Why do corporate insiders trade at the 52-week high and low?

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Abstract

Previous studies concluded that investors suffer from the 52-week high/low anchoring biases. We expand this evidence to corporate insiders, the conventionally viewed as informed traders. We find that they do trade closer to when stock prices reach these extreme levels. They adopt contrarian strategies, as they are more likely to sell (buy) at the 52-week high (low). Their trades at these price extremes systematically predict future returns, after controlling for their dissimulation strategies to conceal their informational advantage. Our results suggest that insiders do not suffer from the 52-week high and low behavioural anchoring biases, and a trading strategy that combines these price extremes and insider trades results is significant excess returns.

Keywords: Insider Trading; 52-Week Price High/Low; Anchoring Bias; Recency Bias; Trading Strategies; Stock Market Anomalies
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"When Pfizer and German partner BioNTech announced on Monday [9 Nov 2020] that their Covid-19 vaccine was highly effective, shares in Pfizer rose 7 per cent and chief executive Albert Bourla sold $5.6m of stock at the company's all-time high. If Pfizer's news had come on Tuesday … Dr Bourla would have raised only $4.8m." Financial Times 13 Nov 2020 https://www.ft.com/content/6d494c88-f971-481d-90d2-4e678155209e

A week later [16 Nov 2020], the shares decreased by -3.3% ($CAR_{8\ to\ 16\ Nov}$ = -5.5%) when rival Moderna reported higher success rate and its share price rose by 8%.

1. Introduction

George and Hwang (2004) document 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 by selling at the peak, referred to as the anchoring bias.[2] Their results are puzzling as the 52-week high is fundamentally irrelevant historical price level that should only appear in the information sets of investors, yet it predicts future returns. They provide a possible explanation 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 the nearness to the 52-week high dominates past returns in terms of predictive power and largely explains momentum profits, which do not reverse when past performance is measured by proximity to the 52-week high. These findings challenge the behavioural models that consider that short-term momentum and long-term reversals are an integrated process.[3]

In this paper, we extend George and Hwang (2004) analysis by assessing the trading behaviour of insiders around the 52-week high/low. We examine two possible explanations. First is the private information. Since insiders are truly privy of the firms' future cash flow realisations (Piotroski and Roulstone, 2005; Jiang and Zaman, 2010), they tend to trade against investors' existing sentiment and correct stock misevaluation (Rozeff and Zaman, 1998)[4]. Second is the anchoring bias. The role of informed market participant is not mutually exclusive with the role of biased trader. Although insiders are sophisticated traders on average, they may suffer from the 52-week high anchoring bias like uninformed traders if they both employ loss-making contrarian strategies. We, therefore, assess whether, at these extreme price levels, insiders suffer from anchoring bias like uninformed investors, or they are informed traders.

[2] In the literature, contrarian trading is only proxied by momentum, which we control for to isolate anchoring bias.
[3] The behavioural models include Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), and Hong and Stein (1999) who propose that short-run under-reaction (delayed overreaction) and long-run overreaction are sequential components of the same process by which investors react to information.
[4] Seyhun (1986, 1990), Lakonishok and Lee (2001), Huddart and Ke (2007), Agrawal and Cooper (2015), Beneish and Markarian (2019) provide general reviews of the relatively vast insider trading and its profitability literature.

We use a sample of 586,742 transactions undertaken by US insiders between 1994 and 2018 to assess whether they are likely to be contrarians and possessors of private information, in line with previous evidence on insider trading patterns (e.g., Piotroski and Roulstone, 2005). We contribute to this literature by focussing on insider trading around the 52-week high or low. While we cannot detect insiders' trade incentives ex-ante, we attempt to infer their motivation ex-post from the performance of their trades. We find that they adopt contrarian strategies as they are more likely to sell at 52-week high and buy at 52-week low, but our first results provide mixed evidence as to whether they are subject to George and Hwang (2004) anchoring bias. We show that their overall net sell trades result in post-trade annualised 4-factor model α of 2.4%, and one-year BHARs of 0.4%, consistent with the anchoring bias. However, in line with informed trading, we find that their net purchases result in one-year BHARs of 9.8% and annualised 4-factor model α of 12.04%. It is possible that these contradictory results between the net buys and net sells reflect the arguments of Lakonishok and Lee (2001) who state that insiders sell a stock for a variety of reasons, but the main motivation to purchase a stock is to seek profit. Moreover, insiders may also avoid depressing further the stock price when they sell on insider information and attract regulatory scrutiny and shareholder potential lawsuits.

We extend these findings in several ways. We first consider the impact of the timing of the insiders' trades. Previous studies suggest that the closer the time distance between the previous 52-week price extremes and the current price, the more likely that uninformed investors will be employing a form of heuristics in decision-making (Bhootra and Hur, 2013). Admittedly, the recency of previous price extremes bears a more considerable significance in insider trading because corporate insiders differ from other informed traders as they do not only trade for a profit-seeking reason, but to signal, particularly stock undervaluation, if their compensation packages include stock-performance-based incentives. We match insider trading events with the dates when stocks reach their 52-week/low. We find that, at the 52-week high, both their buy and sell trades are evenly distributed; their buy trades generate one-year BHARs of 12.8%, but their post-sell trades BHARs are positive, albeit lower. At 52-week low, their sell trades are more delayed than their purchases, but in line with informed trading, the one-year BHARs are 9.6% after their buy trades, and -9.7% after their sell trades. The unconditional on insider trading one-year BHARs of all CRSP stocks after the 52-week high is reached are 4.4%, in line with George and Hwang (2004), but we also find that after the 52-week low is reached, stock prices increase by an average of 4.7%. Since stocks where insiders sell after reaching 52-week low decrease by -9.7%, we conclude that both their buy and sell trades at the 52-week low are informative, unlike their sell trades at 52-week high.

We next consider that the information content of insider trading depends on the intensity of the 52-week high/low and recency of their trades to these price extremes. We devised a trading strategy based on a portfolio built on the top decile 52-week high (low) recency. We find that such a portfolio generates a one-year BHARs of 30.8%. A similar trading strategy that does not account for the recency to the 52-week high/low results in 19.2% one-year BHARs. We contrast such portfolio with that of George and Hwang (2004). We show that one-year BHARs post-52-week high in the top decile among all stocks in CRSP database are 8.4%. We extend George and Hwang (2004) evidence by documenting that when prices of all US stocks reach their 52-week low, the one-year BHARs are -5.7%. However, a buy at peak and a sell at bottom trading strategy based on this unconditional strategy on insider trades leads to only 14.2% one-year BHARs. We find similar results when we use the Fama and French (1993)-Carhart (1997) 4-factor α and when we include numerous control variables in our regressions.

We then consider that, since their sell trades are likely to attract the regulators' attention, insiders are likely to use dissimulation strategies, a possibility overlooked by recent studies, such as Lee and Piqueira (2019) and Li, Wang and Yan (2019). Using a theoretical model, Kyle (1985) proposes that when insiders possess long-lived information, they will split the information into many transactions to minimise the price impact of their transactions and camouflage their informational advantage by hiding behind random noise traders. Similarly, Kose and Ranga (1997) argues that informed insiders manipulate the market by trading against their information to preserve their information advantage and increase their trading profits. Huddart, Hughes and Levine (2001) suggest that insiders will also dissimulate their information by randomly making noisy transactions to disguise their informed transactions. We follow Biggerstaff, Cicero and Wintokie (2020) and identify insider sell trades based on only long-lived information, and identify dissimulation sell as *Sequence Sell*. We further differentiate two types of returns, the unconditional Buy-and-Hold Abnormal Return (BHAR) that the literature has predominately focused on, and the *Scaled Holding Return* that assumes insiders close all their positions in a *Sequence Sell* at the same time. We find the *Sequence Sell* at the 52-week high generates statistically significant BHAR of 2.00%, declining to -3.00%, after accounting for dissimulation. The results of our buy trades remain unchanged. Overall, these findings suggest that insiders do not suffer from anchoring bias because of their ability to dissimulate their trades. Our results are robust when we account for the nine asset pricing anomalies including momentum to proxy for contrarian strategy in Stambaugh, Yu and Yuan (2012).

We analyse further the information content embedded in insiders' dissimulation transactions at the 52-week high by focussing on the predictability of future fundamentals and earnings surprises. We use the 3-day cumulative abnormal return (CAR) and Standardised Unexpected Earnings (SUE) as two proxies for the future earnings surprises. We find that insiders' dissimulation transactions remain predictive of the future negative earnings surprise proxied by 3-day CAR but not by SUE at the 52-week high up to the fourth quarterly earnings announcements. These results suggest that the profitability of insiders' sell trades under dissimulation strategy emanates from announcement-based, rather than accounting-based information. Insiders may endogenously release pessimistic news regarding firm's prospect to push down the stock price and gain from their sell transactions at the 52-week high.

Finally, we deepen our understanding of corporate insiders who frequently employ dissimulation strategy by identifying their heterogeneous characteristics. We follow Akbas, Jiang and Koch (2020) methodology and show that insiders with short (SH) or long (LH) investment horizons are more likely to dissimulate their private information compared to insiders with middle investment horizons. In line with Akbas *et al.* (2020), we find that SH insiders are more sophisticated in materialising their private information and LH insiders are more likely to trade on long-lived information. We also explore the possibility that the gender difference contributes to the use of dissimulation strategy, as males, who are relatively less risk-averse than females (Barber and Odean, 2001), are predominately in high-rank positions in a firm and have better access to private information (Inci, Narayanan and Seyhun, 2017). We find that male insiders are more likely to dissimulate their private information at the 52-week high. We also document that the board members, particularly CEOs, that Cohen, Malloy and Pomorskie (2012) define as opportunistic traders, are both more likely to dissimulate their trades. Overall, our results imply that opportunistic insiders are not more susceptible to the 52-week high anchoring bias, in contrast to Lee and Piqueira (2019) and Li *et al.* (2019) findings.

To our best knowledge, only Lee and Piqueira (2019) and Li *et al.* (2019) analyse insiders' anchoring bias, but they did not study the post-transaction returns nor control for the role of recency of insiders' trade to 52-week high/low dates. When insiders have private information regarding the subsequent return after stocks hit the 52-week high, they will trade strategically to reap any subsequent positive and negative abnormal returns. Consequently, to overcome misspecification bias, we use a conditional expectation to infer the informativeness of insider trading in the context of anchoring bias. We examine the insiders' post-trading performance by probing recency to investigate the motivation behind their trading decisions at the 52-week high/low and deduce that corporate insiders do not suffer from the anchoring bias.

Overall, we provide additional evidence to the ongoing debate as to whether informed market participants are susceptible to the anchoring bias. Unlike Cen, Hilary and Wei (2013) and Clarkson, Nekrasov, Simon and Irene (2020) that claim that financial analysts suffer from anchoring bias, we show that corporate insiders are not likely to be subject to anchoring bias, in line with Lee and Piqueira (2017) and Kelly and Telock (2017) that focus on short sellers, particularly because insiders are able to possess private information and dissimulate their trades.

The remainder of the paper proceeds as follows. In Section 2, we review the relevant literature on anchoring bias and informed trading. Section 3 describes our sample and the constructions of variables. Section 4 presents the summary statistics, the results from the univariate and multivariate analysis, and the impact of insider dissimulation strategy. Section 5 presents the robustness test by controlling for alternative asset pricing anomalies and other sample screens. Section 6 studies the informational content embedded in insider dissimulation strategy and further extends the topic into the heterogeneous characteristics of insiders who frequently employ dissimulation strategy. The conclusions are in Section 7.

2. Literature Review on Anchoring bias in informed trading

Tversky and Kahneman (1974) proposes that humans often utilise simple heuristics under an uncertain and complex situation. Individuals often have arbitrary reference values (anchor) in their minds and subsequently, use the anchoring number to estimate values. Any deviation from the anchoring value is conservative and insufficient (Slovic and Lichtenstein, 1971). Despite its convenient use in daily lives when processing readily accessible and available information in decision-making by setting up some reference point, anchoring can lead to a systematic bias[5].

Financial studies considered, amongst other factors, the share price 52 week/low as a reference point. George and Hwang (2004) discover that a trading strategy that is long (short) on stocks that are closer (furthest) to their 52-week high generates positive abnormal returns in the mid to long term. This zero-cost trading strategy dominates both the conventional Jegadeesh and Titman (1993) momentum and the Moskowitz and Grinblatt (1999) industry-

[5] For example, in an economics experiment conducted by Kahneman, Slovic and Tversky (1982), participants were showing a randomly generated number before they are asked to estimate the number of African nations in the UN. The estimates were systematically high (lower) for the group presented with a higher (lower) random number. The result suggests that subjects are using the randomly generated and intrinsically irrelevant number as a reference point, referred to as "anchoring bias" in the literature. Subsequently, financial economists used the impact of anchoring bias financial markets and investors' decision-making. Genesove and Mayer (2001), Ginsburgh and van Ours (2003), Kaustia, Alho, Puttonen (2008) provide further tests of this effect.

momentum trading strategies. They suggest that investors systematically underreact to good news when the stock prices approach their 52-week high because they recognise the 52-week high as resistant price level with relatively lower probability of subsequent price increases. Hence, the current price is below the fundamentals because of weaker buying pressure. However, firms eventually release good news, leading to price increases to reflect the new fundamentals, yielding positive abnormal returns.

Hong, Jordan and Liu (2015) advance the study of George and Hwang (2004) and attribute the abnormal return generated by the 52-week high trading strategy to anchoring bias. They conclude that investors only under- or overreact to industry-specific news, not firm-specific news. Hao, Chou, Ko and Yang (2018) highlight the link between the profitability of 52-week high trading strategy and market sentiment. They use Baker and Wurgler (2006) sentiment index to show that investors are more vulnerable to anchoring bias when the market sentiment is high. Consequently, the profitability of George and Hwang (2004)'s trading strategy is enhanced, implying that anchoring bias is the source of the trading strategy returns. Li and Yu (2012) demonstrate that investors anchor their investment decisions on the 52-week high of the individual stock price, but also on the Dow Jones 52-week and historical highs.

Empirical evidence demonstrates that investors suffer from anchoring bias on aggregate, but less conclusive as to whether informed traders are also vulnerable to the behavioural bias. Since informed traders have superior information than retail traders, they are not expected to suffer from behavioural biases, but will use their comparative advantage to reap abnormal return by exploiting retail traders' anchoring bias. However, since they are also humans, they may be susceptible to various behavioural biases widely recognised in the economics and finance literature (e.g., Baker and Wurgler, 2013; Custodio and Metzger, 2014; Davidson, Dey and Smith, 2015; Malemendier, Tate and Yan, 2011; Yim, 2013).

Several studies focus on differentiating between various types of informed traders and assess how behavioural bias asymmetrically distort their trading decisions. Grinblatt and Keloharju (2001) show that both retail and institutional investors suffer from anchoring bias, as they tend to purchase (sell) when stocks approach their historical lows (highs). In contrast, Hong, Jordan and Liu (2015) report that informed and sophisticated investors, such as institutional investors, overcome the anchoring bias by buying stocks that are closer to their 52-week high. Lee and Piqueira (2016) and Kelly and Telock (2017) report that informed traders, such as short sellers, do not exhibit anchoring bias. They argue that 52-week high is historic information and should be fundamentally irrelevant to the future valuation of the firm. If short sellers genuinely know the firm's prospects, they should be able to identify the noisy price movement driven by other investors' anchoring bias in and not to trade on it. They find that short sellers exploit other retail investors' anchoring bias by decreasing short-selling activity when a stock price approaches to its 52-week high to avoid the positive abnormal returns that may result from the retail investors' underreaction to the good news. On the other hand, Cen *et al.* (2013) find that financial analysts, conventionally recognised as informed stock market participants, make over-optimistic (over-pessimistic) forecasted earnings per share (FEPS) because they anchor them to the industry mean FEPS. Clarkson *et al.* (2020) further confirm the existence of anchoring bias in financial analysts' information sets, and Campbell and Sharpe (2009) also document experts' consensus forecasts of macroeconomic indicators systematically deviate from the previous estimates.

Other studies recognise that the recency of the reference point is important but usually omitted factor to consider when studying the anchoring bias. In an experiment, Murdock (1962) reports a tendency of participants to recall the last words from a series of words where the order is irrelevant, implying recency bias[6]. Bhootra and Hur (2013) characterise recency as one of the alternative explanations for anecdotal evidence in empirical finance and news in media[7]. They argue that stocks that reached their 52-week high recently significantly outperform, on average, those that attained theirs in the distant past, because investors react to positive news when stock has attained its 52-week high recently, suggesting that investors accentuate their underreaction to good news when stocks attain their 52-week high more recently than they would otherwise if the distance between 52-week high and the trading day were longer. These results highlight the necessity to differentiate the recency from the anchoring bias. Ma, Whidbee and Zhang (2014) conclude that the 52-week high recency bias suffered by outside investors, who are uninformed in aggregate, explains abnormal return earned by trading on the post-earnings announcement drift anomaly. Hao, Chu, Ho and Ko (2016) re-examine the profitability of 52-week high trading strategy and recency trading strategy in Taiwan stock market. They show that the 52-week high momentum trading strategy dominates the recency strategy, and the anchoring and recency biases coexist.

However, previous studies have not extensively studied the role of anchoring bias in the corporate insiders, the most widely recognised informed traders in the stock markets (Jaffe,

[6]The presence of recency bias is widely documented in various settings outside the financial market. Mohrman, Susan and Edward (1991) provide evidence to demonstrate recency bias in business management. Dickey and Pearson (2005) document recency bias in student course evaluation.
[7]For example, chasing fund performance reported in Gruber (1996), the surging gold demand after a period when gold yields abnormal high return, the reluctance of retail investors to take positions in the stock market after the stock market crash in 2008-2009.

1974; Seyhun, 1986; Lin and Howe, 1990). The exceptions are Lee and Piqueira (2019) and Li *et al.* (2019); both studies report that insiders suffer from 52-week high/low anchoring bias. However, they do not control for the recency of these two price extremes nor extensively study the insider's dissimulation strategies. Corporate insiders may also not be uninformed at the 52-week high as claimed by Ma *et al.* (2014) and Hao *et al.* (2016), because they can use dissimulation strategy to randomly make noisy transactions to thwart outsiders to mimic their trades when their private information is long-lived (Huddart *et al.*, 2001). Consequently, the anchoring bias of insiders will depend on their trading strategy. We follow Biggerstaff *et al.* (2020) who argue that when insiders possess long-lived information, they will gradually materialise it in a sequence, rather than single, transaction. We, therefore, disentangle the duration of information and further investigate insider dissimulation strategy at the 52-week high. Overall, we contribute to the literature by re-examining the role of anchoring bias after controlling for recency and dissimulation strategy in explaining insider trading predictabilities when stock prices reach their 52-week highs/lows.

3. Sample and Variable Construction.

We use Smart Insider Ltd, which collects all insider transactions information from Form 4 submitted to SEC to compile our sample of all U.S. insider transactions from January 1994, when the coverage is comprehensive, to December 2018.[8] In line with previous insider trading literature, we only consider listed common share transactions (CRSP share codes 10 or 11) traded on NYSE, AMEX and NASDAQ (CRSP exchange code 1 or 2 or 3). We manually review all the different classes of common share of the same company to ensure that the transactions match the correct identifier as different common share classes of one company are generally priced differently.[9] We only keep the open market buy and sell trades because they are likely to be information-driven transactions, as they are executed at the current market price (Seyhun, 1988; Lakonishok and Lee, 2001; Roulstone, 2003; Ravina and Sapienza, 2010).

We exclude any trades relating to the exercise of options because they are often motivated by personal liquidity demand or portfolio rebalancing reasons, and hence, not

[8] Formerly known as Directors Deal Ltd, Smart Insider data vendor (https://www.smartinsider.com/) collects worldwide insider trading data. It also gathers information from Form 5, which is the annual statement of change in beneficial ownership and reports any exempt transactions not reported on Form 4, to complete their database Previous studies, including Fidrmuc, Korczak and Korczak (2013), Hoque and Lasfer (2015) and Goergen, Renneboog and Zhao (2019) and mainstream financial Henderson (2020) used it.

[9] For example, four different insiders traded their shares in March 2017 in Lions Gate Entertainment Corporation, but two traded Class-A common share (cusip: 53591940), and others Class-B common Share (cusip: 53591950). These two separate securities are both traded on the NYSE at the same time with different prices, and consequently, yielding different returns. It was, therefore, necessary to correctly identify security classes in the entire sample.

considered to be informative (Ofek and Yermack, 2000).[10] We also exclude non-discretionary trades, such as open market sell forced by brokerage firm due to a violation in margin requirement, and mandatory trades to cover the tax and/or issuing cost of the new shares companies award freely to their insiders and/or allow them to purchase below the prevailing market price. SEC classifies these mandatory trades as open market sells but Smart Insider identifies them separately.[11] We exclude any pre-scheduled trades, known as 10b5-1 plan trades, because the information content embedded is likely to be trivial.[12] In line with previous studies (e.g., Lakonishok and Lee, 2001; Lee and Piqueira, 2019), we focus on insider trading with transactions price between 1 and 999 US dollars and trading volume greater than 100 shares to minimise noise and remove outliers.

Finally, Smart Insider Ltd groups corporate insiders according to their executive status. Insiders who are not actively involved in the daily operation of the business, such as large block shareholders, former and incoming directors, are less likely to possess private information (Seyhun, 1986; Kahle, 2000). Therefore, we only focus on the executive status classified by Smart Insider Ltd as Executive, Non-Executive and Senior Officer, which account for about 92% of the raw sample.[13] The former two are board members, and the last is not a board member but likely to possess price-sensitive information and subject to the same reporting regulation rules as board members.[14] We aggregate these trades at the insider-day level. our final insider-trading sample consists of 586,742 insider-day observations comprised of 103,530 distinct insiders and 11,090 unique firms. We report the screening details in Table 1.

