0.358*	69.558**			−0.363*	−103.204**		
	(0.042)	(30.536)			(0.042)	(43.325)		
$OIBTRD_{i,t}$			0.414*	82.122**			−0.420*	−124.270**
			(0.053)	(40.988)			(0.052)	(61.171)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	50,841	50,841	50,841	50,841	50,841	50,841	50,841	50,841
Pseudo R^2	0.114	0.002	0.113	0.002	0.113	0.015	0.112	0.015

decreases the probability of insider purchases by 1.47 percentage points and the number of shares bought by 5,134.

In contrast, the coefficients on log(ABSVI) are attenuated and, in some specifications, even insignificant, compared to their counterparts in Table 4. The result suggests that at least part of the explanatory power of log(ABSVI) in predicting insider trading is associated with retail sentiment. Additionally, the coefficients on OIBVOL and OIBTRD are positive and significant for insider sales variables in columns 1–4, and negative and significant for insider purchases in columns 5–8. Overall, our findings in this section are consistent with the explanation that retail sentiment acts as a channel through which investor attention drives insider trading.

C. The Herding of Robinhood Investors

Our second proxy for investor sentiment is based on the herding behavior of investors on Robinhood's trading platform. Barber et al. (2022) demonstrate that Robinhood users are more influenced by attention compared to other retail investors and more actively engage in attention-driven buying. Their behaviors result in correlated purchases of stocks and episodes of herding. Consistent with models suggesting that attention triggers more net buying by retail investors and leads to stock overvaluation (e.g., Barber and Odean (2008), Barber et al. (2022), and Pedersen (2022)) document significant negative abnormal returns following Robinhood buy herding episodes.

Motivated by this, we utilize data from Robinhood to measure retail investor attention and sentiment, covering the period of May 2018 to July 2020.[25] We define *users_close* as the total number of users in a stock for a given day and *userratio* as the ratio of users_close on consecutive days. Consistent with Barber et al. (2022), we focus on observations where the previous day's users_close is at least 100. We then identify stock-day observations associated with significant changes in the number of users. Specifically, for a given day, stocks with a userratio that belongs to the top 0.5% of its distribution and that is greater than 1 are classified as buy herding stocks. Similarly, sell herding stocks are those with a userratio in the bottom 0.5% and having a value less than 1.

We define herding at the monthly level, and classify a stock-month observation into three categories: i) Buy Herding Month if any buy herding event occurs during that month, ii) Sell Herding Month if a sell herding event occurs, and iii) Neutral Month if there are no buy or sell herding days in the month.[26]

Panel A of Table 9 compares retail attention and insider trades across the three categories. The levels of ABSVI and insider sales are highest during Robinhood's buy-herding months and lowest during its sell-herding months. In contrast, Robinhood's sell-herding months are accompanied by significantly more insider purchases than its buy-herding or neutral months. The findings indicate that insiders trade against Robinhood investors, selling more during periods of significant increases in Robinhood buyers, and buying more when Robinhood investors herd to sell.

Panel B of Table 9 reports the results of regression analysis. To better measure the intensity of Robinhood herding events for a firm in a given month, we define log(Buy Herding) and log(Sell Herding) as the natural logarithm of 1 plus the number of daily buy and sell herding events, respectively. The results indicate that buy (sell) herding intensity is positively associated with insider sales (purchases). In economic terms, the coefficients in columns 1 and 3 indicate that a 1-standard-

[25]We thank Xing Huang for sharing the Robinhood stock popularity data used in Barber et al. (2022).

[26]Excluding 258 firm-month observations with both buy and sell herding events, our sample consists of 488, 292, and 19,897 firm-month observations, corresponding to buy-herding, sell-herding, and neutral months, respectively.

