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Corporate insiders' exploitation of investors' anchoring bias at the 52-week high and low

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Abstract

We find that insiders adopt dissimulation strategies to conceal their informational advantage and trade profitably when their firms' stock prices reach 52-week highs and lows, exploiting the anchoring biases of uninformed investors. Insiders' trading profitability depends on their firms' future stock returns, operating efficiency, and investment sentiment, but not on earnings surprises. We document that male board members and insiders with long investment horizons are more likely to use dissimulation strategies. Overall, we provide evidence that insiders benefit from these price extremes, despite their status as publicly available, irrelevant, historical price levels that normally should not predict future stock returns.

KEYWORDS
52-week price high/low, anchoring bias, insider trading, recency bias, stock market anomalies, trading strategies

JEL CLASSIFICATION
G11, G12, G14, G40, G41

1 | INTRODUCTION

George and Hwang (2004) report a robust positive relationship between the current price to the 52-week high price ratio and future abnormal stock prices increases. However, uninformed investors, mistakenly reckoning the 52-week high as the resistance level, adopt a contrarian trading strategy that illustrates the anchoring bias by selling at the peak. George and Hwang's (2004) results are puzzling because the 52-week high predicts future returns despite being, fundamentally, an irrelevant, historical price level that should not appear in the information sets of investors. George and Hwang (2004) provide a possible explanation for this by arguing that when good (bad) news has pushed a stock's price near (far from) the 52-week high reference point, investors are reluctant to bid the price higher (lower)—even if the information warrants it—but revert their decision without overreaction. This implies that nearness to the 52-week high dominates past returns in terms of predictive power and largely explains momentum profits—that do not reverse when past performance is proxied by its proximity to the 52-week high.

We extend George and Hwang's (2004) analysis by assessing whether insiders are subject to or exploit other investors' anchoring biases when prices approach their 52-week high and low. Because insiders are privy to their firms' future cash flow realizations,[1] they may use their comparative advantage and exploit outside investors' anchoring bias to reap abnormal profits. However, they are also susceptible to anchoring and other behavioral biases widely recognized in the literature (e.g., Baker & Wurgler, 2006; Choy & Wei, 2022).

We use a sample of 586,742 transactions undertaken by U.S. insiders between 1994 and 2018 to test our research question. Although we cannot detect insiders' trade incentives ex ante, we attempt to infer their motivation ex post from the performance of their trades. In line with Lee and Piqueira (2019) and Li et al. (2019), we find that insiders are more likely to sell at 52-week highs and buy at 52-week lows. However, although their Net Purchases are profitable, with a post-trade annualized four-factor model α of 12.04%, their net sell trades, which result in an equivalent α of 2.4%, are not loss-averting, suggesting the influence of anchoring bias. These contradictory results between the net buys and net sells may reflect the arguments of Lakonishok and Lee (2001), and Cohen et al. (2012), that although insiders buy stock to seek profit, they may sell for reasons other than averting losses—for instance, rebalancing objectives, liquidity needs, uncertainty over market outlook, or when their firm reached a period of relative stability. They may also refrain from selling on private information to avoid depressing stock prices and attracting regulatory scrutiny and potential shareholder lawsuits. Alternatively, they may suffer from asymmetric allocation of cognitive resources such as attention. This aligns with institutional investors, who may, according to Akepanidtaworn et al. (2023), display skill in buying, despite underperforming in sell trades. This is because they are subject to systematic, costly, heuristic processes when selling, but not when buying.

We address these possibilities by accounting for insiders' cross-sectional heterogeneity, recognizing that some are sophisticated and can avoid regulators' attention by using dissimulation strategies to randomly make noisy transactions that disguise their informed trades (Huddart et al., 2001; Kose & Ranga, 1997), even though the recent short-swing regulation prevents combined purchase and sale (or sale and purchase) trades within 6 months (Cziraki & Gider, 2021). We follow Biggerstaff et al. (2020) and identify insider sell trades as informed by long-lived information, and classify dissimulation sells as sequence sells.[2] We further differentiate between the unconditional buy-and-hold abnormal returns (BHARs), which the literature has predominantly focused on, and scaled holding returns, which assume that insiders close all their positions in simultaneous sequence sells. After accounting for these strategies, we find that sequence sells at the 52-week high became loss-averting, and net buy trades remain unchanged. Our results are robust when we account for the nine asset pricing anomalies, including momentum to proxy for contrarian strategy identified in Stambaugh et al. (2012). To the extent that, as reported by George and Hwang (2004), uninformed investors trade at a loss, our overall results suggest that sophisticated insiders who dissimulate their trades exploit these investors' anchoring biases associated with the 52-week high and low.

We subject our results to various robustness tests. We first consider the effects of the timing of trades. Previous studies suggest that the closer the time distance between the previous 52-week price extremes and the current price, the more likely it is that uninformed investors will adopt some form of heuristics in their decision-making (Bhootra & Hur, 2013).[3] We expect recency to be more important for corporate insiders because they do not trade for a

[1] Seyhun (1988), Lakonishok and Lee (2001), Beneish and Markarian (2022), Hao and Li (2021), among others, provide evidence and reviews of the relatively vast insider trading and its profitability literature.

[2] Insiders with short-lived information cannot adopt this strategy because it will soon be revealed to the market (Huddart et al., 2001; Kose & Ranga, 1997).

[3] Bhootra and Hur (2013) consider recency as a reference point and as an alternative explanation of empirical findings. They argue that investors react to positive news when stock has attained its 52-week high recently—meaning that this stock outperforms—accentuating investors' more usual underreaction

profit-seeking reason only, but also to signal stock undervaluation—particularly if their compensation packages include stock-performance-based incentives. We match insider trade events with the dates when stocks reach their 52-week highs and lows. We find that, at the 52-week high, insiders' sell trades are eight times their buy trades, but that their 1-year loss BHAR of 1.8% is significantly lower than their respective profit of 12.8% from their buy trades. In contrast, at the 52-week low, insiders' sell trades are only half their buy trades, but their 1-year loss-avoidance is a significant −9.7%, compared with their respective buy trades' profits of 9.6%. We find that 1-year BHARs without insider trading signals at the 52-week high are 4.4%, in line with George and Hwang (2004), and 4.7% after reaching the 52-week low. Because these returns are lower than the profits generated by insiders, we conclude that the buy and sell trades undertaken by insiders at the 52-week high and low are both likely to be informative.

We also consider that the information content of insider trading depends on the intensity of the 52-week high (low) and the recency of insiders' trades to these price extremes. We find that a trading strategy in accordance with a portfolio built on the top decile 52-week high (low) recency generates a 1-year net BHAR of 30.8%. This is compared with a BHAR of 19.2% when recency to the 52-week high (low) is not accounted for. Compared with George and Hwang (2004), we find that 1-year BHARs post-52-week high in the top decile among all U.S. stocks in the Center for Research in Security Prices (CRSP) database are 8.4%, and −5.7% when they reach their 52-week low. However, a buy-at-peak and sell-at-bottom trading strategy using this unconditional approach on insider trades generates only 14.2% 1-year BHARs. We find similar results when we use the Carhart four-factor α, and when we include numerous control variables in our regressions.

We analyze the information content embedded in insiders' dissimulation transactions at the 52-week high by focusing on the predictability of future fundamentals and earnings surprises. These are proxied by the 3-day cumulative abnormal returns (CARs), which capture the surprise in all aspects of a company's quarterly earnings announcements, and standardized unexpected earnings (SUE), which exclude any endogenously released news such as private communications and conference calls. We find that insiders' dissimulation transactions are not related to SUE at the 52-week high up to the fourth quarterly earnings, but that their trades predict future negative changes in efficiency, investor sentiment, and 3-day CARs. Insiders' sell trades' profitability emanates from announcement-based, rather than accounting-based, information, given that predictability is strong when firms release more discretionary news.

Finally, we deepen our understanding of corporate insiders who frequently employ dissimulation strategies by identifying their cross-sectional heterogeneous characteristics. We follow Akbas et al.'s (2020) method and show that insiders with short (*SH*) or long (*LH*) investment horizons are more likely to dissimulate their private information than insiders with middle investment horizons. This is because *SH* insiders are more sophisticated in materializing their private information and *LH* insiders are more likely to trade on long-lived information. We also find that female insiders are less likely to dissimulate their private information at the 52-week high, supporting the argument that males—who are relatively less risk-averse than females—are predominantly in high-rank positions in a firm, and have better access to private information (Inci et al., 2017). Finally, we document that the board members, particularly CEOs—defined by Cohen et al. (2012) as opportunistic traders—are more likely to dissimulate their trades.

To our knowledge, only two studies—Lee and Piqueira (2019) and Li et al. (2019)—are like ours.[4] Lee and Piqueira (2019) find that insiders are, on average, susceptible to anchoring biases because they are reluctant to purchase (sell) stocks when stock prices are near (far) from the 52-week high—and conversely at the 52-week low—meaning that their biased trades are not profitable. In contrast, although we report similar trading behavior, insiders' trades are

to good news and highlighting the need to differentiate recency from anchoring bias. However, Hao et al. (2016) show that these two biases coexist, and that the 52-week high momentum trading strategy dominates the recency strategy.

[4] Other studies expand encoring bias. For example, Hao et al. (2018) show that investors are more vulnerable to anchoring bias when the Baker and Wurgler (2006) market sentiment is high, and Li and Yu (2012) find that investors anchor their decisions also to the Dow Jones 52-week historical highs. Hong et al. (2015), Lee and Piqueira (2017), and Kelley and Tetlock (2017) report that institutional investors and short sellers do not exhibit anchoring bias. Overall, these findings do not account for market frictions, such as transaction costs and liquidity constraints, also assuming that all investors have equal access to information and can process it rationally and quickly. These findings do, however, challenge the behavioral models of Daniel et al. (1998) and Hong and Stein (1999), which consider that short-term momentum and long-term reversals are an integrated process. Although the testing of momentum is beyond the scope of our analysis, we control for it to isolate anchoring bias because the literature uses momentum as a proxy for contrarian trading.

largely profitable after accounting for dissimulation strategies. Li et al. (2019) show that although insiders, on average, exhibit anchoring bias—because they buy (sell) more shares of a stock when its price nears its 52-week low (high)—their trading is profitable when they trade against uninformed investors' anchoring bias. Our baseline results are relatively similar insofar as we find that insiders fixate on 52-week lows (highs) as anchor levels in their trading decisions and that outsiders can reap some profits by piggybacking on insiders. However, we account for insiders' dissimulation strategies—specifically, their randomly undertaking noisy sequential transactions to overcome regulation constraints and to thwart outsiders from mimicking their trades when their private information is long-lived (Huddart et al., 2001). We follow Biggerstaff et al. (2020) who argue that insiders trade sequentially on long-lived information. We, therefore, strive to disentangle the duration of information to investigate insiders' dissimulation strategies and trading profitability at the 52-week high (low). We extend insider trading profitability to 6 months—the shortest holding period that insiders must wait to realize their capital gain under the short-swing rule—and 1 year. We find that, like short sellers (Kelley & Tetlock, 2017; Lee & Piqueira, 2017), but unlike financial analysts (Clarkson et al., 2020), opportunistic insiders do not exhibit anchoring bias because they possess private information and dissimulate their trades. Overall, in line with Anginer et al. (2018) who find that insiders exploit anomalies in the market, we show that insiders are likely to use the 52-week high and low as reference points and to take advantage of the anchoring behavioral bias of uniformed investors, whose behavioral pulses rather than fundamentals are likely to govern their emotional investing at these price extremes.

The remainder of the paper proceeds as follows. Section 2 describes our data and methodology. Section 3 presents the empirical results. Section 4 discusses the various robustness tests. Our conclusions are presented in Section 5.

2 | DATA AND METHODOLOGY

To compile our sample of all U.S. insider transactions from 1994—when the coverage is comprehensive—to 2018, we use Smart Insider Ltd. Smart Insider collects all insider transaction information from Form 4 submitted to the Securities and Exchange Commission (SEC). In line with previous studies, we consider only listed common share transactions (CRSP share codes 10 or 11) traded on the NYSE, AMEX, and NASDAQ (CRSP exchange codes 1, 2, or 3). We keep only the open market buy and sell trades because they are likely to be information-driven transactions, given that they are executed at the current market price (Lakonishok & Lee, 2001; Seyhun, 1988). We exclude trades with trivial information content, such as prescheduled trades under the SEC's Rule 10b5-1, exercise of options, nondiscretionary trades—such as open market sell forced by brokerage firm because of a violation in margin requirement—and mandatory trades to cover the tax and issuing costs of the new shares firms may award freely to their insiders or allow them to purchase below the prevailing market price. We focus on executive, nonexecutive, and senior officers only, accounting for about 92% of the raw sample. This is because others—such as large block shareholders, and former and incoming directors—are not actively involved in the daily operation of the business, and less likely to possess private information (Seyhun, 1988).[5] We aggregate these trades at the insider-day level. Finally, as in Lakonishok and Lee (2001) and Lee and Piqueira (2019), we focus on trades with transaction prices between 1 and 999 U.S. dollars and trading volumes above 100 shares to remove outliers and minimize noise. Our final sample consists of 586,742 insider-day observations, comprising 103,530 distinct insiders and 11,090 unique firms.[6]

We use CUSIP code to merge the insider trading sample with stock price and holding period return data from CRSP. We extract accounting and financial data from Compustat, and financial analysts' coverage from the Institutional

[5] "Former," "Incoming," "Shareholder," "Supervisory," "Unknown," and "Other" executives account for 2.03, 0.001, 5.65, 0.02, and 0.03% of the unfiltered sample, respectively. Unlike executives and nonexecutives, senior officers are not board members, but are likely to possess price-sensitive information.

[6] Internet Appendix S1 compares our database with the widely used Thomson Reuters and Appendix A provides the screening details of our data. In 2002, the SEC adopted Rule 10b5-1 to allow insiders to set up planned pre-announced trades to protect them against allegations of illegal insider trading, but Larcker et al. (2021) and Fich et al. (2023) report its opportunistic use. The SEC classifies the exercise of options, nondiscretionary trades, and mandatory trades—accounting for around 39% of the original sample—as open market sells, but Smart Insider identifies them separately. We find the same results if we include Rule 10b5-1 and Sale Post-Exercise trades.

Brokers' Estimate System (I/B/E/S). Our sample size varies in our tests because of data availability across these three databases. We manually checked all the firm identifiers between Smart Insiders and other commonly used databases to ensure maximum matching accuracy.[7]

We use the CRSP value-weighted market index return to adjust the holding period return and compute the BHAR for holding period h as follows:

$$BHAR_{j,h} = \prod_{t=1}^{h}(1 + return_{j,i,t}) - \prod_{t=1}^{h}(1 + mkt_{m,t}) \tag{1}$$

where $return_{j,i,t}$ is the holding period return for firm j, insider i and $mkt_{m,t}$ is the benchmark return for the holding period h. We measure BHAR 1 day after the transaction date of insider trading. Previous studies use 1 and 6-month holding periods to measure the return predictability (e.g., Lakonishok & Lee, 2001). The 1-month period captures insiders' clustering of their trades with colleagues, and their tendency to split trades over several days (Alldredge & Blank, 2019), even though Section 16(b) of the Security Act of 1934 requires them, under the "short-swing profit rule," to return profits from two opposite transactions that occur within 6 months. Following Anginer et al. (2018), we use 365, but also 30 and 180 calendar days holding periods, with, as in Agrawal and Nasser (2012), a minimum of 20, 120, and 243-day valid return data for each of the respective cumulating periods. This is to assess the price discovery and long-term market efficiency improvement attributed to insider trading.[8]

We find that the daily mean (median) number of transactions executed by the same insider in the same company is 1.086 (1.00). Previous studies (e.g., Lakonishok & Lee, 2001; Lee & Piqueira, 2019; Seyhun, 1988) aggregate insider trading monthly, disregarding how many insiders trade in a single firm and treating all firms equally, regardless of different intensities of insider trading. Alldredge and Blank (2019) and Li et al. (2019) aggregate trades daily, and Beneish and Markarian (2022) clean the sample on a firm-day level frequency. We consider firms' insider trading intensities to be significant and see the equal weighting of firms with one or various insider trading events in a month as being misleading. We, therefore, aggregate insider trades at the insider-day level and provide a weighted-average measure for return profitability, where the weight equals the number of firm's daily insider trading. We compute the net purchasing value (NPV) of insider i, in day d, for firm j, as

$$\text{NPV}_{i,d,j} = \frac{\$\ \text{Insider Purchase}_{i,d,j} - \$\ \text{Insider Sell}_{i,d,j}}{\$\ \text{Insider Purchase}_{i,d,j} + \$\ \text{Insider Sell}_{i,d,j}} \tag{2}$$

We follow George and Hwang (2004) to identify the relative 52-week high (low) ratio as

$$\text{52\_W\_H}_{d,j} = \frac{\text{Closing price}_{d,j}}{\text{52\_Week\_High Price}_{d,j}} \text{ and}$$

$$\text{52\_W\_L}_{d,j} = \frac{\text{Closing price}_{d,j}}{\text{52\_Week\_Low Price}_{d,j}} \tag{3}$$

We also follow Bhootra and Hur (2013) to measure the recency of the 52-week high (low) as

$$\text{52\_W\_H\_Rec}_{d,j} = 1 - \frac{N_H}{365} \text{ and}$$

$$\text{52\_W\_L\_Rec}_{d,j} = 1 - \frac{N_L}{365} \tag{4}$$

[7] To better capture the return predictability, we replace any missing last trading day return with the delisting return, which can include a price on other exchanges or the total value of distributions to shareholder.