[Insert Table1 here]

We use CUSIP code to merge the insider transactions sample with stock price and holding period return data from CRSP. We extract all accounting and financial data from the

[10]Smart Insider Ltd offers a unique flag to differentiate the open market sell executed after insiders have exercised buy options from the stand-alone open market sell. More specifically, the database classifies any open market sell up to the number of shares acquired in stock option programme in the next three weeks as Sale-Post Exercise. We exclude these trades from our sample because they are simply options cashing-out to fulfil insiders' the personal liquidity and/or portfolio diversification needs rather than information-related. The ideal is to keep only information-driven open market sells where insiders use their personal wealth to sell rather than cashing-out shares their company awarded them. However, it is not possible to detect the motivation behind sell transactions ex ante.

[11]Ravina and Sapienza (2010) and Brochet (2019) explicitly included these trades. In the raw data, these trades account for around 39% of the sample. All our results remain unchanged if we include Sale-Post Exercise trades. Brochet (2019) uses the same database to find robust results to the exclusion of these option-related transactions.

[12]To mitigate the impact of non-informative insider trades on the stock price, insiders can pre-announce trades or schedule their trading plan before the transaction date and instruct their brokers to execute the trade, generally at a fixed time interval, regardless of the market condition and/or private information. For example, Bill Gates has a long-term 10b5-1 plan and regularly sold more than 2 million Microsoft shares each year over the last 20 years.

[13]The other executive status, "Former", "Incoming", "Shareholder", "Supervisory", "Unknown" and "Other" accounts for 2.03%, 0.001%, 5.65%, 0.02%, 0.03% of the unfiltered sample, respectively.

[14]Goergen *et al.* (2019) include former and incoming directors but not senior officers because it was infeasible for them to collect data on senior officers from other databases they used.

annual or quarterly financial statement from COMPUSTAT. We use CRSP and COMPUSTAT Link table to match the stocks in CRSP with COMPUSTAT identifiers, and I/B/E/S to get Financial Analysts' coverage. We eliminate firms with incomplete coverage from these three databases; therefore, our sample size varies in our regressions because of data availability across these three databases. We manually checked all the 586,742 transactions-stock and corresponding financial and accounting data to ensure the maximum matching accuracy. We use the CRSP Cumulative Factor to adjust stock prices, the number of shares outstanding, and transaction volume. We add the delisting return to the holding period return (including dividend) on the last trading day of a stock to reflect fully shareholders' return. If the return on the last trading day is missing, we replace the last trading day return with delisting return.[15] Appendix 1 presents the details of variable constructions and data sources.

We use CRSP value-weighted market index return to adjust the holding period return to compute the buy-and-hold (BHAR) abnormal return for holding period t as follows:[16]

$$BHAR_{it} = \prod_{i=1}^{t}(1 + return_{t+i}) - \prod_{i=1}^{t}(1 + mkt_{t+i})$$

where $return_i$ is the holding period return, and mkt_i is the benchmark return for the holding period t. We measure BHAR one day after the transaction date of insider trading. The literature applies different holding periods to measure the return predictability of insider trading, generally between one and six months (Lakonishok and Lee, 2001; Huddart *et al.* 2007; Chiang *et al.*, 2017). When testing for the short-term predictability, one month is appropriate because insiders in the same firm tend to cluster their trades with colleagues, and they tend to split their trades over several days (Alldredge and Blank, 2019; Wolfgang, Emil and Christian, 2020). However, Section 16(b) of the Security Act of 1934 regulates corporate insiders to return any profit from two opposite transactions occur within the six months, it is known as "short-swing profit rule". Therefore, the six months is the shortest realistic investment horizon for insiders to materialise their private information, making this period particularly attractive to analyse. Besides, literature commonly focuses on twelve-month holding return for studying the price discovery and long-term market efficiency improvement attributed to insider trading (Anginer, *et al.* 2018). Following the literature, we will use 30, 180 and 365 calendar day as the holding

[15]Delisting return is the return of security after it is delisted. The value after delisting can include a price on another exchange or the total value of distributions to shareholders. The inclusion of delisting return can better capture the return predictability of insider transactions.
[16]The main result of the paper is robust and unchanged (untabulated) if we use size, book-to-market two-way sorted 10×10 value-weighted portfolio return, 10-industry value-weighted portfolio and 49-industray value-weighted portfolio as the benchmark return.

period. A common problem that any daily sample will encounter is that the number of the trading day varies within the different holding period and depends on stock's listing and delisting dates. As suggested by Agrawal and Nasser (2012), we require a minimum 20-, 120- and 243-day valid return data for each of the respective accumulation period.

We use Kenneth French's Data Library[17] to gather the Size, Value, Momentum factors, risk-free rate to compute the alpha from Carhart (1997)'s Four-Factor model, which builds on the Fama-French Three-Factor model (Fama and French, 1993) as follows:

$$return_{it} - rf_t = \alpha + \beta_1(MKT_t - rf_t) + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 MOM_t + \epsilon_t$$

α, the risk-adjusted return is estimated from one day after the transaction date over the next 30/180/365 calendar days. $return_{it}$ is the daily return adjusted for dividend, rf_t is the risk-free rate. MKT_t is the CRSP value-weighted market index. $SMB/HML/MOM$ denote the conventional size, book-to-market, and momentum factors. 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, stressed by Korthari and Warner (1997), Barber and Lyon (1997) and Mitchell and Stafford (2000).

Previous studies document that insiders' trading decision is affected by stock market aggregate sentiment (Baker and Wurgler, 2006; Korczak, Korczak, and Lasfer, 2010; Huang, Jiang, Tu and Zhou; 2015). We use Baker-Wurgler investor sentiment index to alleviate the concern that market sentiment instead of behavioural bias drives insiders to trade around the 52-week high/low. This index is the first principal component of five standardised sentiment proxies where each proxy is orthogonalised with respect to a set of six macroeconomic factors. These are value-weighted dividend premium (the log difference of the average book-to-market ratios of dividend payers and non-payers), first-day returns on IPO, IPO volume, closed-end fund discount and the percentage of equity share in the total volume of the equity and debt issues in the prior 12-month period (Baker and Wurgler, 2006).[18] The first principal component of the orthogonalized five components is the Baker-Wurgler index. However, Sibley, Wang, Xing and Zhang (2016) show that T-bill and Lee (2011)'s liquidity factor can still explain around 41% of the variation in Baker-Wurgler index, and thus this index is not fully orthogonalized with respect to fundamentals. Therefore, we follow the procedure of Sibley *et al.* (2016) and Chue, Gul and Mian (2019) to further orthogonalise the Baker-Wurgler index

[17] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. We thank Professor French for making these data publicly available.
[18] See http://people.stern.nyu.edu/jwurgler/. We are grateful to Prof. Wurgler for making the index publicly available.

by regressing it on the 3-month T-bill rate, we obtain from WRDS, and Lee (2011) liquidity factor, we calculate using CRSP. We use the residual from this regression, denoted as Sento, as a proxy for the market investor sentiment.

We use the stock price data from CRSP to compute Amihud's (2002) illiquidity measure, defined as the monthly average of the daily ratio between absolute stock return and dollar stock volume. Korczak et al. (2010) show that insiders strategically trade on both exogenous news announcement such as quarterly earnings announcement and endogenous news announcement such as research update. These announcements frequently push the stock price to the 52-week high or low. We control for the effects of such short-term abnormal price movements by following Lasfer, Melnik and Thomas (2003). We define *UpDummy (DownDummy)* equals to one for stock *i* on day *t* when any of the stock daily return in the event window of *t-7* to *t* is higher (lower) than its mean μ plus $(minus)$ $2 \times \sigma$; zero otherwise. The mean μ and standard deviation σ are both estimated by using (t-60, t-11) window.

Insiders may trade frequently in a short period. We find that the daily mean (median) number of transactions executed by the same insider in the same company is 1.086 (1). Previous studies aggregate insider trading monthly (Seyhun, 1988; Lakonishok and Lee, 2001; Lee and Piqueira, 2019), but Alldredge and Blank (2019), Li *et al.* (2019) aggregate these trades daily, and Beneish and Markarian (2019) chose to clean the sample on a firm-day level frequency. The aggregation of insiders' trades at the firm-month frequency disregards the information of how many insiders trade in a single firm and treat all firms with different intensity of insider trading equally. We consider the insider trading intensity as a piece of information by itself and placing equal importance on a firm with one insider trading in a month and a firm with many insider trades in a month to be misleading. Insider-day level aggregation is an alternative approach to take to account for the intensity and provide a weighted-average measure for return profitability where the weight is the number of firm's daily insider trading. Thus, we aggregate the insider transaction data at the insider-day level to better capture the short-term insider trading momentum and return predictability. In an unreported result, we replicate all the regression analysis at the firm-month level for a battery of robustness test and find that all results remain robust.[19] Throughout the paper, we mainly employ the net purchasing value (NPV), computed as the net dollar value over the total dollar value, computed as:[20]

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[19]These results are available upon on request.

[20]In the literature, net purchasing ratio, which is ratio between the amounts of shares traded over the total amount of shares traded, is an alternative measure of insider trading direction (Lakonishok and Lee, 2001). In unreported result, we repeat all regression by using NPR as well, and the result is virtually unchanged.

$$NPV = \frac{\$\,Insider\ Purchase - \$\,Insider\ Sell}{\$\,Insider\ Purchase + \$\,Insider\ Sell}$$

We follow George and Hwang (2004) to identify the relative 52-week high (low) ratio as:[21]

$$52\_W\_H_t = \frac{Closing\ price_t}{52\_Week\_High\ Price_t}$$

$$52\_W\_L_t = \frac{Closing\ price_t}{52\_Week\_Low\ Price_t}$$

We also follow Bhootra and Hur (2013) to measure the recency of 52-week high/low as:[22]

$$52\_W\_H\_Rec_t = 1 - \frac{Daily\ average\ number\ of\ days\ since\ 52\ week\ high\ price_t}{364}$$

$$52\_W\_L\_Rec_t = 1 - \frac{Daily\ average\ number\ of\ days\ since\ 52\ week\ low\ price_t}{364}$$

The relative 52-week high/low ratio mainly measures insiders' trading decision prior to the upcoming 52-week high/low whereas the recency ratio gauges the reaction of insiders to the attainment of the previous 52-week high/low. If the $52\_W\_H_t$ ($52\_W\_L_t$) ratio is 1, then insiders are trading at the 52-week high (52-week low) share price. A high relative 52-week high (low) price ratio indicates that the stock price is approaching the 52-week high (low). A $52\_W\_H\_Rec_t$ ($52\_W\_L\_Rec_t$) equal to 1 means that insiders are trading on the day that their firms hit a new 52-week high (52-week low). A high (low) $52\_W\_H\_Rec_t$ ($52\_W\_L\_Rec_t$) means on the day that insiders trade, the 52-week high (low) is in the recent (distance) past.

4. Empirical Result

4.1 Summary Statistics

Table 2 Panel A reports the summary statistics for insider trading over our sample period 1994-2018. We divide all insider trading into four relevant sub-periods: 1994-2001 (pre-Sarbanes-Oxley), 2002-2007 (Sarbanes-Oxley), 2008-2009 (financial crisis) and 2010-2018 (Dodd-Frank Act). We report for each sub-period the number of net buy and net sell transactions, the number of distinct insiders, firms, and un-aggregated insider-day transactions, and time-series averages of NPV, US dollar value, and share volume of both buy and sell trades. Unless stated, we aggregate all insider transactions at the insider-day level.

[21] Our conclusions remain robust if we follow Li et al. (2019) to define the 52-week high/low ratio on day t as the average closing price from (t-30, t-1) over 52-week high/low price on t-1, also robust if we use the ratio between the closing price on day t-1 over the 52-week high/low price on day t-1.

[22] Our conclusions remain robust if we use the one minus the ratio of the average time distance from the 52-week high/low in (t-30, t-1) over 364, also robust if we use the one minus the ratio of the time distance from the 52-week high/low in t-1 over 364.

The last column of Table 2 shows that there is no clear trend in insider trading. The number of net sells is almost twice that of net buys, in line with previous evidence, suggesting that they are likely to sell also stocks they receive via stock options, grants, or as part of their remuneration package, not disclosed to the public, and, thus, not recorded in the dataset (Lakonishok and Lee, 2001; Ali *et al.*2011). The negative NPV of -33.87% further confirms that insiders are net sellers on average, but, since we excluded Sale-Post Exercise, it is higher than the -57.67% reported by Lee and Piqueira (2019) for the management group in 1990-2014.[23] The average NPV differs significantly across the sub-sample period, in line with Hsieh, Ng and Wang, (2019), and Lee and Piqueira (2019). After the enactment of SOX, insiders are less likely to execute open market buy, as the NPV is -39.81% for 2002-2007, increasing slightly to -21.80% during the financial crisis as insiders are likely to concentrate their portfolios on their companies to provide price support, and reaches -44.28% in 2010-2018 after the implementation of the Dodd-Frank Act.[24] The median reporting lag before 2003 is 22 days, and two days after 2003 in our un-aggregated sample, in line with Cohen *et al.* (2012), and Wang (2019). The average number (dollar volume) of shares purchased is 17,040 ($151,000), is significantly small that the 39,900 ($820,000) shares sold.[25]

We investigate further the trend in insider trading intensity. We calculate the monthly average and yearly average transaction size for each month and year between 1994 and 2018 for buy and sell trades separately. Figure 1 shows that the sell trades are more pronounced than buy trades throughout the entire sample period. The value of average insider sells increased and reached its peak in January 2000, the dot-com bubble month when the NASDAQ was at its peak. After the burst of the dot-com bubble and the enactment of SOX, the amount of insider's sell permanently dropped. On the other hand, there is no clear trend in insider buy. Figure 2 shows that during the financial crisis (2008-2009), the level of insider trading decreased drastically, especially in 2009, whereas the level of insider purchase increased slightly in 2008 and then dropped to its valley in 2009, in line with Jagolinzer, Larcker, Ormazabal and Taylor (2020) who only focus on the insider trading behaviour during the financial crisis. Panel B indicates that insiders trade relatively less in January than in other months, except for the significant sell trades in January 2000, as reflected in Figure 3.

[23] Sarbanes-Oxley act came into force in 30 July 2002. The implementation of this act shortened the reporting deadline to SEC from 10 days to 2 days after the end of the month in which insiders executed the transactions.
[24] Dodd-Frank Act targets only illegal insider trading by introducing protection provision for whistle blowers. Hsieh *et al.* 2019 also report the Dodd-Frank Act did not affect the random trend in insider trading.
[25] The average dollar volume in our sample is smaller than previous studies as our minimum insider transactions share price is $1, compared to $5 in e.g., Lee and Piqueira (2019).

Panel C presents the number of purchases and sells at the periodic peak and trough. We define a transaction is executed at the peak (trough) when the $\_52\_W\_H$ ($\_52\_W\_L$) is greater or equal (less or equal) to 0.98 (1.02).[26] The results show that, at the price peak, insiders are more likely to sell (79,658; 84.95%) than to buy (14,104; 15.04%), while, at the 52-week low, they predominately buy (28,089; 72.83%) than sell (10,478; 27.17%). These results provide further evidence of insiders' contrarian trading behaviour. We also report the recency days. At 52-week high, insiders appear to trade, on average, 17 to 18 days from the previous 52-week high, but, at 52-week low, they tend to sell later than when they buy (19 vs. 11 days, $p < 0.00$), suggesting that they are more confident to buy stocks that plummeted to their trough recently then to sell them. Skinner (1994) attributes such empirical finding to the asymmetry in the expected legal cost associated with insider buys and sales as the former will only lead to an opportunity loss, but the latter is responsible for an out-of-pocket loss for outsiders, which is less likely to prevail before juries than the former. Insiders are more likely to adopt contrarian trading strategies in stock that recently hit its 52-week high or low, though with lower intensity.

[Insert Table 2 and Figures 1-3 here]

Table 3 presents the summary statistics of our key variables. We winsorise all variables at bottom 0.5% and top 99.5% to avoid unnecessary noise in our data. The t-test (Wilcoxon rank-sum test) results for the equal mean (median) between net purchaser sample and net seller sample are reported by using superscript in column (5) (column (7)). The average 52-week-high ratio, not reported, is 78.54%, in line with the 76.28% reported by Lee and Piqueira (2019), suggesting that insiders often trade when stock prices are, on average, close to their peak. However, the average ratio of 83.769% for net sellers is statistically higher than the 67.967% for net purchasers, implying that net buyers are likely to trade when the prevailing market price is far away from the 52-week high price, and net sellers are more active when the price is close to a 52-week high. The overall average 52-week high recency ratio, not reported, is 58.374%, equivalent to 151 calendar days. However, the 194 days average for net purchasers is statistically higher than the 131 days of net sellers, suggesting that insiders are relatively more likely to sell closer to the previous 52-week high. Overall, these results support our hypotheses that insiders consider 52-week high price in their information sets when they trade, but relatively more for their sell than their buy trades.

[26]The cut-off point is arbitrary. Our results are robust to cut-off points of 0.9 (1.1), 0.95 (1.05) and 0.99 (1.01).

The average firm size, not reported, is $4.36 billion dollars, in line with $3.53 billion reported by Lee and Piqueira (2019).[27] However, Table 3 shows that net purchasers are more likely to trade in small firms with an average (median) market capitalisation of $2.04 billion ($177 million), whereas net sellers often occur in large firms valued, respectively, at $5.49 billion ($448 million). The difference is statistically significant at 99% confidence level. This right-skewed distribution of firm size is representative for the large public companies in the U.S and is in line with Beneish and Markarian (2019), who report the average (median) firm size for the net buyer is $1.7 billion ($183 million). We account for these large discrepancies by taking log transformation of firm size.

The average momentum is 31.48% for net sellers and 7.51% for net buyers, in line with existing literature that insiders are contrarian (Lakonishok and Lee, 2001), they buy when the stock prices have been declining, and they sell when the stock price has been surging. The unreported mean (median) of book-to-market (*bm)* of 0.644 (0.495) is in line with 0.591(0.592) reported by Lee and Piqueira (2019). The mean *ROE* is negative for net purchasers, but the median is positive 6%, suggesting that the distribution is also left-skewed, but a typical firm is profitable.

We use both the Buy-and-Hold abnormal return adjusted by using CRSP value-weighted market index and Fama-French-Carhart 4-factor alpha to measure the profitability of insider trading. For insider purchase transactions, the 30-, 180- and 365-day cumulative (median) BHAR_m_i are 2.714% (1.072%), 5.671% (0.709%) and 9.808% (-0.043%), respectively. The corresponding average (median) 30-, 180- and 365-day cumulative alphas are 3.092% (1.797%), 7.503% (5.773%) and 12.043% (10.408%) if cumulated by using the median number of trading days of 22, 126 and 252 within each holding period. The results confirm the finding in the literature that insiders' buys are on average profitable, informative and convey a strong signal to the market participant (Seyhun, 1998; Lakonish and Lee, 2001; Wolfgang *et al.*, 2020). Jagolinzer *et al.* (2011) report a six-month average daily profit of 0.06% which cumulates to 7.56%, and Beneish and Markarian (2019) find a six-month daily return of 0.07% which cumulates to 8.82%, both are in line with our result.[28] The decrease in median demonstrates the entire distribution is right skewed with a long tail, consistent with Wolfgang

[27]Nonetheless, these figures suggest that Smart Insider has higher coverage on large firms and more insiders trade their shares in large firms.

[28] For two alternative measures of BHAR, 10×10 size, book-to-market two-way sorted value-weighted portfolio return is also used to proxy for market return. Insider buy trades remain informative for all holding periods, independently of the alternative benchmark return used, and the right skewness is robust across different market returns. If we adjust BHAR by using Fama-French 10-industry portfolio returns or 49-industry portfolio returns, the results are similar, and all our conclusions remain robust.

et al. (2020) who postulate that corporate insiders' purchases are followed by an increase in the idiosyncratic skewness.[29] For the net seller, the *BHAR_m* are statistically significant at the 99% confidence level only for the 365-day holding period. These results confirm the findings in the literature that insider sell trades are on average uninformative mainly because of relatively higher regulatory risk as insiders sell a stock for a variety of reasons, but the main motivation to purchase a stock has is to seek profit, as argued by Lakonishok and Lee (2001).

[Insert Table 3 here]

4.2 Aggregated insider's return 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 the result in George and Hwang (2004) with the additional inclusion of _52_W_H_Rec and _52_W_L_Rec. The results reported in Appendix 2 show that the 52-week high return anomaly persists. There are return predictabilities embedded in both the relative price and the recency to the previous 52-week high. However, the relative price to the 52-week low does not predict future return whereas the recency to the previous 52-week low is associated with a negative return momentum. These results highlight that investors without private information should buy at the 52-week high or short sell immediately after the stock plummeted to its 52-week low to profit from their positions.

Nevertheless, George and Hwang (2004)'s findings cannot support the argument in Lee and Piqueira (2016) that insiders must buy (sell) at the 52-week high (low) to materialise their private information, otherwise they are suffering from the anchoring bias. Insiders are informed market participants; they will trade at any direction at any price level if their private information heralds trading opportunities. We cannot infer the motivation behind their trading decisions without a thorough study on their post-transaction returns. In this section, we specifically focus on the subsequent return of two types of stocks: (i) stocks that reached 52-week high/low in the last fifteen days, equivalent to restricting our sample to $52\_W\_H\_Rec_t$, or $52\_W\_L\_Rec_t$ greater or equal to 0.96, or (ii) stocks breaking their 52-week high or low in the next fifteen days. By focusing on these typical stocks and studying the return predictability of insider trading, we can detect the motivation of insiders trading ex-post.