TABLE 9

Robinhood Users, Retail Attention, and Insider Trading

Table 9 presents the findings regarding Robinhood user herding episodes, retail attention, and insider trading. Panel A examines retail attention and insider trades during Buy Herding, Sell Herding, and Neutral months. ABSVI represents the abnormal Google search volume index for a stock's ticker symbol. Panel B reports the results of regression analysis. log(Buy Herding) and log(Sell Herding) are the natural logarithm of 1 plus the number of daily buy and sell herding events for a month, respectively. The dependent variable is the Sale or Purchase Indicator in columns 1, 2, 5, and 6, and it represents the number of shares sold or purchased in columns 3, 4, 7, and 8. Control variables include log(Size), log(BM), Adv/Sales, firm contemporaneous return (Ret$_i$), the value-weighted market return (Ret$_{m,t}$), log(Price), and log(Turnover), as defined in Table 4. Two-way (firm and month) clustered standard errors at the firm level are reported in parentheses. *, **, and *** indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Retail Attention and Insider Trades During Herding and Neutral Months

	Buy Herding Months	Sell Herding Months	Neutral Months	Diff.		
	1	2	3	(1 − 2)	(1 − 3)	(2 − 3)
ABSVI	1.122	0.878	0.988	0.244*	0.134*	−0.110**
No. of trades (Sales)	1.572	1.379	1.452	0.193*	0.120*	−0.073
No. of trades (Purchases)	1.259	1.569	1.395	−0.310*	−0.136***	0.174***
Shares Sold	45.526	24.388	27.388	21.138*	18.138*	−3.000
Shares Purchased	30.302	44.771	22.945	−14.469*	7.357	21.826*
No. of firm months	488	292	19,897			

Panel B. Regression Analysis

	Probit		Tobit		Probit		Tobit	
	Sale		Shares Sold		Purchase		Shares Purchased	
	1	2	3	4	5	6	7	8
log(Buy Herding)$_{i,t}$	0.315*	0.405*	7.178***	11.348***		−0.107		−10.157
	(0.099)	(0.101)	(4.013)	(6.117)		(0.108)		(12.131)
log(Sell Herding)$_{i,t}$		−0.142		−4.438	0.503*	0.562*	30.234***	43.96**
		(0.108)		(10.921)	(0.114)	(0.121)	(15.868)	(17.714)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	12,516	12,516	12,516	12,516	12,516	12,516	12,516	12,516
Pseudo R^2	0.202	0.203	0.006	0.006	0.203	0.203	0.028	0.028

deviation increase in log(Buy Herding) raises the probability of insider sales by 1.11 percentage points and the number of shares sold by 674. Likewise, in columns 5 and 7, a 1-standard-deviation increase in log(Sale Herding) increases the probability of insider purchase by 1.79 percentage points and the number of shares bought by 1,050. The regression analysis aligns with the univariate results presented in Panel A and supports the narrative that insiders exploit mispricing arising from intensive buying or selling pressure from naive retail investors.

VII. Further Analysis and Robustness Checks

In this section, we conduct additional tests to check the robustness of our basic findings.

A. Rule 10b5-1 Trades

In our main analysis, the oppotunistic insider trading measure is constructed following the widely used method of Cohen et al. (2012). In this subsection, we

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consider an alternative way to differentiate routine from oppotunistic trades. Specifically, we take advantage of the SEC Rule 10b5-1, which allows insiders to voluntarily pre-schedule trades.[27] To the extent that it is difficult for insiders to predict future retail attention and sentiment, the pre-scheduled 10b5-1 trades are less likely to be opportunistic trades intended to exploit attention-driven mispricing. Consequently, we perform robustness checks by utilizing insider trades that are not associated with 10b5-1 plans as an alternative measure of opportunistic trades. We obtain information about 10b5-1 trades from Thomson Reuters, which collects the data from footnotes in the SEC Form 4 filings.

To analyze opportunistic insider trades, we exclude all 10b5-1 trades from our sample and replicate the analysis presented in Table 4. The results, shown in Table 6 in the Supplementary Material, are consistent with those in Table 4. For example, in Tobit regressions, the coefficients on log(ABSVI) are 15.987 and −23.887 in columns 2 and 4 in Table 6 in the Supplementary Material, which are similar to the corresponding coefficients of 13.123 and −23.31 in Table 4. In Probit regressions, the coefficients remain robust at 0.269 and −0.263, as shown in columns 1 and 3.[28] The analyses therefore provide further assurance of the robustness of our findings.