[8] Appendix B details the construction of other variables and their data sources. For robustness, we also adjusted BHAR by using 10×10 portfolios sorted by using the size and market-to-book ratio, 10-industry portfolios, and 49-industry portfolios. The results are similar and omitted for brevity purposes.

where $N_{H(L)}$, the number of days since 52-week high (low), measures insiders' trades prior to prices reaching their 52-week high (low). This is one if insiders trade at the 52-week high (low).[9] In line with previous evidence (Lee & Piqueira, 2019; Li et al., 2019), whereas insiders predominantly sell (85%) at the 52-week high, they buy (73%) at the 52-week low. At the 52-week high, as reflected in the higher recency ratio and relatively lower 52-week high price ratio, insiders are net buyers (sellers) when the prevailing market price is far away from (close to) the 52-week high price. However, at the 52-week low, insiders' trades are further away from the low price. In accordance with Lakonishok and Lee (2001), insiders are net sellers in large, profitable, and low-growth firms, but with high momentum. In line with previous evidence (Beneish & Markarian, 2022; Jagolinzer et al., 2020; Seyhun, 1988), insiders' net buys, unlike their sells, are not strongly profitable. These findings are consistent with Lakonishok and Lee's (2001) and Cohen et al.'s (2012) argument that although insiders buy to seek profit, they sell for many reasons, some of which are not to make profit.

3 | EMPIRICAL RESULTS

3.1 | Aggregated insiders' profit predictability at 52-week high or low

George and Hwang (2004) show that investors tend to underreact to good news when the stock price is closer to its 52-week high, leading to a positive return momentum associated with the relative price to the 52-week high. We first validate this return predictability in our sample period by replicating their result.[10] Because return predictabilities are embedded in the relative price, but also in the recency to the previous 52-week high, we find that the 52-week high return anomaly persists. However, the relative price to the 52-week low does not predict future returns when the recency to the previous 52-week low is associated with a negative return momentum. These results suggest that uninformed investors, to profit from their positions, should buy at the 52-week high or sell just after the stock has plummeted to its 52-week low.

George and Hwang's (2004) findings do not, however, support the argument in Lee and Piqueira (2019) that insiders must buy (sell) at the 52-week high (low) to materialize their private information, and that otherwise they suffer from the anchoring bias. That is, because insiders are informed, they will trade in any direction at any price level if their private information heralds trading opportunities (Li et al., 2019). To infer the motivation behind insiders' trading decisions (what they were thinking), we focus on the subsequent returns of (i) stocks that reached 52-week high (low) in the last 15 days, equivalent to restricting our sample to *Recency* greater or equal to 0.96; and (ii) stocks breaking their 52-week high (low) in the next 15 days.

We first identify the event date 0, the day the stock reached its 52-week high (low), defined as when the price is higher (lower) than the 52-week high (low) in the previous trading day. This eliminates all cases that a stock reached its 52-week high (low) from the lapse of time. We only consider the first hit if a stock breaks its 52-week high many times in the next 30 days. Next, we aggregate all insiders' trades in the stock within three distinct window periods—(−15,−1), (0,0), and (1,15)—and calculate their corresponding NPV, where $\mathrm{NPV}_{(1,15)} > 0$ ($\mathrm{NPV}_{(-15,-1)} < 0$) indicates that insiders are net buyers (sellers) 15 days after (before) the stock has reached its 52-week high (low). $\mathrm{NPV}_{(0,0)}$ is when insiders traded exactly on the day the stock reached its 52-week high (low). Then, we calculate the subsequent BHARs, excluding day 0.

Table 1 reports these results.[11] In line with previous evidence (e.g., Lee & Piqueira, 2019), at the 52-week high, 67% of insiders' trades are sells, whereas at the 52-week low, 88% of their trades are buys. Panel A indicates that when

[9] We find robust results when we replicate our regressions at the firm-month level and when, given the number of shares traded, we use a net purchasing ratio, as in Lakonishok and Lee (2001). Robust results are also found when we (i) define the 52-week high (low) ratio as the average closing price from $t-30$, $t-1$ over the 52-week high (low) price on $t-1$, as in Li et al. (2019), or as the closing price on day $t-1$ over the 52-week high (low) price on day $t-1$; and (ii) use one minus the ratio of the average time distance from the 52-week high (low) in $t-30$, $t-1$ over 364, or one minus the ratio of the time distance from the 52-week high (low) in $t-1$ over 364. Appendix A, panel B reports the effects of regulation enactments and market shocks, such as the 2001 Sarbanes–Oxley, the 2008–2009 Global Financial Crisis, the 2010 Dodd–Frank Act, and the 2003 reporting lag. Panel C show the January (portrayed in Figures S1 and S2), and the recency of the trade effects. We account for these factors in our analysis. Appendix C provides the summary statistics of our variables.

[10] We report these results in Internet Appendix S2.

[11] Internet Appendix S3 reports the risk-adjusted return (four-factor model α) for robustness checks.

TABLE 1 BHARs after 52-week high (low) has been reached.

	BHAR_m_30			BHAR_m_180			BHAR_m_365		
	Buy	Sell	Diff	Buy	Sell	Diff	Buy	Sell	Diff
Panel A: 52-week high reached									
$N_{(-15,+15)}$	3090	23,018		3593	26,522		3476	25,822	
$NPV_{(0,0)}$	0.026***	0.006***	0.020***	0.105***	0.010**	0.095***	0.128***	0.018***	0.110***
	(0.006)	(0.002)	(0.006)	(0.014)	(0.004)	(0.015)	(0.020)	(0.006)	(0.021)
	448	3534		513	4061		499	3933	
$NPV_{(1,15)}$	0.041***	0.021***	0.020***	0.098***	0.021***	0.077***	0.113***	0.027***	0.086***
	(0.004)	(0.001)	(0.004)	(0.008)	(0.001)	(0.008)	(0.012)	(0.003)	(0.012)
	1207	12,010		1,383	13,655		1,336	13,319	
$NPV_{(-15,-1)}$	0.017***	0.004***	0.013***	0.081***	0.010***	0.071***	0.112***	0.013***	0.099***
	(0.003)	(0.001)	(0.003)	(0.007)	(0.003)	(0.008)	(0.011)	(0.004)	(0.012)
	1435	7474		1697	8806		1641	8570	
Panel B: 52-week low reached									
$N_{(-15,+15)}$	8536	4078		9497	4635		9107	4456	
$NPV_{(0,0)}$	0.020***	−0.02***	0.040***	0.040***	−0.07***	0.118***	0.096***	−0.097***	0.192***
	(0.005)	(0.007)	(0.009)	(0.012)	(0.013)	(0.018)	(0.019)	(0.020)	(0.027)
	1081	517		1244	590		1190	573	
$NPV_{(1,15)}$	−0.001	−0.007*	0.006	0.037***	−0.010	0.047***	0.060***	0.012	0.049***
	(0.002)	(0.004)	(0.004)	(0.006)	(0.008)	(0.010)	(0.009)	(0.012)	(0.015)
	5880	1949		6443	2187		6156	2101	
$NPV_{(-15,-1)}$	0.030***	−0.013***	0.043***	0.074***	0.014	0.060***	0.103***	−0.011	0.114***
	(0.004)	(0.004)	(0.006)	(0.011)	(0.010)	(0.015)	(0.016)	(0.012)	(0.020)
	1575	1612		1810	1858		1761	1782	

(Continues)

TABLE 1 (Continued)

Panel C: Unconditional return	BHAR_m_30	BHAR_m_180	BHAR_m_365
52-week high reached	0.011***	0.032***	0.044***
	(0.000)	(0.001)	(0.001)
	125,860	138,589	131,848
52-week low reached	0.008***	0.009**	0.047***
	(0.001)	(0.002)	(0.003)
	103,419	110,751	102,404

Panel D: Price ratio	52-Week high reached		52-Week low reached	
	Buy	Sell	Buy	Sell
$NPV_{(0,0)}$	1.00	1.00	1.00	1.00
$NPV_{(1,15)}$	1.01	1.02	0.97	1.00
$NPV_{(-15,-1)}$	0.92	0.94	1.11	1.14

This table reports insiders' profitability as measured by Buy-and-Hold abnormal return (BHAR_m_i) adjusted using CRSP Value-Weighted market index from ($t + 1$, $t + i$), after a 52-week high (low) is reached for first time within a 30-day period as day t. $N_{(-15,+15)}$ is the total number of trades in days −15 to +15. NPV is the Net Purchase value scaled by the total value of shares traded by all insiders at firm i in pre- and post-event periods. Panel C reports the returns unconditional on insider trades. Panel D reports the *price_ratio* between the closing trading price on the day of insider transaction over the 52-week high (low) price in its corresponding event. Standard errors are in parentheses. We aggregate all insider transactions at firm level and minorize the BHAR_m_*i* at the top 99.5% and the bottom 0.5%.

***, **, and * indicate that the coefficients are statistically significant at 0.01, 0.05%, and 0.01 levels, respectively.

insiders are net buyers at exactly the 52-week high, their trading decisions are informative and have consistently predicted positive BHARs of 2.6, 10.5, and 12.8% for the next 30, 180, and 365-day holding periods, respectively. We observe the same positive return predictability if we define insider net buying pressure by aggregating insider transactions 15 days before or after the stock reached a 52-week high. However, insiders' net sells are also followed by positive returns, albeit significantly lower than those from the net buys. These results suggest that only insider buy trades at 52-week high are profitable. Panel B shows that at exactly the 52-week low, insiders' buy and sell trades are both profitable, but not their trades 15 days pre- and post-event.

Panel C reports the unconditional return for stocks that reached their 52-week high (low) independently of insiders' trading activity. Compared to the results in panel A, stocks that reached their 52-week high with insiders' buy trades outperform, and relative to panel B, insiders' sell trades at 52-week low are more loss-averting The difference between insider profits and average sample return—not reported—is statistically significant. These results suggest that insiders are likely to be informed when they trade at the price extremes.

3.2 | Trading strategy based on insiders transactions at the 52-week high (low)

George and Hwang (2004) report that outsiders gain if they form a profitable zero-cost trading strategy by simply going long (short) on the highest (lowest) 52-week high ratio portfolio. Their results on the 52-week low are not statistically significant. Bhootra and Hur (2013) show that further sorting on the 52-week high recency ratio will enhance the profitability of the zero-cost trading strategy. Inspired by these results, we first sort stocks that recently reached their 52-week high (low) and insiders' buy (sell) trades. At the end of each month, day *t*, we aggregate the total insider transactions to compute the *NPV* for stock *s* in the given month. If the *NPV* is larger (less) than 0, stock *s* is net-bought (net-sold) by insiders. We then sort these two categories of stocks according to their 52-week high (low) price ratio on day *t* and go long (short) on portfolios with stocks that are in the top (bottom) 52-week high (low) ratio decile and net-bought (net-sold) by insiders.[12] We rebalance these portfolios monthly.

Table 2, panel A, shows that the difference between the BHARs of the top and bottom 52-week high (low) ratio portfolios is 1.7, 9.3, and 19.2% in the 1, 6, and 12-month holding periods, respectively. In Columns 5 and 6, we report that, without conditioning on insider trading, a long (short) strategy of the portfolio with the top (bottom) 52-week high (low) results in nonsignificant differences in trading profitability for all the 1, 6, and 12-month holding periods. Column 9 indicates that the lower return predictability is attributed to the positive BHARs generated by the short-leg, which generate higher yields of 0.8% than the short-leg conditioning on insider trading for the 1-month holding period, respectively. Both the long-leg and the short-leg trading strategies without insider trading underperform their counterparts with insider trading. These asymmetries in profitability between these two zero-cost portfolios further highlight the role of insiders as sophisticated investors. Their return predictability persists for their sell trades at the 52-week low.

However, panel B shows that profitability increases to 2.7, 15.2, and 30.8% in the 1, 6, and 12-month holding periods, respectively, when we sort stocks according to their 52-week high (low) recency ratios on day *t*. We classify as long (short) those portfolios whose stocks are in the top 52-week high (low) recency decile—that is, immediately after they reached their 52-week high (low)—and are net-bought (net-sold) by insiders, and we rebalance the portfolio monthly. Without conditioning on insider trading, sorting on the recency ratio improves the short-leg of the trading strategy, with loss-averting sell trades of 0.4, 2.5, and 5.7%. However, the trading strategy yields only 1.1, 6.4, and 14.2%, significantly less than that with insider trading counterpart in both the long- and short-leg, as shown in column 9.[13]

[12] We skip all January returns in our BHARs to avoid their effect, but our results are robust if we include them.

[13] Our results, in Internet Appendix S4, are robust if we use the Carhart four-factor α.

TABLE 2 Trading strategy based on the relative price and recency.

	Insiders' net-bought (net-sold) top and (bottom) portfolios			Average	Unconditional on insider trading			Average	Difference (1)–(5)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
BHAR_m_i	1-month	6-month	12-month		1-month	6-month	12-month		
Panel A: 52-week high (low) sorted portfolios									
Top 52-week high portfolio	0.013***	0.069***	0.141***	0.97	0.004***	0.022***	0.049***	0.99	0.009***
	(0.002)	(0.006)	(0.009)		(0.002)	(0.004)	(0.005)		(0.003)
Bottom 52-week low portfolio	−0.004*	−0.024***	−0.051***	1.06	0.003*	0.020***	0.041***	1.03	−0.008**
	(0.002)	(0.006)	(0.009)		(0.002)	(0.005)	(0.007)		(0.003)
Top−Bottom portfolio	0.017***	0.093***	0.192***		0.000	0.002	0.007		
	(0.003)	(0.008)	(0.012)		(0.002)	(0.006)	(0.009)		
Panel B: 52-week high (low) recency sorted portfolios									
Top 52-week high recency portfolio	0.017***	0.093***	0.194***	14.65 days	0.007***	0.038***	0.084***	5.87 days	0.010***
	(0.002)	(0.006)	(0.011)	(0.96)	(0.002)	(0.004)	(0.007)	(0.98)	(0.003)
Bottom 52-week low recency portfolio	−0.011***	−0.059***	−0.114***	39.80 days	−0.004*	−0.025***	−0.057***	9.28 days	−0.007**
	(0.003)	(0.007)	(0.011)	(0.89)	(0.003)	(0.006)	(0.009)	(0.97)	(0.003)
Top−bottom portfolio	0.027***	0.152***	0.308***		0.011***	0.064***	0.142***		
	(0.004)	(0.010)	(0.016)		(0.003)	(0.007)	(0.011)		

The table reports the BHARs in the top and bottom deciles defined by the level of the 52-week high (low) to the current price (panel A) and insiders' trading recency (panel B) over the sample period 1994–2018. At the end of each month, we calculate the total insider trading pressure *NPV* for stock *s*. If *NPV* is higher (less) than 0, the stock *s* is net-bought (net-sold) by insiders. We further sort stocks which are either net–bought or net–sold by insiders according to their ratios between the 52-Week high (low) price and the closing price on day t. We long (short) the portfolio which contains stocks in the top (bottom) 52-week high (low) ratio decile and net-bought (net-sold) by insiders. We rebalance the long and short portfolios monthly. Similarly, in panel B, we sort stocks according to their 52-week high (low) recency ratios on day *t*. We long (short) stocks in the top (top) 52-week high (low) recency decile and net-bought (net-sold) by insiders. The BHAR, for the next 6 or 12-month holding periods, excluding January returns, are CRSP value-weighted market index adjusted. Columns 4 and 8 are average 52-week high (low) ratio in panel A (recency days (Ratio) panel B). All return variables are minorized at bottom 0.5% and top 99.5%. Standard errors are in parentheses.
***, **, and * significant at 0.01, 0.05, and 0.1 levels, respectively.