[29] Our results remain unchanged if we winsorise the right tail of the return distribution to restrict the median is not below the mean to alleviate the concern that our result is driven by extreme returns.

Firstly, we identify the event date 0, which is the day that the stock reached its 52-week high/low. If a stock breaks its 52-week high multiple times in the next 30 days from day 0, we only consider the first time it hits the high and ignore the others. In other words, only the first time a stock reaches its 52-week high/low is day 0 in every 30-day fixed window. We define a stock reached its 52-week high (low), when the new 52-week high (low) is higher (lower) than the 52-week high (low) in the previous trading day. Consequently, we eliminate all cases that a stock reached its 52-week high/low because of the lapse of time. Secondly, we aggregate all insiders' transactions for the stock within three distinct window periods, annotated as (-15, -1), (0, 0) and (1, 15). Then we calculate their corresponding NPV, where $NPV_{(1,15)} > 0$ indicates corporate insiders increase their holdings 15 days after the stock has reached its 52-week high/low, and $NPV_{(-15,-1)} < 0$ when they are net selling 15 days before the stock breaks its 52-week high/low. More interestingly, $NPV_{(0,0)}$ implies the aggregated insider trading position on the day that the stock reached its 52-week high/low with little hesitation. Lastly, we calculate the BHAR from day 1 to the next 30-, 180- and 365-calender days, excluding day 0. We present the subsequent BHAR adjusted returns using CRSP market value-weighted index for the holding period of these holding periods, $BHAR\_m\_i$.[30] We report the results in Table 4 for all stocks with either net buying pressure or net selling pressure.[31] Appendix 3 reports the risk-adjusted return (4-factor alpha) for robustness.

[Insert Table 4 here]

The results indicate that when corporate insiders are net buyers of a stock that reached the 52-week high, their trading decisions are informative and have consistently predicted a positive BHAR. The $BHAR\_m\_i$ is 4.1%, 9.8% and 11.3% for the next 30-, 180- and 365-day holding periods, respectively. We can observe the same positive return predictability if we define insider net buying pressure by aggregating insider transactions fifteen days before the stock reached a 52-week high. Corporate insiders are informative because their buy-at-peak transactions yields positive returns in the mid to long-term. The results are in line with Lee and Piqueira (2019) and Li *et al.* (2019) who claim uninformed investors display a tendency to sell stocks when the stock price is approaching the 52-week high. Corporate insiders, who possess private information, will take advantage of those uninformed investors who are suffering from anchoring bias and increase their holdings at the peak to profit from the future positive

[30] 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.
[31] Since the numbers of trading days in these three holding periods are time-varying for different securities at different point of time, we require at least 20, 120 and 243 valid trading days to compute the respective BHARs.

abnormal return. Consequently, these insider transactions are highly profitable, and the return predictability in their trades is high and robust. Insiders that are net sellers within fifteen days after the stock broke its 52-week high, yield a loss of 0.4%, 1.0% and 1.3% of $BHAR\_m\_i$ in the 30-, 180- and 365-day holding periods, respectively. These positive returns indicate that insiders generate losses when they reduce their holdings at the 52-week high, and the motivation behind their trades are not private information. A comparison of the net buying sample ($NPV > 0$) and the net selling sample ($NPV < 0$), indicates that buy-at-peak transactions significantly outperforms sell-at-peak transactions at all holding periods. These results remain robust when we consider risk-adjusted returns to proxy for insider returns.

Panel B reports the results when the stock reaches its 52-week low. Insiders' purchases remain highly informative, regardless of return measures. $BHAR\_m\_i$ for $NPV_{(1,15)}$ is -0.1%, 3.7% and 6% for the holding horizons of 30-, 180- and 365-day, respectively. If insiders are buying prior to the arrival of stock price to a 52-week low, $BHAR\_m\_i$ is 3%, 7.4% and 10.3% for short-, mid-, and long-term, respectively. However, when insiders sell at a 52-week low, the returns are relatively random. If insiders are selling after the stock breaks its support price level, $BHAR\_m\_i$ is -0.7% % for 30-day holding horizon, and not significant in the 180-day and 365-day holding periods. Moreover, if insiders are selling before the stock hits its valley ($NPV_{(-15,-1)} < 0$), insiders can only earn negative return in 30-day period, but not in 180- and 365-day holding periods. More significantly, if insiders buy (sell) on the day that the stock dropped to its 52-week low, both their purchase and sell transactions remain highly informative. Their buy (sell) trades generate statistically significant 2% (-2%), 4% (-7.7%) and 9.6% (-9.7%) for 30-, 180- and 365-day holding periods, respectively. These results highlight the importance of controlling 52-week high/low recency when studying insiders' trading decisions.

Panel C reports the unconditional return for stocks that reached its 52-week high/low, whether insiders traded or not. We compare the stocks where insiders trade in Panel A with all stocks that reached its 52-week high, insiders' purchase transactions outperform the average sample return. While their sell transactions generate a positive return, which are losses to the seller, the positive return is lower than the average sample return. In unreported result, the difference between insider sell return and average sample return is statistically significant at 99% and 95% confidence level for the next 180- and 365-day holding periods. These results suggest that insiders are informed traders at 52-week high. We can observe the similar informativeness embedded in insider trading at the 52-week low.

Moreover, the sample size for stocks that experienced aggregated net selling pressure from the inside personnel at the 52-week high is 23,018, 26,522 and 25,822 for these three holding periods, respectively. On the other hand, there are only 3,090, 3,593 and 3,476 observations for stocks that witnessed aggregated net selling pressure at the 52-week high. At the 52-week low, there are three times more stock with positive than negative NPV. These results are consistent with Lee and Piqueira (2016) who show that insiders predominately reduce (increase) their ownership at the 52-week high (low). Insiders who buy at the peak, are often those who possess private information, and they exploit other investors' anchoring bias. The trading propensity further reaffirms our result in summary statistics that insiders also predominately buy at the 52-week low but with weaker intensity compared with their sell trades at the 52-week high. However, the finding is inconsistent with the conjecture in Lee and Piqueira (2016) that insiders are subject to anchoring bias at both the 52-week high and low. While insider 52-week low sell trades incur losses, their purchases are inarguably profitable. Evident by many insiders' purchases executed at the 52-week low, insiders should systematically generate a negative return if they genuinely suffer from 52-week low anchoring bias as argued by Lee and Piqueira (2019) and Li *et al.* (2019). Nevertheless, the high return predictability embedded in these transactions indicate insiders do actively pre-empt their positions at the 52-week low to signal undervaluation, a result that has been overlooked by Lee and Piqueira (2016). The trading pattern of increased buying activities at the 52-week low cannot support the notion that insiders suffer from behavioural bias claimed.

4.3 Trading Strategy based on Insiders Transactions at the 52-week High/Low

George and Hwang (2004) report that outsiders can form a profitable zero-cost trading strategy by simply going long (short) on the highest (lowest) the 52-week high ratio portfolio. 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. In the previous section, we have inferred insiders' ex-ante informativeness in their trading decisions from their ex-post return predictability by sorting on the 52-week high/low price ratio. Insiders' informational advantage is more pronounced at these two price extremes because they are truly privy of the future cash-flow realisation of their firms. If insiders also trade at the 52-week high/low, their trading decisions will likely be a signal to the uninformed investors in addition to the 52-week high ratio and the recency ratio. Furthermore, the rigorous insider trading regulation has provided an opportunity for uninformed investors to form a zero-cost trading strategy by following insiders' trading decision at the 52-week high and low with minimum delay. Inspired by these results, we explore the possibility of forming a zero-cost trading strategy by focusing on both the insiders' trading decisions and the level of 52-week high/low ratio or the relative recency.

To answer the question, we first employ a sorting scheme to form a zero-cost trading strategy based on the 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 *NPV* is larger (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 52-week high/low price ratio on day *t*. We then go long (short) on the portfolio with stocks that are in the top (bottom) 52-week high (low) ratio decile and net-bought (net-sold) by insiders. To avoid January effect, we skip all January returns when cumulating all the BHAR.[32] We rebalance the long and short portfolios monthly and report the BHAR for the holding periods of 6 and 12-month in Table 5 Panel A. Panel B is similar to Panel A except we sort stocks according to their 52-week high/low recency ratios on day *t*. We long (short) the portfolio whose stocks are in the top (top) 52-week high (low) recency decile and net-bought (net-sold) by insiders and rebalance the portfolio monthly. In other words, we long (short) stocks that insiders also buy (sell) immediately after the stock reached its 52-week high (low).

[Insert Table 5 here]

From Panel A, we can observe that the BHAR between the top and bottom 52-week high/low ratio portfolio is 9.3% and 19.2% in the 6- and 12-month holding periods, respectively. In column (4) and (5), we report the BHAR without conditioning on insider trading. If we simply long (short) the portfolio with the top (bottom) 52-week high (low), the average BHAR between the top and bottom 52-week high/low ratio portfolio is statistically indifferent from zero for both the 6- and 12-month holding periods. The lower return predictability is attributed to the positive BHAR generated by the short-leg, which yields a 4.4% and 9.2% higher BHAR than the short-leg conditioning on insider trading for the 6- and 12-month holding periods, respectively. Both the long-leg and the short-leg of the trading strategy without insider trading underperform its counterpart with insider trading evident in column (7) and (8). These asymmetries in the BHAR between these two zero-cost portfolios further highlight the role of corporate insider as sophisticated investors, and their return predictability even persists when they sell their firms at the 52-week low.

[32] Our results are robust to the inclusion of January.

In Panel B, we sort the stocks into deciles in accordance with their 52-week high/low recency ratio. The trading strategy further improves the BHAR to 15.2% and 30.8% in the 6- and 12-month holding periods, respectively. If we do not condition on insider trading, sorting on the recency ratio improves the short leg of the trading strategy. The short leg yields a negative -2.5% and -5.7% BHAR which indicate monetary gains for short sellers for the 6- and 12-month holding periods, respectively. The trading strategy without insider trading signal generates a 6.4% and 14.2% BHAR in the 6- and 12-month periods, respectively. However, the trading strategy without insider trading still underperform its counterpart with insider trading in both the long- and short-leg as presented in column (7) and (8).

Our results, reported in Appendix 4, are robust if we use Fama-French-Carhart 4 factor alpha instead of BHAR. The trading strategy based on 52-week high/low ratio with insider trading still generates a statistically significant 7% and 5% alpha for the 6-and 12-month investment horizons, respectively. For trading strategy based on 52-week high/low recency and insider trading, the αs of 5.4% and 5.5% for these two holding periods, respectively, are statistically significant. Similarly, both trading strategies outperform their counterparts which are unconditional on insider trading. These results are consistent with our previous findings that corporate insiders are informationally driven when they buy (sell) at the top (bottom). Furthermore, the responding time of corporate insiders in reaction to the hit of the 52-week high and low which is proxied by the 52-week high/low recency, shed additional lights on their firms' future valuation and highlights the importance to control for the recency when studying the motivations behind their trading decisions at these two price extremes.

4.4 Insider Trading Propensity and Post Trade Returns at the 52-week high and low

From our univariate analysis, we conclude that the responsiveness of insiders which is proxied by recency sheds light on their motivation behind their trades at the 52-week high and low. We use multivariate analysis in this section to control for other potential effects to assess the role of relative price played in insider trading. We first investigate the propensity of insiders to trade conditional on the relative price and recency using the following logit specification:

$$\begin{aligned}
\mathrm{P}(\mathrm{y}=1|\mathbf{z}) = \mathrm{G}(&\alpha + \beta_1 \times _52_W_H_{t-1} + \beta_2 \times _52_W_H_Rec_{t-1} + \beta_3 \times mom_{t-1} \\
&+ \beta_4 \times ret_t + \beta_5 \times lnmcap_{t-1} + \beta_6 \times bm_{t-1} + \beta_7 \times illiq_{t-1} + \beta_8 \times roe_{t-1} \\
&+ \beta_9 \times leverage_{t-1} + \beta_{10} \times RD_{t-1} + \beta_{11} \times numest_{t-1} + \beta_{12} \times Sento_{t-1} + \beta_{13} \\
&\times UpDummy_{t-1} + \beta_{14} \times DownDummy_{t-1} + u_t)
\end{aligned}$$

G represents the logistic function in logit.[33] The dependent variable is equal to one if an insider is a net purchaser (NPV>0) defined by net purchasing value, on a given day or month depending on the aggregating level, zero otherwise. We describe in Appendix 1 the constructions of all variables. We use the last fiscal year to construct the accounting variables. We estimate the coverage of analysts, *numest* a proxy for information asymmetry, by counting the number of analysts who submitted earnings per share estimates for a given stock for the next fiscal year in each month. If I/B/E/S does not report any analysts' forecast for the next fiscal year earnings per share, *numest* is restricted to be zero. *Illiq* is the Amihud's (2002) illiquidity measure, computed as the monthly average of the daily ratio of absolute stock return to dollar volume. *Sento* is the residual from the regression that regressing the Baker-Wurgler index (Baker and Wurgler, 2006) of aggregate investor sentiment on 3-month T-bill rate and Lee's (2011) liquidity risk factor. We carefully followed the procedure outlined in Sibley *et al.* (2016) and compared our summary statistics of the liquidity risk factor with Lesmond, Ogden and Trzcinka (1999) which Lee's (2011) liquidity risk factor primarily built on, to ensure our sample and methodology are correct. *UpDummy* (*DownDummy*) is dummy variable constructed according to Lasfer, *et al.* (2003). If a stock's return on day t is greater (smaller) than its mean return in (t-60, t-11) plus (minus) two times its standard deviation computed between (t-60, t-11), the return is abnormal positive (negative) return. The *UpDummy* (*DownDummy*) dummy variable equals one if there is at least one abnormal positive (negative) return occurred between (t-7, t). The variable will capture the effect of both exogenously and endogenously released news by insiders. Standard Errors are clustered at the firm level because Alldredge and Blank (2019) have provided evidence for insiders' herding behaviour within a firm. Clustering at the firm level also allows for controlling both arbitrary time-series correlation within a firm and arbitrary cross-section dependence between different insiders within a firm (Jagolinzer, *et al.* 2020). Table 6 reports the regression output.[34]

[Insert Table 6 here]

Table 6, Column 1, shows that the coefficients of $\_52\_W\_H$ and $\_52\_W\_H\_Rec$ are both negative and significant, implying that the shorter the distance between stock's current price to its 52-week high, and the shorter period after the attainment of 52-week high, the higher the selling propensity of insiders. Columns (2) of Table 6 reports the equivalent results for the

[33]All results remain robust if we use probit instead of logit.

[34] Less than 0.01% of the sample has NPV that is equal to zero, which implies insiders rarely close their positions in the same day that they open their positions, and hence more than 99% of our sample have either NPV less than zero or NPV greater than zero. Therefore, the coefficient is virtually one minus the coefficients in Table 6 if the dependent variable is set to be one for the net seller instead of the net buyer.

52-week low. The coefficient of $\_52\_W\_L$ is negative, that of $\_52\_W\_L\_Rec$ is positive, implying that if the current stock price is closer to the 52-week low, insiders are more likely to buy, and they would increase holding immediately after the 52-week low. The results provide support to the arguments of Bhootra and Hur (2013), and Lee and Piqueira (2019) who articulate that insiders are reluctant to decrease their positions when the current price is close to the 52-week low. In conjunction with our previous univariate findings, our results suggest that insiders predominately make sell transactions at the 52-week high, and, on average, incur losses. In contrast, insiders are likely to trade on their optimistic private information at the 52-week low with little delay by increasing holdings to signal their firms' under-valuation. On the other hand, insiders are reluctant to sell when the price is at through even though they may possess negative private information to avoid scrutiny, in line with Korczak *et al.* (2010).

The coefficients of control variables are in line with the existing literature (e.g., Seyhun, 1992; Lakonishok and Lee, 2001; Cheng and Kin, 2006; Beneish and Markarian, 2019). The negative coefficient of *mom* implies insiders trade in a contrarian fashion by selling (buying) when the stock returns are high (low). *Lnmcap* is negative, suggesting that insiders are the net sellers in larger firms and buyers in a smaller one. The positive and significant coefficient of *bm* and *RD*, and the negative coefficient of *numest* both serve as proxies for a higher information asymmetry environment and indicate when the information asymmetry is higher, the likelihood of insiders being caught by outsiders for materialising their private information becomes lower, and thus face lower litigation risk. Consequently, the propensity of insiders to buy stocks in their firms is higher. The positive coefficient of *Sento* indicates that insiders increase their holdings during periods of high market sentiment, in line with the findings of Chue *et al.* (2019), who argue that, in bullish markets, the importance of informed trading diminishes, and contributes less to the price discovery because of constrained arbitrage, leading insiders not to trade in a contrarian fashion. The positive coefficients of *UpDummy* and *DownDummy* demonstrate that insiders actively respond to an extreme abnormal return by increasing their holdings and thus facilitate private information into the stock price, in line with Ali *et al.* (2011) and Anginer *et al.* (2018). Noteworthy, *DownDummy* is positive, consistent with the coefficients of $\_52\_W\_L$ and $\_52\_W\_L\_Rec$, suggesting that insiders tend to quickly increase their holding when the stock price decreases to its valley.

In columns (3) to (8), we use the fixed-effect estimator to regress the post transactions returns on the same set of independent variables. We control for both the firm and month fixed effects and cluster standard error at firm level because of insider trading clustering within a firm (Alldredge and Blank, 2019). Columns (3) to (5) show that, for an average insider purchase, 1% increase in the relative price to the 52-week high is associated with 0.157% increase in BHAR in 365-day time. In the same vein, if insiders trade 7 days earlier that is equivalent to a 2% increase in the recency after the 52-week low, their return in 365-day time is 0.178% lower. The coefficients for _52_W_L and _52_W_H_Rec for 365-holding periods are both statistically indifferent from zero. In columns (6) to (8), all results remain roughly unchanged. The coefficients of the relative price to the 52-week low remain insignificant. In particular, a 1% increase in the relative price to the 52-week high is associated with 0052% increase in BHAR in 365-day time. If insiders net sell 7 days earlier after the 52-week high (low) is, their return in 365-day time is 0.056% higher (0.064% lower). These results suggest that if insiders want to buy, they should buy when the price is close to its 52-week high, and immediately after the 52-week high. Similarly, insiders should sell at a price that is far from the 52-week high or immediately after the 52-week low. There is a short-term positive price momentum associated with the 52-week high, and therefore, insiders should sell at a longer time distance from the previous high.

We consider that insiders' trading decision may also vary depending on the difference between the stock's 52-week high and 52-week low, which is the tightness of the price range. To investigate whether the documented trading behaviour is robust across different level of price tightness, we sort all insider trading transactions into quintiles in every month in accordance with their tightness, which is the difference between stock's 52-week high and 52-week low, normalised by dividing the current stock price.[35] We include the quantiles as a variable named *Tightness*, and interaction terms between the *Tightness* and $\_52\_W\_H$, and between *Tightness* and $\_52\_W\_H\_Rec$. Table 7 Panel A reports the descriptive analysis of this tightness and quintiles. The top (bottom) quantile indicates low (high) price tightness. Panel B displays the regression results without the coefficients of control variables, which remained relatively consistent, for brevity purposes. Panel A shows that the stock price is far (close) from its 52-week high when the price tightness is low (high). Similarly, when the tightness is high (low), insiders are prone to trade with a shorter time distance from the last 52-week high, because tightness is normalised by the current price, and when it is high the current price is high and, thus, closer to the 52-week high. The result in Panel B indicate, that the larger the distance between the 52-week high and 52-week low, the less likely that an insider will sell at

[35]Results remain the same if we use either 52-week high or 52-week low to normalise the difference in 52-week high and 52-week low.

52-week high evident by the positive and statistically significant coefficients of the interaction variable $\_52\_W\_H * tightness$ computed in both logit and fixed-effect estimators.

For the 52-week low, we observe the same scenario. These positive and statistically significant coefficients for $\_52\_W\_L$ and $\_52\_W\_L\_Rec$ imply for the same level of relative price or recency, insiders are more likely to increase their holding when the price range is broader. In other words, when the 52-week high is distant from the 52-week low, the insider selling pressures are attenuated because they are less concerned about the potential that stock prices may decline.

Overall, these empirical results have shown that insiders unambiguously demonstrate a trend to reduce holding at the 52-week high and increase ownership at the 52-week low, and their sell-at-peak transactions are systematically followed by positive stock returns which indicate losses to insiders whereas their buy-at-through trades generate positive returns that represent trading profits to themselves. Although these results appear to be in support of the argument of Lee and Piqueira (2019) that insiders are on average unformed at the 52-week high because they suffer from anchoring bias, there is another possibility that have been overlooked by most of the literature that is insider dissimulation introduced by Huddart *et al.* (2001). Thus, we attempt to disentangle the insider trading strategy in the next section.

