What Do Insiders Know? The Informational Content of Insider Trading around Three Corporate Events

Xiaoke Ye

Supervisor

Professor Meziane Lasfer

Bayes Business School

City, University of London

A thesis is submitted for the degree of *Doctor of Philosophy*

November 2022

Acknowledgements

I am grateful to my supervisor, Professor Meziane Lasfer, for his guidance and overall insights during the whole PhD journey. This dissertation would not be possible without his support. I thank external examiner Professor Ian Tonks and internal examiner Anh Tran for their valuable suggestions. I also thank Professor Giovanni Cespa, Professor Ian Marsh, and Professor Richard Payne for their generic support. I thank Dr Giacinta Cestone as PhD programme director for her valuable suggestions and for providing inspiration for my thesis. I also thank Ms Malla Pratt and Mr Abdul Momin for their help and administrative support. I thank my fellow PhD students as Bayes for offering their supports whenever I needed. I thank my father Yong Ye and my mother Haiyan Tu and my girlfriend Yichun Xu for supporting me during the entire compilation of this thesis. You all have made the PhD as an inspiring experience for me.

ABSTRACT

Corporate insiders, such as CEOs, CFOs and other senior managers, are commonly recognised in the stock market as possessors of private information about the future prospects of their company. These high-rank managers are informed investors because they are closely involved in the daily operations of their firms and have superior access to price-sensitive information than outside investors. They frequently execute open market transactions to purchase or sell shares. They do so for various reasons. They trade legally if they consider their firm is mispriced or to execute stock options the board rewarded them to align their incentives with the shareholders'. However, regulators strictly prohibit corporate insiders to trade the shares of their companies based on any material private information. Nevertheless, previous literature has unanimously documented a robust return predictability embedded in their trades, indicating corporate insiders frequently trade on their private information for personal monetary gain (Seyhun, 1988; Lakonishok and Lee, 2001; Roulstone, 2003; Ravina and Sapienza, 2010; Cohen, Malloy, and Pomorski, 2012). Whilst many previous studies in the last decade attempt to understand the motivation behind these informed transactions, the issue is still contentious and there is ongoing debate concerning the determinants, the legality, the timing, and the profitability of insider trading.

Motivated by the recent advancement in the insider trading literature, the objective of this thesis is threefold. *First*, to investigate the incentives for corporate insiders to make more informed transactions around three pivotal events: (i) CEO turnover, (ii) M&A announcements of their supply-chain firms, and competitors and (iii) when their firm's stock price reaches its 52-week high/low. I use a large sample of insider trades announcements spanning 25-year from the US. I focus on both the changes in trading activity and profitability in response to these three events.

Second, to assess the informational content behind these more informed insider transactions to better understand the implications of these events for their firms. Existing literature has contradictory predictions for the impact of these corporate events on future firm performance. I employ insider trading activity as an indicator to examine these predictions because insiders have the advantage to understand better their firms' growth prospects, and their decision and post-transaction profitability are viewed as a function of the impact attributed to these events on their firm's future performance on which their personal wealth is hinged.

Third, to empirically test and bridge tournament incentives, M&A, and behavioural finance literature with the insider trading literature. The thesis not only contributes to the insider trading literature but also to these three different streams of literature. Tournament incentives and insider trading literature both study the managers' behaviours, the ongoing investigations in these two domains are largely parallel and do not intersect. To the best of my knowledge, the second chapter is the first empirical analysis to bridge these two streams of literature. Similarly, the existing M&A literature mostly focus on the insider trading activity either in the acquirer or target firms (Agrawal and Nasser, 2012; Fidrmuc and Xia, 2021; Davis *et al.* 2021). My third chapter is the first to focus on insider trading activity in a firm that is not directly involved in the M&A deal, but the protagonists are in its supply chain either as a competitor, supplier, or customer. Lastly, the fourth chapter challenges and revises an existing finding in the behaviour finance literature that corporate insiders, who are informed investors, also suffer from the 52-week high anchoring bias. I further analyse whether corporate insiders trade in the direction predicted by the existing literature or do they behave differently because they have private access to the future fundamentals of their firms.