B. Exogenous Shocks to Attention

We have shown that our results are robust to controlling for market-wide and firm-level news arrivals, institutional investor attention, and possible strategic firm disclosure decisions. These tests alleviate the concern that our results are driven by fundamental information instead of retail attention. In this subsection, we provide further evidence by taking advantage of plausible exogenous shocks to retail investor attention and conduct instrumental variable analysis to provide identification. The approach is motivated by Peress and Schmidt (2020), who find that episodes of sensational news distract investor attention, especially for stocks with high retail ownership. Given that such episodes are not associated with any material information about the firm, it is plausible that the events do not have a significant direct impact on insider incentive to engage in opportunistic trading.

Following Eisensee and Strömberg (2007) and Peress and Schmidt (2020), we obtain daily news pressure based on the median number of minutes that U.S. news broadcasts devote to the first three news segments.[29] We select the top 5% of business days with the highest news pressure while excluding days of major financial market movements and denote these days as "distraction days." We then construct a monthly news pressure variable, Distraction, which is the natural logarithm of 1 plus the total number of distraction days for a given month. We

[27]Rule 10b5-1 offers executives a means to liquidate their stock holdings on a regular basis, for purposes like financing their children's education, without the inadvertent risk of facing insider trading allegations. Nevertheless, there is considerable skepticism regarding the potential unintended consequences of providing insiders with this specific form of legal defense, often referred to as a "safe harbor."

[28]Based on the standard deviation of the dependent variables with this alternative measure, a 1-standard-deviation increase in log(ABSVI) increases the probability of sales by 9.71%, which is 13.86% of the variable's standard deviation. The magnitude is comparable to the value of 10.28% obtained using the coefficient estimates in Table 4.

[29]We thank David Strömberg for the daily news pressure variable for the period of July 1, 2004, through Dec. 31, 2018. We obtain 229 distraction days for the sample period from July 2004 to Dec. 2018.

employ an instrumental variable approach with Distraction as an instrument for log(ABSVI).

Panel A of Table 9 in the Supplementary Material presents univariate analysis showing that Distraction months are accompanied by lower abnormal retail attention, confirming the validity of using Distraction as an instrument. Panel B performs the first-stage regression by regressing log(ABSVI) on Distraction.[30] The coefficient of Distraction is negative and significant at the 1% level, consistent with the univariate analysis in Panel A. In the second stage, we regress insider trading variables on the instrumented log(ABSVI), with all control variables from the first-stage regression included.[31] Table 10 in the Supplementary Material reports the results and shows that the coefficients on log(ABSVI) are significant and have the same signs as those from our baseline regression, suggesting that the relationship between retail attention and insider trading that we document is likely causal.[32]

C. Heterogeneity and Regulatory Regimes

We next explore the heterogeneity of attention-insider trading relation by insider type and by other firm characteristics. Because most of the characteristics are available annually, we aggregate the insider-firm-month observations into insider-firm-year observations. For a given insider in a given calendar year, we define an Insider Sale indicator that equals 1 if the number of months for which the insider is a net seller is greater than the number of months for which the insider is a net buyer, and 0 otherwise. For a given firm-year, we define a high-attention indicator, $I_{\text{attn}}^{\text{high}}$, which equals 1 if ABSVI is greater than 1 for at least 6 of 12 calendar months.

Following Cohen et al. (2012), we employ a Logit model to regress the Insider Sale indicator on firm and insider characteristics, $I_{\text{attn}}^{\text{high}}$, and the interaction variables between $I_{\text{attn}}^{\text{high}}$ and characteristics. The coefficients on the interactions

[30]We also include the following control variables: log(Size), log(BM), Earn (a contemporaneous earnings indicator), Ret and |Ret| (previous monthly return and its absolute value), Ret_m (previous monthly market return), |SUE| (absolute value of earnings surprise), log(No. of Earningnews) (the natural logarithm of 1 plus the number of earnings announcements in the previous month for the same Fama–French 17-industry), and year and industry fixed effects.

[31]The inclusion of Distraction contributes to an F-statistic of 47.72, significantly greater than the "rule of thumb" critical value of 10 (Staiger and Stock (1997)). Furthermore, the Cragg–Donald Wald F-statistic value is 26.08 for the instrument, also well above the critical value of 16.38 (Stock and Yogo (2005)). These statistics suggest that Distraction is not a weak instrument.