[Insert Table 7 here]

4.5 Insider sell dissimulation at these price extremes

Huddart *et al.* (2001) proposes a theory of insider dissimulation. They propose that the implementation of the U.S security law [36] will increase the market scrutiny of insiders' transactions and reduce insider dealing profitability by strictly regulating corporate insiders to publicly disclose their transactions in 2 days after execution. Despite potential lessening of insiders' returns by as much as a half because of the improved market efficiency, trading on private information remains a profitable strategy for insiders. Consequently, if insiders are profit-maximizing agents and are actively materialising their private information, they have the incentive to dissimulate their private information by randomly trading in a manner that is inconsistent with their informational agent role. In other words, they will intentionally make noisy transactions to thwarts the outsider who intend to follow them if their private information

[36] When the paper was published, the Sarbanes-Oxley act which imposes a stricter regulation than the U.S security law on insider trading, was not in effect.

is long-lived[37]. The dissimulation strategy is relevant to our study because We have not ruled out the possibility that insiders are not suffering from anchoring bias but dissimulating their private information at the price extremes. Existing literature has documented that when the stock price is approaching the 52-week high, uninformed investors are less able to study the fundamental of a stock and cannot make rational investment decision on average (George and Hwang (2004)). Consequently, we expect a higher likelihood that uninformed investors will blindly follow the trading decision of informed investors. In response to the severe miss-pricing at the price peak, we hypothesise that insiders will more actively make uninformative sell transactions to disguise their private information. To the best of our knowledge, the paper is the first to advance insider dissimulation strategy at the 52-week high, partly attribute to the difficulty of differentiating long-lived information from short-lived information.

We follow Biggerstaff *et al.* (2020) who conclude that when insiders possess long-lived information, they will split their information into multiple sell transactions, referred to as sequence sells, instead of executing one large-size sell transaction, referred to as isolated sell. The motivation behind the trading strategy is that a sequence of sell transactions can better minimise the impact of incorporating private information on the stock price than a single transaction, and thus to fully exploit their private information. Inspired by these findings, we stress the importance of differentiating two types of returns which are transaction return denoted as *All* and sequence return denoted as *Scaled Holding Return*. Transaction return is the naïve unconditional average return of transactions by implicitly assuming each transaction is independent and closed at different points of time. *Scaled Holding Return* is the return of a sequence in which all positions are assumed to be closed at 30/180/365 calendar days after the termination sell. Because the length of different sequence is varying, we calculate the average BHAR and then scale the average BHAR by multiplying the median number of trading days for 30, 180 and 365-holding periods, which are 22, 126 and 252, respectively. We hypothesise that if insiders indeed dissimulate their long-lived private information and gradually incorporate them into the stock price, their transactions in sequence sell should generate positive transaction returns which indicate a loss for sellers whereas their *Scaled Holding Return* must be negative which implies that they indeed possess private information. The positive return can thwart outsiders to believe they are on average not informed at the 52-week high, and the negative return hints that they eventually reap a gain for themselves at the end of

[37]Insiders with short-lived information cannot adopt dissimulation strategy because the information will soon be revealed to the market.

the sequence. Furthermore, it is not possible for insiders to generate negative BHAR without disclosing it to the public; otherwise, it would be illegal insider trading which is not the focus of our study. The *Scaled Holding Return* best mimics the return that an insider would be able to realise in the entire duration of a sequence sell[38]. The hypothesis implies that if an uninformed investor opts to replicate insider's sell transactions at the 52-week high, they will incur a loss if they randomly pick and replicate insiders' sell transactions because the average return is positive. The outsider can only generate a negative return if they are able to identify those noisy sells or replicate the entire sequence of sell. In the paper, we make the logical assumption that uninformed investors, by definition, are not capable of differentiating dissimulating sell from informative sell.

Following Biggerstaff *et al.* (2020), we define a sequence of sell transactions as sell trades executed with a maximum time distance of 60 calendar days from the last sell transaction or the next sell transaction. These two criteria can identify all the initiation sell, termination sell and sells in-between. We define the rest of sell transactions as isolated sell[39]. While Biggerstaff *et al.* (2020) aggregate insider transactions at the end of month, we keep all our sample at the insider-day level to conduct a finer analysis. We classify Sell-At-Peak insider transaction when the $\_52\_W\_H \geq 0.98$[40]. We focus on those sequences that contain at least one sell transaction classified as Sell-At-Peak. To better capture the sequence that occurred at the 52-week high, we restrict that the sequence must be initiated at most 30 days before and terminated 30 days after the Sell-At-Peak transaction (hereafter referred to as *sequence (30)*). For robustness, we also present the results for sequence that initiated at most 60 days before and terminated at most 60 days after the Sell-At-Peak transactions (hereafter referred to as *sequence (60)*). The choices of 30 and 60 days are arbitrary, a longer period will allow a larger sample size but at the same time reduce the relevance of insiders' trading informativeness and

[38] To provide an example of insider dissimulation sell. Mr Katzenberg, Jeffrey, the CEO of DreamWorks Animation (cusip: 26153C10), sold 25,935 shares and 20,700 shares of his company in 28/10/2014, 06/11/2014 respectively. We recognise these two sells as one *sequence sell*. The 30-,180- and the 365-day holding BHAR for the former sell is -3.81%, 1.79% and -12.00%, respectively. The 30-,180- and the 365-day holding return for the latter sell is 4.29%, 8.10% and 1.78%, 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 cumulated from 28/10/2014 to 30, 180 and 365 days after 06/11/2014, is -0.044%, -1.134% and -6.804%, respectively. We classify the *sequence sell* as dissimulating sell for 30- and 180-day holding periods.

[39] To illustrate, if an insider made four sell transactions on each of 1st of January, 15th of January, 2nd of February and 10th of March, the first four sell transactions are defined as one sequence sell and the one occurred in March is recognised as one isolated sell.

[40] Our result is robust if we use 0.9, 0.95 or 0.99 cut-off points, and robust to the top decile classification we used in section 4.3.

the 52-week high. If a sequence is initiated long time ago before the price approaches the 52-week high, it is difficult to believe insiders has factored the price peak into their information sets at the time they initiated the sequence. We do not focus on buy transactions because we already showed that these transactions are on average informative at the 52-week high and low and are less likely to be employed to dissimulate their private information. We remove Sale-Pose Exercise in the construction of sequence. In addition to the *All* and *Scaled holding return*, we also calculate the termination sell return denoted as *Following Sequence*. To maximise the comparability, we multiply the average BHAR for 30-, 180- and 365-day holding periods by the median number of transaction days which are 22, 126 and 252 days respectively. We present the results in Table 8.

[Insert Table 8 here]

Table 8 Panel A reports the summary statistics of sequence and isolated sell by dividing the sample into *Sell-At-Peak* group and *Other* group. We classify 392,692 sell transactions as either isolated or sequence sell, more than half of total sells are sequence sell[41]. At the 52-week high, the number of isolated sells is 38,868, very close to sequence sell of 34,036. Out of 34,036 sequence sells, 18,804 of them occurred in *Sequence (30)*. In column (4) to (6), we observe 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)* occurred not at the peak. The result is expected as *Sequence (30)* is closer to the peak by construction. On average, there are 3.21 transactions in a signal *Sequence (30)*, and the sequence only last for 13 days on average. The result implies that if we aggregate our sample at month instead of day, all this information will be disregard[42]. The average sequence length is 1267 days at the 52-week high and is statistically shorter compared with the average length of 158 days when price is away from its peak.

We report the unconditional BHAR in Panel B. After separating sales into isolated sell and sequence sell, we find isolated sell become informative on average whereas sequence sells remain uninformative. The result is in line with Biggerstaff, *et al.* (2020) which report unconditional isolated sell is informative. The average daily transaction return *All* for sequence sell is statistically significant 0.2%, 0.5% and 1.3% for these three horizons, respectively. However, as we stressed before, treating each sell in a sequence as independent transaction is

[41] 55.3% sell transactions are sequence sell: （34,036+176,326）/392,692=0.536

[42] Biggerstaff *et al.* (2020) report a higher number of trades per sequence, because they aggregate sample at monthly frequency. To illustrate, a trade executed on the 1st of January will be included in the same sequence with a trade executed on the 31st of March because they allow for one-month gap between two months. In our identification scheme, they are two different isolated sells.

misleading because some dissimulation sells are noisy and driving the average daily return biased upward. Furthermore, a sequence of sell transactions will yield -0.1%, -3.3% and -6.6% *Scaled holding return*in the next 30-, 180- and 365-day holding periods, respectively. All these returns are statistically significant at the 99% confidence level. If we focus on the last transaction in a sequence, the daily *Following Sequence* is -1.5%, -2.1% and -1.3% in 30-, 180- and 365-day holding periods, respectively, and all significant at the 99% confidence level. These results are consistent with the main findings in Biggerstaff, *et al.* (2020) which report insiders trade on long-lived information, and they will on average terminate their sell sequence with a profitable sell. Panel B reaffirms the finding 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 isolated sell at the 52-week high, they systematically generate positive returns for all holding periods, the result is consistent with our previous findings that insiders are less informed at the 52-week high. The same positive returns can be observed if we calculate the average transaction return of each sell in a sequence. If we assume each transaction in a sequence is closed at different point of time, then on insider sell transactions will generate 0.5%, 1.8% and 2.0% positive and statistically significant BHAR in the next 30-. 180- and 365-day investment horizons, respectively. If we assume insiders realise their profit or loss of all positions in a sequence at the same time, the *Scaled holding return* can best gauge their actual returns. *Scaled holding return (30)* is a statistically significant -0.6%up to 180-days after the termination sell. Under the short-swing rule, 180-day since the termination transactions is also the shortest holding period that insiders must wait to realise their capital gain. *Scaled holding return (60)* generates a statistically significant 0.7% for the mid-term. For the 365-day holding period, *Scaled holding return (30)* predicts a statistically significant negative return of -3%, whereas *Average holding return (60)* displays a statistically significant -0.1.7%. BHARs for the *Following Sequence (30)* and *Following Sequence (60)* are -0.005% and -0.008% for the next 30-day period, and both are statistically significant at the 99% confidence level, respectively. However, *Following Sequence (30)* and *Following Sequence (60)* will generate zero return in the long term. These results highlight that if the sequence is initiated closer to the Sell-At-Peak transactions and closed soon thereafter, the predictability for a future negative BHAR is higher. The positive return predictability embedded in *All* and the negative return predictability of *Scaled holding return (30)* both are consistent with our hypothesis and further confirm that insiders do dissimulate their private information by conducting uninformative sell transactions at the 52-week high.

Nonetheless, we reckon the change from the unconditional positive BHAR predictability of sequence sell to the negative BHAR predictability of *Scaled holding return (30)* or *Scaled holding return (60)* of sequence sell may be caused by the exclusion of sequence that is initiated long time prior to the 52-week high. Therefore, we further calculate the unconditional BHAR for the sample of sequence sell we used to calculate *Scaled holding return (30)* and *Scaled holding return (60)*. In an untabulated result, these BHARs for three holding periods for both series are all positive and statistically significant at the 99% confidence level. That is, for the same sample of sequence sell that initiated and terminated close to the 52-week high, the change in return predictability persists. Therefore, the result reaffirms the importance to consider the sequence return rather than transaction returns and shows the change in return predictability is robust to the removal of sequence sell began in the remote past.

Moreover, Kose and Ranga (1997) theoretically show that insiders will intentionally trade at the wrong direction or trade against their own private signal to manipulate the market and, then, capitalise a higher return, as uninformed investors will mis percept their transactions at the wrong direction. We consider this possibility for both the buy and sell trades with transactions in a sequence can only occurring at the most 60 days apart. We aggregate all the transactions in a sequence by value and report the results for those net-selling sequences in Panel D. In Column (1) and (2), we report the unconditional sequence return. We compare the net-selling sequences that are not mixed with any insider buy with mixed sequences that contain buy and sell. The mixed sequence systematically generates a lower 0.5%, 1.4% 2.7% *Scaled holding return* in the 30-, 180- and 365-day holding periods, respectively. These differences are all statistically significant at the 99% confidence level. These results are consistent with the prediction in Kose and Ranga (1997) that insiders may switch their trading directions to disguise their private information and to minimise the price impact of their transactions. In Column (4) and (5), we solely focus on the sequence occurred at the 52-week high and both initiated and terminated 30 days around the 52-week high. The *Scaled holding return* for mixed sequences is statistically indifferent from zero in the 30- and 180-day periods but lowers to a significant -8.7% at the 95% confidence level at the 365-day investment horizon. However, the difference between column (4) and column (5) are not significant . The sample size of net-selling sequence mixed with buy is extremely small. For unconditional sequence, only 2.8% of the sample is mixed sequence, the ratio further lowers to 1.3% if we focus on the sequence occurred at the 52-week high. According to the short-swing rule, insiders are not allowed to realise any capital gain from two off-setting trades within the first 6-month. The short-swing rule will inevitably apply to those buy transactions identified in a mixed net-selling sequence and weakens the market reaction to these mixed sequence (Kose and Ranga, 1997). Consequently, corporate insiders rarely mix buy and sell transactions in a sequence. Nevertheless, there is weak evidence to show that when insiders mix buy and sell in a net-selling sequence at the 52-week high, the return is lower.

Lastly, we re-estimate the Table 6 by removing sequence sell at the 52-week high and low. We document that insiders still demonstrate 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 our previous findings remain robust. In sum, we conclude that not all insiders at the 52-week high are suffering from anchoring bias, around half of the sells occurred at the 52-week high are information-driven, the other sells are indeed initiated by non-information motivations. Many insiders dissimulate their private information by executing noisy transactions. After correcting for return of dissimulation trade, insiders are informed on average when they sell at the 52-week high and low.

5. Robustness test

5.1 Anchoring bias with the presence of asset pricing anomalies

Although we have successfully found the evidence to support the insider trading pattern of systematically reducing holding at the 52-week high, other factors such as pricing anomalies will motivate insiders to trade other than the 52-week high price level. Stambaugh *et al.* (2012) investigate eleven asset-pricing anomalies. Hwang and Liu (2012) and Lee and Piqueira (2017) both provide evidence to show that informed participants, such as arbitrageurs and short-sellers, actively trade on these eleven anomalies and to reap an abnormal profit. As one of the sophisticated traders, corporate insiders also frequently consider asset-pricing anomalies as a signal to trade. Contreras, Fidrmuc and Kozhan (2017), Dargenidou, Tonks and Tsonligkas (2018), Contreras and Marcet (2020) provide evidence to show that corporate insiders actively trade on the Post-Earnings Announcement Drift, correct the mispricing caused by the famous anomalies, and therefore facilitate price discovery. Anginer *et al.* (2018) examine insider trading in the content of thirteen asset-pricing anomalies. They conclude there is often a discord between insiders' trading direction and asset-pricing anomalies' normative directions. If insiders trade in the same direction as suggested by asset pricing anomalies, the return predictability and profitability are both higher. On the other hand, if insiders trade against market anomalies, then the return momentum associated with these anomalies vanishes. Consequently, our previous results do not rule out the possibility of that insider is exploiting on these market anomalies instead of trading on the 52-week high price levels when the stock price approaches the past extremes. Thus, in the section, we aim to investigate whether our main result is robust with the inclusion of asset pricing anomalies.

We repeat the regression analysis in Table 6 after accounting for the effect of asset pricing anomalies suggested by Stambaugh *et al.* (2012). Following Anginer *et al.* (2018) and Lee and Piqueira (2017), we replicate eight out of eleven anomalies introduced in Stambaugh *et al.* (2012) and omit Ohlson's (1980) O-score and composite equity issues because they capture the same underlying risks as Campbell, Hilscher and SzilagyWe (2008)'s failure probability (FP) and net stock issue (NSI). Furthermore, we already controlled momentum anomaly, suggested by Jegadeesh *et al.* (1993) and is one of eleven anomalies. These eight anomalies are Total Accruals (TA), Net Operating Assets (NOP), Gross Profitability (GP), Asset Growth (AG), Return on Assets (ROA), Investment-to-Assets (IA), FP and NSI. We follow the original reference papers as closely as possible to construct these anomalies. Appendix 5 describes the construction of these eight anomalies in details, together with their reference papers. Because FP is a fitted value of regression with eight independent variables whose coefficients are computed by Campbell *et al.* (2008), and therefore Appendix 6 describes the construction of FP in more details. Appendix 7 explains which Compustat items are employed to construct these anomalies. Summary statistics of these eight variables to compute FP are carefully compared with Chen, Novy-Marx and Zhang (2011) to ensure the sample accuracy. In an unreported result, we also check the correlation between these eight anomalies plus momentum, the correlation between these nine variables are generally low, the highest correlation is -0.33 between FP and ROA, the low correlation is consistent with the result reported in Anginer *et al.* (2018).

All these eight anomalies have a clear normative direction, which indicates the relationship between the anomaly variable and subsequent abnormal return. Among these eight anomalies, only ROA and GP are positively associated with the stock future abnormal return, and all other six are negatively associated with the stock future abnormal return (Stambaugh *et al.*, 2012). However, Anginer *et al.* (2018) have provided evidence to show that insiders do not necessarily trade with the normative direction indicated by the anomaly; the discord among insiders and anomaly is not unusual. If insiders possess private information that the price has not incorporated, they will trade against the market anomaly and exploit outside investors who naively follow these normative directions. Therefore, readers should not place too much importance on the coefficient on anomaly variable in our logit model because it can take either direction. Nonetheless, the anomaly variable is statistically significant at the 99% confidence level in all columns except for NSI and TA, and the result is broadly consistent with the finding that insiders actively react to market anomalies and trade on them.

[Insert Table 9 here]

Table 9 Panel A reports the regression result for 52-week high and 52-week low separately. We control for one anomaly variable at a time, indicated at the bottom of each column. For 52-week high, the coefficients for the $\_52\_W\_H$ and $\_52\_W\_H\_Rec$ are negative and statistically significant. The result for 52-week low is mixed. While the positive coefficient for $\_52\_W\_L\_Rec$ is statistically significant at the 99% confidence level across all columns, the negative coefficient of $\_52\_W\_L$ is significant, except that it is not significant when anomaly is defined as IA and becomes positive for TA.

Overall, our main results survive a battery of robustness test after controlling for other market anomalies and suggest that insiders' trading decision at 52-week high and low are not merely a reflection of insiders' exploitation on other asset pricing anomalies documented in the existing literature.

5.2 Other robustness tests

To account for the type of insider, we focus on only executive and non-executive board members. We exclude non-board members who are subject to the same regulation as board members because they also have access to material information, but their relatively lower seniorities imply that they only have limited access to price-sensitive information compared to board members. Thus, their trading decisions are nosier and contain less price-sensitive information. To alleviate the concern that our previous findings were driven by these less informative transactions, and their exclusion will improve the external validity of the study because our sample consists of more sophisticated market participants. Noteworthy, the reason that our sample size is larger than the existing literature that has employed Thomson Reuter Insider Filling is that Smart Insider has better coverage on senior officers. By excluding the transactions submitted by senior officers, the comparability between the study and the existing literature further improves. Table 9 Panel B displays the regression output. We lose around 34% of the entire sample because of the exclusion of senior officers. All signs of coefficients and significance remain consistent with Table 6. For the 52-week low. the evidence for insiders' increasing demand is significant. When the $\_52\_W\_L$ decreases, which implies the current price is dropping to the 52-week low, insiders who are board members unambiguously increase their holding and signal undervaluation of the stock. The result is expected because board members are primarily responsible for the stock performance, and liable to shareholders, and therefore have higher incentives to signal undervaluation. Furthermore, the recency of 52-week low is robust and remains as one of the key determinants for insider trading throughout the study. In conclusion, our result is robust to the exclusion of senior officers.

We,then, use an alternative measure for the relative price and recency ratio. Instead of using the 30-day average price and 30-day average distance, we use the ratio that uses the price and 52-week high or low at the end of last calendar month, which is consistent with the previous literature in Lee and Piqueira (2019).

$$\_52\_W\_H_t = \frac{Price_{m-1}}{52\_Week\_High\ Price_{m-1}}$$

$$\_52\_W\_L_t = \frac{Price_{m-1}}{52\_Week\_Low\ Price_{m-1}}$$

$$\_52\_W\_H\_Rec_t = 1 - \frac{time\ distance\ between\ 52\ week\ high\ \ and\ m-1}{364}$$

$$\_52\_W\_L\_Rec_t = 1 - \frac{dtime\ distance\ between\ 52\ week\ low\ \ and\ m-1}{364}$$

That is, for any insider transactions occurs on day t, the ratio is computed by using the stock price and 52-week high or low on day $m-1$, which is the last trading day at the end of last calendar month. Then We repeat the logit and fixed-effect regression with the same regression specification in Table 6. In an untabulated result, all the signs of coefficients of both variables with interests remain unchanged. All significance remains consistent with the previous result.

Next, we restrict our sample to stocks that have truly broken the 52-week high/low, rather than the change in 52-week/low was due to the lapse of time.We define a stock truly breaks its 52-week high/low when the new 52-week high (lower) is high (lower) than its 52-week high (low) in the previous trading day. We repeat the Table 6 with the same specification on the sample of firms that truly broke either the 52-week high or low at least once between (t-1, t-365). For brevity, we omit the regression output. All significance and sign of coefficients obtained from both the logit and fixed effect regression remain consistent with Table 6.

As the fourth robustness test, we restrict the sample to stocks that reached their 52-week high or low in the past 30 days. Because the mean (median) recency is 194 (203) days for net purchaser and 131 (86) days for net sellers as presented in summary statistics, our result could be driven by samples that is irrelevant to the previous 52-week high or low. We repeat the Table 6 without $\_52\_W\_H\_Rec_t$ and $\_52\_W\_L\_Rec_t$. In untabulated result, we find the sign and significance of $\_52\_W\_H$ remain robust regardless the sample size and sample screen.

However, the coefficient of the 52-week low ratio becomes statistically insignificant. The results do not alter our conclusion that insiders predominately sell at the 52-week high.