The research findings in the second chapter indicate that non-CEO corporate insiders who have lost their promotion opportunity to the next CEO actively sell their shares in their own company. They trade on their private negative information to make higher loss-averting abnormal return. The empirical results are consistent with the prediction of tournament incentives model that senior executives endure pay below the optimal market rates because they incorporate the implicit value of the future promotion opportunity into their contracts. Once the expected value of the implicit compensation has drastically declined, these senior executives trade to compensate themselves for the forgone incentives. I subject my results to various robustness checks. I find that they undertake loss-averting sell trades when their pay gap with the CEO is high, they are relatively young with short-term horizon, and when their firm's governance is comparatively weak. I show that they trade on their firm's future declining performance, increase in its cost of capital, and worsening in investor sentiments. My results also show that this trading opportunity weakens the well-documented positive relationship between tournament incentives and firm performance. The conclusion indicates that having a large pay disparity between CEO and other senior managers is not as effective and efficient as the literature has so far documented. Moreover, my results imply that regulators need to focus also on the non-CEO executives who appear to trade on insider information with relatively low regulatory risk.

The third chapter shows that that corporate insiders significantly alter their trading activities and make more informed transactions when their competitors or customers firms become an M&A target. The results show that corporate insiders recognise that their operating and innovation efficiencies will be improved attributed to the M&A deal, and they will increase their holdings to benefit from the better firm performance. I further show that corporate insiders not only have informational advantage in private information but can understand public information better than outside investors. Their trades also predict their firm's potential takeover bid. I subject my results to a battery of robustness test and find that incomplete M&A announcements do not lead to the significant change in both insider trading activity and profitability. Moreover, insider trading measure can predict the probability of the deal completion, and the predictive power is in addition to the market-estimated probability.

The fourth chapter focuses on insider trading around the 52-week high/low. Previous studies concluded that the aggregate investors suffer from the 52-week high/low anchoring biases as they are more likely to sell high and buy low, and corporate insiders who are conventionally viewed as informed traders, are not exempt from the bias. In contrast, I find that insiders systematically trade at these price extremes, but they do not suffer from anchoring biases. Some insiders, such as male, CEOs and opportunistic insiders employ dissimulation strategies to conceal their informational advantage and engage in highly profitable transactions. A long-short strategy based on a portfolio built on the top decile 52-week high (low) recency of their transactions generates an annual abnormal return of approximately 31%.

Studies on insider trading are subject to several limitations. First, it is not clear why insiders trade. They may do so to take advantage of their private information, to correct misevaluation or for liquidity and portfolio diversification motives. I use in all my chapters various econometric specifications, including diff-in-diff and IV methods to mitigate any bias driven by reverse causality. I also account for insiders' sequential transactions and dissimulation strategies to mitigate regulatory risk. In Chapter 4, I undertook an out of sample test by assessing insiders' trading propensity and profitability during the COVID period when many stocks reached their 52-week low. I find that, overall, my results hold to all these specifications. Second, this study does not investigate other than the US insider trading regulation systems, which are relatively similar but differ in their implementations (Bhattacharya and Daouk, 2002). Third, I do not assess insiders' personal attributes as in Hillier, Korczak and Korczak (2015), beyond their gender, because of data unavailability. The extent to which these limitations will alter or confirm my US results is the subject of further research.