[32]One might argue that during Distraction months, insiders' attention could also be reduced, leading to less trading, or that the overall market liquidity is low, hence insiders are less able to trade aggressively. We find these alternative hypotheses less likely. Insiders are significantly *more* likely to engage in purchases during Distraction months than during non-Distraction months. The average number of trades corresponding to insider purchases is 4.7 for Distraction months, significantly higher than the 2.6 trades during non-Distraction months. In terms of the number of shares, insiders purchase an average of 20,042 shares during Distraction months, significantly more than the 12,248 shares purchased during non-Distraction months. Therefore, the more aggressive purchasing activities by insiders during Distraction months are inconsistent with a direct effect of Distraction on insider trading through an indirect, liquidity-based channel.

indicate whether a characteristic is important in explaining the relation between retail attention and insider sales.[33] Table 10 reports the results of this analysis. In column 1, we interact $I_{\text{attn}}^{\text{high}}$ with insider characteristics of Insider Tenure and Number of Trades. The coefficients on these interaction terms are positive and significant, suggesting that insiders with a longer tenure in a firm or who have engaged in more opportunistic trades in the past are more likely to sell during periods of high retail attention.

Turning to firm characteristics, the results shown in columns 2–5 indicate that insiders of firms with poorer governance, weaker social responsibility, or lower reputation tend to be more active participants in attention-driven sales. In column 2, the coefficient on the interaction of Poor Governance with $I_{\text{attn}}^{\text{high}}$ is positive and significant, indicating a greater propensity for attention-driven sales by insiders of firms exhibiting poor governance. The effect of corporate social responsibility is similar. In column 3, the coefficient on the interaction of CSR with $I_{\text{attn}}^{\text{high}}$ is negative and significant, indicating that insiders in more socially responsible firms are less likely to sell amid high retail attention. On firm reputation, we check the relevance of a firm belonging to the Fortune 100 best companies. Columns 4–5 show significant and negative coefficients on the interaction terms of $I_{\text{attn}}^{\text{high}}$ with the Fortune100 indicator and also with Fortune100_Rank, indicating a lower propensity for attention-driven sales by insiders of more reputable firms.

We further examine whether our results are robust across different regulatory regimes by using a change in U.S. political administrations as an exogenous shock to insider trading. We consider two subsample periods of 2004 to 2008 and 2009 to 2016. The first corresponds to the more laissez-faire Republican Bush administration and the second to the more activist Democratic Obama administration.[34] Presumably, during the latter, the government would be more active in enforcing laws and regulations against illegal insider trading. Any deterrent effects on opportunistic insider trades would be stronger during this period. Panels A and B of Table 11 in the Supplementary Material present the subsample results during the two administrations. The coefficients on log(ABSVI) remain similar in both subsample periods, suggesting that the relation between retail attention and insider trading is robust to different regulatory regimes.

[33]We consider an extensive list of insider and firm characteristics, including Insider Tenure (the natural logarithm of the number of years an insider is active in a firm), Number of Trades (the natural logarithm of the number of opportunistic trades an insider has made so far, which captures the propensity of opportunistic trading for the insider), Poor Governance (an indicator variable that equals 1 if a firm's G-index is at least 12, which is the 90th percentile of the sample distribution), KLD CSR scores, the Fortune100 (an indicator variable that equals 1 if a firm is among *Fortune* magazine's 100 best companies to work for, and 0 otherwise), and Fortune100_Rank (the numerical ranking of a firm in the Fortune 100 list). In addition to our variable of interest (interaction between each firm or insider characteristics and $I_{\text{attn}}^{\text{high}}$), we separately include each variable in the regression. For brevity, we do not present results for individual variables; they are available from the authors.

[34]E. Schwartz and C. Mahoney, "SEC Enforcement in the Second Term of the Obama Administration," Harvard Law School Forum on Corporate Governance, Feb. 14, 2013.