3.3 | Insider trading propensity and profitability at the 52-week high and low

We analyze the motivations of insiders to trade at the 52-week high and low after controlling for other potential effects. We investigate their propensity to trade conditional on the relative price and recency using the following logit specification:

$$\begin{aligned} P\ (y=1|z) = {} & G(\alpha + \beta_1\_52\_W\_H_{j,d-1} + \beta_2\_52\_W\_H\_Rec_{j,d-1} + \beta_3 mom_{j,m-1} + \beta_4 ret_{j,d} \\ & + \beta_5 \ln mcap_{j,m-1} + \beta_6 bm_{j.t-1} + \beta_7 illiq_{j,m-1} + \beta_8 roe_{j,t-1} + \beta_9 leverage_{j,t-1} + \beta_{10} RD_{j,t-1} \\ & + \beta_{11} numest_{j,t-1} + \beta_{12} Sento_{j,m-1} + \beta_{13} UpDummy_{j,m-1} + \beta_{14} DownDummy_{j,m-1} + u_i) \end{aligned} \quad (5)$$

where G is the logistic function, m is for month, and t is for year. The dependent variable is equal to one if an insider is a net buyer (NPV > 0) in a day, zero otherwise. We cluster standard errors at the firm and month levels to account for insiders' herding behavior within a firm (Alldredge & Blank, 2019),[14] as well as to control for arbitrary time series correlations within a firm and cross-section dependence between a firm's abnormal returns (Jagolinzer et al., 2020).

Table 3 reports these results.[15] Column 1 shows that the coefficients of *52_W_H* and *52_W_H_Rec* are both negative and significant, implying a higher insiders' selling propensity when the distance between a stock's current price and its 52-week high, and the period after the attainment of its 52-week high, are small. The results for the 52-week low reported in column 2 are similar, except that the coefficient of *52_W_L_Rec* is positive, implying that if the current stock price is closer to the 52-week low, insiders are likely to buy—and immediately signal their firm's undervaluation—but reluctant to sell, even though they may possess negative private information to avoid scrutiny. For a one standard deviation change, the marginal effects are 6 and 2% of the 52-week high and its recency, and 1 and 7% for the 52-week low and its recency. Overall, our results are consistent with Bhootra and Hur (2013) and Lee and Piqueira (2019). The coefficients of control variables are also in line with previous studies (e.g., Anginer et al., 2018; Beneish & Markarian, 2022; Lakonishok & Lee, 2001).

In columns 3–8, we use the fixed-effect estimator to regress the post-transactions returns on the same set of independent variables, controlling for the firm, month, and director-fixed effects. Columns 3–5 show that, for an average insider purchase, a 1% increase in the relative price to the 52-week high is associated with a 0.157% increase in profitability in the next 365 days. The coefficients of *52_W_H_Rec* are not strongly different from zero. In contrast, whereas the coefficients of *52_W_L* are statistically indifferent—suggesting that insiders do not gain by buying or selling stocks when prices reach their 52-week low—trading 7 days earlier is equivalent to a 2% increase in recency, and their profitability in the following 365 days will be 0.178% (−0.089 × 2) lower. In column 8, a 1% increase in the relative price to the 52-week high recency is associated with a 0.056% (0.028 × 2) increase in annual profitability. If insiders net sell 7 days earlier from the 52-week low, their annual profitability is 0.064% (0.032 × 2) lower. Overall, these results suggest that whereas insiders buy strategically when the price is close to its 52-week high, and immediately after the 52-week high, they sell when the price is far from the 52-week high or immediately after the 52-week low. The short-term positive price momentum after the 52-week high implies that insiders should sell at a longer time distance from the previous high.

We further consider the possibility that some corporate insiders exploit other investors' anchoring bias by systematically buying (selling) at the 52-week high (low) because uninformed investors sell (buy) at the high (low) when they have no material information regarding firm's true valuation. We define sophisticated buyers (sellers) as those who

[14] Our results remain robust if we use a probit model. We use the last fiscal year to construct the accounting variables. For longer holding horizons of 3 and 5 years, we acknowledge that using Lyon et al.'s (1999) skewness-adjusted standard error would correct for the underlying positive bias. However, as our focus is on 30-, 180-, and 365-day holding periods, we do not expect significant positive bias in our excess return test statistics.

[15] Less than 0.01% of the sample has a NPV of zero, suggesting that insiders rarely close their positions in the same day that they open them. Therefore, the coefficient is virtually one minus the coefficients in Table 3 if the dependent variable is set to be one for the net seller instead of the net buyer.

TABLE 3 Multivariate analysis on insider trading propensity and post transactions returns at the 52-week high and low.

Panel A: Baseline regression								
	Logit		Fixed-effect					
	Net purchaser	Net purchaser	Net purchaser		Net seller			
			BHAR_m_30	BHAR_m_180	BHAR_m_365	BHAR_m_30	BHAR_m_180	BHAR_m_365
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$52\_W\_H_{j,d-1}$	−1.476***		−0.045***	0.072**	0.157***	0.008	0.080***	0.052
	(0.026)		(0.014)	(0.033)	(0.048)	(0.011)	(0.031)	(0.036)
$52\_W\_H\_Rec_{j,d-1}$	−0.125***		0.018***	0.016	0.000	0.008***	0.028***	0.028**
	(0.014)		(0.005)	(0.014)	(0.019)	(0.003)	(0.009)	(0.012)
$52\_W\_L_{j,d-1}$		−0.025***	0.003	0.006	0.001	−0.000	−0.000	−0.003
		(0.007)	(0.003)	(0.005)	(0.006)	(0.002)	(0.003)	(0.004)
$52\_W\_L\_Rec_{j,d-1}$		0.777***	−0.017***	−0.064***	−0.089***	−0.009***	−0.025***	−0.032***
		(0.013)	(0.004)	(0.015)	(0.022)	(0.003)	(0.008)	(0.011)
$mom_{j,m-1}$	−0.660***	−0.633***	−0.016**	−0.076***	−0.136***	−0.014***	−0.074***	−0.095***
	(0.010)	(0.012)	(0.006)	(0.018)	(0.027)	(0.004)	(0.011)	(0.016)
$ret_{j,d}$	−2.831***	−3.254***	−0.027*	−0.169***	−0.266***	−0.023***	−0.182***	−0.268***
	(0.029)	(0.030)	(0.015)	(0.028)	(0.045)	(0.009)	(0.018)	(0.026)
$lnmcap_{j,m-1}$	−0.280***	−0.334***	−0.034***	−0.199***	−0.372***	−0.027***	−0.169***	−0.306***
	(0.004)	(0.004)	(0.004)	(0.012)	(0.017)	(0.002)	(0.009)	(0.014)
$bm_{j,t-1}$	0.294***	0.279***	0.006*	0.011	0.020	0.006**	0.019**	0.034***
	(0.007)	(0.007)	(0.003)	(0.009)	(0.014)	(0.003)	(0.008)	(0.011)
$illiq_{j,m-1}$	0.385***	0.365***	−0.004**	−0.001	−0.008	−0.004	0.001	0.010
	(0.013)	(0.012)	(0.002)	(0.005)	(0.009)	(0.002)	(0.005)	(0.008)
$roe_{j,t-1}$	−0.049***	−0.084***	−0.000	−0.006	−0.010	−0.000	0.001	−0.013
	(0.006)	(0.006)	(0.002)	(0.007)	(0.012)	(0.002)	(0.005)	(0.009)

(Continues)

TABLE 3 (Continued)

Panel A: Baseline regression								
	Logit		Fixed-effect					
	Net purchaser	Net purchaser	Net purchaser		Net seller			
			BHAR_m_30	BHAR_m_180	BHAR_m_365	BHAR_m_30	BHAR_m_180	BHAR_m_365
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$leverage_{j,t-1}$	0.723***	0.781***	−0.004	0.013	0.016	0.000	0.024	0.026
	(0.018)	(0.018)	(0.013)	(0.053)	(0.071)	(0.008)	(0.033)	(0.054)
$RD_{j,t-1}$	0.018***	0.031***	−0.001	−0.003	−0.007	0.000	0.001	−0.002
	(0.003)	(0.003)	(0.001)	(0.004)	(0.006)	(0.002)	(0.006)	(0.009)
$numest_{j,t-1}$	−0.033***	−0.025***	−0.000	−0.002	−0.003	−0.000	−0.002*	−0.001
	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)	(0.000)	(0.001)	(0.002)
$sento_{j,m-1}$	0.067***	0.070***	0.006	0.042***	0.044***	−0.001	0.007	0.011
	(0.007)	(0.007)	(0.004)	(0.009)	(0.013)	(0.002)	(0.007)	(0.009)
$UpDummy_{j,m-1}$	0.064***	0.031***	−0.004*	−0.015***	−0.028***	−0.002*	−0.007***	−0.015***
	(0.009)	(0.009)	(0.002)	(0.004)	(0.006)	(0.001)	(0.003)	(0.003)
$DownDummy_{j,m-1}$	0.516***	0.525***	0.005**	0.009**	0.020***	−0.000	0.004	0.013***
	(0.010)	(0.010)	(0.002)	(0.004)	(0.006)	(0.001)	(0.003)	(0.004)
Constant	2.093***	0.863***	0.234***	1.105***	2.058***	0.187***	1.137***	2.132***
	(0.023)	(0.024)	(0.026)	(0.070)	(0.103)	(0.018)	(0.067)	(0.096)
N	451,941	451,941	96,498	120,712	116,916	244,094	291,963	282,715
R-squared	0.220	0.220	0.386	0.509	0.602	0.270	0.416	0.515
Month FE			Yes	Yes	Yes	Yes	Yes	Yes
Firm FE			Yes	Yes	Yes	Yes	Yes	Yes
Director FE			Yes	Yes	Yes	Yes	Yes	Yes

(Continues)

TABLE 3 (Continued)

Panel B: Sophisticated insiders								
$52\_W\_H_{j,d-1}$	−2.132***		−0.061***	0.034	0.109**	0.008	0.079***	0.054
	(0.279)		(0.015)	(0.033)	(0.050)	(0.011)	(0.031)	(0.036)
$High\_TraderD_i$	−0.450***		−0.038***	−0.063	−0.062			
	(−0.053)		(0.014)	(0.042)	(0.060)			
$High\_TraderD \times 52\_W\_H_{j,d-1}$	2.882***		0.055***	0.127***	0.154**			
	(0.062)		(0.017)	(0.045)	(0.065)			
$52\_W\_H\_Rec_{j,d-1}$	−0.328***		0.015***	0.005	−0.016	0.008***	0.027***	0.027**
	(0.015)		(0.005)	(0.013)	(0.018)	(0.003)	(0.009)	(0.012)
$52\_W\_L_{j,d-1}$		−0.029***	0.003	0.005	0.000	−0.001	−0.001	−0.002
		(0.008)	(0.003)	(0.005)	(0.006)	(0.002)	(0.003)	(0.005)
$Low\_TraderD_i$		−2.727***				0.006	0.026**	0.075***
		(0.055)				(0.004)	(0.012)	(0.021)
$Low\_TraderD \times 52\_W\_L_{j,d-1}$		0.300***				0.001	0.004	−0.011
		(0.037)				(0.002)	(0.006)	(0.012)
$52\_W\_L\_Rec_{j,d-1}$		0.984***	−0.016***	−0.064***	−0.089***	−0.010***	−0.027***	−0.038***
		(0.014)	(0.004)	(0.015)	(0.022)	(0.003)	(0.008)	(0.011)
N	451,941	451,941	96,498	120,712	116,916	222,727	270,920	262,419
R-squared	0.28	0.26	0.03	0.10	0.16	0.02	0.10	0.16
Month FE			Yes	Yes	Yes	Yes	Yes	Yes
Firm FE			Yes	Yes	Yes	Yes	Yes	Yes
Director FE			Yes	Yes	Yes	Yes	Yes	Yes

This table reports the Logit and fixed-effect regression outputs. The dependent variable in columns 1 and 2 is one if NPV > 0 (net purchaser), zero otherwise, and BHARs in columns 3–8. In panel B, dummy variable *High_TraderD* (*Low_TraderD*) is equal to one when the transaction is made by a sophisticated trader who have made at least one purchase (sell) transaction at the 52-week high (low), zero otherwise. We define all variables in Appendix B. Each return estimation window is restricted to have at least 20/120/243 observations. We control for firm, month, and director fixed effects in columns 3–8. Independent variables are minorized at bottom 0.5% and top 99.5%. The sample is restricted to net purchasers in columns 3–5, and net sellers in columns 6–8 Robust standard errors for Logit and clustered standard errors at the firm and month levels for fixed-effect regression are in parentheses.
***, **, and * indicate that the coefficients are statistically significant at 0.01, 0.05%, and 0.01 levels, respectively.

have made at least one purchase (sell) transaction at the 52-week high (low). Among all the 103,530 distinct managers, 38% traded at the 52-week high (31% at the low), but only 9.3% increased their ownerships (7.2% sold). We define a dummy variable *High_TraderD* (*Low_TraderD*) as equal to one when the trade is made by sophisticated traders who bought-at-top (sold-at-bottom), zero otherwise. We interact this dummy with the 52-week high and low ratio. Table 3, panel B, shows that this interaction term is positive and significant in columns 1 and 2, suggesting that these sophisticated traders are more likely to exploit investors' anchoring bias because they are more likely to buy at the top (sell at the bottom). However, their trades are not always profitable. That is, although columns 3–5 show that the return predictability embedded in the transactions made by sophisticated buyers is higher when the price is closer to its 52-week high—because the interaction term is positive and statistically significant—columns 6–8 report that there is no significant difference in the return predictability between sophisticated sellers and other sellers when the current price is close to the 52-week low. The other variables, not reported, are consistent with our previous results.

We further assess whether, as in Lee and Piqueira (2019), insiders' trading decisions depend on the difference between the stock's 52-week high and 52-week low—referred to as the tightness of the price range—by sorting all their monthly transactions into quintiles by tightness, normalized using the current stock price.[16] We include these quantiles as a variable named *Tightness*, and its interaction term with *52_W_H* and *52_W_H_Rec*. Table 4, panel A, reports these descriptive statistics. The top quantile indicates low price tightness and the bottom indicates high price tightness. Panel A shows that the stock price is far from its 52-week high when the price tightness is low, and close when the price tightness is high. For the sake of brevity, panel B displays the regression results without the coefficients of control variables, which remained relatively consistent. The results in columns 1 and 3 indicate that the larger the distance between the 52-week high and the 52-week low, the less likely it is that an insider will sell at 52-week high. This is evident by the positive and statistically significant coefficients of the interaction variable *52_W_H×tightness*, as computed in both logit and fixed-effect estimators. Columns 2 and 4 report similar results for the 52-week low, implying that insiders are more likely to increase their holding when the price range is broader—as when the 52-week high and low are distant. At this point, insiders' selling pressures are attenuated because they are less concerned about the possibility that stock prices will decline.