As the fifth robustness test, we exclude insider trading occurred in January from our sample. George and Hwang (2004) and Bhootra and Hur (2013) show demonstrated that investors' trading behaviour is systematically different in January compared with other calendar months. The removal of January sample will significantly improve the profitability of a long-short trading strategy based on either the relative price or the recency of stock price to its 52-week high because the losers on their short-side witnessed a surge in return. In the untabulated result, all the previous findings remain robust when we exclude January trades, and the significance of variables with interests remain virtually unchanged. When we repeat our regressions using a much smaller January sample, all the results remian robust, execept the coefficient of the 52-week low ratio becomes insignificant. Hence, our previous finding was not driven by the January sample, and insiders' trading behaviour remains broadly consistent with the previous.

6. Extension

6.1 Informational content in dissimulation sell

In the previous sections, we documented that some managers execute profitable dissimulation sell transactions when the stock price is close to the 52-week high. These managers outperform the average insider sell transactions. They materialise their private information by generating more negative BHAR. The return predictability originates from either the future fundamental or the subsequent price correction process. In this section, we examine whether insider's dissimulation trading decisions predict future earnings surprises or not to disentangle the source of return predictability behind their trading decisions.

We employ two commonly used proxies to measure earnings surprises. The first is the 3-day Cumulative Abnormal Return (CAR) around the next one to four quarterly earnings announcements estimated using market model[43]. We use CRSP value-weighted index as the benchmark return and set the estimation window to be $(-250, -100)$ with at least 100 days of valid return data. For the second measure, we follow Bernard and Thomas (1990) to construct Standardised Unexpected Earnings, SUE, as follows:

$$SUE = \frac{(EPS_{j,q} - EPS_{j,q-4} - \mu_{q-7,q})}{\sigma_{q-7,q}}$$

[43]Our result remains consistent if We use 5-day event window or estimate the CAR using Market-Adjusted Model.

where EPS is the earnings 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 past 8 quarters earnings. CAR captures the surprise in all aspects of company's quarterly earnings announcement whereas SUE only captures the surprise in earnings but not endogenously released information such as private communications, conference calls etc. Furthermore, Kishore, Brandt, Santa-Clara and Venkatachalam (2011) have concluded that these two measures are independent because investors can react to both earnings surprise captured by SUE and other relevant information proxied by CAR, and one effect does not subsume the other. Therefore, we expect the regression coefficients and statistical significance could be different between the regressions using these two different dependent variables.

We take these two measures for the next four 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 $NPV < 0$. *Dissimulation30D, Dissimulation185D, Dissimulation365D* are dummy variables that equal to one if *Scaled Holding Return* is negative while unconditional *BHAR* is positive for 30-, 180- and 365-day holding periods. Control variables are the same as Table 6 with the additional inclusion of lagged dependent variable[44]. Variables with interests are the *DissimulationD* and the interaction variable between *SellpeakD* and *DissimulationD*. If insiders are trading on their private information regarding the firm's future fundamental (earnings surprise), we expect the coefficient is statistically significant and negative when the dependent variable is CAR (SUE). If insiders are correcting misspricing without any material information regarding the future fundamentals or earnings information, then the coefficient should be either insignificant or inconsistent with their trading directions. We control for the firm, month, director fixed effects and cluster standard error at firm-month level. We run the regression by using insider sell sample only and present the regression result in Table 10. For brevity, we do not report all control variables whose signs and significance are consistent with the existing literature.

[Insert Table 10 here]

In Table 10, we report that the coefficients for *SellpeakD* is mostly insignificant except when the dependant variable is $SUE_{(q+2)}$ and $SUE_{(q+4)}$. The insignificance of *SellpeakD* is consistent with our previous findings that insiders' sell at the peak is on average non-information-driven. These results are as expected because the sample only consists of insider

[44]All our results and statistical significance remain robust with the exclusion of lagged dependent variable.

sell. We already documented in the previous sections that average sell-at-peak transactions are uninformative and embed a positive BHAR predictability. Stock prices keep increasing after insiders reduce holding. The original of the upward price movement is the future earnings surprise. These results are inconsistent with Ke, Huddart and Petroni (2003) who employ return-based measure and report insiders' sale, on average, can anticipate negative earnings up to 2 years in advance.

In contrast, *DissimulationD* are all negative and statistically significant when the dependent variable is CAR, but mostly insignificant when the dependent variable is SUE. Our results suggest that the documented unconditional earnings predictability embedded in insider sale is only witnessed in dissimulation sell transactions at the 52-week high, not in the average sell transactions. More importantly, the interaction terms between *SellpeakD* and *DissimulationD* are statistically negative only for $CAR_{(q+4)}$ but not SUE, suggesting that the profitability of insider dissimulation sell at the 52-week high originates not from accounting-based information but announcement-based information. Insiders are strictly prohibited to trade on future accounting information because this information are not disclosed to the public prior to their transactions, trading on accounting-based information will impose higher litigation and social risks (Anderson et al., 2020). However, our result suggests that they affect the stock price through other channels such as private communication, conference calls etc. Undoubtedly, this information is endogenously released, and managers can profit from this information. For 365-day holding periods, they mainly express their concerns regarding the firm’s future in the next and fourth quarterly earnings announcements. Overall, our results shed light on the information content embedded in the insider dissimulation sell.

6.3 Heterogeneous characteristics of insiders who employ dissimulation strategy.

In this section, we attempt to identify four heterogeneous characteristics of insiders who employ dissimulation sell at the 52-week high. We recognise that insider dissimulation strategy is only feasible with their sell transactions because their purchases are informed on average. Consequently, we run all regressions by only using net selling sample in this section because the inclusion of insider purchase will falsely decrease the occurrence of insider dissimulation sell. The first characteristic is the investment horizon. Akbas *et al.* (2020) is the first paper that proposes a method to differentiate insiders’ investment horizons. They define insiders with 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 realise profit or loss. They discover that SH insiders are systematically more informed than LH, and thus, there is more informational content embedded in their trading decisions. Motivated by their results, we further expand our study to the relationship between the insider dissimulation sell and insider investment horizon.

The role played by investment horizon in insiders' dissimulation trading motivation is not conclusive in the context. On the one hand, SH insiders may be more likely to employ dissimulation strategy because their transactions are more profitable on average as evident in Akbas *et al.* (2020). Dissimulation strategy will improve their return predictability when they sell. On the other hand, LH insiders may better possess long-lived information that will enhance their dissimulation strategy's return predictability. Noteworthy, these two types of insiders can also employ dissimulation strategy at the same time, the strategy is not mutually exclusive depending on their horizons. We investigate the propensity of these two types of insiders to employ dissimulation strategy by constructing SH and LH horizons following Akbas *et al.* (2020). Firstly, we define Horizon, HOR, as:

$$HOR_{i,j,t} = \left|\frac{\sum_{Year-10}^{Year-1} NPR_t}{N}\right| \times (-1)$$

That is, for each year, we compute the annual NPV, calculated in the same way as We outlined in the methodology section but in yearly frequency, for each insider We in firm *j* in year *t* in the last ten calendar years. Then, we compute the average NPV by summing the annual NPV and divide by the number of calendar years that an insider has traded in the last ten calendar years. We take the absolute value of the average annual NPV and times -1, which means HOR can only take a value between 1 and -1 because NPV is between 1 and -1 as well. If an insider only sold (bought) in the last ten years, then each of its NPV is -1 (1), and therefore, the average will be -1 (or 1) as well. If we take the absolute value of the average NPV and times -1, the HOR will be -1 for an insider who has only traded in one direction. Remarkably, the measure disregards the directions of insider trading by construction. If insiders had executed both buy and sell transactions in the last ten calendar years, their NPV would be between -1 and 1. Consequently, their HORs will be higher than -1. Therefore, the higher the HOR, the shorter the investment horizon the insider has in mind. Insiders who traded in less than four calendar years in the previous ten calendar years are excluded from the exercise, and they are neither SH nor LH insiders. I, then, sort HOR, calculating for each insider in each year, into quantiles. Insider in the top (bottom) quantile is defined as SH (LH) insider. We reclassify each insider at the beginning of each year. Noteworthy, we apply a different method to define SH and LH insiders because of different screening process and database used. Akbas *et al.* (2020) have a large number of LH insiders with $HOR = -1$. They define SH insiders as those with HOR above the median of the rest of the sample[45]. Our main variable of interest is *Short-Term_Dummy* and *Long-Term_Dummy* that equals to one for SH and LH insiders respectively, and zero otherwise. The dependent variables are Dissimulation30D, Dissimulation185D, Dissimulation365D, dummy variables that equal to one if *Scaled Holding Return* is negative while unconditional *BHAR* is positive for 30-, 180- and 365-day holding periods. As we use the first 10-year data to identify the investment horizon of insiders, the regression only uses net selling sample after 2003[46]. Table 11 Panel A displays the output.

[Insert Table 11 here]

Panel A shows that both SH and LH insider are more actively adopting dissimulation strategy at the 30- and 365-day holding horizons when selling. In an untabulated result, we include mid-term dummy for mid-term insiders and exclude SH and LH dummies. The coefficients of mid-term dummy are all negative and statistically significant at the 30- and 365-day holding horizons. Overall, these results suggest that both SH insiders and LH insiders prone to use dissimulation strategy, and they are not necessarily conflicting as while SH insiders are more informed and their higher informativeness can be partly attributed to their use of dissimulation strategy, LH insiders use dissimulation strategy by better accessing their long-lived private information.

The second characteristic is the gender. Inci *et al.* (2017) focus on the U.S throughout January 1975 to December 2012 and demonstrate that when female and male insiders have the equal formal status within a firm, female insiders face a greater difficulty to access private information and have an informational disadvantage compared with male insiders. Overall, male executives can make a 3.2% abnormal return over a fifty-day event window after the insider purchase date, whereas female executives can only gain 1.6%. Eckbo and Odegaard (2019) focus on the Oslo Stock Exchange where the presence of both genders of executives on the board is more balanced because of the enactment of board gender-balancing law in 2005, which restricts the board, must have at least 40% of each gender. The paper shows that female purchased more, in both relative and absolute terms than male insiders during the financial crisis, and the evidence is not supporting the conventional view that female is more risk-averse than male investors, in contrast, they are less risk-averse than male. We contribute to past

[45] In untabulated result, all our conclusion and significance remain unchanged if We strictly follow the definition proposed by Akbas *et al.* (2020).
[46] In untabulated result, our conclusion is robust if We use an identification period of 7 or 13 years.

literature by investigating whether male investors are more likely to conduct dissimulation trade than females. Smart Insider does not collect the gender information of corporate insider, and therefore, we use the following procedure to obtain the gender of an insider in our sample. Firstly, we use Lax-Martinez and Saito (2016)'s worldwide gender-name dictionary to match insiders' first name with their gender. This approach allows me to partition our sample into three sub-samples, insiders with a male first name such as Robert, insiders with a female first name such as Christina, and insiders with a unisex first name such as Joey. Another advantage of using this dictionary is to easily match non-Anglo-Saxon-name because of its worldwide coverage, such as the male first name of Aagman. Second, we use BoardEx to manually collect the gender information of these insiders with the unisex first name. The final sample consists of 7.3% of female transactions and 92.7% of male transactions, in line with the 4% of overall female transactions reported in Inci *et al.* (2017)[47]. We drop around 5% of the transactions that account for 6% of insiders either, because their gender information is missing in both BoardEx and worldwide gender-name dictionary, or their first name does not have gender implication[48]. We create a dummy variable that equals to one for male and zero otherwise. Table 11 Panel B displays the regression outputs. In summary, we find evidence to support that male insiders are more likely to employ dissimulation trading strategy. The result provides additional insight to the finding in Inci, et al. (2017) and suggest that the better access to private information that male insiders possess may motivate them to employ dissimulation strategy.

For the third characteristics, we focus on the propensity of board member to employ dissimulation strategy. We use Smart Insider to extract Board members' information. Table 11 Panel C displays the regression results. Board members display a higher propensity to dissimulate their long-lived information when they sell because the coefficients are all positive and statistically significant at the 99% confidence level. We further create dummy variables for CEO and CFO who have the most superior access to sensitive information. Panel D displays the result. The coefficients for CEOs and CFOs are both significant (insignificant) at the 30-day (180-day) holding horizon. For 365-day holding horizon, the coefficient for CEO (CFO) dummy is significant (insignificant). Overall, these results show that CEOs are more likely to employ dissimulation strategy whereas there is no significant difference between CFO and other insiders.

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[47]IncWe *et al.* (2017) cover the period from 1975 to 2012. The presence of female board member is rare in the early years, and therefore, a lower proportion of female transactions is reasonable.

[48]For instance, some Chinese unisex first names are commonly shared between male and female. We drop insiders whose gender information is missed on BoardEx.

For the fourth characteristics, we focus on the propensity of opportunistic insiders to employ dissimulation strategy. We define opportunistic insiders based on Cohen *et al.* (2012) who define routine traders as insiders who have previously traded in either direction in the same calendar month for at least three consecutive calendar years, and all other insiders are opportunistic traders. They reclassify each insider by using a three-year rolling window identification period at the beginning of each calendar year. To qualify to be a routine or opportunistic insider trader, a given insider must have traded at least once in the last three calendar years. We replicate Cohen *et al.* (2012) identification method precisely. We hypothesis that board members have better access to long-lived information and therefore more likely to employ dissimulation strategy. Similarly, opportunistic insiders are privy to private information by definition, and therefore, they will actively employ dissimulation strategy to materialise their informational advantages over uninformed investors. Table 11 Panel E displays the regression results. Opportunistic insiders actively dissimulate their informational advantage by randomly making noisy trades. The coefficients for all holding periods dissimulation dummy are significant. The result can explain and directly challenge the puzzling finding in Lee and Piqueira (2019) and Li *et al.* (2019) that opportunistic traders who have higher profitability empirically, are more susceptible to the anchoring bias. our result suggests the opposite story that because opportunistic traders are more likely to employ dissimulation strategy and therefore, they display a higher propensity to sell at the 52-week high.

7. Conclusion

In this study, we conduct a comprehensive analysis of insiders' transactions at the 52-week high and low and reassess the recent findings that insiders suffer from the anchoring bias at these two price levels. We firstly examine insider's transaction returns around 52-week high and low and conclude that there is no evidence to support that insiders suffer from 52-week low anchoring bias because their purchase transactions are informative. In contrast, insiders' sell transactions at the 52-week high indeed incur losses. Second, we form two 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. We found that if we long the portfolio that insiders buy at the 52-week high and short the portfolio that insiders sell at the 52-week low, the strategy will generate a 19.2% BHAR in 12-month holding period. However, if we long the portfolio that insiders increase their holding shortly after the 52-week high has been achieved and short the portfolio that insiders decrease their holding immediately after the stock price dropped to the 52-week low, the trading strategy return further increases to 30.8% BHAR in 12-month holding period. Third, We further purge out of effects of recency, firm-specific characteristics, market sentiments and abnormal price returns prior to insider transactions in our multivariate study, and the insider sells at the 52-week high remain to be uninformed. Lastly, we argue that insiders may trade on long-lived information and therefore adopt dissimulation strategy in a sequence of sell transactions at the 52-week high. After calculating the return for a sequence of sell, we successfully classify around half of the insiders sell transactions at the 52-week high into sequence sell, and these sells transactions are on average informed. The remaining sell transactions are either made for non-information-driven reason such as personal liquidity need and portfolio diversification, or insiders suffer from the 52-week high anchoring bias.

Furthermore, we attempt to identify the informational content embedded in these dissimulation sells. We find that dissimulation sells contain little future fundamental information, but they embed the predictability power for future market reaction proxied by 3-day CAR around the next four quarterly earnings announcements. We argue insiders may endogenously release news on the announcement to depress the stock price and therefore to profit from it. Finally, we show that insiders with short-term and long-term investment horizons are both more likely to employ dissimulation strategy whereas mid-term investment horizon insiders are less likely to do. Male insiders, board members and opportunistic insiders are more likely to execute dissimulation sell.

We recognise there are limitations in our research method. First, we have not addressed endogeneity concern. Although We have constructed *UpDummy* and *DownDummy* to control for the short-term abnormal price movement, used firm and month fixed effects and included various covariates, insiders' trading decision at the 52-week high/low may still be endogenous. Corporate insiders intentionally decrease (increase) the price prior to their purchase (sell) transactions by releasing price-sensitive information (Korczak *et al.*, 2010). As a subject for future research, we should investigate the news announcements that drive stocks to their 52-week high/low and differentiate endogenously released news announcements, such as new products, cancellation of contracts, research updates, from exogenously released news announcements, such as earnings announcement. If the 52-week high/low is truly in insiders' information sets, then We should observe that they systematically sell (buy) even after stock prices have been pushed to their 52-week high (low) by exogenously released news announcement. Furthermore, we only focus on corporate insiders. Other market participants such as politicians are also informed, it is unclear whether they consider 52-week high/low as predictive price level or not.

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Figure 1: Monthly average size of insider transactions between 1994 and 2018

This figure displays the average size of insider transactions for each month between January 1994 and December 2018. All open market buy and open market sell are treated separately and un-aggregated. The dollar amounts are winsorised at the top and bottom 1% and 99% to eliminate outliers.

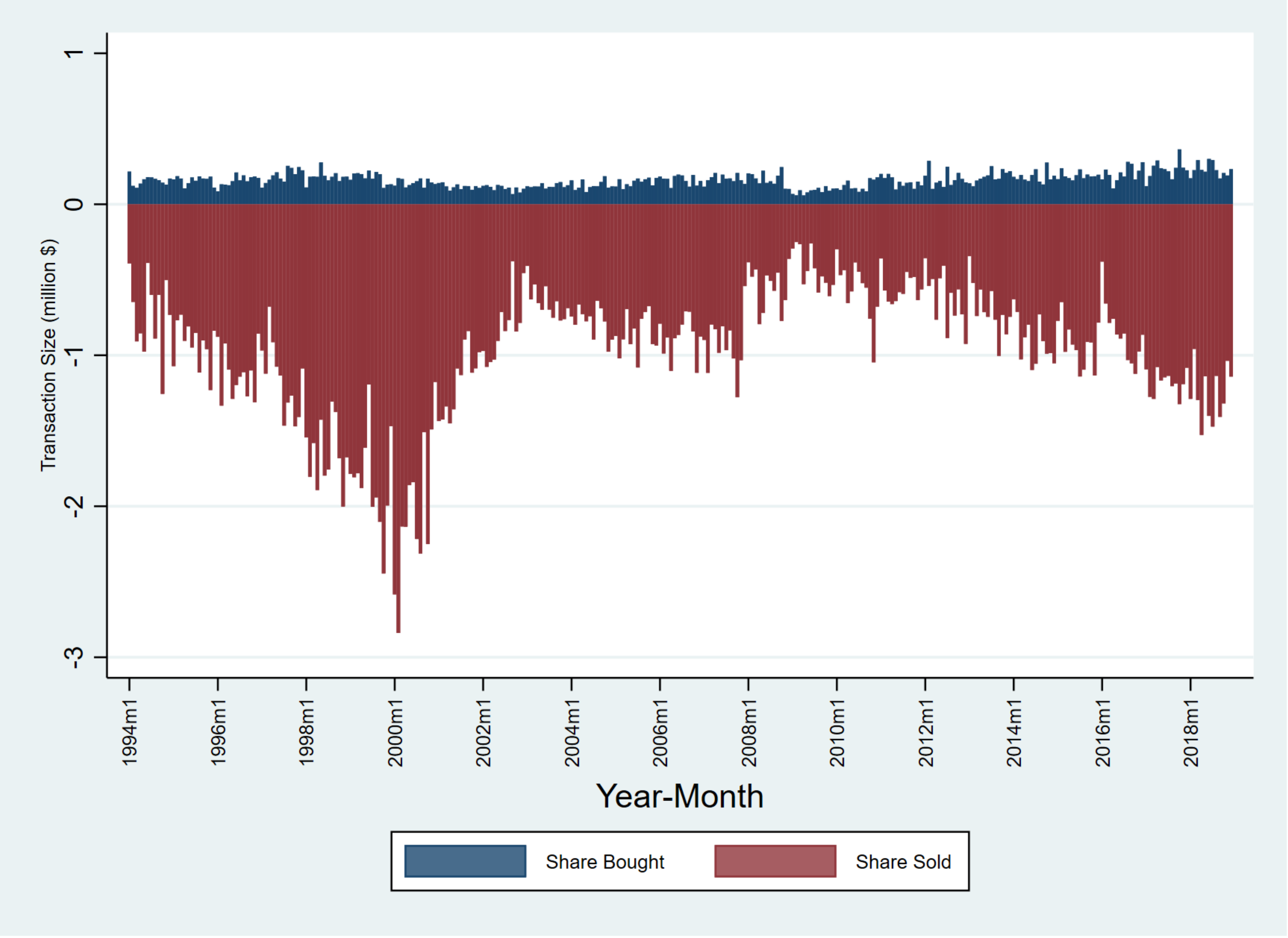

Figure 2: Annual average size of insider transactions between 1994 and 2018

This figure displays the average size of insider transaction for each year between 1994 and 2018. All open market buy and open market sell are treated separately and un-aggregated. The dollar sizes of all open market transactions are winsorised at the top and bottom 1% and 99% to eliminate outliers.