TABLE 10

Retail Attention and Insider Trading, by Insider and Firm Types

Table 10 reports the results of retail attention and insider trading by insider types and other firm and insider characteristics. The dependent variable is the Insider Sale Indicator, which equals 1 if the number of sales months is greater than the number of purchase months for an insider given a calendar year. The high abnormal SVI indicator (I_{att}^{high}) is 1 if the abnormal Google search volume index, ABSVI, is greater than 1 for at least 6 of 12 calendar months. Other independent variables are measured using data available at the time of insider sales and include the following: Insider Tenure (the natural logarithm of the number of years an insider is active in trading), Number of Trades (the natural logarithm of the number of trades an insider has been trading), Poor Governance (an indicator variable that equals 1 if the G-index based on Gompers, Ishii, and Metrick (2003) is greater than or equal to 12), CSR (measured as the net score of CSR rating from the KLD Social Rating database), and a Fortune100 indicator and rankings. Control variables include the previous year-end log(SIZE), log(BM), Adv/Sales, log(Price), average previous 12-month value-weighted market returns ($RET_{m,t}$) and log(Turnover), as defined in Table 4. Volatility$_i$ is the standard deviation of the past 36-month returns. Clustered standard errors at the firm level are in parentheses. *, **, and *** denote significance at the 1%, 5%, and 10% levels, respectively.

	1	2	3	4	5
Insider Tenure × $I_{att}^{high}{}_Y$	0.070*				
	(0.005)				
No. of Tradesy × $I_{att}^{high}{}_Y$	0.022*				
	(0.002)				
Poor Governance$_y$ × $I_{att}^{high}{}_Y$		0.363**			
		(0.151)			
CSR$_y$ × $I_{att}^{high}{}_Y$			−0.021*		
			(0.006)		
Fortune100$_y$ × $I_{att}^{high}{}_Y$				−0.159*	
				(0.055)	
Fortune100_RANK$_y$ × $I_{att}^{high}{}_Y$					−0.068***
					(0.041)
Controls	Yes	Yes	Yes	Yes	Yes
No. of obs.	120,972	9,816	59,112	120,972	2,413
Pseudo R^2	0.111	0.022	0.045	0.074	0.041

D. Seasoned Equity Offerings

If mispricing provides opportunities for insider trades, it might also influence corporate policies. We explore this possibility by examining the likelihood of seasoned equity offerings (SEOs). There are several reasons for this choice. First, SEOs provide a natural setting to examine managerial decisions in the context of perceived overvaluation (Khan et al. (2012)). Second, a substantial number of SEOs are announced and issued overnight (Gustafson (2018)), making it plausible that such decisions are made in response to attention-driven overvaluation. Third, we can accurately capture the timing of an SEO and relate it to retail attention.

Panel A of Table 11 shows the results of Probit regressions for the seasoned equity issuance decision. The dependent variable is an indicator variable (SEO) that equals 1 if a firm announces an SEO in the month, and 0 otherwise. Column 1 presents the results for the full sample. We also present matched sample results, for which each SEO firm is matched with a Fama–French 17-industry peer that is also similar in two additional variables known to be the main determinants of an SEO decision (Jenter (2005), Fama and French (2005)).[35] The coefficients on log(ABSVI) are all positive and highly significant in all columns, indicating that firms are more likely to conduct SEOs following periods of high retail attention.

[35]The additional matching variables for columns 2–4 are prior 12 months' return and firm size, BM and size, and asset growth and size. If there are multiple matches, we choose the one closest in terms of the first matching variable.

TABLE 11

Retail Investor Attention and Timing of Seasoned Equity Offerings

Table 11 shows the relationship between retail attention and future seasoned equity offerings (SEOs). Panel A reports the coefficients from the Probit regressions of equity issuance decisions. The dependent variable is an indicator variable (SEO) that equals 1 if a firm announces an SEO in month *t*. All independent variables are lagged. log(ABSVI) is the natural logarithm of the abnormal Google search volume index on a stock's ticker symbol. log(Size) and log(BM) are defined in Table 4. 1-Year Ret is the stock return over the previous 12 months. $\text{Ret}_{i,t-1}$ and $\text{Ret}_{m,t-1}$ are the previous month stock and value-weighted market return, respectively. The next set of variables is measured as of the prior year. ROA is the operating income before depreciation over total assets. Cash is the cash and short-term investments over total assets. Leverage is the long-term debt plus long-term debt in current liabilities over the total assets. Dividend Yield is defined as dividends per share divided by the stock price. Ivol and $\Delta\text{Ivol}_{i,t} - 1$ are the previous month idiosyncratic volatility and change of idiosyncratic volatility, respectively. Asset Growth is the change in the natural logarithm of total assets. Column 1 shows the results for the full sample. Columns 2–4 show the results for a matched sample in which each firm-month is matched on month, industry based on Fama–French 17-industry classifications, first matching variable, and second matching variable. The first and second matching variables are presented at the top of columns 2–4. After we obtain the matched sample, a regression is estimated. Two-way (firm and month) clustered standard errors at the firm level are in parentheses. * and ** denote significance at the 1% and 10% levels, respectively. Panel B reports the SEO frequencies for three matched samples and shows the *p*-value from a test of difference in SEO relative frequencies during months of high and low investor attention, respectively. We define a month as a high-attention month if log(ABSVI) is positive and as a low-attention month if log(ABSVI) is negative.