We additionally employ proxies for market volatility, firm-level information environments, insider trading litigation risk, board-level conservatism, and insider-level opportunism as moderator variables to better understand the motivations behind insiders' transactions at these price extremes. We report these results in Internet Appendix S5 for brevity. We use the 30-day average CBOE Volatility Index (VIX) to proxy for market volatility and follow Piotroski and Roulstone (2004) and estimate stock return synchronicity to measure firm-specific information. We find that although insiders trade independently of market volatility, they are more likely to buy-at-peak (sell-at-bottom) when the stock price informativeness is low. We observe the same results when we use the number of patents to proxy for firm-level information asymmetry. These results suggest that when insiders possess a greater informational advantage, they are more likely to exploit the anchoring bias of uninformed investors to generate abnormal returns. We follow Kacperczyk and Pagnotta (2019) to identify industries with high illegal insider trading litigation risk, Khan and Watts (2009) to measure board-level conservatism, and Cohen et al. (2012) to identify opportunistic traders. We find that insiders are more likely to buy-at-peak when their firms are in high-litigation risk industries, or have a more conservative board, or they are opportunistic traders. The results reported in Internet Appendix S5 suggest that insiders mainly make purchase transactions to generate abnormal returns as these transactions are less risky.

3.4 | Effects of the insider dissimulation strategy

Huddart et al. (2001) argue that the implementation of the U.S. security Act of 1934 will increase the market scrutiny of insiders' transactions and reduce their dealing profitability by strictly regulating corporate insiders to publicly disclose their transactions 2 days after execution. Consequently, profit-maximizing insiders who actively materialize their

[16] Results remain the same if we use either the 52-week high or the 52-week low as a denominator.

TABLE 4 Insider trading propensity with interaction term on tightness.

Panel A. Summary statistics for tightness

	Top quantile (Low tightness)					Bottom quantile (High tightness)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variable	Mean	Std	Quantile 1	Median	Quantile 3	Mean	Std	Quantile 1	Median	Quantile 3
52_W_H	0.530***	0.243	0.345	0.513	0.703	0.921***a	0.072	0.880	0.939	0.979
52_W_H_Rec (days)	218***	239	336	252	104	128***a	243	230	92	13
52_W_L	2.032***	2.147	1.102	1.376	2.171	1.223***a	0.171	1.102	1.198	1.306
52_W_L_Rec (days)	147***	227	293	101	12	207***a	241	323	229	102
Tightness	1.772***	1.371	0.857	1.192	2.110	0.265***a	0.102	0.201	0.253	0.315

Panel B. Regression result

	Logit		Fixed-effect	
	Net purchaser	Net purchaser	NPV	NPV
	(1)	(2)	(3)	(4)
$52\_W\_H_{j,d-1}$	−5.005***		−0.930***	
	(0.088)		(0.126)	
$52\_W\_H\_Rec_{j,d-1}$	−0.069**		0.012	
	(0.030)		(0.013)	
$52\_W\_L_{j,d-1}$		−1.462***		−0.062***
		(0.056)		(0.014)
$52\_W\_L\_Rec_{j,d-1}$		0.127***		0.031*
		(0.028)		(0.016)
$Tightness_{j,d-1}$	−0.674***	−0.478***	−0.081***	−0.008
	(0.016)	(0.014)	(0.021)	(0.005)
$52\_W\_H \times tightness_{j,d-1}$	0.524***		0.076***	
	(0.020)		(0.022)	

(Continues)

TABLE 4 (Continued)

Panel B. Regression result	Logit		Fixed-effect	
	Net purchaser	Net purchaser	NPV	NPV
	(1)	(2)	(3)	(4)
52_W_H_Rec × tightness$_{j,d-1}$	0.047***		0.013***	
	(0.010)		(0.005)	
52_W_L × tightness$_{j,d-1}$		0.299***		0.013***
		(0.011)		(0.003)
52_W_L_Rec × tightness$_{j,d-1}$		0.206***		0.039***
		(0.009)		(0.005)
Control	Yes	Yes	Yes	Yes
N	451,941	451,941	420,136	420,136
R-squared	0.228	0.223	0.786	0.785
Fixed effect			FMD	FMD
S.E	Robust	Robust	Firm, Month	Firm, Month

The table reports the summary statistics for *tightness* (panel A) and the Logit regression where the dependent variable is one if NPV > 0 (net purchaser), zero otherwise and fixed-effect regression with NPV as the dependent variable (panel B). In each month, we sort all insider transactions into quantiles in accordance with their tightness, the difference between stock's 52-week high and 52-week low, normalized using the current stock price. We define all variables in Appendix B. We minorize all the independent variables at bottom 0.5% and top 99.5%. Standard errors in parentheses in panel B are robust in columns 1 and 2 and clustered in columns 3 and 4, where we control also for firm, month, and director (FMD) fixed effects. [a], [b], and [c] in column 6 indicate significance of the *t*-test for the difference between the mean of Net Buyer sample and Net Seller sample by assuming unequal variance, and the result of the Wilcoxon rank–sum test at 0.01, 0.05, and 0.1 levels, respectively.

***, **, and * indicate that the coefficients are statistically significant at 0.01, 0.05%, and 0.01 levels, respectively.

private information have incentives to dissimulate their private information by randomly trading in a manner that is inconsistent with their informational agent role. For example, if their private information is long-lived, these insiders will intentionally perform noisy transactions to thwart regulators and outside investors who cannot make rational investment decisions on average at the 52-week high (George & Hwang, 2004). To the best of our knowledge, we are the first to advance insider dissimulation strategy at the 52-week high and differentiate between long-lived and short-lived private information.

Biggerstaff et al. (2020) argue that when insiders possess long-lived information, they will split it into multiple transactions—referred to as sequence buy or sell trades—instead of executing one large-size transaction, referred to as isolated trade. The motivation behind this trading strategy is that a sequence of transactions can better minimize the effects of incorporating private information on the stock price than a single trade, and thus helps insiders to fully exploit their private information. Inspired by these findings, we split our insiders' sample into *Isolated* and *Sequence* trades and identify the *Scaled Holding Returns* from a sequence in which all positions are assumed to be closed at 30, 180, and 365 calendar days after the termination trades.[17] We hypothesize that if insiders indeed dissimulate their long-lived private information and gradually incorporate them into the stock price, their transactions in sequence sells should be loss-averting, with their *Scaled Holding Return* negative. The positive return can make outsiders believe insiders are on average not informed at the 52-week high, and the negative return hints that insiders eventually reap a gain for themselves at the end of the sequence. The *Scaled Holding Return* best mimics the return that an insider would be able to realize in the entire duration of a sequence sell.[18] The hypothesis implies that uninformed investors who replicate insiders' sell transactions at the 52-week high will incur a loss if they randomly pick and replicate such sell transactions because the average return is positive. They can only generate a negative return if they are able to identify the noisy sells or replicate the entire sell trades sequence. We make a logical assumption that uninformed investors, by definition, cannot differentiate between insiders' dissimulated sell and informative sell trades.

Following Biggerstaff et al. (2020), we define sequence sell trades as those executed with a maximum time distance of 30 calendar days from the last or the next *Sell-At-Peak* insider transaction when the $52\_W\_H \geq 0.98$—hereafter referred to as *sequence (30)*.[19] These two criteria can identify all the initiation sells, termination sells, and sells in-between. We define the rest of the sell transactions as isolated sells. Whereas Biggerstaff et al. (2020) aggregate insider transactions at the end of the month, we keep our entire sample at the insider-day level to conduct a finer analysis. We also combine buy and sell transactions. In addition to the *All* and *Scaled Holding Return*, we calculate the termination sell return denoted as *Following Sequence*.

Table 5, Part 1, panel A, reports the summary statistics of sequence and isolated sells by dividing the sample into a *Sell-At-Peak* group and *Other* group. We classify 392,692 sell trades as either isolated or sequence sells, with some 55% being sequence sells. At the 52-week high, the number of isolated sells is 38,868, very close to sequence sells of 34,036, with 18,804 (55%) occurring in *Sequence (30)*. Columns 4–6 indicate that most sells occur when the stock price is away from the peak. The recency of *Sequence (30)* for *Sell-At-Peak* is 18 days, statistically less than the 157 days for *Sequence (30)* that occurred outside of the peak. This is expected because *Sequence (30)* is closer to the peak by construction, and because there are 3.21 transactions in a signal *Sequence (30)*, with the sequence lasting only 13 days

[17] Since the length of different sequence is varying, and to maximize comparability, we scale the average BHAR by multiplying the median by 22, 126, and 252 trading days, respectively.

[18] As an example of insider dissimulation sell, Jeffrey Katzenberg, the CEO of DreamWorks Animation (CUSIP: 26153C10), sold 25,935 shares and 20,700 shares of his company on October 28, 2014, and November 6, 2014, respectively. We recognize these two sells as one sequence sells. The 30, 180, and the 365-day holding BHARs are −3.81, 1.79, and −12.00% for the former sell and 4.29, 8.10, and 1.78%, for the latter sell, respectively. The daily "All" BHAR in the case is $\frac{-3.81+4.29}{2\times22} = 0.011\%$, $\frac{1.79+8.10}{2\times126} = 0.039\%$, and $\frac{-12+1.78}{2\times252} = -0.020\%$, respectively. The *Scaled Holding Return* is the average daily return calculated from the total return accumulated from October 28, 2014, to 30, 180, and 365 days after November 6, 2014, this comprising −0.044, −1.134, and −6.804%, respectively. We classify the *Sequence Sells* as dissimulating sell for the 30 and 180-day holding periods.

[19] Our results are robust if we use 0.9, 0.95, or 0.99 cutoff points. The choice of 30 days is arbitrary—a longer period will allow a larger sample size but will reduce the relevance of insiders' trading informativeness. If a sequence is initiated well before the price reaches its 52-week high, insiders are less likely to have factored the price peak into their information sets at the time they initiated the sequence. We test for robustness using sequences initiated at most 60 days before and terminated at most 60 days after the *Sell-At-Peak* transactions (*sequence (60)*).

TABLE 5 BHAR for isolated and sequenced insider transactions at the 52-week high (low).

Part 1. Sell trades						
Panel A: Summary statistics						
	Sell-At-Peak: _52_W_H ≥ 0.98			**Other: _52_W_H < 0.98**		
	Isolated	**Sequence (30)**	**Sequence (all)**	**Isolated**	**Sequence (30)**	**Sequence (all)**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
N (All Sell: 392,692)	38,868	18,804	34,036	136,708	78,473	176,326
	(9.90%)	(4.79%)	(10.39%)	(34.81%)	(19.98%)	(44.90%)
Average 52 W H Rec (days)	18	18	17	163	157***a	157***a
Average sequence trade number		3.21	21.61		3.62***a	26.34***a
Average sequence length (days)		13.20	126.7		12.94***a	158.1***a
Panel B: Unconditional BHAR						
	Isolated sell			**Sequence sells**		
	BHAR_m_30	**BHAR_m_180**	**BHAR_m_365**	**BHAR_m_30**	**BHAR_m_180**	**BHAR_m_365**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
All	−0.004***	−0.008***	−0.006***	0.002***	0.005***	0.013***
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
N	141,695	165,351	159,478	183,388	211,604	205,370
Scaled holding return				−0.001***	−0.033***	−0.066***
				(0.000)	(0.001)	(0.001)
N				216,456	213,107	207,034
Following sequence				−0.015***	−0.021***	−0.013***
				(0.000)	(0.001)	(0.001)
N				178,788	209,633	202,918

(Continues)

TABLE 5 (Continued)

Panel C: BHAR for Sell-At-Peak: _52_W_H ≥ 0.98						
All	0.001*	0.005***	0.012***	0.005***	0.018***	0.020***
	(0.000)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)
N	30,139	34,622	33,293	34,222	39,325	38,207
Scaled holding return (30)				0.016***	−0.006***	−0.030***
				(0.001)	(0.002)	(0.003)
N				18,583	18,045	17,400
Scaled holding return (60)				0.020***	0.007***	−0.017***
				(0.000)	(0.002)	(0.002)
N				26,490	25,604	24,730
Following sequence (30)				−0.005***	−0.004*	0.002
				(0.001)	(0.002)	(0.003)
N				15,289	17,990	17,373
Following sequence (60)				−0.006***	−0.003***	0.003
				(0.001)	(0.002)	(0.003)
N				21,683	25,463	24,666

(Continues)

TABLE 5 (Continued)

Panel D: Sequence sells mixed with buy						
	Unconditional sequence in a net-selling			Sell-At–Peak: _52_W_H ≥ 0.98 in a net-selling sequence		
	Without buy	With buy	Diff (2)–(1)	Without buy	With buy	Diff (5)–(4)
Scaled holding return_30	−0.001***	−0.006***	−0.005***	0.016***	0.010	−0.006
	(0.000)	(0.001)	(0.001)	(0.001)	(0.007)	(0.007)
	212,945	6143		18,694	247	
Scaled holding return_180	−0.033***	−0.047***	−0.014***	−0.007***	−0.028	−0.021
	(0.001)	(0.004)	(0.004)	(0.002)	(0.024)	(0.024)
	209,637	6071		17,925	225	
Scaled holding return_365	−0.066***	−0.093***	−0.027***	−0.031***	−0.087**	−0.056
	(0.001)	(0.006)	(0.006)	(0.003)	(0.036)	(0.036)
	203,621	5958		17,280	222	
Part 2. Buy trades						
Panel E: Summary statistics						
	Buy-at-Peak: _52_W_H ≥ 0.98			Other: _52_W_H < 0.98		
	Isolated	Sequence (30)	Sequence (all)	Isolated	Sequence (30)	Sequence (all)
	(1)	(2)	(3)	(4)	(5)	(6)
N (All buy: 194,016)	9591 (4.93%)	2193 (1.13%)	4513 (2.32%)	106,329 (54.80%)	41,389 (21.33%)	73,583 (37.93%)
Average 52 W H Rec (days)	15	22	21	201	217***a	215***a
Average sequence trade number		3.19	26.58		3.51***a	29.48***a
Average sequence length (days)		12.27	127.34		12.66***a	128.97***a

(Continues)

TABLE 5 (Continued)

Panel F: Unconditional BHAR	Isolated buy			Sequence buys		
	BHAR_m_30	BHAR_m_180	BHAR_m_365	BHAR_m_30	BHAR_m_180	BHAR_m_365
	(1)	(2)	(3)	(4)	(5)	(6)
All	0.030***	0.054***	0.091***	0.023***	0.061***	0.109***
	(0.000)	(0.001)	(0.002)	(0.000)	(0.001)	(0.002)
N	94,947	111,766	108,094	63,821	75,712	73,273
Scaled holding return				0.007***	−0.019***	−0.056***
				(0.000)	(0.001)	(0.002)
N				77,654	76,270	73,687
Following sequence				0.034***	0.058***	0.107***
				(0.000)	(0.002)	(0.002)
N				62,342	75,475	72,664

(Continues)

TABLE 5 (Continued)

Panel G: BHAR for Buy-at-Peak: _52_W_H ≥ 0.98						
All	0.027***	0.047***	0.071***	0.028***	0.086***	0.119***
	(0.000)	(0.004)	(0.005)	(0.002)	(0.005)	(0.007)
N	7929	9338	9117	3759	4385	4273
Scaled holding return (30)				0.042***	0.076***	0.060***
				(0.002)	(0.006)	(0.009)
N				2183	2143	2076
Scaled holding return (60)				0.041***	0.084***	0.076***
				(0.002)	(0.005)	(0.008)
N				3133	3070	2976
Following sequence (30)				0.026***	0.081***	0.112***
				(0.003)	(0.007)	(0.010)
N				1792	2116	2074
Following sequence (60)				0.027***	0.084***	0.117***
				(0.002)	(0.006)	(0.008)
N				2559	3029	2967

This table reports the BHAR, calculated using CRSP value-weighted index as benchmark for the next 30, 180, and 365 calendar days, for isolated and sequenced transactions at the 52-week high (low). All returns are restricted to have at least 20/180/243 observations within each estimation window. *N* is the number of observations. As in Biggerstaff *et al.* (2020), sequenced sell trades are executed by the same insider for the same stock with the maximum gap of 60 calendar days between each transaction. The remaining sell trades are defined as isolated sell. *Scaled holding return* is the BHAR calculated from 1 day after the initiation sell of the sequence up to the 30/180/365 calendar days after the termination of the sequence. Following sequences is the BHAR for the last sell transaction of a sequence. Panel C reports the results for sell transaction in a sequence executed when the 52_W_H is ≥0.98. In panel D, we combine insider buy trades within insider sell sequence. Columns 4 and 5 present returns of sequence initiated and terminated at most 30 days around the before the insider Sell-At-Peak transaction. All returns are minorized at bottom 0.5% and top 99.5%. Columns 3 and 6 display *t*-test of different mean assuming unequal variance. Standard errors are reported in parentheses. [a], [b], [c] in columns 5 and 6 indicate that the rank–sum test for the difference in the median of column 2 minus column 5 and column 3 minus column 6 is rejected at the 99, 95, and 90% confidence level, respectively.