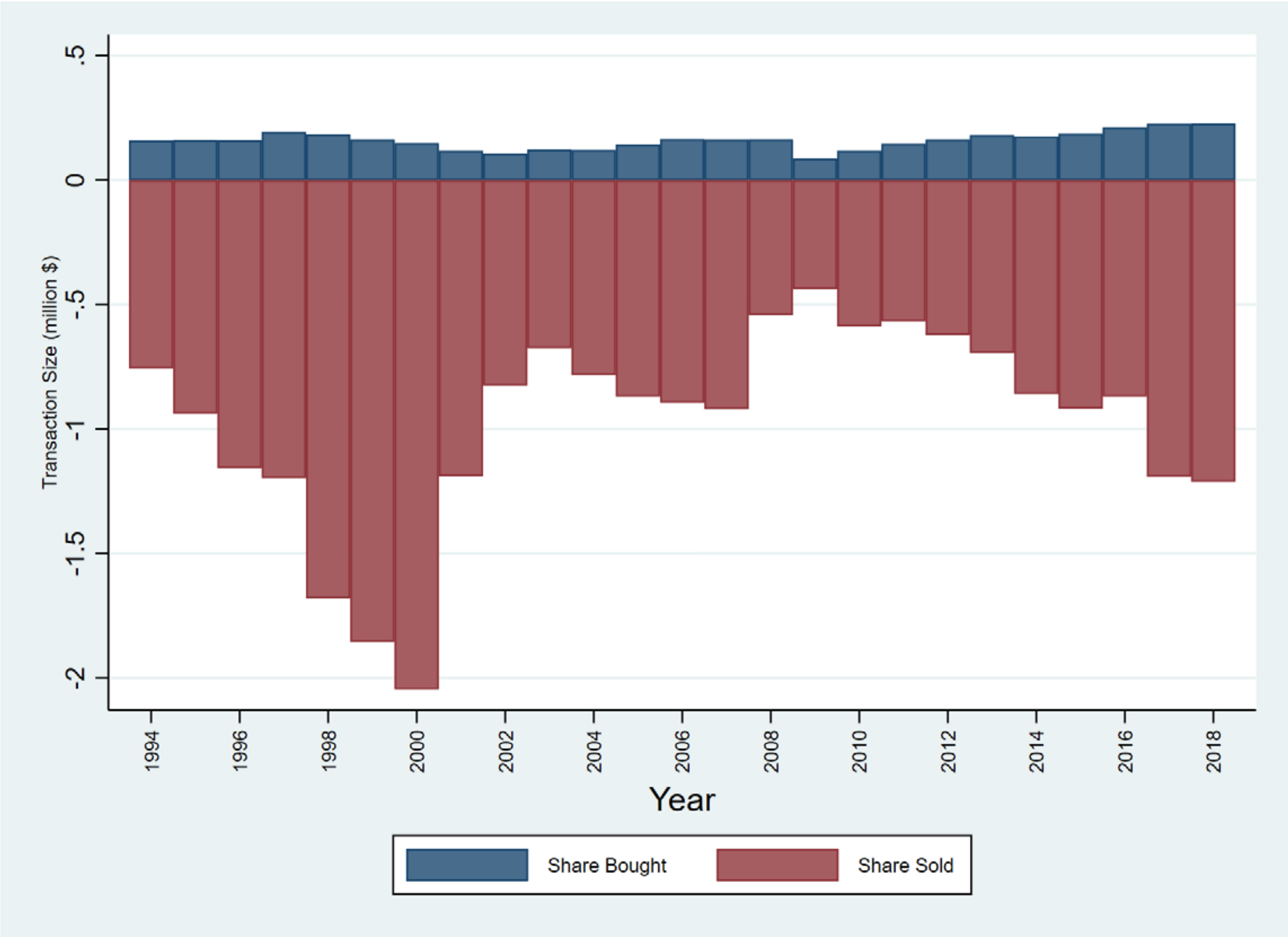

Figure 3: Average insider transactions size in January and non-January between 1994 and 2018

This figure compares the average size of insider transactions in January and remaining months of the year. All open market buy and open market sell are treated separately and un-aggregated. The dollar sizes of all open market transactions are winsorised at the top and bottom 1% and 99% to eliminate outliers.

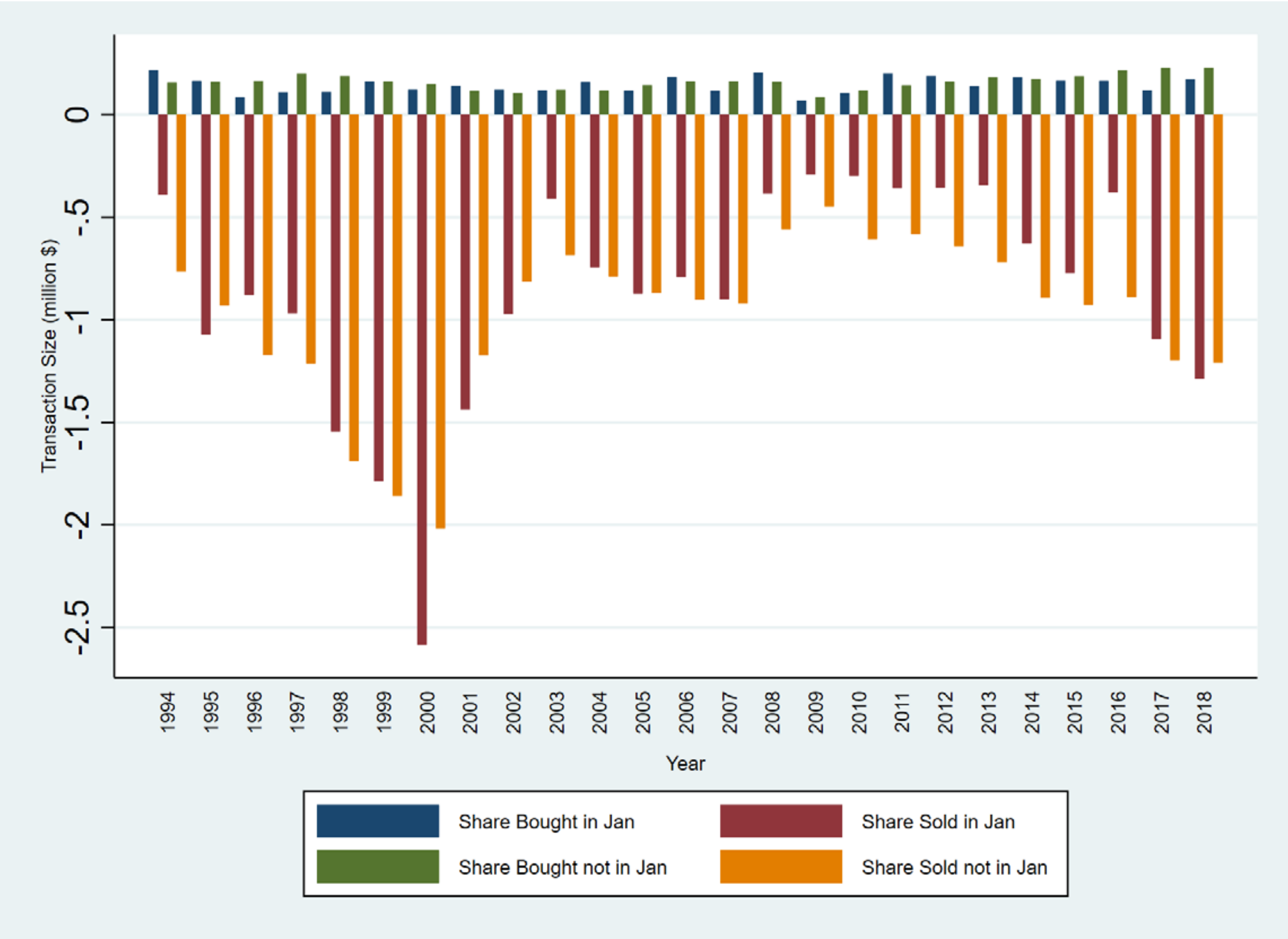

Table 1 : Detailed Information on Loss of Sample Size

	Change in Sample Size %	Sample Size
Raw US Sample	100%	1,614,800
Drop if is not between 1994 and 2018	(1.77%)	(28,515)
Drop if it is not common share transactions	(3.15%)	(50,806)
Drop if the share traded is less than 100 or transaction price is not between $1 and $999	(5.37%)	(86,646)
Drop if it is a programmed trade under the 10b5-1 plan	(4.52%)	(73,043)
Drop if the trade is not an open market Buy/Sell	(34.51%)	(557,229)
Drop if the insider is not either executive or non-executive or senior officer	(5.43%)	(87,651)
Drop if stocks is not on NYSE, AMEX and Nasdaq and stocks with missing CRSP record	(8.34%)	(134,745)
Aggregate at insider-day level	(0.58%)	(9,423)
Final Sample	36.34%	**586,742**

This table shows the loss of observations at each stage of data cleaning process. All numbers are in transaction level.

Table 2: Summary Statistics I

Panel A. reports the summary statistics of the main sample. *No. of Net Buy* (*No. of Net 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. *No. of transactions* is the transactions numbers reported before aggregating at insider-day level. *NPV* is defined in Appendix 1. In last five rows of panel A, ***, **, * indicate the t-test result for the equal means between the subsample and the whole sample is statistically significant at 99%, 95% or 90%, respectively. Panel B reports the insider transactions in January and remaining months. All variables are winsorised at bottom 0.5% and top 99.5% level. *Difference in Mean* is t-test assuming unequal variance, and *Difference in Median* is based on Wilcoxon rank-sum test.

	1994-2001	**2002-2007**	**2008-2009**	**2010-2018**	**All**
			Panel A. Summary statistics		
No. of Net Buy	42,591	50,638	32,251	68,536	194,016
No. of Net Sell	47,463	117,607	50,234	117,388	392,692
No. of Distinct Insiders	39,319	42,271	24,983	47,9401	103,530
No. of Distinct Firms	7,871	5,777	3,989	5,154	11,090
No. of Insider-Day Observations	90,055	168,258	82,493	245,936	586,742
NPV (%)	-5.41***	-39.81***	-21.80***	-44.28***	-33.87
Average Dollar Volume (000,000) Buy	0.15	0.13***	0.13***	0.17***	0.15
Average Dollar Volume (000,000) Sell	1.48***	0.83	0.49***	0.74***	0.82
Average Shares Buy (000)	21.33***	14 .12***	16.49*	16.81	17.04
Average Shares Sell (000)	98.38***	40.55	23.61***	28.45***	39.90

		Panel B. January effect		
	January	Non-January	Difference in Mean	Difference in Median
Average Dollar Buy (000)	143.04	152.47	-9.42*	-26.82***
Average Dollar Sell (000)	653.96	836.10	-182.14***	-34.47

		Panel C. Recency effects		
	Insider Purchase	Insider Sell	Difference in Mean	Difference 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***
At-Bottom: _52_W_L≤ 1.02	28,089(72.83%)	10,478(27.17%)		
Recency-Bottom (days)	11	19	-8***	0***

Table 3: Summary Statistics II

This table presents the summary statistics of key variables for the period of 1994-2018. All variables are winsorised at 0.5% and 99.5% level and described in Appendix 1. Insider transactions are aggregated at the insider-day level. The 4-factor αs for 30/180/365 holding period is multiplied by the respective median numbers of trading days of 22, 126 and 252. ***, **, * indicate the coefficients are statistically significant at 99%, 95% and 90%, respectively. [a,b,c] in column (5) and (7) test for the mean difference between Net Buyer and Net Seller assuming unequal variance, and the result of the Wilcoxon rank-sum test, respectively.

	Net Purchaser				Net Seller			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
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	90.022[a]	97.014
_52_*W_H_Rec* (Days)	194***	317	204	71	131***[a]	244	86[a]	12
_52_*W_H_Rec* (%)	46.825***	12.912	43.956	80.495	64.080***[a]	32.967	76.374[a]	96.703
_52_*W_L* (%)	141.388***	106.195	119.242	144.590	177.141***[a]	123.366	145.241[a]	184.430
_52_*W_L_Rec* (Days)	147***	288	109	9	231***[a]	339	264[a]	135
_52_*W_L_Rec* (%)	59.580***	20.879	70.055	97.527	36.536***[a]	6.868	27.473[a]	62.912
Pre-trade 30-day ret (%)	-4.553***	-13.464	-2.703	4.882	4.715***[a]	-2.329	3.768[a]	10.948
Mcap ($billion)	2.038***	0.059	0.177	0.685	5.487***[a]	0.314	0.927[a]	3.091
Bm	0.771***	0.341	0.616	0.957	0.584***[a]	0.251	0.448[a]	0.746
Illiq ($\times 10^5$)	0.214***	0.000	0.005	0.054	0.029***[a]	0.000	0.000[a]	0.002
Mom (%)	7.506***	-20.907	6.872	32.646	31.480***[a]	4.925	25.204[a]	51.405
ROE (%)	-6.492***	-6.606	6.361	12.813	3.775***[a]	1.772	9.962[a]	16.869
RD (%)	30.750***	0.000	0.000	1.374	18.788***[a]	0.000	0.000[a]	8.634
Leverage (%)	21.310***	4.431	15.007	32.102	18.740***[a]	0.873	13.282[a]	29.692
Numest	4.000***	0.000	2.000	6.000	8.000***[a]	3.000	6.000[a]	12.000
NPV (%)	99.915***	1.000	1.000	1.000	99.973***[a]	-1.000	-1.000[a]	-1.000
BHAR m 30 (%)	2.714***	-5.037	1.072	8.436	-0.033[a]	-5.651	-0.279[a]	5.145
BHAR m 180 (%)	5.671***	-16.107	0.709	19.947	-0.079[a]	-16.913	-1.879[a]	0.135
BHAR m 365 (%)	9.808***	-25.822	-0.043	30.054	0.457***[a]	-25.417	-3.605[a]	0.191
αt+1, t+30 (%×22)	3.092***	-4.833	1.797	9.802	-0.127**[a]	-6.241	-0.084[a]	5.960
αt+1, t+180 (%×126)	7.503***	-10.232	5.773	24.258	0.743***[a]	-13.283	1.160[a]	15.322
αt+1, t+365 (%×252)	12.043***	-13.290	10.408	36.596	2.418***[a]	-17.127	2.794	22.282

Table 4: BHARs after 52-week high/low has been reached

This table reports the cumulative abnormal returns after a 52-week high/low is reached for first time within a 30-day period as day *t*. NPV is the net purchase value scaled by the total value of shares traded by all insiders at firm i from $(t+1, t+15)$ or $(t-7, t-15)$ or on day t. BHAR_m_i is the Buy-and-Hold abnormal return adjusted by using CRSP Value-Weighted market index from $(t+1, t+i)$. In Panel C, we report the BHAR_m_i returns unconditional on insider transactions for these holding periods accumulated from one day after the stock hits the 52-week high or low for these three holding periods. For all return variables, we restrict there must be at least 20/120/243 trading days within the corresponding 30/180/365 estimation windows. We exclude stocks that listed less than 120 trading days and reached a 52-week high because of time elapse. In Panel D, we report the price ratio at which these insider transactions occurred related to the 52-week high/low event. *Price_ratio* is the ratio between the closing price on the day of insider transaction over the 52-week high/low price in its corresponding event. Standard errors are in the parentheses. All insider transactions are aggregated at firm level. ***, **, * indicates the coefficients are statistically significant at 99%,95% and 90% respectively. All BHAR_m_i are winsorised at the top 99.5% and the bottom 0.5%.

Panel A: 52-Week High Reached									
	BHAR_m_30			BHAR_m_180			BHAR_m_365		
	Purchase	Sell	Diff	Purchase	Sell	Diff	Purchase	Sell	Diff
$\boldsymbol{NPV_{(1,15)}}$	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)
	1,207	12,010		1,383	13,655		1,336	13,319	
$\boldsymbol{NPV_{(-15,-1)}}$	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)
	1,435	7,474		1,697	8,806		1,641	8,570	
$\boldsymbol{NPV_{(0,0)}}$	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	3,534		513	4,061		499	3,933	
Panel B: 52-Week Low Reached									
	BHAR_m_30			BHAR_m_180			BHAR_m_365		
	Purchase	Sell	Diff	Purchase	Sell	Diff	Purchase	Sell	Diff
$\boldsymbol{NPV_{(1,15)}}$	-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)
	5,880	1,949		6,443	2,187		6,156	2,101	
$\boldsymbol{NPV_{(-15,-1)}}$	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)
	1,575	1,612		1,810	1,858		1,761	1,782	
$\boldsymbol{NPV}_{(\mathbf{0,0})}$	0.020***	-0.020***	0.040***	0.040***	-0.077***	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)
	1,081	517		1,244	590		1,190	573	

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	
	Purchase	Sell	Purchase	Sell
$\boldsymbol{NPV}_{(\mathbf{1,15})}$	1.01	1.02	0.97	1.00
$\boldsymbol{NPV}_{(\mathbf{-15,-1})}$	0.92	0.94	1.11	1.14
$\boldsymbol{NPV}_{(\mathbf{0,0})}$	1.00	1.00	1.00	1.00

Table 5: Trading strategy based on the relative price and recency

This table reports the Buy-and-Hold return in the top and bottom deciles defined by the level and the recency the 52-week high/low by using sample period of January 1994 to December 2018. In Panel A, We report the portfolios sorted by the level of the 52-week high/low to the current price. Panel B reports the portfolios sorted by the recency of the 52-week high/low. At the end of each monthon day t, We calculate the total insider trading pressure *NPV* for stock s in the given month. If *NPV* is larger (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 those stocks are 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. Panel B is similar to Panel A except we sort stocks according to their 52-week high/low recency ratioson day t. 52-week high/low recency ratio is $(1-\frac{distance\ to\ the\ 52{-}week\ high/low_t}{364})$. We long (short) the portfolio which contains those stocks are in the top (top) 52-week high (low) recency decile and net-bought (net-sold) by insiders. We report the BHAR adjusted by using CRSP value-weighted market index for the next 6 or 12-month holding periods and exclude the January return. Standard errors are reported in the parentheses below the BHAR. The standard error of two-sample t-test of different mean between Top and Bottom portfolios BHAR by assuming unequal variance is reported in the parentheses. ***, **, * indicates the coefficients are statistically significant at 99%,95% and 90% respectively. All return variables are winsorised at bottom 0.5% and top 99.5%.

Panel A: 52-Week High/Low Sorted Portfolios-January Excluded								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Insiders net-bought the top and net-sold the bottom portfolios		Average 52-Week High/Low Ratio	Unconditional on Insider trading		Average 52-Week High/Low Ratio	Difference between (1)-(4)	Difference between (2)-(5)
BHAR_m_i	6-Month	12-Month		6-Month	12-Month			
Top 52-Week High portfolio	0.069***	0.141***	0.97	0.022***	0.049***	0.99	0.047***	0.092***
	(0.006)	(0.009)		(0.004)	(0.005)		(0.008)	(0.010)
Bottom 52-Week Low portfolio	-0.024***	-0.051***	1.06	0.020***	0.041***	1.03	-0.044***	-0.092***
	(0.006)	(0.009)		(0.005)	(0.007)		(0.008)	(0.012)
Top-Bottom	0.093***	0.192***		0.002	0.007			
	(0.008)	(0.012)		(0.006)	(0.009)			
Panel B: 52-Week High/Low Recency Sorted Portfolios-January Excluded								
	Insiders net-bought the top and net-sold the bottom portfolios		Average 52-Week High/Low Recency Days (Ratio)	Unconditional on Insider trading		Average 52-Week High/Low Recency Days (Ratio)		
BHAR_m_i	6-Month	12-Month		6-Month	12-Month			
Top 52-Week High Recency portfolio	0.093***	0.194***	14.65 days	0.038***	0.084***	5.87 days	0.055***	0.110***
	(0.006)	(0.011)	(0.96)	(0.004)	(0.007)	(0.98)	(0.008)	(0.013)
Bottom 52-Week Low Recency portfolio	-0.059***	-0.114***	39.80 days	-0.025***	-0.057***	9.28 days	-0.033***	-0.057***
	(0.007)	(0.011)	(0.89)	(0.006)	(0.009)	(0.97)	(0.010)	(0.014)
Top-Bottom	0.152***	0.308***		0.064***	0.142***			
	(0.010)	(0.016)		(0.007)	(0.011)			

Table 6: Multivariate Analysis on Insider Trading Propensity and Post Transactions Returns at the 52-week High and Low

This table reports the Logit and Fixed-effect regression outputs. Dependent variables for Logit regression is one if NPV>0 (net purchaser), zero otherwise. In column (3) to (8), the dependent variable is the BHAR for 30-, 180- and 365-holding periods as shown in the first row. All independent variables are defined in Appendix 1. All return variables are restricted to have at least 20/120/243 observations within each estimation window. Standard errors are reported in parentheses below coefficient estimates. We use robust S.E for Logit, and We cluster S.E at the firm level for fixed-effect regression. We control for firm, month and director fixed effects in column (3) to (8). All independent variables are winsorised at bottom 0.5% and top 99.5%. The sample is restricted to be net purchaser in column (3) to (5), and net sellers in column (6) to (8). ***, **, * indicates the coefficients are statistically significant at 99%,95% and 90% respectively.