Panel A. Seasoned Equity Offerings (Probit)

		Matched Samples		
	Full Sample	By (Return Size)	By (BM Size)	By (Asset Growth ROA)
	1	2	3	4
$\log(\text{ABSVI})_{i,t-1}$	0.043*	0.050*	0.046*	0.044*
	(0.014)	(0.016)	(0.016)	(0.015)
log(Size)	−0.051*	−0.050*	−0.050*	−0.052*
	(0.008)	(0.009)	(0.009)	(0.009)
log(BM)	−0.083*	−0.084*	−0.093*	−0.089*
	(0.016)	(0.017)	(0.018)	(0.017)
1-Year Ret	0.130*	0.144*	0.132*	0.146*
	(0.015)	(0.016)	(0.018)	(0.015)
$\text{Ret}_{i,t-1}$	−0.110	−0.049	−0.087	−0.043
	(0.102)	(0.112)	(0.112)	(0.109)
$\text{Ret}_{m,t-1}$	1.020*	1.066*	1.072*	1.128*
	(0.337)	(0.372)	(0.373)	(0.358)
ROA	−0.868*	−0.866*	−0.857*	−0.848*
	(0.094)	(0.104)	(0.102)	(0.099)
Cash	−0.004	−0.027	−0.023	−0.026
	(0.073)	(0.079)	(0.079)	(0.076)
Leverage	0.682*	0.650*	0.616*	0.632*
	(0.058)	(0.063)	(0.064)	(0.061)
Dividend Yield	0.017	0.095	0.189	0.130
	(0.346)	(0.413)	(0.378)	(0.327)
$\text{Ivol}_{i,t-1}$	0.100**	0.088	0.095**	0.085
	(0.053)	(0.056)	(0.055)	(0.052)
$\Delta\text{Ivol}_{i,t-1}$	0.082*	0.094*	0.096*	0.098*
	(0.030)	(0.031)	(0.035)	(0.031)
Asset Growth	0.203*	0.215*	0.205*	0.205*
	(0.024)	(0.026)	(0.026)	(0.026)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
No. of obs.	81,370	68,376	68,235	72,932
Pseudo R^2	0.079	0.075	0.074	0.078

Panel B. Seasoned Equity Offerings Frequencies

	Matched Samples		
Attention	By (Return Size)	By (BM Size)	By (Asset Growth ROA)
Low	576	573	599
High	707	703	763
p–value (high–low)	<0.01	<0.01	<0.01

Economically, based on the coefficient estimates from column 1, a 1-standard-deviation increase in log(ABSVI) increases the probability of an SEO by 8.70% in the following month.

Panel B of Table 11 reports SEO frequencies for high-attention and low-attention months, respectively, for the three matched samples. The result shows that the probability of an SEO following a high-attention month is significantly higher than following a low-attention month, consistent with the evidence in Panel A. Together, the evidence presented in our article suggests that insiders take advantage of attention-driven mispricing by trading on their own accounts, and by timing their firms' seasoned equity issuances.

VIII. Conclusion

We find strong evidence that corporate insiders engage in opportunistic trades to exploit mispricing opportunities associated with retail investor attention on the stock. Insiders are more likely to sell their shares during periods of high retail attention and buy when attention is low. The results are particularly pronounced for stocks with high retail ownership or those that exhibit strong lottery features. The attention-insider trading relationship is associated with measures of mispricing, retail order imbalance, and the herding behavior of users on the Robinhood trading platform.