***, **, and * indicate that the coefficients are statistically significant at 0.01, 0.05%, and 0.01 levels, respectively.

on average. The average sequence length is 126.7 days at the 52-week high and is statistically, but not economically, shorter compared with the average length of 158 days when the price is away from its peak.

As measured by BHARs, we report unconditional profitability in panel B. On average, and in line with Biggerstaff et al. (2020), isolated, but not sequence, sell trades are loss-averting. However, these results treat each sell in a sequence as an independent transaction despite some dissimulated sells being noisy, biasing the average daily returns upward. Conversely, the *Scaled Holding Returns*—where all positions are assumed to be closed at the end of the respective calendar days—are all negative and significant. If we focus on the last transaction in a sequence, the daily *Following Sequence* are also all negative and statistically significant. These results are consistent with the findings in Biggerstaff et al. (2020), who report that insiders trade on long-lived information, and, on average, will terminate their sell sequence with a profitable sell, reaffirming that insider sell informativeness depends on our return measures.

In panel C, we condition the isolated and sequence samples to be close to the 52-week high. For both types of trades at the 52-week high, insiders' sell trades are loss-making in all holding periods. This is in line with our previous findings that insiders are less informed at the 52-week high. The results are similar when we calculate the average transaction return of each sell in a sequence. However, the *Scaled Holding Return (30)* is a statistically significant −0.6% up to 180 days after the termination sell, which, under the short-swing rule, is the shortest holding period insiders must wait to realize their capital gain. The results are similar for the *Following Sequence (30)* and *Following Sequence (60)*, but not in the long run of 365 days. This suggests that sequenced sell trades initiated closer to *Sell-At-Peak* trades and closed soon thereafter are loss-averting. The positive returns predictability embedded in *All* and the negative return predictability of *Scaled Holding Return (30)* confirm that insiders do dissimulate their private information by conducting uninformative sell transactions at the 52-week high.[20]

Kose and Ranga (1997) develop a theoretical model that predicts that insiders will intentionally trade in the wrong direction, or against their own private signal, to manipulate the market and then earn higher returns, insofar as uninformed investors will read these transactions incorrectly. We consider this possibility for both the buy and sell trades with sequence transactions occurring, at the most, 60 days apart. We aggregate all the transactions in a sequence by value and report the results for net-selling sequences in panel D. In columns 1 and 2, we report the unconditional sequence return. We compare the net-selling sequences that are not mixed with any insider buys with mixed sequences that contain both buy and sell trades. The mixed sequence systematically generates significantly lower *Scaled Holding Return* in the 30-, 180-, and 365-day holding periods, respectively 0.5, 1.4, and 2.7%. This is consistent with the prediction in Kose and Ranga (1997) that insiders may switch their trading directions to disguise their private information and minimize the price effects of their transactions.

In columns 4 and 5, we focus solely on the sequences that occurred at the 52-week high and those initiated and terminated 30 days either side of the 52-week high. The *Scaled Holding Returns* for mixed sequences are statistically indifferent from zero in the 30- and 180-day periods, but are −8.7%, significant, in the 365-day period. However, the difference between columns 4 and 5 is not significant. The sample size of net-selling sequences mixed with buys is relatively small. For unconditional sequences, only 2.8% of the sample are mixed sequences, decreasing to 1.3% for the 52-week high sequence. According to the short-swing rule, insiders are not allowed to realize any capital gains from two off-setting trades within 6 months. The short-swing rule will inevitably apply to the buy trades identified in a mixed net-selling sequence, weakening the market reaction to these mixed sequences (Kose & Ranga, 1997). Consequently, corporate insiders rarely mix buy and sell transactions in a sequence.

Finally, we re-estimate results in Table 3 by removing sequence sells at the 52-week high and low. We document, but do not report given space considerations, that insiders still have a higher propensity to sell (buy) more stocks when the 52-week high (low) relative price increases and when the 52-week high recency increases. All of our previous findings remain robust: insiders do not suffer from anchoring bias at the 52-week high, around half of the sells at the 52-week

[20] We also find, but do not report, similar results when we calculate the unconditional BHAR for the sample of sequence sells we used to calculate Scaled Holding Returns. This calculation assesses whether the exclusion of a sequence that is initiated well prior to the 52-week high drives the change from the unconditional positive BHAR predictability of sequence sells to the negative BHAR predictability of our Scaled Holding Returns, reaffirming the importance of considering the sequence returns rather than transaction returns.

high are loss-averting, and insiders dissimulate their private information by executing noisy transactions. The results for the buy trades in Table 5 Part 2 are all as expected.

3.5 | Insider trading profitability at the 52-week high with dissimulation strategy

We have documented that corporate insiders employ dissimulation strategies at the 52-week high to disguise their informational advantage. In this section, we revise the findings of Lee and Piqueira (2017). We replicate Table 3, panel A, by including *DissimulationD* dummy. This is equal to one if the *Scaled Holding Return* is negative while the unconditional *BHAR* is positive for a given holding period, zero otherwise. Table 6 reports the regression results. In panel A, columns 1–3, the coefficient of *DissimulationD* dummy is negative and statistically significant at 99% confidence level, implying that the dissimulated trades are loss-averting in our holding periods. The coefficient of *52_W_H* is negative and significant. Our results remain unchanged when we focus only on the Sell-At-Peak sample columns 4–6. Overall, our results suggest that the findings of Lee and Piqueira (2017) are not robust once we account for dissimulation trades, and that insiders do not suffer from the 52-week high anchoring bias—rather, they adopt dissimulation strategies to trade profitably at these price extremes.

3.6 | Informational content of insiders' trades

In this section, we disentangle the source of insiders' profitability. We employ two commonly used proxies to measure earnings surprises. The first is the 3-day CAR around the $q + 4$ quarterly earnings announcements estimated using a market model with a CRSP value-weighted index for the benchmark return and days (−200, −100) estimation window with at least 100 days of valid return data.[21] The second is Bernard and Thomas's (1990) standardized unexpected earnings, SUE, constructed as follows:

$$SUE_{j,q} = \frac{\left(EPS_{j,q} - EPS_{j,q-4} - \mu_{q-7,q}\right)}{\sigma_{q-7,q}} \tag{6}$$

where EPS is the earning per share for firm j in quarter q, $\mu_{q-7,q}$ and $\sigma_{q-7,q}$ are the mean and standard deviation of ($EPS_{j,q}$—$EPS_{j,q-4}$) calculated using the last eight-quarters earnings. CAR captures the surprise in all aspects of the firm's quarterly earnings announcement. However, SUE captures the surprise in earnings only, not encompassing such endogenously released information as private communications and conference calls. Kishore et al. (2011) conclude that these two measures are independent, and that one effect does not subsume the other because investors can react to both earnings surprises captured by SUE's and CAR's other relevant information.

We also examine whether these transactions can predict changes in return on assets (ROA) from $(t, t + 1)$ denoted as ΔROA, with year t being the insider transaction year and investor sentiment, $\Delta Sentiment$. We compute the market-to-book ratio decomposition of Rhodes–Kropf et al. (2005), defined as the residual from the following regression:

$$\begin{aligned} \ln(\text{market\_value})_{i,t} = {} & \alpha + \beta_{1j,t} \ln(\text{book\_value})_{i,t} + \beta_{2j,t} \ln(\text{net\_income})^{+}_{i,t} \\ & + \beta_{3j,t} \text{I}_{(<0>)} \ln(\text{net\_income})^{+}_{i,t} + \beta_{4j,t} \text{leverage}_{i,t} + \varepsilon_i \end{aligned} \tag{7}$$

where j is for Fama French 12 industries, i for firms, and t for year. We estimate the regression for each industry-year. $I_{(\langle 0 \rangle)}$ is a dummy variable equal to one for loss-making firms, and zero otherwise. The firm-specific residual obtained from the regression is the part of the firm's market value not explained by fundamentals or by changes in the common market valuation across firms in the same industry. This method can separate firm-specific sentiment from industry-level sentiment and is appealing because insiders are more likely to possess private information on the former than on the latter (Cziraki et al., 2021).

21 Our results remain consistent if we use a 5-day event window or estimate the CAR using a Market-Adjusted Model.

TABLE 6 Multivariate analysis on post transactions returns at the 52-week high and low with dissimulation strategy.

	All insider sell sample			Sell-At-peak sample		
	BHAR_m_30	BHAR_m_180	BHAR_m_365	BHAR_m_30	BHAR_m_180	BHAR_m_365
	(1)	(2)	(3)	(4)	(5)	(6)
DissimulationD$_i$	−0.038***	−0.139***	−0.227***	−0.021***	−0.079***	−0.203***
	(0.002)	(0.009)	(0.014)	(0.004)	(0.016)	(0.033)
52_W_H$_{j,d-1}$	−0.094***	−0.094**	−0.185***	−0.357**	−1.059***	−1.111**
	(0.013)	(0.046)	(0.064)	(0.168)	(0.361)	(0.482)
52_W_H_Rec$_{j,d-1}$	0.010***	0.029***	0.044**	−0.006	−0.008	0.018
	(0.003)	(0.011)	(0.020)	(0.008)	(0.023)	(0.030)
52_W_L$_{j,d-1}$	0.004***	−0.011**	−0.018	−0.004	−0.022*	−0.015
	(0.001)	(0.006)	(0.012)	(0.003)	(0.012)	(0.021)
52_W_L_Rec$_{j,d-1}$	−0.006	−0.034***	−0.048**	−0.011	−0.024	−0.034
	(0.004)	(0.013)	(0.020)	(0.009)	(0.026)	(0.046)
N	131,755	160,015	155,369	21,882	26,986	26,246
Dissim. Horizon	30	180	365	30	180	365
Control	Yes	Yes	Yes	Yes	Yes	Yes
Adj. *R*-squared	0.32	0.52	0.59	0.28	0.57	0.60
Fixed effect	FMD	FMD	FMD	FMD	FMD	FMD

This table reports the Fixed-effect regression outputs. The dependent variable is BHAR for 30, 180, and 365 calendar days. Dummy variable *DissimulationD* is equal to one if the BHAR_365_i > 0 but the *Scaled Holding Return*_t ≤ 0, and zero otherwise. We include the same set of control variables in Table 3 and define all variables in Appendix B. Each return estimation window is restricted to have at least 20/120/243 observations. We control for firm, month, and director fixed effects in columns 3–8. Independent variables are minorized at bottom 0.5% and top 99.5%. The sample is restricted to net purchasers in columns 3–5, and net sellers in columns 6–8. Standard errors are in parentheses. We cluster the standard errors at the firm and month levels for fixed-effect regression.

***, ** and * indicate that the coefficients are statistically significant at 0.01, 0.05%, and 0.01 levels, respectively.

We take these four measures for the $t + 4$ quarterly earnings announcements as dependent variables and regress them on dummy variables for insider Sell-At-Peak transactions and insider dissimulation variables. We define *SellpeakD* as one when $52\_W\_H \geq 0.98$ and $NPV < 0$. *Dissimulation365D* is a dummy variable equal to one if the *Scaled Holding Return* is negative while the unconditional *BHAR* is positive for 365-day holding periods, zero otherwise. The control variables are the same as in Table 3 with the additional inclusion of a lagged dependent variable. The variable of interest is the interaction variable *SellpeakD* × *DissimulationD*, which is expected to be negative and significant if insiders trade on their private information about their firm's future fundamentals. We control for the firm, month, and director-fixed effects, and cluster standard error at the firm-month level. We run the regression by using the insider sell sample only and present the regression results in Table 7, panel A. For brevity, we do not report all control variables whose signs and significance are consistent with the existing literature.

Consistent with our previous findings that insiders' sell at the peak is, on average, driven by noninformation-driven motives, *SellpeakD* is mostly insignificant except when the dependent variable is $\Delta ROA_{(t,t+1)}$, which is expected as the sample consists of insider-sell trades only. Stock prices keep increasing because of future earnings surprise, after insiders reduce their holdings. This is in line with Ke et al. (2003), who employ return-based measures and report that insiders' sales, on average, can anticipate negative earnings up to 2 years in advance.

In contrast, *Dissimulation365D* is negative and statistically significant when the dependent variable is CAR, $\Delta ROA_{(t,t+1)}$, and $\Delta Sentiment_{(t,t+1)}$, but positive when the dependent variable is $SUE_{j,q+4}$. This suggests that dissimulated sell trades can systematically predict future decreases in the first three factors. More importantly, the interaction variable *SellpeakD* × *Dissimulation365D* is statistically negative for $CAR_{(q+4)}$ but not for $SUE_{j,q+4}$, suggesting that the profitability of insider dissimulation sells at the 52-week high originates not from accounting-based information but announcement-based information, including information endogenously released such as private communication and conference calls. The interaction term is also negative and statistically significant for $\Delta ROA_{(t,t+1)}$ and $\Delta Sentiment_{(t,t+1)}$, although at a lower confidence level, suggesting that insiders dissimulate their private negative information at the 52-week high by trading on material information regarding worsening in the firm's future ROA and changes in investor sentiment.

These results suggest that corporate insiders may discretionarily release news to incorporate private information into their dissimulation trades. To explore this possibility further, we follow Edmans et al. (2018) to employ *key development* to count the amount of discretionary corporate news released in the insider trading month. We define dummy variable *ReleaseD* equal to one for firm-month observations that are in the top quantile of the amount of discretionary news released in the year, zero otherwise. We focus on Sell-At-Peak sell transactions and interact the *ReleaseD* with *Dissimulation365D*. Panel B reports these results. The coefficients of the interaction term are statistically significant for $SUE_{j,q+4}$, $\Delta ROA_{(t,t+1)}$, and $\Delta Sentiment_{(t,t+1)}$. From this, we conclude that corporate insiders incorporate more negative private information into their dissimulation sell transactions by releasing more discretionary news to exploit uninformed investors at the 52-week high.

In panel C, we focus on the buy trades insiders made when their firm's stock price is close to its 52-week high. We define *BuypeakD* as one when $52\_W\_H \geq 0.98$ and $NPV > 0$. We examine the informational content embedded in these transactions to investigate how sophisticated buyers exploit the anchoring bias of other investors. *BuypeakD* is positive and statistically significant at the 99% confidence level in columns 2–4, highlighting that buy-at-top trades predict increases in $SUE_{j,q+4}$, $\Delta ROA_{(t,t+1)}$, and $\Delta Sentiment_{(t,t+1)}$. Unlike the dissimulation sell, buy-at-top trades do not predict $CAR_{(q+4)}$. Overall, our results shed light on the information content embedded in insider dissimulation sell and buy-at-peak transactions.

3.7 | Heterogeneous characteristics of insiders who employ dissimulation strategy

In this section, we identify four heterogeneous characteristics of insiders who employ dissimulation sells at the 52-week high. We recognize that insider dissimulation strategy is only feasible with sell transactions because insider purchases are, on average, informed and the inclusion of purchases will falsely decrease the occurrence of insider

TABLE 7 Informational content embedded in insider transactions.