Contents

List of Tables

List of Appendix

List of Figures

Chapter 1

Introduction

Corporate insider trading pertains to open-market transactions executed by corporate employees for the securities of their own company. In the US, corporate insiders have been defined to include the CEO, CFO, officers, key employees, 10% large shareholders and anyone who possesses inside information because of his or her relationship with the Company or with an officer, director, or principal stockholder of the Company (Bhatacharya and Daouk, 2002)[1]. Manne (1966) was the first study to support the concept of corporate insider trading, because the agency problem between managers and shareholders would be alleviated if these insiders were permitted to derive advantage from the increased share price of their own firms. The trading policy will enhance both firm performance and the market's informational efficiency. The board usually awards managers many shares to align their incentives with the shareholders' interests. Meulbroek (1992) shows that stock market compounds insider trading information into the current stock price on the day of execution, and the price discovery will increase stock price accuracy. A contrasting perspective is the belief that corporate insider trading harms market liquidity, thus leading to decreased market efficiency (Fishman and Hagerty, 1992). Opponents argue that corporate insiders have superior access to their company's price sensitive information, permitting them to trade on the information, increasing market efficiency and, thereby, deterring outside investors to pay information acquisition costs. Since the initiation of the debate on corporate insider trading, almost all accounting and finance empirical research is focused on insiders' informativeness through three inter-related research themes: (1) insider trading performance; (2) insider trading timing, and (3) the motivation behind insider trading.

The initial surge in insider trading research predominantly focused on insider transactions' trading performance. Following nearly three decades of arguing about the correct method to measure insider trading performance, the literature has settled on adopting post-transaction abnormal return as a proxy for insider trading informativeness. Researchers unanimously concur that corporate insider purchase transactions are informative, meaning when corporate insiders are increasing their holdings in their own company, their company will outperform in the market in the future, with insiders benefitting from the subsequent share price

[1] Bhatacharya and Daouk (2002) document that insider trading rules existed in many countries but their enforcement, as measured by prosecutions, is only in few of them. The context of who is an insider may also differ, making some trades legal in some countries but illegal in others (Sturc, Sagayam, Barabas, and Tran, 2012).

increase. However, no clear evidence supports the proposition that insiders sell their shares in their company for personal gain. These results are unsurprising, given that managers receive part of their compensation in the form of stock options, making their personal portfolios over-concentrated on their company. Therefore, they are likely to sell shares to diversify their personal portfolio or for personal liquidity reasons, which are not likely to bring abnormal profits (Cohen *et al.* 2012). The informativeness embedded in insider purchase transactions is generally witnessed in different stock markets with differing insider trading regulations (Bhattacharya and Daouk, 2003; Bris, 2005; Cline, Williamson, and Xiong, 2021).

The second major theme concerns insider trading's timing. Financial signaling theory implies that outside investors will consider senior managers' execution of insider transactions prior to significant corporate events as a credible signal of the firm's future performance. Examples of such corporate events include earnings announcements, as well as M&A announcements. Since insiders have optimal access to their firm's future fundamentals, they can signal stock mispricing by trading on it. The central research method is to concentrate on insider transactions in an event window around a specific corporate event, seeking to study the corresponding abnormal returns. Despite relatively strict regulations explicitly prohibiting corporate insiders from trading on any material information, researchers have documented that corporate insiders systematically trade on their private information for private gains, with such more informed insider transactions rarely leading to prosecution, suggesting that the regulation is not binding (Bhatacharya and Daouk, 2002).

The ongoing investigations into insider transactions' timing have documented some counter-intuitive empirical findings, challenging corporate insiders' role as informed investors. Insider transactions are not necessarily informed decisions, with corporate insiders occasionally trading as noisy trader. To list a few, corporate insiders are likely to purchase stocks when the short interest is high (Wu, 2019), when they are in their early tenure as CEO (Armstrong *et al.* 2021) as well as when their firms' stock prices are close to the 52-week high (Lee and Piqueira, 2019). Such results compel researchers to question the motivation underpinning these insider transactions.