	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	-1.476***		-0.045***	0.072**	0.157***	0.008	0.080***	0.052*
	(0.026)		(0.010)	(0.031)	(0.045)	(0.008)	(0.023)	(0.031)
_52_W_H_Rec	-0.125***		0.018***	0.016	0.000	0.008***	0.028***	0.028***
	(0.014)		(0.004)	(0.012)	(0.016)	(0.002)	(0.006)	(0.009)
_52_W_L		-0.025***	0.003	0.006	0.001	-0.000	-0.000	-0.003
		(0.007)	(0.003)	(0.005)	(0.005)	(0.001)	(0.003)	(0.004)
_52_W_L_Rec		0.777***	-0.017***	-0.064***	-0.089***	-0.009***	-0.025***	-0.032***
		(0.013)	(0.003)	(0.010)	(0.015)	(0.002)	(0.006)	(0.009)
mom	-0.660***	-0.633***	-0.016***	-0.076***	-0.136***	-0.014***	-0.074***	-0.095***
	(0.010)	(0.012)	(0.005)	(0.012)	(0.018)	(0.003)	(0.007)	(0.012)
ret	-2.831***	-3.254***	-0.027***	-0.169***	-0.266***	-0.023***	-0.182***	-0.268***
	(0.029)	(0.030)	(0.010)	(0.020)	(0.027)	(0.007)	(0.014)	(0.018)
lnmcap	-0.280***	-0.334***	-0.034***	-0.199***	-0.372***	-0.027***	-0.169***	-0.306***
	(0.004)	(0.004)	(0.003)	(0.009)	(0.014)	(0.002)	(0.007)	(0.012)
bm	0.294***	0.279***	0.006**	0.011	0.020	0.006***	0.019***	0.034***
	(0.007)	(0.007)	(0.003)	(0.008)	(0.013)	(0.002)	(0.007)	(0.010)
illiq	0.385***	0.365***	-0.004***	-0.001	-0.008	-0.004*	0.001	0.010
	(0.013)	(0.012)	(0.001)	(0.004)	(0.006)	(0.002)	(0.005)	(0.008)
roe	-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)	(0.001)	(0.006)	(0.008)
leverage	0.723***	0.781***	-0.004	0.013	0.016	0.000	0.024	0.026
	(0.018)	(0.018)	(0.013)	(0.052)	(0.070)	(0.008)	(0.032)	(0.051)
RD	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	-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	0.067***	0.070***	0.006***	0.042***	0.044***	-0.001	0.007*	0.011*
	(0.007)	(0.007)	(0.002)	(0.006)	(0.010)	(0.001)	(0.004)	(0.006)
UpDummy	0.064***	0.031***	-0.004**	-0.015***	-0.028***	-0.002**	-0.007***	-0.015***
	(0.009)	(0.009)	(0.002)	(0.004)	(0.005)	(0.001)	(0.002)	(0.003)
DownDummy	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)	(0.016)	(0.052)	(0.084)	(0.013)	(0.047)	(0.081)
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
S.E	Robust	Robust	Firm	Firm	Firm	Firm	Firm	Firm

Table 7: Insider trading propensity with interaction term on tightness

This table reports the Logit and Fixed-effect regression outputs. Dependent variable for Logit regression is one if NPV>0 (net purchaser), zero otherwise. In each month, we sort all insider transactions into quantiles in accordance with their tightness, which is defined as $tightness = \frac{52\text{−}week\ high\text{−}52\text{−}week\ low}{Current\ price}$. All independent variables are defined in Appendix 1. All return variables are restricted to have at least 20/180/243 observations within each estimation window. In Panel A, we report the summary statistics for *tightness*. ***, **, * in column (1) and (6) indicate the coefficients are statistically significant at 99%,95% and 90% respectively. The superscripts a, b, c in column (6) report the result 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, respectively. a, b, c indicate the test is rejected at the 99%, 95% and 90% confidence level, respectively. In Panel B, we report the regression result. Dependent variable is NPV. Standard errors are reported in parentheses below coefficient estimates. We use robust standard error in Panel B column (1) and (2) and clustered standard error in column (3) and (4). We control for firm, month and director fixed effects in column (3) and (4). All independent variables are winsorised at bottom 0.5% and top 99.5%. ***, **, * indicates the coefficients are statistically significant at 99%, 95% and 90% respectively.

Panel A

	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

	Logit		Fixed-Effect	
	Net Purchaser	Net Purchaser	NPV	NPV
	(1)	(2)	(3)	(4)
_52_W_H	-5.005***		-0.930***	
	(0.088)		(0.054)	
_52_W_H_Rec	-0.069**		0.012	
	(0.030)		(0.012)	
_52_W_L		-1.462***		-0.062***
		(0.056)		(0.012)
_52_W_L_Rec		0.127***		0.031**
		(0.028)		(0.013)
tightness	-0.674***	-0.478***	-0.081***	-0.008

	(0.016)	(0.014)	(0.011)	(0.005)
_52_W_H*tightness	0.524***		0.076***	
	(0.020)		(0.013)	
_52_W_H_Rec*tightness	0.047***		0.013***	
	(0.010)		(0.004)	
_52_W_L*tightness		0.299***		0.013***
		(0.011)		(0.002)
_52_W_L_Rec*tightness		0.206***		0.039***
		(0.009)		(0.004)
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			Firm, Month, Directors	Firm, Month, Directors
S.E	Robust	Robust	Clustered-Firm	Clustered-Firm

Table 8: BHAR for isolated and sequenced insider sell transactions at the 52-week high

This table reports the BHAR for isolated and sequenced sell transactions at the 52-week high. BHAR is the buy-and-hold return calculated by using CRSP value-weighted index as benchmark for the next 30, 180 and 365 calendar days. All returns are restricted to have at least 20/180/243 observations within each estimation window. Sequenced sell is defined in Biggerstaff, Cicero and Babajide (2020) that is the sequence of sell transactions executed by the same insider for the same stock with the maximum gap of 60 calendar days between each transaction. The rest of sell transactions are defined as isolated sell. If any one of sell transactions in a sequence is executed when the _52_W_H is ≥ 0.98, we define the entire sequence as Sell-At-52-Week High and We focus on these sequences in Panel C. Sale-post exercise of stock option is not considered in constructing sequence sell. *Scaled holding return* is the BHAR calculated from the one day after the initiation sell of the sequence up to the 30/180/365 calendar days after the termination of the sequence. Because the length of different sequence is varying, we report the average daily return times the median number of trading days for 30, 180 and 365-holding periods, which are 22, 126 and 252, respectively. Following Sequences is the BHAR for the last sell transaction of a sequence. In Panel C, we focus on sequence that is initiated at most 30 or 60 days before the insider Sell-At-Peak transaction and terminated at most 30 or 60 days after the insider sell transaction, we denote these samples with "(30)" and "(60)", respectively. In Panel D, we combine insider purchase transactions within insider sell sequence. The definition of a sequence remains the same and we aggregate all insider buys and sells in a sequence and present the results for the net-selling sequence. All returns in Panel D are *Scaled holding returns*. Panel D column (4) and (5) present returns of sequence which initiated and terminated at most 30 days around the before the insider Sell-At-Peak transaction. Column (3) and (6) display t-test of different mean assuming unequal variance . Standard errors are reported in parentheses below coefficient estimates. The superscripts a ,b , c in column (5) and column (6) report the result of the rank-sum test for the difference in the median of column(2) minus column(5) and column(3) minus column(6), respectively. a ,b , c indicate the test is rejected at the 99%, 95% and 90% confidence level, respectively. ***, **, * indicates the statistics are statistically significant at 99%, 95% and 90% respectively. All returns are winsorised at bottom 0.5% and top 99.5%.

	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)
Number of observations (All Sell: 392,692)	38,868 (9.90%)	18,804(4.79%)	34,036(10.39%)	136,708(34.81%)	78,473(19.98%)	176,326(44.90%)
Average 52 W H Rec (days)	18	18	17	163	157^{***a}	157^{***a}
Average sequence transaction 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 Sell		
	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)
Observations	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)

Observations				216,456	213,107	207,034
Following Sequence				-0.015***	-0.021***	-0.013***
				(0.000)	(0.001)	(0.001)
Observations				178,788	209,633	202,918

Panel C: BHAR for Sell-At-Peak: _52_W_H≥0.98

	Isolated Sell			Sequence Sell		
	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	0.001*	0.005***	0.012***	0.005***	0.018***	0.020***
	(0.000)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)
Observations	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)
Observations				18,583	18,045	17,400
Scaled holding return (60)				0.020***	0.007***	-0.017***
				(0.000)	(0.002)	(0.002)
Observations				26,490	25,604	24,730
Following Sequence (30)				-0.005***	-0.004*	0.002
				(0.001)	(0.002)	(0.003)
Observations				15,289	17,990	17,373
Following Sequence (60)				-0.006***	-0.003***	0.003
				(0.001)	(0.002)	(0.003)
Observations				21,683	25,463	24,666

Panel D: Sequence Sell mixed with Buy

	Unconditional Sequence			Sell-At-Peak: _52_W_H≥0.98		
	No Buy in A Net-Selling	With Buy in A Net- Selling	Diff (1)-(2)	No Buy in A Net-Selling Sequence	With Buy in A Net- Selling	Diff (4)-(5)
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	6,143		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	6,071		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	5,958		17,280	222	

Table 6:Robustness Tests

This table reports the robustness tests. In both Panel A and Panel B, the dependent variables is one if NPV>0 (net purchaser), zero otherwise. Explanatory variables are 52-week high/low ratio and 52-week high/low recency ratio. In Panel A, we include eight anomaly variables by following Stambaugh *et al.* (2012) and discussed in detail in Appendix 5 and Appendix 6. NSI, TA, NOA, GP. AG, IA use last two fiscal years' accounting information to construct. FP and ROA use last two fiscal quarters' accounting information to construct. In Panel B, the sample only consists of board members in a firm and exclude senior officers. Panels A, B, and C include the same set of control variables as Table 6. All return variables are restricted to have at least 20/180/243 observations within each estimation window. Standard errors are reported in parentheses below coefficient estimates. We use robust standard error. All independent variables are winsorised at bottom 0.5% and top 99.5%. . ***, **, * indicates the coefficients are statistically significant at 99%, 95% and 90% respectively.

	Panel A: Probability Model with Asset Pricing Anomalies-Logit							
	Net Purchaser (1)	Net Purchaser (2)	Net Purchaser (3)	Net Purchaser (4)	Net Purchaser (5)	Net Purchaser (6)	Net Purchaser (7)	Net Purchaser (8)
_52_W_H	-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	-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_W_L	-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	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)
Anomaly Variable	FP	NSI	TA	NOA	GP	AG	ROA	IA
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Normative Direction	Negative	Negative	Negative	Negative	Positive	Negative	Positive	Negative
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

	Panel C: Insider trading propensity on board members only-Logit	
	Net Purchaser	Net Purchaser
	(1)	(2)
_52_W_H	-1.501***	
	(0.032)	
_52_W_H_Rec	-0.167***	
	(0.017)	
_52_W_L		-0.028***
		(0.008)
_52_W_L_Rec		0.793***
		(0.016)
Control	Yes	Yes
N	287,225	287,225
R-squared	0.201	0.200
S.E	Robust	Robust

Table 10: Managers dissimulation transactions' earnings informativeness

This table reports the regressions of earning surprise on the set of group dummies. In column (1) to (4), the earning surprise is proxied the 3-day earnings announcement CARs for the next 1/2/3/4 quarterly earnings announcement. Th event window is (-1,1), day 0 is the earnings announcement day. Benchmark return is the CRSP value-weighted index. We use 250 days for estimation period, and there are minimum 100 days. Estimation period end 50 days before Event Date. In column (5) to (8), earnings surprise is proxied by SUE following Bernard *et al*. (1990). $SUE_{j,q} = \frac{(EPS_{j,q} - EPS_{j,q-4} - \mu_{q-7,q})}{\sigma_{q-7,q}}$ 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. SellpeakD is dummy variable that takes value of one for the stocks with _52_W_H ≥0.98 and NPV<0, and zero otherwise. We restrict our sample must have non-missing value of both *Scaled Holding Return*_t and BHAR_m_i. The *Dissimulation_tD* is dummy variable equal to one if the BHAR_m_i>0 but the *Scaled Holding Return*_t≤0, and zero otherwise. The construction of *Scaled Holding Return*_t is described in Table 8. The constructions of control variables are reported in Appendix 1. The regression is only using insider sell sample. We control for firm, month and director fixed effects. Standard errors are reported in parentheses below coefficient estimates. Standard error is clustered at firm-month level. All independent variables are winsorised at bottom 0.5% and top 99.5%. ***, **, * indicates the coefficients are statistically significant at 99%, 95% and 90% respectively.

	$CAR_{(q+1)}$	$CAR_{(q+2)}$	$CAR_{(q+3)}$	$CAR_{(q+4)}$	$SUE_{(q+1)}$	$SUE_{(q+2)}$	$SUE_{(q+3)}$	$SUE_{(q+4)}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SellpeakD	-0.002	0.000	-0.002	0.001	0.018	0.054**	0.021	0.042**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.020)	(0.022)	(0.025)	(0.020)
Dissimulation30D	-0.017***				-0.004			
	(0.003)				(0.026)			
Dissimulation180D		-0.014***				-0.023		
		(0.003)				(0.039)		
Dissimulation365D			-0.017***	-0.008**			0.008	-0.017***
			(0.004)	(0.004)			(0.043)	(0.004)
SellpeakD*Dissimulation30D	0.007				-0.048			
	(0.005)				(0.050)			
SellpeakD*Dissimulation180D		-0.005				0.003		
		(0.005)				(0.056)		
SellpeakD*Dissimulation365D			0.008	-0.016**			0.098	0.084
			(0.005)	(0.007)			(0.059)	(0.060)
Lag(Surprise)	-0.139***	-0.048***	-0.028*	-0.018	0.244***	0.114***	0.008	0.244***
	(0.018)	(0.017)	(0.015)	(0.018)	(0.013)	(0.013)	(0.013)	(0.013)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effect	Firm, Month, Directors	Firm, Month, Directors	Firm, Month, Directors	Firm, Month, Directors	Firm, Month, Directors	Firm, Month, Directors	Firm, Month, Directors	Firm, Month, Directors
Clustered S.E	Firm-Month	Firm-Month	Firm-Month	Firm-Month	Firm-Month	Firm-Month	Firm-Month	Firm-Month
N	49,149	56,233	53,062	53,143	47,860	54,527	52,031	51,668
Adjusted R-squared	0.34	0.35	0.35	0.34	0.40	0.42	0.41	0.47

Table 11: Heterogeneity in insiders who frequently use dissimulating strategy

This table reports the logit regression result with only Net Sell trades. The dependent variable is *Dissimulation_Dummy_t*, which is equal to one if the BHAR_m_i>0 but the *Scaled Holding Return* ≤ 0, and zero otherwise. The construction of *Scaled Holding Return* is described in Table 8. In column (1), (2), (3), the *Dissimulation_Dummy_We* is defined by using the 30-, 180- and 365- holding periods, respectively. In Panel A, the main variable with interest is *Long-Term Dummy* and *Short-Term_Dummy* . The identification method for SH and LH insiders is following Akbas *et al.* (2020). We define $HOR_{i,j,t} = \left|\frac{\sum_{Year-10}^{Year-1} NPV_t}{N}\right| \times (-1)$ That is, for each month, we compute the annual NPV for each insider We in firm j in year t in the last 10 calendar years, then We compute the average NPV by summing the annual NPV and divide by the number of calendar years that the insider has traded in the last 10 calendar years. Then We take the absolute value of the average annual NPV and times -1. For each month, we divide *HOR* into quintiles, the top quintiles which has the highest *HOR* is SH, the bottom quintiles which has the lowest *HOR* is LH. Then We create dummy variables that equal to one for LH insiders, otherwise zero. If an insider has traded less than 4 years in the last 10 years, the insider is excluded from the exercise. When define *HOR*, Sale-Post Exercise is included. The sample period in Panel A starts in 2004. In Panel B, the main variable with interest is *Gender_Dummy* that equal to one if the insider is male, and zero otherwise. In Panel C, the main variable with interest is *Board_Dummy* that equal to one if the insider is a board member, and zero otherwise. In Panel D, the main variable with interest is *CEO_Dummy (CFO_Dummy*) that equal to one if the insider is a CEO (CFO) as identified by Smart Insider, and zero otherwise. In Panel E, the main variable with interest is *Opportunistic_Dummy* that equal to one if the insider is a board member, and zero otherwise. Opportunistic trade is defined as Cohen *et al.* (2012). That is, for a given trade, if the insider has executed a trade in the same calendar month in the last three calendar year, the insider is recognised as routine trade, otherwise it is opportunistic trade. 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. Standard errors are reported in parentheses below coefficient estimates. We use robust standard error. All independent variables are winsorised at bottom 0.5% and top 99.5%. The control variables are identical to Table 6. ***, **, * indicates the coefficients are statistically significant at 99%, 95% and 90% respectively.

	Dissimulation_Dummy_30 (1)	***Dissimulation_Dummy_180*** (2)	***Dissimulation_Dummy_365*** (3)
	Panel A: Investment Horizon-Logit Regression		
Short-Term_Dummy	0.080***	0.019	0.090***
	(0.024)	(0.027)	(0.032)
Long-Term_Dummy	0.082**	0.034	0.257***
	(0.036)	(0.042)	(0.046)
_52_W_H	-1.720***	-1.684***	-1.020***
	(0.089)	(0.099)	(0.116)
_52_W_H_Rec	-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
S.E	Robust	Robust	Robust
	Panel B: Insider Gender-Logit Regression		
Gender_Dummy(Male)	0.168***	0.069**	0.289***
	(0.031)	(0.033)	(0.042)
_52_W_H	-1.403***	-1.347***	-1.165***
	(0.076)	(0.083)	(0.096)
_52_W_H_Rec	-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
S.E	Robust	Robust	Robust

	Panel C: Board Member-Logit Regression		
Board_Dummy	0.198***	0.290***	0.338***
	(0.020)	(0.023)	(0.027)
_52_W_H	-1.427***	-1.385***	-1.224***
	(0.076)	(0.083)	(0.096)
_52_W_H_Rec	-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
S.E	Robust	Robust	Robust
	Panel D: CEO/CFO-Logit Regression		
CEO_Dummy	0.213***	0.004	0.127***
	(0.032)	(0.037)	(0.043)
CFO_Dummy	0.139**	-0.003	-0.079
	(0.063)	(0.075)	(0.093)
_52_W_H	-1.403***	-1.348***	-1.171***
	(0.076)	(0.083)	(0.096)
_52_W_H_Rec	-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
S.E	Robust	Robust	Robust
	Panel E: Opportunistic Insider -Logit Regression		
Opportunistic_Dummy	0.051***	0.048**	0.117***
	(0.020)	(0.022)	(0.026)
_52_W_H	-1.411***	-1.354***	-1.189***
	(0.076)	(0.083)	(0.096)
_52_W_H_Rec	-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
S.E	Robust	Robust	Robust

Appendix 1: Definition of Variables

Variable Notation	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 the following: $BHAR\_m\_i = \prod_{t=1}^{i}[1+R_{it}] - \prod_{t=1}^{i}[1+R_{mt}]$
$\boldsymbol{\alpha_{t+1,t+i}}$	CRSP, 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).
$\boldsymbol{\_52\_W\_H_t}$	CRSP	Calculated as a ratio between the adjusted price on day *t* and the 52-week high adjusted price, where t is the insider transaction date.
$\boldsymbol{\_52\_W\_L_t}$	CRSP	Calculated as a ratio between the adjusted price on day *t* and the 52-week low adjusted price, where t is the insider transaction date.
$\boldsymbol{\_52\_W\_H\_Rec_t}$	CRSP	Calculated as 1 minus the distance between 52-week high and day *t* over 364. *t* is the insider transaction date.
$\boldsymbol{\_52\_W\_L\_Rec_t}$	CRSP	Calculated as 1 minus the distance between 52-week high and day *t* over 364. t is the insider transaction date.
illiq	CRSP	Amihund's (2002) measure of illiquidity, which is calculated as the monthly average of the daily ratio of absolute stock return to dollar volume.
lnmcap	CRSP	Logarithm of market capitalisation
mom	CRSP	The cumulative raw return from (t-395, t-31), insider transaction occurs in day t.
ret	CRSP	The cumulative raw return from (t-30, t-1), insider transaction occurs in day t.
$\boldsymbol{UpDummy_{i,t}}$	CRSP	We follow Lasfer *et al.* (2003) to define UpDummy for controlling short-term abnormal price movement. UpDummy equals to one for stock We on day *t* when the any of the stock daily return in the event of $(t-7,t)$ is higher than its mean μ plus $2\times\sigma$ .The mean μ and standard deviation σ are both estimated by using $(t-60,t-11)$ window; zero otherwise
$\boldsymbol{DownDummy_{i,t}}$	CRSP	We follow Lasfer *et al.* (2003) to define UpDummy for controlling short-term abnormal price movement. UpDummy equals

		to one for stock We on day t when the any of the stock daily return in the event of $(t-7, t)$ is higher than its mean μ $minus$ $2 \times \sigma$ .The mean μ and standard deviation σ are both estimated by using $(t-60, t-11)$ window; zero otherwise
bm	CRSP, COMPUSTAT	Book-to-market ratio calculated as ratio of last fiscal year book value over the market capitalisation in the last trading day in December. Book value is computed as the following. Book value is equal to stock holder equity + deferred taxes and investment tax credit (Compustat: txditc, zero if missing) −preferred stock value. Stock holder equity is parent stock holder 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.
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 calculated as the research and development expense (Compustat: xrd) over sales (Compustat: sale). If Compustat reports missing research and development expense, it is set to be zero.
Leverage	COMPUSTAT	Leverage ratio calculated as 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 that regressing the Earnings surprises, Baker-Wurgler index (Baker and Wurgler, 2006) of aggregate investor sentiment on 3-month T-bill rate and Lee's (2011) liquidity risk factor.The procedure follows closely to Sibley, Wang, Xing and Zhang (2016).
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 transacitons in day *t*, calculate as the ratio of the net dollar

		amount of insider transactions over the total dollar amount of insider transactions.
$\boldsymbol{SUE_{j,q}}$	COMPUSTAT	Proxy for earnings surprise. We follow Bernard *et al.* (1990). Specifically, EPS is the split-adjusted earning 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.
$\boldsymbol{CAR_{j,q}}$	CRSP	Three-day cumulative abnormal return centered around the quarterly earnings announcement (-1,1) for firm *j* in quarter *q*. CAR is calculated using market model where the benchmark return is the CRSP value-weighted index return and We restrict the estimation window is (-250, -50), and there are at least 100 days in the estimation window.
$\boldsymbol{Following\ Sequence_s}$	CRSP	The BHAR accumulated between one 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. Benchmark return is the CRSP value-weighted index return.
$\boldsymbol{Average\ Holding\ Return_s}$	CRSP	The BHAR accumulated between one 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. Benchmark return is the CRSP value-weighted index return.