Panel A: Informational content embedded in dissimulation sell				
	$CAR_{(q+4)}$	$SUE_{j,q+4}$	$\Delta ROA_{(t,t+1)}$	$\Delta Sentiment_{(t,t+1)}$
	(1)	(2)	(3)	(4)
SellpeakD_i	0.001	0.042	0.003**	0.019
	(0.002)	(0.024)	(0.001)	(0.020)
$\text{Dissimulation365D}_i$	−0.008**	0.020**	−0.007**	−0.150***
	(0.004)	(0.041)	(0.003)	(0.026)
$\text{SellpeakD} \times \text{Dissimulation365D}_i$	−0.016**	0.084	−−0.008**	−0.081*
	(0.007)	(0.060)	(0.004)	(0.045)
Lag(CAR)	−0.018			
	(0.018)			
Lag(SUE)		−0.315***		
		(0.013)		
Control	Yes	Yes	Yes	Yes
Fixed effect	FMD	FMD	FMD	FMD
Clustered S.E	Firm-month	Firm-month	Firm-month	Firm-month
N	119,731	116,155	149,655	111,575
Adjusted *R*-squared	0.30	0.47	0.64	0.52
Panel B: Discretionary news releases when Sell-At-Peak				
	$CAR_{(q+4)}$	$SUE_{j,q+4}$	$\Delta ROA_{(t,t+1)}$	$\Delta Sentiment_{(t,t+1)}$
$\text{ReleaseD}_{j,m-1}$	0.010	0.127**	0.013**	0.072
	(0.007)	(0.057)	(0.006)	(0.080)
$\text{Dissimulation365D}_i$	−0.024**	0.183*	−0.011*	−0.069
	(0.012)	(0.101)	(0.006)	(0.043)
$\text{ReleaseD} \times \text{Dissimulation365D}_i$	−0.016	−0.331*	−0.023*	−0.115**
	(0.024)	(0.149)	(0.014)	(0.052)
Control	Yes	Yes	Yes	Yes
Fixed effect	FMD	FMD	FMD	FMD
Clustered S.E	Firm-month	Firm-month	Firm-month	Firm-month
N	19,142	22,783	24,487	30,872
Adjusted *R*-squared	0.56	0.63	0.76	0.57
Panel C: Informational content embedded in buy-at-top				
BuypeakD_i	−0.001	0.071***	0.009***	0.066***
	(0.002)	(0.024)	(0.002)	(0.012)
$\text{Lag(CAR)}_{j,t}$	−0.060			
	(0.011)			
$\text{Lag(SUE)}_{j,t}$		−0.398***		
		(0.008)		
Control	Yes	Yes	Yes	Yes

(Continues)

TABLE 7 (Continued)

Panel C: Informational content embedded in buy-at-top				
Fixed effect	FMD	FMD	FMD	FMD
Clustered S.E	Firm-month	Firm-month	Firm-month	Firm-month
N	86,347	81,444	116,746	77,189
Adjusted R-squared	0.27	0.30	0.60	0.40

This table reports the regressions of earning surprise, change in return on asset, and change in investor sentiment on a set of group dummies. We proxy earning surprise by the 3-day earnings announcement CARs over event window (−1,1) with CRSP value-weighted index as market return and 250 days for estimation period, for the next $q + 4$ quarterly earnings announcement day 0. In column 2, earnings surprise is proxied by SUE following Bernard and Thomas (1990). In column 3, the dependent variable is the change in return on asset between fiscal year (t, $t + 1$). In column 4, the dependent variable is the change in investor sentiment computed by following Rhodes-Kropf et al. (2005). The variable of interest is the interaction variable SellpeakD × DissimulationD, in panel A and ReleaseD *Dissimulation365D in panel B. In panel A, *SellpeakD* is dummy equal to one for the stocks with 52_W_H ≥ 0.98 and NPV < 0, and zero otherwise. We restrict that our sample must have nonmissing value of both *Scaled Holding Return_t* and BHAR_m_i. The *Dissimulation_365D* is dummy equal to one if the BHAR_365_i > 0 but the *Scaled Holding Return_t* ≤ 0, and zero if both return measures are in the same direction. We define all variables in Appendix B. The regression is only using insider sell sample. In panel B, we condition the sample on sell-at-top insider transactions. *ReleaseD* is a dummy variable equal to one for the firms in the top quantile that released the most discretionary news in the insider trading month, zero otherwise. We follow Edmans et al. (2018) to define discretionary news. In panel C, *buypeakD* is a dummy equal to one for the stocks with 52_W_H ≥ 0.98 and NPV > 0, and zero otherwise. FMD is for firm, month, and director fixed effects. We minorize all our independent variables at bottom 0.5% and top 99.5%. Standard errors in parentheses are clustered at firm-month level.

***, **, and * indicate that the coefficients are statistically significant at 0.01, 0.05%, and 0.01 levels, respectively.

dissimulation sells. Consequently, in this section, we run all regressions using only the net-selling sample. The first characteristic is the investment horizon. Akbas et al. (2020) define insiders with a long-term investment horizon (*LH*) as those who often trade in one direction and keep their positions open. Insiders with short-term opportunism (*SH*) are those who often trade in opposite directions and frequently open and close their positions to realize profit or loss. They discover that *SH* insiders are systematically more informed than *LH*, and, thus, there is more information content embedded in their trading decisions. We investigate the propensity of these insiders to use dissimulation strategy by constructing *SH* and *LH* horizons following Akbas et al. (2020). First, we define Horizon, *HOR*, as

$$HOR_{i,j,t} = \left| \frac{\sum_{y=T-10}^{t-1} NPV_{i,j,y}}{N} \right| \times (-1) \tag{8}$$

The numerator is NPV in Equation (2) in yearly frequency, for each insider i in firm j in year t over the last 10 calendar years, which is divided by the number of calendar years that an insider has traded in the last 10 calendar years, N. We multiply its absolute value by −1 to establish *HOR* value between +1 and −1. If an insider only sold (bought) in the last 10 years, then each of its NPV is −1 (+1), same as the average, and *HOR* −1. However, if insiders executed both buy and sell transactions in the last 10 calendar years, their NPV would be between −1 and +1, and their *HOR* will be higher than −1, indicating that the higher *HOR*, the shorter the investment horizon the insider had in mind. Insiders who traded in fewer than four calendar years in the previous 10 calendar years are excluded from the exercise because they are neither *SH* nor *LH* insiders. We then sort each insider in each year *HOR* into quantiles, defining those in the top (bottom) quantile as *SH* (*LH*) insiders. We reclassify each insider at the beginning of each year.[22] Our main variables of interest are *Short-Term_Dummy (STD)* and *Long-Term_Dummy (LTD)* equal to one for *SH* and *LH* insiders, respectively, zero otherwise. The dependent variables are *Dissimulation30D*, *Dissimulation185D*, *Dissimulation365D*,

[22] Akbas et al. (2020) have many *LH* insiders with *HOR* = −1, as their *SH* insiders have *HOR* above the median. Although our screening process is different, if we follow their methodology we find, but not report, the same results.

dummy variables equal to one if *Scaled Holding Return* is negative and unconditional *BHAR* is positive for 30, 180, and 365 days. Because we use the first 10 years of data to identify the investment horizon of insiders, the regressions use the net-selling sample after 2003. Table 8, panel A, shows that both *SH* and *LH* insiders are more likely to actively adopt dissimulation strategy at the 30- and 365-day holding horizons when selling, but they are not necessarily conflicting because although *SH* insiders possess more short-lived information, *LH* insiders use dissimulation strategy by better accessing their long-lived private information.

The second characteristic is gender. Inci et al. (2017) find that when female and male insiders have the same formal status within a firm, female insiders face greater difficulties in accessing private information. Indeed, female insiders can face an informational disadvantage. Overall, male executives can make a 3.2% abnormal return over a 50-day event window after the insider purchase date, whereas female executives gain 1.6%. In Norway, where boards must have at least 40% female representation following the enactment of a board gender-balancing law in 2005, Eckbo and Ødegaard (2021) show that females purchased more than male insiders during the financial crisis, suggesting that they are less risk-averse than their male counterparts. We investigate whether male investors are more likely to dissimulate their trades. We first use Lax-Martinez et al.'s (2016) worldwide gender–name dictionary to match insiders' first names with their gender, and then refer to BoardEx to manually collect the gender information of insiders with unisex first names. In line with the 4% of overall female transactions reported in Inci et al. (2017), our final sample consists of 7.3% (92.7%) of female (male) transactions. We create a dummy variable that equals to one for male and zero otherwise. In line with Inci et al. (2017), Table 8, panel B, provides evidence that male insiders are more likely to employ dissimulation trading strategies, suggesting that male insiders with better access to private information use dissimulation strategies to conceal their information to trade profitably.

Next, we focus on the propensity of board members to employ dissimulation strategies. We use Smart Insider to extract board members' information. Panel C shows that board members display a higher propensity to dissimulate their long-lived information when they sell because all the coefficients are positive and significant. Panel D shows that the coefficients of the dummy variables for CEOs and CFOs who have superior access to sensitive information are both significant at the 30-day holding horizon but mixed for the remaining periods.

We assess the propensity of opportunistic insiders to use dissimulation strategies. We follow Cohen et al. (2012) and define routine traders as insiders who have previously traded in either direction in the same calendar month for at least 3 consecutive calendar years; all other insiders are defined as opportunistic traders. Panel E shows that opportunistic insiders actively dissimulate their informational advantage by randomly making noisy trades. Because they are more likely to employ dissimulation strategies, they also display a higher propensity to sell at the 52-week high. This is in contrast to the puzzling findings of Lee and Piqueira (2019) and Li et al. (2019) that insiders are more susceptible to the anchoring bias. Finally, we investigate insiders' propensity for using a dissimulation strategy when market volatility is high. We calculate the 30-day average VIX return before insider trades. Panel F shows that they are less likely to employ the dissimulation strategy when they perceive the market to be too volatile.

4 ROBUSTNESS TESTS

In this section, we assess whether our results hold for various specifications. We first check whether our results are robust when we include asset pricing anomalies. Lee and Piqueira (2017) show that informed participants, such as arbitrageurs and short sellers, actively trade on Stambaugh et al.'s (2012) 11 anomalies to reap abnormal profits. Similarly, Anginer et al. (2018) examine insider trading in the context of 13 asset pricing anomalies to find a discord between insiders' trading direction and the normative directions of asset pricing anomalies. If insiders trade in the same direction as asset pricing anomalies, both the return predictability and profitability will be higher, but if they trade against them, the return momentum associated with these anomalies vanishes.

TABLE 8 Heterogeneity in insiders who frequently use dissimulating strategy.

	Dissimulation_ 30 (1)	*Dissimulation_ 180* (2)	*Dissimulation _365* (3)
Panel A: Investment horizon			
SHD_i	0.080***	0.019	0.090***
	(0.024)	(0.027)	(0.032)
LHD_i	0.082**	0.034	0.257***
	(0.036)	(0.042)	(0.046)
$52\_W\_H_{j,d-1}$	−1.720***	−1.684***	−1.020***
	(0.089)	(0.099)	(0.116)
$52\_W\_H\_Rec_{j,d-1}$	−0.229***	−0.326***	−0.644***
	(0.040)	(0.045)	(0.051)
Control	Yes	Yes	Yes
N	57,149	63,881	60,108
R-squared	0.043	0.040	0.055
Panel B: Insider gender			
$Gender\_Dummy_i$	0.168***	0.069**	0.289***
	(0.031)	(0.033)	(0.042)
$52\_W\_H_{j,d-1}$	−1.403***	−1.347***	−1.165***
	(0.076)	(0.083)	(0.096)
$52\_W\_H\_Rec_{j,d-1}$	−0.238***	−0.255***	−0.420***
	(0.038)	(0.042)	(0.048)
Control	Yes	Yes	Yes
N	67,901	76,200	71,866
R-squared	0.040	0.036	0.051
Panel C: Board member			
$Board\_Dummy_{i,j,t}$	0.198***	0.290***	0.338***
	(0.020)	(0.023)	(0.027)
$52\_W\_H_{j,d-1}$	−1.427***	−1.385***	−1.224***
	(0.076)	(0.083)	(0.096)
$52\_W\_H\_Rec_{j,d-1}$	−0.239***	−0.258***	−0.420***
	(0.038)	(0.042)	(0.048)
Control	Yes	Yes	Yes
N	67,901	76,200	71,866
R-squared	0.041	0.039	0.053
Panel D: CEO/CFO			
$CEO\_Dummy_{i,j,t}$	0.213***	0.004	0.127***
	(0.032)	(0.037)	(0.043)
$CFO\_Dummy_{i,j,t}$	0.139**	−0.003	−0.079
	(0.063)	(0.075)	(0.093)

(Continues)

TABLE 8 (Continued)

Panel D: CEO/CFO			
$52\_W\_H_{j,d-1}$	−1.403***	−1.348***	−1.171***
	(0.076)	(0.083)	(0.096)
$52\_W\_H\_Rec_{j,d-1}$	−0.240***	−0.255***	−0.420***
	(0.038)	(0.042)	(0.048)
Control	Yes	Yes	Yes
N	67,901	76,200	71,866
R-squared	0.040	0.036	0.050
Panel E: Opportunistic insider			
$Opportunistic\_Dummy_i$	0.051***	0.048**	0.117***
	(0.020)	(0.022)	(0.026)
$52\_W\_H_{j,d-1}$	−1.411***	−1.354***	−1.189***
	(0.076)	(0.083)	(0.096)
$52\_W\_H\_Rec_{j,d-1}$	−0.239***	−0.255***	−0.419***
	(0.038)	(0.042)	(0.048)
Control	Yes	Yes	Yes
N	67,901	76,200	71,866
R-squared	0.039	0.036	0.050
Panel F: Volatility			
$VIX\_30\_mean_{j,d}$	−7.852***	−9.329***	−5.296***
	(0.996)	(1.127)	(1.335)
$52\_W\_H_{j,d-1}$	−1. 382***	−1.326***	−1.159***
	(0.076)	(0.084)	(0.096)
$52\_W\_H\_Rec_{j,d-1}$	−0.237***	−0.259***	−0.420***
	(0.038)	(0.042)	(0.048)
Control	Yes	Yes	Yes
N	67,869	76,153	71,834
R-squared	0.040	0.036	0.050

This table reports the logit regression results with only Net Sell trades. The dependent variable is *Dissimulation_ t*, which is a dummy equal to one if the BHAR_m_i > 0 but the *Scaled Holding Return* ≤ 0, and zero otherwise. In columns 1–3, the *Dissimulation_t* is defined by using the 30-, 180- and 365- holding periods, respectively. In panel A, the main variable of interest is Short-Term dummy (*STD*) and Long–Term dummy (*LHD)* equal to one for SH and LH insiders, respectively, and zero otherwise. The sample period in panel A starts in 2004. In panel B, *Gender*, is a dummy equal to one if the insider is male, and zero otherwise. In panel C, *Board*, is a dummy equal to one if the insider is a board member, and zero otherwise. In panel D, *CEO (CFO)*, is a dummy equal to one if the insider is a CEO (CFO) as identified by Smart Insider, and zero otherwise. In panel E, *Opportunistic* is a dummy equal to one if the insider is an opportunistic board member who, as in Cohen et al. (2012), for a given trade, has not executed a trade in the same calendar month in the last three calendar years, and zero otherwise. If the insider has not traded at least once in the previous three calendar year, then the trade is excluded from the study. The insider is re-classified at the beginning of each calendar year. In panel F, VIX_30_mean, is the last 30-day average VIX index return. Robust standard errors are in parentheses. All independent variables are minorized at bottom 0.5% and top 99.5%. The control variables are identical to Table 3.

***, **, and * indicate that the coefficients are statistically significant at 0.01, 0.05%, and 0.01 levels, respectively.