Importantly, we observe a significant difference in the responsiveness of insider trading toward SEC enforcement actions. While increased SEC enforcement actions against insider trading reduce the overall level of insider sales, the fraction attributable to retail attention *increases*, and attention-based trades are less likely to be targeted by SEC investigations.

This channel of insider trading, previously unexplored in the literature, may be increasingly attractive to insiders in an era of growing retail participation in the securities markets. However, this opportunistic trading benefits insiders at the expense of unsophisticated investors who are susceptible to social media or sentiment effects, raising important considerations for insider trading regulation in this new era. Future research can further inform policy discussions on corporate governance and investor protection, particularly concerning securities like meme stocks or special purpose acquisition company (SPAC) stocks.[36]

Appendix. Variable Definitions

Investor Attention Measures

log(ABSVI): Natural logarithm of ABSVI, where ABSVI is the ratio of monthly Google search volume index (SVI) to the median SVI during the previous 6 months.

Att: Indicator variable that equals 1 if Google SVI is nonmissing, and 0 otherwise.

log(ABSVI^{TS}): Natural logarithm of ABSVI^{TS}, constructed using the measure provided by deHaan, Lawrence, and Litjens (2024).

[36]Palma, S. and N. Asgari, "SEC Chair Orders Staff to Recommend New Investor Protections for Spacs," *Financial Times*, Dec. 9, 2021.

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$\log(\text{ABSVI})_{\text{fund}}$: Component of log(ABSVI) that is attributed to fundamental information.

$\log(\text{ABSVI})_{\text{resid}}$: Component of log(ABSVI) that cannot be explained by fundamental information.

log(ABSVI_Duration): Natural logarithm of the number of months between the trading month and the month of first valid ABSVI.

$\log(\text{ABSVI}^{\text{TS}})$ Duration: Natural logarithm of the number of months between the trading month and the month of first valid ABSVI^{TS}.

log(ABDMR): Natural logarithm of ABDMR, an institutional attention proxy, where ABDMR is the ratio of the monthly average of daily maximum readership score (DMR) to its prior month value.

$I_{\text{attn}}{}^{\text{high}}$: Indicator variable that equals 1 if ABSVI is greater than 1 for at least 6 of 12 calendar months.

Insider Trading and Characteristics

Shares Sold/Purchased: Number of shares sold/purchased by insiders, in thousands.

Sale/Purchase: Indicator variable that equals 1 if firm-month is a net sale/purchase month.

Insider Sale: Indicator variable that equals 1 if the number of sales months is greater than the number of purchase months for an insider given a calendar year.

I (I_Buy): Indicator variable that equals 1 if the firm-month observation corresponds to a net insider sales month (a net insider purchase month), and 0 if it corresponds to a net insider purchase month (a net insider sales month).

Insider Tenure: Natural logarithm of the number of years an insider is active in trading.

#TRADES(#TRADERS): Number of opportunistic insider trades (opportunistic insider traders) per firm-month.

Number of Trades: Natural logarithm of the number of trades made by an insider.

SVI Sales: Indicator variable that equals 1 if an insider is a net seller in a month that has a positive log(ABSVI).

Total Insider Trades: Total number of trades an insider makes for the month.

SVI (Non_SVI) Trades: Total number of trades that are (un)related to the SVI.

Stock and Firm Characteristics

log(BM): Natural logarithm of the previous year-end book-to-market equity value ratio.

log(Size): Natural logarithm of the previous year-end market value of a firm: share price times number of shares outstanding.

log(Analysts): Natural logarithm of the number of analysts covering the firm.

Anews: Natural logarithm of 1 plus the number of news articles published on the Dow Jones newswire during the month over the previous month.

Adv/Sales: Previous year-end ratio of advertising expense to sales.

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log(Price): Natural logarithm of previous year-end stock price.

CAR: Firm market-adjusted or NYSE size decile portfolio-adjusted cumulative abnormal returns.

log(Turnover): Natural logarithm of the average monthly turnover in the previous year, where the monthly turnover is defined as the month's trading volume scaled by the number of shares outstanding: (VOL × 100)/ (SHROUT × 1000).