Appendix 2: Regression result for return on 52-week high and 52-week recency measures.

This table reports the regression output where the dependent variables are the average raw return for month t+1, t+6 and t+12. _52_W_H is the stock price at the end of last month over the 52-week high price at the end of last month. _52_W_H_Rec is one minus the ratio of the distance between the stock price and its 52-week high at the end of last month over the 364. _52_W_L and _52_W_L_Rec are defined similarly. All variables are defined in Appendix 1. Standard errors are Newey-West Standard Error up to lag 5, and p-values are reported in parentheses below coefficient estimates. Sample is aggregated at firm-month level. ***, **, * indicates the coefficients are statistically significant at 99%,95% and 90% respectively. All variables are winsorised at bottom 0.5% and top 99.5%.

	OLS						OLS					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	(t, t+1)	(t, t+6)	(t, t+12)	(t, t+1)	(t, t+6)	(t, t+12)	(t, t+1)	(t, t+6)	(t, t+12)	(t, t+1)	(t, t+6)	(t, t+12)
_52_W_H	0.011***	0.011***	0.004***	0.005***	0.007***	-0.001						
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.541)						
_52_W_H_Rec				0.009***	0.007***	0.006***						
				(0.000)	(0.000)	(0.000)						
_52_W_L							-0.001	0.001	0.000	0.001	0.001	0.001
							(0.781)	(0.782)	(0.836)	(0.703)	(0.429)	(0.489)
_52_W_L_Rec										-0.009***	-0.007***	-0.006***
										(0.000)	(0.000)	(0.000)
mom	-0.001***	-0.004***	-0.005***	-0.004***	-0.006***	-0.007***						-0.004**
							0.004	0.001	-0.001	-0.000	-0.003	
	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.124)	(0.775)	(0.548)	(0.964)	(0.212)	(0.034)
ret	0.004**	-0.001	-0.001***	0.004**	-0.001	-0.002***	-0.020***	0.001	0.000	-0.020***	0.001	0.000
	(0.011)	(0.412)	(0.005)	(0.019)	(0.234)	(0.001)	(0.000)	(0.588)	(0.831)	(0.000)	(0.682)	(0.913)
lnmcap	-0.001***	-0.001***	-0.001***	-0.002***	-0.001***	-0.001***	-0.000	-0.001*	-0.001**	-0.001	-0.001**	-0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.260)	(0.078)	(0.049)	(0.128)	(0.038)	(0.023)
bm	0.005***	0.005***	0.005***	0.005***	0.005***	0.005***	0.002***	0.002**	0.002**	0.003***	0.002**	0.002**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.021)	(0.015)	(0.002)	(0.018)	(0.014)
illiq	0.000***	0.001***	0.001***	0.000***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.004)	(0.000)	(0.000)	(0.004)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)
Constant	0.008***	0.008***	0.013***	0.008***	0.009***	0.013***	0.010**	0.011***	0.012***	0.013***	0.014***	0.015***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.015)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)
N	991,175	954,396	905,771	991,175	954,396	905,771	991,175	954,396	905,771	991,175	954,396	905,771
R-squared	0.001	0.007	0.015	0.002	0.008	0.016	0.001	0.009	0.017	0.002	0.012	0.020
Newey-West S.E	Lag (5)	Lag (5)	Lag (5)	Lag (5)	Lag (5)	Lag (5)	Lag (5)	Lag (5)	Lag (5)	Lag (5)	Lag (5)	Lag (5)

Appendix 2: Regression result for return on 52-week high and 52-week recency measures – Continued

	Fama-MacBeth						Fama-MacBeth					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	(t, t+1)	(t, t+6)	(t, t+12)	(t, t+1)	(t, t+6)	(t, t+12)	(t, t+1)	(t, t+6)	(t, t+12)	(t, t+1)	(t, t+6)	(t, t+12)
_52_W_H	0.017**	0.015**	0.010*	0.015*	0.013*	0.009						
	(0.050)	(0.043)	(0.094)	(0.083)	(0.068)	(0.143)						
_52_W_H_Rec				0.004***	0.002**	0.002**						
				(0.002)	(0.048)	(0.015)						
_52_W_L							-0.001	0.001	0.000	0.001	0.001	0.001
							(0.781)	(0.782)	(0.836)	(0.703)	(0.429)	(0.489)
_52_W_L_Rec										-0.009***	-0.007***	-0.006***
										(0.000)	(0.000)	(0.000)
mom	0.001	-0.001	-0.003**	0.000	-0.002	-0.003***	0.004	0.001	-0.001	-0.000	-0.003	-0.004**
	(0.572)	(0.411)	(0.028)	(0.913)	(0.229)	(0.007)	(0.124)	(0.775)	(0.548)	(0.964)	(0.212)	(0.034)
ret	-0.022***	0.001	0.000	-0.022***	0.001	0.000	-0.020***	0.001	0.000	-0.020***	0.001	0.000
	(0.000)	(0.697)	(0.942)	(0.000)	(0.722)	(0.969)	(0.000)	(0.588)	(0.831)	(0.000)	(0.682)	(0.913)
lnmcap	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.000	-0.001*	-0.001**	-0.001	-0.001**	-0.001**
	(0.004)	(0.000)	(0.001)	(0.003)	(0.000)	(0.001)	(0.260)	(0.078)	(0.049)	(0.128)	(0.038)	(0.023)
bm	0.002**	0.001*	0.002**	0.002**	0.001*	0.002**	0.002***	0.002**	0.002**	0.003***	0.002**	0.002**
	(0.011)	(0.060)	(0.029)	(0.011)	(0.063)	(0.030)	(0.003)	(0.021)	(0.015)	(0.002)	(0.018)	(0.014)
illiq	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)
Constant	-0.001	0.004	0.007	-0.001	0.004	0.007	0.010**	0.011***	0.012***	0.013***	0.014***	0.015***
	(0.954)	(0.610)	(0.267)	(0.932)	(0.590)	(0.253)	(0.015)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)
N	991,175	954,396	905,771	991,175	954,396	905,771	991,175	954,396	905,771	991,175	954,396	905,771
Newey-West S.E	Lag (5)	Lag (5)	Lag (5)	Lag (5)	Lag (5)	Lag (5)	Lag (5)	Lag (5)	Lag (5)	Lag (5)	Lag (5)	Lag (5)

Appendix 3: BHARs after 52-week high/low has been reached

This table reports the cumulative abnormal returns after a 52-week high/low is reached for first time within a 30-day period as day t. NPV is the net purchase value scaled by the total value of shares traded by all insiders at firm i from $(t+1, t+15)$ or $(t-7, t-15)$ or on day t. BHAR_m_i is the Buy-and-Hold abnormal return adjusted by using CRSP Value-Weighted market index from $(t+1, t+i)$. In Panel C, we report the BHAR_m_*i* returns unconditional on insider transactions for these holding periods accumulated from one day after the stock hits the 52-week high or low for these three holding periods. For all return variables, we restrict there must be at least 20/120/243 trading days within the corresponding 30/180/365 estimation windows. We exclude stocks that listed less than 120 trading days and reached a 52-week high because of time elapse. In Panel D, we report the price ratio at which these insider transactions occurred related to the 52-week high/low event. *Price_ratio* is the ratio between the closing price on the day of insider transaction over the 52-week high/low pirce in its corresponding event. Standard errors are in the parentheses. All insider transactions are aggregated at firm level. ***, **, * indicates the coefficients are statistically significant at 99%,95% and 90% respectively. All BHAR_m_*i* are winsorised at the top 99.5% and the bottom 0.5%.

				Panel A: 52-Week High Reached					
	BHAR_m_30			BHAR_m_180			BHAR_m_365		
	Purchase	Sell	Diff	Purchase	Sell	Diff	Purchase	Sell	Diff
$NPV_{(1,15)}$	0.041***	0.009***	0.033***	0.101***	0.005***	0.096***	0.129***	0.024***	0.105***
	(0.004)	(0.001)	(0.004)	(0.008)	(0.001)	(0.008)	(0.012)	(0.003)	(0.011)
	1,186	12,010		1,371	13,322		1,324	12,987	
$NPV_{(-15,-1)}$	0.098***	0.051***	0.047***	0.155***	0.055***	0.099***	0.191***	0.070***	0.120***
	(0.004)	(0.001)	(0.004)	(0.007)	(0.002)	(0.007)	(0.011)	(0.004)	(0.010)
	1,422	7,270		1,671	8,488		1,613	8,258	
$NPV_{(0,0)}$	0.034***	0.006***	0.028***	0.108***	0.010**	0.098***	0.151***	0.029***	0.122***
	(0.007)	(0.006)	(0.007)	(0.012)	(0.004)	(0.013)	(0.017)	(0.006)	(0.018)
	448	3,534		513	4,061		499	3,933	
				Panel B: 52-Week Low Reached					
	BHAR_m_30			BHAR_m_180			BHAR_m_365		
	Purchase	Sell	Diff	Purchase	Sell	Diff	Purchase	Sell	Diff
$NPV_{(1,15)}$	0.040***	0.004	0.036***	0.073***	0.006	0.067***	0.098***	0.032***	0.066***
	(0.003)	(0.004)	(0.005)	(0.004)	(0.008)	(0.009)	(0.007)	(0.011)	(0.013)
	5,667	1,800		6,374	2,062		6,089	1,983	
$NPV_{(-15,-1)}$	-0.047***	-0.058***	0.012*	0.013	-0.035***	0.049***	0.074***	-0.010	0.084***
	(0.005)	(0.005)	(0.000)	(0.010)	(0.009)	(0.013)	(0.014)	(0.011)	(0.018)
	1,526	1,522		1,769	1,699		1,723	1,627	
$NPV_{(0,0)}$	0.039***	-0.005	0.044***	0.094***	-0.016	0.111***	0.163***	-0.007	0.171***
	(0.007)	(0.009)	(0.011)	(0.011)	(0.014)	(0.018)	(0.017)	(0.020)	(0.025)
	1,081	517		1,244	590		1,190	573	
				Panel C: Unconditional Return					
	BHAR_m_30			BHAR_m_180			BHAR_m_365		

52-Week High Reached	0.013***	0.046***	0.080***
	(0.000)	(0.001)	(0.001)
	125,853	138,558	131,821
52-Week Low Reached	0.043***	0.143**	0.256***
	(0.001)	(0.002)	(0.002)
	103,417	110,724	102,351

Appendix 4: BHARs after 52-week high/low has been reached

This table reports the Buy-and-Hold return in the top and bottom deciles defined by the level and the recency the 52-week high/low by using sample period of January 1994 to December 2018. In Panel A, we report the portfolios sorted by the level of the 52-week high/low to the current price. Panel B reports the portfolios sorted by the recency of the 52-week high/low. At the end of each month day *t*, we calculate the total insider trading pressure *NPV* for stock *s* in the given month. If *NPV* is larger (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 those stocks are in the top (bottom) 52-week high (low) ratio tercile and net-bought (net-sold) by insiders. We rebalance the long and short portfolios monthly. Panel B is similar to Panel A except we sort stocks according to their 52-week high/low recency ratios on day *t*. 52-week high/low recency ratio is $(1-\frac{distance\ to\ the\ 52-week\ high/low_t}{364})$. We report the 4-factor α_(t+1,t+i) 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 6/12 month. 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). Standard errors are reported in the parentheses below the 4-Factor Alpha. The standard error of two-sample t-test of different mean between Top and Bottom portfolios Alpha by assuming unequal variance is reported in the parentheses. We multiply Alpha by 6 or 12 for 6- and 12-month holding period, respectively. ***, **, * indicates the coefficients are statistically significant at 99%,95% and 90% respectively. All return variables are winsorised at bottom 0.5% and top 99.5%.

Panel A: 52-Week High/Low Sorted Portfolios-January Excluded								
	(1)	(2)	(3)	(4)	(5)	(6)		
	Insiders net-bought the top and net-sold the bottom portfolios		Average 52-Week High/Low Ratio	Unconditional on Insider trading		Average 52-Week High/Low Ratio	Difference between (1)-(4)	Difference between (2)-(5)
4-Factor Alpha	6-Month	12-Month		6-Month	12-Month			
Top 52-Week High portfolio	0.050***	0.058***	0.97	0.021***	0.025***	0.99	0.029**	0.033***
	(0.011)	(0.009)		(0.004)	(0.003)		(0.011)	(0.010)
Bottom 52-Week Low portfolio	-0.018	0.010	1.06	-0.004	0.003	1.03	-0.015	0.014
	(0.012)	(0.007)		(0.008)	(0.005)		(0.014)	(0.011)
Top-Bottom	0.070***	0.050***		0.024***	0.021***			
	(0.020)	(0.012)		(0.009)	(0.004)			
Panel B: 52-Week High/Low Recency Sorted Portfolios-January Excluded								
	Insiders net-bought the top and net-sold the bottom portfolios		Average 52-Week High/Low Recency Days (Ratio)	Unconditional on Insider trading		Average 52-Week High/Low Recency Days (Ratio)		
4-Factor Alpha	6-Month	12-Month		6-Month	12-Month			
Top 52-Week High Recency portfolio	0.038**	0.047***	14.65 days (0.96)	0.016***	0.018***	5.87 days (0.98)	0.022	0.029***
	(0.015)	(0.009)		(0.005)	(0.004)		(0.016)	(0.009)

Bottom 52-Week Low Recency portfolio	-0.016	-0.008	39.80 days (0.89)	-0.004	0.004	9.28 days (0.97)	-0.012	-0.011
	(0.016)	(0.009)		(0.008)	(0.005)		(0.017)	(0.010)
Top-Bottom	0.054**	0.055***		0.020***	0.014**			
	(0.022)	(0.013)		(0.005)	(0.006)			

Appendix 5: Construction of Anomalies.

Anomaly	Reference Paper	Construction
Failure Probability(FP)	Chen, *et al.* (2011)	Please see Chen, Novy-Marx, and Zhang (2010) for a detailed description. The construction of the variable is discussed in Appendix 6.
Net Stock Issuance(NSI)	Stambaugh *et al.* (2012)	$\log\left[(csho_{i,t-1} \times ajex_{i,t-1})/(csho_{i,t-2} \times ajex_{i,t-2})\right]$ Net stock issues are measured as the growth rate of the split-adjusted number of shares outstanding for stock We in fiscal year *t*.
Total Accruals (TA)	Sloan (1996)	$\frac{\Delta act_{i,t-2,t-1} - \Delta che_{i,t-2,t-1} - \Delta lct_{i,t-2,t-1} + \Delta dlc_{i,t-2,t-1} + \Delta txp_{i,t-2,t-1} - dp_{i,t-1}}{(at_{i,t-1} + at_{i,t-2})/2}$ Net stock issues are measured as changes in non-cash working capital minus depreciation expense scaled by average total assets for the previous two fiscal years.
Net Operating Assets (NOA)	Hirshleifer, Hou, Teoh and Zhang (2004)	$\frac{\left(at_{i,t-1} - che_{i,t-1}\right) - (at_{i,t-1} - dlc_{i.t-1} - dltt_{i,t-1} - mib_{i,t-1} - pstk_{i,t-1} - ceq_{i,t-1})}{at_{i,t-2}}$ Net Operating Assets are measured as the difference between all operating assets and all operating liabilities divided by total assets in the previous fiscal quarter.
Gross Profitability (GP)	Novy-Marx (2013)	$\frac{(sale_{i,t-1} - cogs_{i,t-1})}{at_{i,t-1}}$ Gross Profitability is the gross profits scaled by assets.
Asset Growth (AG)	Cooper, Gulen and Schill (2008)	$\frac{(at_{i,t-1} - at_{i,t-2})}{at_{i,t-2}}$ Asset growth is the growth rate of total assets.
Return on Asset (ROA)	Fama and French (2006)	$\frac{ibq_{i,t-1}}{atq_{i,t-2}}$ Return on assets is measured as the ratio of quarterly earnings to total assets.
Investment-to-Assets (IA)	Titman, WeWe and Xie (2004)	$\frac{(\Delta ppget_{i,t-2,t-1} + \Delta invt_{i,t-2,t-1})}{at_{i,t-2}}$ Investment-to-asset is measured as changes in gross property, plant and equipment plus changes in inventories divided by total assets.

Appendix 6: Construction of Failure Probability

This table displays the construction of Failure Probability (FP). The procedure follows closely with Campbell *et al.* (2008) and Chen *et al.* (2011). All variables are computed by using either Compustat or CRSP. The variable FP is calculated as the following:

$$FP = -9.164 - 20.264 \times NIMTAAVGt + 1.416 \times TLMTAt - 7.129 \times EXRETAVGt$$
$$+ 1.411 \times SIGMAt - 0.045 \times RSIZEt - 2.132 \times CASHMTAt + 0.075 \times MBt$$
$$- 0.058 \times PRICEt$$

All variables are winsorised at bottom 5% and top 95% level. Definition of Compustat variable is presented in Appendix 7. All variables are constructed by using last fiscal quarter's accounting information. A detailed construction of these variables are presented below.

Variable	Construction
NIMTAAVG	$NIMTAAVG_{t-1,t-12} = \frac{1-\phi^3}{1-\phi^{12}}\left(NIMTA_{t-1,t-3} + \cdots + \phi^9 NITMTA_{t-10,t-12}\right)$ Where $\phi = 2^{-1/3}$. $NIMTA = \frac{niq}{(ltq+prccq\times cshoq)}$ NIMTA is the net income divided by the sum of market equity and total liabilities.
TLMTA	$TLMTA = \frac{ltq}{(ltq + prccq \times cshoq)}$ It is the ratio of total liabilities over the sum of market equity and total liabilities.
EXRETAVG	$EXRETAVG_{t-1,t-12} = \frac{1-\phi}{1-\phi^{12}}\left(EXRET_{T-1} + \cdots + \phi^{11} NITMTA_{t-12}\right)$ Where $\phi = 2^{-1/3}$. $EXRET = \log(1 + R_{i,t}) - \log(1 + R_{S\&P500,t})$ EXRET is the monthly log excess return on each firm's equity relative to the S&P 500 Index.
SIGMA	$SIGMA = \sqrt{\frac{252}{N-1}\sum_{k\in\{t-1,t-2,t-3\}} r_k^2}$ *k* is the index of trading days in month $t-1, t-2, t-3$. *N* is the number of trading days in the previous three months. r_k^2 is the firm daily return volatility by assuming the mean return is zero. SIGMA is the three-month rolling sample standard deviation. Following Campbell *et al.* (2008), if there are less than five nonzero observations over the three months, SIGMA is set to be missing.
RSIZE	RSIZE is the relative size of each firm measured as log ratio of its market equity over the total market equity of S&P500 index.
CASHMTA	$CASHMTA = cheq/(ltq + prccq \times cshoq)$ CASHMTA is the ratio of cash and short-term investment over the sum of market equity and total liabilities.
MB	Market-to-Book ratio. Book equity is defined as in Davis, Fama and French (2000). Book equity is the sum of shareholder's equity and

	balance sheet de- ferred taxes and investment credit (txditcq) if available, minus the book value of preferred stock. Book value of preferred stock is redeemable preferred stock value (pstkrq) or carrying value for the book value of total preferred stock (pstkq) depending on the availability in this order. Shareholder's equity is stockholders' equity (seqq) or the sum of common equity (ceqq) and carrying value of preferred stock (pstkq), or total asset (atq) minus total liabilities (ltq) in this order, depending on the availability. Following Campbell *et al.* (2008), We add 10% of the difference between market equity and book equity to book equity to eliminate outliers. For those stocks that still have negative book eq- uity value, we replace those negative values to be $1 to ensure that all firms are in the right tail of the distribution.
PRICE	PRICE = log(prccq). It is each firm's log closing price, truncated above at $15. In other words, if the closing price of a stock is larger than 15, then it is restricted to be $15.

Appendix 7: Compustat Item Definition

Compustat Notation	**Definition**
csho	Common Share Outstanding
ajex	Adjustment Factor (Cumulative)
act	Total Current Assets
che	Cash and Short-Term Investment
cheq	Cash and Short-Term Investment-Quarterly
lct	Total Current Liabilities
dlcq	Total Debt in Current Liabilities-Quarterly
txp	Income Tax Payable
dp	Depreciation and Amortisation
at	Total Assets
atq	Total Assets-Quarterly
dlttq	Total Long-Term Debt-Quarterly
mib	Non-Controlling Interest-Quarterly
pstk	Total Preferred/Preference Stock
ceq	Total Common/Ordinary Equity
sale	Sales/Turnover
cogs	Cost of Goods Sold
ibq	Income Before Extraordinary Items
atq	Total Assets-Quarterly
ppegt	Total Property,Plant and Equipment
invt	Total Inventories
niq	Net Income-Quarterly
ltq	Total Liabilities-Quarterly
prccq	Close Price-Quarterly
cshoq	Common Share Outstanding-Quarterly
cheq	Cash and Short-Term Investment-Quarterly
seqq	Stockholders' Equity-Quarterly
ceqq	Common/Ordinary Equity-Quarterly
pstkq	Total Preferred/Preference Stock-Quarterly
ltq	Total Liabilities-Quarterly
txditcq	Deferred Taxes and Investment Tax Credit-Quarterly
pstkrq	Preferred/Preference Stock-Redeemable-Quarterly