Following Anginer et al. (2018) and Lee and Piqueira (2017), we repeat the results in Table 3 by replicating eight out of the 11 anomalies introduced by Stambaugh et al. (2012). These are total accruals (*TA*), net operating assets (*NOP*), gross profitability (*GP*), asset growth (*AG*), return on assets (*ROA*), investment-to-assets (*IA*), failure probability (*FP*), and net stock issue (*NSI*).[23] We compare the summary statistics of these eight variables to compute *FP* with Chen et al. (2011) to ensure the sample accuracy. In unreported results, we find that the correlation between these anomaly variables is generally low, in line with Anginer et al. (2018), and only *ROA* and *GP* are positively associated with the stock future abnormal return, in line with Stambaugh et al. (2012). However, Anginer et al. (2018) show that insiders do not necessarily trade with the normative direction indicated by anomalies. This discord between insiders and anomalies is not unusual. If insiders possess private information not incorporated in stock prices, they will trade against an anomaly to exploit outside investors who naively follow these normative directions. Therefore, the anomaly variable coefficient in our logit model can take either direction; it is highly significant in all columns except for *NSI* and *TA*, suggesting that insiders actively react to market anomalies and trade on them. Table 9 reports the regression result for the 52-week high (panel A) and the 52-week low (panel B). The variables are all significant except for *52_W_H_Rec* in column 3 when *TA* is the anomaly.

To alleviate the concern that these less informative transactions drive our previous findings, and to make our results more comparable to previous evidence, we account for the type of insider by focusing on only executive and nonexecutive board members. We exclude nonboard members who are subject to the same regulations as board members. This is because although nonboard members also have access to material information, their relatively lower seniorities imply that they have only limited access to price-sensitive information when compared with board members. Thus, the trading decisions of nonboard members are nosier and contain less price-sensitive information. This exclusion meant that we removed around 34% of the entire sample. These results, not reported because of space considerations, mimic those in Table 3. The 52_W_L is negative and significant, suggesting that when the current price is dropping to its 52-week low, board members unambiguously buy to signal their firm's undervaluation. This is because they are primarily responsible for stock performance, as well as liable to shareholders, and have, therefore, higher incentives to signal undervaluation. Furthermore, the recency of the 52-week low is robust and remains one of the key determinants for insider trading.

We further replicate our results using alternative specifications. Following Lee and Piqueira (2019), instead of using the 30-day average price and 30-day average distance included in Equations (3) and (4), we now base our measures of the relative price and recency ratio on the price and 52-week high or low at the end of last calendar month. Next, we restrict our sample to stocks that have truly broken the 52-week high (low). This is defined as when the new 52-week high (low) is higher (lower) than the 52-week high (low) in the previous trading day—rather than the change in the 52-week high (low) being the result of a lapse of time. Given that George and Hwang (2004) and Bhootra and Hur (2013) show that investors' trading behavior is systematically different in January compared with other calendar months, we also exclude insider trading that occurred in January from our sample. We find, but do not report for reasons of brevity, similar results. Finally, we restrict our sample to stocks that reached their 52-week high (low) in the past 30 days. That is, although the mean recency is 194 days for net purchasers and 131 days for net sellers (with the median recency being 203 days for net purchasers and 86 days for net sellers), our result could be driven by samples that are irrelevant to the previous 52-week high or low. We repeat Table 3 without the recency variable. In nontabulated results, we find that the sign and significance of 52_*W_H* remain robust, but the coefficient of the *52_W_L* is insignificant. These results do not alter our conclusion that insiders predominantly sell at the 52-week high.

Considering, for instance, that our results are driven by the dot-com bubble and financial crisis periods, we conduct other robustness tests.[24] We replicate Tables 3 and 6 by excluding these two periods or using dummy variables

[23] We report details of these computations in Internet Appendices S6 and S7. We omit Ohlson's (1980) O-score and composite equity issues because they capture the same underlying risks as Campbell et al.'s (2008) *FP* and *NSI*. We have already controlled for Jegadeesh and Titman's (1993) momentum eleventh anomaly.

[24] Internet Appendices S8–S10 report these tests. We also replicate our analysis using the 2020 downturn in Internet Appendix S11. Overall, our results remain robust, but insiders become more informed during the crisis, further highlighting their roles in the financial market as informed agents.

TABLE 9 Robustness tests.

	NP	NP	NP	NP	NP	NP	NP	NP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Anomaly variable	FP	NSI	TA	NOA	GP	AG	ROA	IA
Normative direction	Negative	Negative	Negative	Negative	Positive	Negative	Positive	Negative
Panel A: Probability model with asset pricing anomalies–Logit–52-week high								
52_W_H$_{j,d-1}$	−1.301***	−1.473***	−2.389***	−1.482***	−1.682***	−1.485***	−1.437***	−2.318***
	(0.035)	(0.026)	(0.031)	(0.028)	(0.027)	(0.026)	(0.027)	(0.030)
52_W_H_Rec$_{j,d-1}$	−0.147***	−0.129***	−0.024	−0.123***	−0.097***	−0.124***	−0.126***	−0.049***
	(0.014)	(0.014)	(0.017)	(0.015)	(0.014)	(0.014)	(0.014)	(0.016)
Anomaly	0.025***	0.025**	−0.109**	−0.425***	−1.040***	−0.000***	−0.576***	−0.288***
	(0.003)	(0.011)	(0.050)	(0.017)	(0.017)	(0.000)	(0.094)	(0.057)
Panel B: Probability Model with Asset Pricing Anomalies–Logit – 52 Week Low								
52_W_L$_{j,d-1}$	−0.132***	−0.027***	0.026***	−0.024***	−0.006	−0.024***	−0.033***	0.023***
	(0.012)	(0.007)	(0.005)	(0.007)	(0.006)	(0.007)	(0.007)	(0.005)
52_W_L_Rec$_{j,d-1}$	0.637***	0.779***	0.982***	0.792***	0.807***	0.779***	0.770***	0.979***
	(0.014)	(0.013)	(0.016)	(0.014)	(0.013)	(0.013)	(0.013)	(0.016)
Anomaly	0.100***	0.086***	−0.227***	−0.406***	−0.959***	−0.000***	−1.089***	−0.284***
	(0.003)	(0.011)	(0.050)	(0.017)	(0.016)	(0.000)	(0.110)	(0.055)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	445,780	448,714	344,710	409,508	451,756	451,035	450,918	370,780
S.E	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust

This table reports the robustness tests. In both panels A and B, the dependent variable is one if NPV > 0 (net purchaser, NP), zero otherwise. The explanatory variables of interest are 52-week high (low) ratio and 52-week high (low) recency ratio, and the relevant anomaly out of eight following Stambaugh et al. (2012) and discussed in detail in Internet Appendix S6 and Appendix S7. NSI, TA, NOA, GP. We construct AG, and IA using the last two fiscal years' accounting information and FP and ROA using the last two fiscal quarters' accounting information. In panel B, the sample only consists of board members in a firm and exclude senior officers. We include the same set of control variables as Table 3. All return variables are restricted to have at least 20/180/243 observations within each estimation window. We report robust standard errors in parentheses below coefficient estimates. All independent variables are minorized at bottom 0.5% and top 99.5%.

***, **, and * indicate that the coefficients are statistically significant at 0.01, 0.05%, and 0.01 levels, respectively.

to control for them. We also follow Fich et al. (2023) to employ five proxies to control for board-level corporate governance characteristics and identify firms with nonclassified boards, noncoopted boards, a low Bebchuk et al. (2009) entrenchment index, high board diversity, and a high proportion of independent directors. Our results remain similar.

5 | CONCLUSION

We find that insiders are unlikely to suffer from anchoring bias because both their buy and, after dissimulation strategies, their sell trades at the 52-week high (low) are profitable, probably because they are able to take advantage of investors' anchoring bias. We show that zero-cost trading strategies condition on insiders' trading pressure and the 52-week high (low) ratio or the recency of the 52-week high (low) generate excess returns. Insiders' dissimulated sell trades predict 3-day CAR around the next four quarterly earnings announcements. We argue that insiders probably endogenously release news to depress the stock price and then trade profitably. Finally, we show that insiders with short- and long-term—but not mid-term—investment horizons are more likely to employ dissimulation strategies. Male insiders, board members, and opportunistic insiders are more likely to execute dissimulated sell trades. Future research could investigate detailed news announcements and insider trading at 52-week highs (lows) because exogenously released news will drive prices to their 52-week high (low). We focus on corporate insiders only, whereas other market participants, such as politicians, who are also likely to be informed, may trade at the 52-week high (low). The extent to which these factors will alter our results is a subject for further research.

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REFERENCES

Agrawal, A., & Nasser, T. (2012). Insider trading in takeover targets. *Journal of Corporate Finance*, *18*, 598–625. https://doi.org/10.1016/j.jcorpfin.2012.02.006

Akbas, F., Jiang, C., & Koch, P. D. (2020). Insider investment horizon. *Journal of Finance*, *75*, 1579–1627. https://doi.org/10.1111/jofi.12878

Akepanidtaworn, K., Di Mascio, R., Imas, A., & Schmidt, L. (2023). Selling fast and buying slow: Heuristics and trading performance of institutional investors. *Journal of Finance*, *78*, 3055–3098. https://doi/10.1111/jofi.13271

Alldredge, D. M., & Blank, B. (2019). Do insiders cluster trades with colleagues? Evidence from daily insider trading. *Journal of Financial Research*, *42*, 331–360. https://doi.org/10.1111/jfir.12172

Amihud, Y. (2002). Illiquidity and stock returns: Cross-section and time-series effects. *Journal of Financial Markets*, *5*, 31–56. https://doi.org/10.1016/S1386-4181(01)00024-6

Anginer, D., Hoberg, G., & Seyhun, H. N. (2018). *Do insiders exploit anomalies?* [Working paper no. 17-1]. Marshall School of Business, University of Southern California.

Baker, M., & Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *Journal of Finance*, *61*, 1645–1680. https://doi.org/10.1111/j.1540-6261.2006.00885.x

Bebchuk, L., Cohen, A., & Ferrell, A. (2009). What matters in corporate governance? *Review of Financial Studies*, *22*(2), 783–827.

Beneish, M. D., & Markarian, G. (2022). *Why do prices underreact to insider purchases?* Social Science Research Network. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3478344

Bernard, V. L., & Thomas, J. K. (1990). Evidence that stock prices do not fully reflect the implications of current earnings for future earnings. *Journal of Accounting and Economics*, *13*, 305–340. https://doi.org/10.1016/0165-4101(90)90008-R

Bhootra, A., & Hur, J. (2013). The timing of 52-week high price and momentum. *Journal of Banking and Finance*, *37*, 3773–3782. https://doi.org/10.1016/j.jbankfin.2013.05.025

Biggerstaff, L., Cicero, D., & Wintoki, B. M. (2020). Insider trading patterns. *Journal of Corporate Finance*, *64*, 101654. https://doi.org/10.1016/j.jcorpfin.2020.101654

Campbell, J. Y., Hilscher, J., & Szilagyi, J. (2008). In search of distress risk. *Journal of Finance*, *63*, 2899–2939. https://doi.org/10.1111/j.1540-6261.2008.01416.x

Chen, L., Novy-Marx, R., & Zhang, L. (2011). *An alternative three-factor model*. Social Science Research Network. https://ssrn.com/abstract=1418117

Choy, S. K., & Wei, J. (2022). Option trading and returns versus the 52-week high and low. *The Financial Review*, *57*, 691–726. https://doi.org/10.1111/fire.12310

Chue, T. K., Gul, F. A., & Mian, G. M. (2019). Aggregate investor sentiment and stock return synchronicity. *Journal of Banking and Finance*, *108*, 105628. https://doi.org/10.1016/j.jbankfin.2019.105628

Clarkson, P., Nekrasov, A., Simon, A., & Tutticci, I. (2020). Target price forecasts: The roles of the 52-week high price and recent investor sentiment. *Journal of Business Finance & Accounting*, *47*, 1365–1399. https://doi.org/10.1111/jbfa.12497

Cohen, L., Malloy, C., & Pomorski, L. (2012). Decoding inside information. *Journal of Finance*, *67*, 1009–1043. https://doi.org/10.1111/j.1540-6261.2012.01740.x

Cziraki, P., & Gider, J. (2021). The dollar profits to insider trading. *Review of Finance*, *25*, 1547–1580.

Cziraki, P., Lyandres, E., & Michaely, R. (2021). What do insiders know? Evidence from insider trading around share repurchases and SEOs. *Journal of Corporate Finance*, *66*, 101544. https://doi.org/10.1016/j.jcorpfin.2019.101544

Cziraki, P., & Gider, J. (2021). The dollar profits to insider trading, *Review of Finance*, *25*, 1547–1580. https://doi.org/10.1093/rof/rfab010

Daniel, K., Hirshleifer, D., & Subrahmanyam, A. (1998). Investor psychology and security market under- and overreactions. *Journal of Finance*, *53*, 1839–1885. https://doi.org/10.1111/0022-1082.00077

Eckbo, B. E., & Ødegaard, B. A. (2021). *Board gender-balancing, network information, and insider trading* [Working paper no. 3475061]. Tuck School of Business, Dartmouth College.

Edmans, A., Goncalves-Pinto, L., Groen-Xu, M., & Wang, Y. (2018). Strategic news releases in equity vesting months. *Review of Financial Studies*, *31*, 4099–4141. https://doi.org/10.1093/rfs/hhy070

Fich, E., Parrino, R., & Tran, A. L. (2023). When and how are Rule 10b5-1 plans used for insider stock sales? *Journal of Financial Economics*, *149*, 1–26. https://doi.org/10.1016/j.jfineco.2023.04.009

George, T. J., & Hwang, C. Y. (2004). The 52-week high and momentum investing. *Journal of Finance*, *59*, 2145–2175. https://doi.org/10.1111/j.1540-6261.2004.00695.x

Hao, G. Q., & Li, K. (2021). Informed options trading prior to insider trades. *The Financial Review*, *56*, 459–480. https://doi.org/10.1111/fire.12259

Hao, Y., Chou, R. K., Ko, K. C., & Yang, N. T. (2018). The 52-week high, momentum, and investor sentiment. *International Review of Financial Analysis*, *57*, 167–183. https://doi.org/10.1016/j.irfa.2018.01.014

Hao, Y., Chu, H. H., Ho, K. Y., & Ko, K. C. (2016). The 52-week high and momentum in the Taiwan stock market: Anchoring or recency biases? *International Review of Economics and Finance*, *43*, 121–138. https://doi.org/10.1016/j.iref.2015.10.035

Hong, H., & Stein, J. C. (1999). A unified theory of underreaction, momentum trading, and overreaction in asset markets. *Journal of Finance*, *54*, 2143–2184.

Hong, X., Jordan, B. D., & Liu, M. H. (2015). Industry information and the 52-week high effect. *Pacific Basin Finance Journal*, *32*, 111–130.

Huddart, S., Hughes, J. S., & Levine, C. B. (2001). Public disclosure and dissimulation of insider trades. *Econometrica*, *69*, 665–681. https://doi.org/10.1111/1468-0262.00209

Inci, A. C., Narayanan, M. P., & Seyhun, H. N. (2017). Gender differences in executives' access to information. *Journal of Financial and Quantitative Analysis*, *52*, 991–1016. https://doi.org/10.1017/S0022109017000266

Jagolinzer, A. D., Larcker, D. F., Ormazabal, G., & Taylor, D. J. (2020). Political connections and the informativeness of insider trades. *Journal of Finance*, *75*, 1833–1876.

Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *Journal of Finance*, *48*, 65–92. https://doi.org/10.1111/j.1540-6261.1993.tb04702.x

Kacperczyk, M. T., & Pagnotta, E. (2019). *Becker meets Kyle: Legal risk and insider trading*. Social Science Research Network. https://ssrn.com/abstract=3464447

Ke, B., Huddart, S., & Petroni, K. (2003). What insiders know about future earnings and how they use it: Evidence from insider trades. *Journal of Accounting and Economics*, *35*, 315–346. https://doi.org/10.1016/S0165-4101(03)00036-3

Kelley, E. K., & Tetlock, P. C. (2017). Retail short selling and stock prices. *The Review of Financial Studies*, *30*, 801–834. http://dx.doi.org/10.2139/ssrn.2322830

Khan, M., & Watts, R. L. (2009). Estimation and empirical properties of a firm-year measure of accounting conservatism. *Journal of Accounting and Economics*, *48*, 132–150. https://doi.org/10.1016/j.jacceco.2009.08.002

Kishore, R., Brandt, M. W., Santa-Clara, P., & Venkatachalam, M. (2011). *Earnings announcements are full of surprises*. Social Science Research Network. https://ssrn.com/abstract=909563

Kose, J., & Ranga, N. (1997). Market manipulation and the role of insider trading regulations. *Journal of Business*, *70*, 217–247. https://doi.org/10.1086/209716

Lakonishok, J., & Lee, I. (2001). Are insider trades informative? *Review of Financial Studies*, *14*, 79–111. https://doi.org/10.1093/rfs/14.1.79

Larcker, D., Lynch, B., Quinn, P., Tayan, B., & Taylor, D. J. (2021). *Gaming the system: Three "red flags" of potential 10b5-1 abuse* [Working Paper]. Rock Center for Corporate Governance at Stanford University.