Volatility$_i$: Standard deviation of past 36-month returns.

Ret$_m$: Value-weighted market return.

Ret: Firm's monthly stock return.

|Ret|: Absolute value of firm's monthly stock return.

Exret: Stock return minus risk-free rate.

I_lowret: Indicator variable that equals 1 if the month *t* stock return is below the 1st, 5th, 10th, or 20th percentile of the return distribution, respectively.

Vol: Monthly trading volume (scaled by shares outstanding).

log(Max): Natural logarithm of the maximum daily return in the prior month.

Ivol: Idiosyncratic volatility as in Kumar (2009).

Poor Governance: Indicator variable that equals 1 if the G-index based on Gompers, Ishii, and Metrick (2003) is greater than or equal to 12.

CSR: Net score of CSR rating, computed as total strengths minus total concerns based on seven social rating categories of KLD ratings: corporate governance, human rights, community, diversity, employee relations, environment, and product.

Fortune100: Indicator variable that equals 1 if a firm is one of *Fortune*'s 100 best companies to work for.

Fortune100_Rank: Natural logarithm of the rank of 100 best companies to work for.

Lottery: Indicator variable that equals 1 if a stock is a lottery-type stock as in Kumar (2009).

LIO: Indicator variable that equals 1 if the institutional ownership (IO) is in the lowest quintile where IO is measured as the percentage of shares owned by institutional investors scaled by common shares outstanding.

Earn: Indicator variable that equals 1 if the firm announces earnings in a month.

log(No. of Earningnews): Natural logarithm of 1 plus the number of earnings announcements in the previous month released by firms in the industry (Fama–French 17-industry classifications).

|SUE|: Absolute value of SUE, defined as actual EPS minus 90-day median forecasted EPS, scaled by share price.

SEC Litigation Variables

ΔSEC Intensity: Natural logarithmic difference between 1 plus the number of SEC enforcement releases against insider trading and 1 plus the median number of SEC insider trading releases over the past 6 months.

SEC-Investigation: Indicator variable that equals 1 if an insider is subject to SEC enforcement action.

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Mispricing Variables

RIM: The stock's market value divided by its intrinsic value whereas the intrinsic value is derived based on Cong, George, and Wang (2023).

MISP: Rank variable from 0 to 100 based on the 11 anomaly variables defined by Stambaugh, Yu, and Yuan (2012).

Sentiment Variables

OIBVOL: Average of daily volume-weighted OIBVOL, defined as the number of shares bought minus the number of shares sold scaled by the total number of shares traded.

OIBTRD: Average of daily trade-size-weighted OIBTRD, defined as the number of purchases minus the number of sales scaled by the total number of trades.

Distraction Variable

log(Newspressure): Natural logarithm of 1 plus the number of daily-news_pressure in a month, whereas the daily-news_pressure is defined as the news distraction indicator if the concentration of TV news broadcasts on non-market-related events is at the top 5% (Eisensee and Strömberg (2007)).

Robinhood

Buy Herding Months: Indicator variable if a month contains any buy herding events. Buy herding is based on Barber et al. (2022).

Sell Herding Months: Indicator variable if a month contains any sell herding events. Sell herding is based on Barber et al. (2022).

Neutral Months: Indicator variable if a month does not contain any buy or sell herding events. Buy and sell herding are based on Barber et al. (2022).

log(Buy Herding): Natural logarithm of 1 plus number of daily buy herding events.

log(Sell Herding): Natural logarithm of 1 plus number of daily sell herding events.

Seasoned Equity Offerings and Characteristics

SEO: Indicator variable if a firm announces an SEO in the month.

1-Year Ret: Stock return over previous 12 months.

ROA: Operating income before depreciation over total assets.

Cash: Cash and short-term investments over total assets.

Leverage: Long-term debt plus long-term debt in current liabilities over total assets.

Dividend Yield: Dividend per share divided by the stock price.

Asset Growth: Change in the natural logarithm of total assets.

ΔIvol: Change in idiosyncratic volatility (Ivol).

Supplementary Material

To view supplementary material for this article, please visit http://doi.org/10.1017/S0022109024000450.

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