Lasfer, M. A., Melnik, A., & Thomas, D. C. (2003). Short-term reaction of stock markets in stressful circumstances. *Journal of Banking and Finance*, *27*, 1957–1977. https://doi.org/10.1016/S0378-4266(02)00313-8

Lax-Martinez, G., Raffo, J., & Saito, K. (2016). *Identifying the gender of PCT inventors* [Economic Research Working paper no. 33]. World Intellectual Property Organization. https://ideas.repec.org/c/wip/eccode/10.html

Lee, E., & Piqueira, N. (2017). Short selling around the 52-week and historical highs. *Journal of Financial Markets*, *33*, 75–101. https://doi.org/10.1016/j.finmar.2016.03.001

Lee, E., & Piqueira, N. (2019). Behavioral biases of informed traders: Evidence from insider trading on the 52-week high. *Journal of Empirical Finance*, *52*, 56–75. https://doi.org/10.1016/j.jempfin.2019.02.007

Li, J., & Yu, J. (2012). Investor attention, psychological anchors, and stock return predictability. *Journal of Financial Economics*, *104*, 401–419. https://doi.org/10.1016/j.jfineco.2011.04.003

Li, R., Wang, X., Yan, Z., & Zhang, Q. (2019). Trading against the grain: When insiders buy high and sell low. *The Journal of Portfolio Management*, *46*, 139–151. https://doi.org/10.3905/jpm.2019.46.1.139

Lyon, J. D., Barber, B. M., & Tsai, C.-L. (1999). Improved methods for tests of long-run abnormal stock returns. *The Journal of Finance*, *54*(1), 165–201.

Ohlson, J. A. (1980). Financial ratios and the probabilistic prediction of bankruptcy. *Journal of Accounting Research*, *18*, 109–131. https://doi.org/10.2307/2490395

Piotroski, J. D., & Roulstone, D. T. (2004). The influence of analysts, institutional investors, and insiders on the incorporation of market, industry, and firm-specific information into stock prices. *Accounting Review*, *79*, 1119–1151. https://doi.org/10.2308/accr.2004.79.4.1119

Rhodes-Kropf, M., Robinson, D. T., & Viswanathan, S. (2005). Valuation waves and merger activity: The empirical evidence. *Journal of Financial Economics*, *77*, 561–603. https://doi.org/10.1016/j.jfineco.2004.06.015

Seyhun, H. N. (1988). The information content of aggregate insider trading. *The Journal of Business*, *61*, 1–24. https://doi.org/10.1086/296417

Sibley, S. E., Wang, Y., Xing, Y., & Zhang, X. (2016). The information content of the sentiment index. *Journal of Banking and Finance*, *62*, 164–179. https://doi.org/10.1016/j.jbankfin.2015.10.001

Stambaugh, R. F., Yu, J., & Yuan, Y. (2012). The short of it: Investor sentiment and anomalies. *Journal of Financial Economics*, *104*, 288–302. https://doi.org/10.1016/j.jfineco.2011.12.001

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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APPENDIX A: SAMPLE DESCRIPTION

Panel A. Detailed information on loss of sample size

	% Change	Sample size
Raw US sample	100%	1,614,800
Exclude data outside 1994 and 2018	(1.77%)	(28,515)
Exclude noncommon share transactions	(3.15%)	(50,806)
Exclude trades < 100 shares and/or price outside $1 and $999	(5.37%)	(86,646)
Exclude 10b5–1 plan programmed trades	(4.52%)	(73,043)
Exclude nonopen market Buy/Sell	(34.51%)	(557,229)
Exclude trades not by executive/nonexecutive directors/senior officer	(5.43%)	(87,651)
Exclude nonNYSE/AMEX/Nasdaq and missing CRSP record stocks	(8.34%)	(134,745)

Panel B. Summary statistics across subsamples

	1994–2001	2002–2007	2008–2009	2010–2018	All
No. of net buy	47,463	50,638	32,251	68,536	194,016
No. of net sell	39,319	117,607	50,234	117,388	392,692
No. of distinct insiders	7,871	42,271	24,983	47,940	103,530
No. of distinct firms	90,055	5,777	3,989	5,154	11,090
No. of insider-day	−5.41***	168,258	82,493	245,936	586,742
NPV (%)	0.15	−39.81***	−21.80***	−44.28***	−33.87
Mean $ volume (mn) buy	1.48***	0.13***	0.13***	0.17***	0.15
Mean $ volume (mn) sell	21.33***	0.83	0.49***	0.74***	0.82
Mean shares buy (000)	98.38***	14 .12***	16.49*	16.81	17.04
Mean shares sell (000)	42,591	40.55	23.61***	28.45***	39.90

Panel C. January effect

	January	Non-January	Diff in mean	Diff in median
Average $ volume buy (000)	143.04	152.47	−9.42*	−26.82***
Average $ volume sell (000)	653.96	836.10	−182.14***	−34.47

Panel D. Recency effects

	Insider purchase	Insider sell	Diff in mean	Diff in median
At-Peak: 52_W_H≥ 0.98	14,104(15.04%)	79,658(84.95%)		
Recency-Peak (days)	17	18	0.17	0***

(Continues)

Panel D. Recency effects				
	Insider purchase	Insider sell	Diff in mean	Diff in median
At-Bottom: 52_W_L≤ 1.02	28,089(72.83%)	10,478(27.17%)		
Recency-Bottom (days)	11	19	−8***	0***

Panel A shows the loss in sample in cleaning process. All numbers are in transaction level. Panel B reports the summary statistics of the main sample. *No. of Net Buy* (*Sell*) are the numbers of insider-day observations with NPV > 0 (< 0). We aggregate the sample at insider-day frequency. *No. of Insiders* is the distinct insiders that have traded identified in Smart Insider database. *No. of Firms* is the distinct firms that have reported insider trading identified using CRSP permno code. *No. of Transactions* is the total number of insider trading reported to SEC after filtering and before aggregating at insider-day level. In panel B, the subperiods are: 1994–2001 SOX, 2002–2007 Sarbanes–Oxley, 2008–2009 Global Financial Crisis, and 2010–2018 Dodd–Frank Act. Panel C reports the insider transactions in January and remaining months. We define all variables, minorized at bottom 0.5% and top 99.5% level, in Appendix B. We use t–test assuming unequal variance to test for difference in Mean and Wilcoxon rank–sum to test for difference in Median.

***, **, and * indicate that the *t*-test result for the equal means between the subsample and the whole sample is statistically significant at 99, 95, or 90%, respectively.

APPENDIX B: VARIABLE CONSTRUCTIONS AND DATA SOURCES

Variables	Data source	Definition
BHAR_m_i	CRSP	3-month/6-month/12-month Buy-N-Hold return adjusted by using CRSP value-weighted market index. Defined as follows: $BHAR\_m\_i = \prod_{t=1}^{i}[1+R_{it}] - \prod_{t=1}^{i}[1+R_{mt}]$
$\alpha_{(t+1,t+i)}$	CRSP, Kenneth French Data Library	*The* intercept calculated by running regression $r_{i,t} - rf_t = \alpha_{i,t} - \beta_1(r_{crsp,t} - rf_t) + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 UMD_t + \varepsilon_t$ from the day after insider transaction day to 30/180/365 calendar day. rf_t is the risk-free rate, $r_{crsp,t}$ is CRSP value-weighted market index, SMB_t is small-minus-Big factor (size), HML_t is high-minus-low factor (value), and UMD_t is up-minus-down factor (momentum). Jagolinzer, Larcker and Taylor (2011) argue that estimating daily average trading profit will alleviate the concerns of bias and statistical errors inherent in evaluating the long–term buy–and–hold returns.
$52\_W\_H_t$	CRSP	The ratio of the adjusted price on day *t* over the 52-week high adjusted price, where *t* is the insider transaction date.
$52\_W\_L_t$	CRSP	The ratio of the adjusted price on day *t* over the 52-week low adjusted price, where *t* is the insider transaction date.
$52\_W\_H\_Rec_t$	CRSP	1 minus the distance between 52-week high and day *t* over 364. *t* is the insider transaction date.
$52\_W\_L\_Rec_t$	CRSP	1 minus the distance between 52-week high and day *t* over 364. *t* is the insider transaction date
illiq	CRSP	Amihud's (2002) measure of illiquidity, calculated as the monthly average of the daily ratio of absolute stock return to dollar volume
lnmcap	CRSP	Logarithm of market capitalization
mom	CRSP	Cumulative raw return in ($t-395$, $t-31$), insider trade occurs in day *t*
ret	CRSP	Cumulative raw return in ($t-30$, $t-1$) relative to insider trade in day *t*
Up (*Down*)	CRSP	Dummy equals to one for stock *i* on day *t* when the any of the stock daily return in the event of ($t-7$, t) is higher (lower) than its mean μ plus $2\times\sigma$. We estimate the mean μ and standard deviation σ using ($t-60$, $t-11$) window; zero otherwise, following Lasfer et al. (2003) to control short-term abnormal price movement.
bm	CRSP, COMPUSTAT	The ratio of last fiscal yearbook value over the market capitalization in the last trading day in December. Book value is equal to stockholder equity + deferred taxes and investment tax credit (Compustat: txditc, zero if missing)—preferred stock. Stockholder equity is parent stockholder equity (Compustat: seq), or total common equity (Compustat: ceq) plus total preferred stock capital (Compustat: pstk) or the difference between the total asset (Compustat: at) and total liability (Compustat: lt), in that order, as available. Preferred stock value is, preferred stock redemption value (Compustat: pstkrv), or preferred stock liquidation value (Compustat: pstkl), or total preferred stock capital (Compustat: pstk), or zero, in that order as available. Negative bm ratio is restricted to zero.

(Continues)

Variables	Data source	Definition
roe	COMPUSTAT	Return on equity calculated as the net income (Compustat: ni) after taking out preferred dividend (Compustat: dvp), over common equity (Compustat: ceq).
RD	COMPUSTAT	Research and development expense (Compustat: xrd) over sales (Compustat: sale). If Compustat reports missing research and development expense, it is set to zero.
Leverage	COMPUSTAT	The sum of long-term debt (Compustat: dltt) and debt in current liability (Compustat: dlc) over total asset (Compustat: at)
Sento	Wurgler's Website, CRSP, WRDS	The residual from regression of Earnings surprises on Baker–Wurgler index (Baker & Wurgler, 2006) of aggregate investor sentiment and 3-month T-Bill rate and Lee's (2011) liquidity risk factor, following Sibley et al. (2016) and Chue et al. (2019) procedure.
numest	IBES	The number of analysts following a given firm at a given month. If IBES did not report any coverage, it is set to be zero.
NPV	Smart Insider Ltd	Net purchasing value for insider transactions in day *t*, calculate as the ratio of the net dollar amount of insider transactions over the total dollar amount of insider transactions.
$SUE_{j,q}$	COMPUSTAT	Proxy for earnings surprise. We follow Bernard and Thomas (1990). Specifically, EPS is the split-adjusted earnings per share calculated using Earning Per Share-Excluding Extraordinary Items (Compustat: epspxq) over adjustment factor (Compustat: ajexq). $SUE_{j,q} = \frac{(EPS_{j,q} - EPS_{j,q-4} - \mu_{q-7,q})}{\sigma_{q-7,q}}$ where as$\mu_{q-7,q}$ and $\sigma_{q-7,q}$ are the mean and standard deviation of $(EPS_{j,q} - EPS_{j,q-4})$ for the past eight quarters, respectively.
$CAR_{j,q}$	CRSP	Three-day cumulative abnormal return centered around the quarterly earnings announcement (−1,1) for firm *j* in quarter *q*, calculated using market model where the benchmark return is the CRSP value-weighted index return. We restrict that the estimation window is (−250, −50), and there are at least 100 days in the estimation window.
Following Sequence$_s$	CRSP	The BHAR accumulated between 1 day after the termination sell and 30/180/365 days after the termination sell in the sequence *s*. The measure is only used in Section 6.1.
Average Holding Return$_s$	CRSP	The BHAR accumulated between 1 day after the initiation sell and 30/180/365 days after the termination sell in the sequence *s*. The measure is only used in Section 6.1.

APPENDIX C: SUMMARY STATISTICS

	Net purchaser				Net seller			
Variable	Mean	Quartile 1	Median	Quartile 3	Mean	Quartile 1	Median	Quartile 3
52_W_H (%)	67.967***	50.813	72.229	88.484	83.769***a	76.703	90.022a	97.014
52_W_H_Rec (days)	194***	317	204	71	131***a	244	86a	12
52_W_H_Rec (%)	46.825***	12.912	43.956	80.495	64.080***a	32.967	76.374a	96.703
52_W_L (%)	141.388***	106.195	119.242	144.590	177.141***a	123.366	145.241a	184.430
52_W_L_Rec (days)	147***	288	109	9	231***a	339	264a	135
52_W_L_Rec (%)	59.580***	20.879	70.055	97.527	36.536***a	6.868	27.473a	62.912
Pretrade 30-day ret (%)	−4.553***	−13.464	−2.703	4.882	4.715***a	−2.329	3.768a	10.948
Mcap ($billion)	2.038***	0.059	0.177	0.685	5.487***a	0.314	0.927a	3.091
Bm	0.771***	0.341	0.616	0.957	0.584***a	0.251	0.448a	0.746
Illiq (×105)	0.214***	0.000	0.005	0.054	0.029***a	0.000	0.000a	0.002
Mom (%)	7.506***	−20.907	6.872	32.646	31.480***a	4.925	25.204a	51.405
ROE (%)	−6.492***	−6.606	6.361	12.813	3.775***a	1.772	9.962a	16.869
RD (%)	30.750***	0.000	0.000	1.374	18.788***a	0.000	0.000a	8.634
Leverage (%)	21.310***	4.431	15.007	32.102	18.740***a	0.873	13.282a	29.692
Numest	4.000***	0.000	2.000	6.000	8.000***a	3.000	6.000a	12.000
NPV (%)	99.915***	1.000	1.000	1.000	99.973***a	−1.000	−1.000a	−1.000
BHAR m 30 (%)	2.714***	−5.037	1.072	8.436	−0.033a	−5.651	−0.279a	5.145
BHAR m 180 (%)	5.671***	−16.107	0.709	19.947	−0.079a	−16.913	−1.879a	0.135
BHAR m 365 (%)	9.808***	−25.822	−0.043	30.054	0.457***a	−25.417	−3.605a	0.191
$At+1, t+30$ (% × 22)	3.092***	−4.833	1.797	9.802	−0.127**a	−6.241	−0.084a	5.960
$At+1, t+180$ (% × 126)	7.503***	−10.232	5.773	24.258	0.743***a	−13.283	1.160a	15.322
$\alpha t+1, t+365$ (% × 252)	12.043***	−13.290	10.408	36.596	2.418***a	−17.127	2.794	22.282

The table shows summary statistics of key variables, described in Appendix B and minorized at 0.5 and 99.5% level to avoid outliers. The sample period is 1994–2018. We aggregate insider trades at the insider-day level. We multiply the 4-factor α's by the respective median numbers of trading days.

***, **, and * (a, b, c) indicate statistical significance (difference in means and medians, using Wilcoxon rank–sum test, between net buyer and net seller) at 0.01, 0.05, and 0.1 levels, respectively.