The burgeoning research relating to the third theme has documented various reasons and motivations underpinning insider transactions. For instance, insiders will trade for personal gains when their anticipated returns outweigh the litigation risk. Both their purchase and sell transactions during the 21-trading days prior to the quarterly earnings announcement generate over 1% monthly four-factor alphas, far greater than in the previous insider trading literature (Ali and Hirshleifer, 2017). Similarly, newly appointed CEOs make purchase transactions that are noisy and not based on any material information, to prolong their tenure. They pursue this course of action even if their firms underperform their industry peers in future. The board cannot distinguish the genuine motivation behind these noisy insider purchase transactions (Armstrong *et al.* 2021). Corporate insiders will falsely signal confidence in their firms by purchasing shares when the short interest in the market is high (Wu, 2019). Such purchase transactions will thwart outside investors in falsely reckoning that their firm is underpriced, as well as their purchase of more shares. Nevertheless, these firms eventually underperform in the market, leading to capital losses for uninformed investors. These results indicate that the authentic motivation underlaying corporate insider trading remains contentious, with ongoing debate concerning the determinants, timing, legality, and profitability of insider trading.

My research intends to fill in this gap by using detailed legal insider transactions data, combined with other datasets, in order to investigate the informational content underpinning these more informed insider transactions, as well as to infer the motivation behind these trades.

1.1 The Research Objective

Insider trading motivation is a significant factor that the board, regulator, as well as outside investors must consider, because it illuminates their comprehension of their firms' prospects and their personal career plans. Moreover, corporate insiders are deemed informed agents in the stock market in numerous financial models, with their trading decisions providing an ideal setting to test the extent to which the behaviour of the informed agent is consistent with these models' predictions. I will consider the shortcomings and unresolved puzzles in the insider trading literature to undertake further investigation of the true motivation behind the informed transactions of corporate insiders, bridging this to the various relevant literature.

Accordingly, this study's aim is to examine the motivations and informational content behind insider trading, applying this information to test some existing hypotheses in the corporate finance literature. The thesis comprises three independent chapters focusing on the common themes of insider trading. The general research objectives are threefold: first, to investigate the change in both insider trading activity and profitability around three pivotal events: (i) CEO turnover tournaments; (ii) M&A announcements of their supply-chain firms and competitors; (iii) when their firm's stock prices reach their 52-week high/low.

The rationale for focusing on event (i) is that the tournament incentives model implies that high-ranking, non-CEO managers will trade on their private information more aggressively if they lose out in the CEO promotion tournament. I empirically test the prediction of the tournament incentives model. Event (ii) offers a unique venue for testing corporate insiders' informational advantage in terms of comprehending public information. The limited attention constraint theory proposes that a temporary stock mispricing will occur for the focal firm following their supply-chain partners or competitors making a major corporate announcement, which in my setting is the announcement that they have become a target. Consequently, the aggregate market cannot efficiently incorporate the news into the focal firm stock price. I investigate whether insiders also have an informational advantage in terms of understanding the major corporate announcement compared with the aggregate market. Event (iii) shows a contradiction between the behavioural finance literature and insider trading literature. Behavioural finance implies that the 52-week high/low are two fundamentally irrelevant pieces of historical price information that corporate insiders should not consider. Even so, the extant insider trading literature posits that corporate insiders systematically trade on these two price levels, thus making them subject to the 52-week high bias. I revisit this finding, assessing whether corporate insiders remain informed agents at these two price extremes.

The second objective is to examine the informational content underpinning these more informed insider transactions, using this information to address certain dilemmas in the corporate finance literature. The extant literature makes contradictory predictions regarding the effect of these three corporate events on future firm performance. I use insider trading activity as a premise for investigating these predictions, given that corporate insiders have the greatest advantage in terms of comprehending their firm's growth prospects. In the second chapter, I focus on insider purchase and sell transactions separately, due to there being an abnormally high turnover rate among insiders who failed to become the next CEO, meaning they are systematically less likely to further increase their holdings. In the third and fourth chapter, I follow Lakonishok and Lee (2001) approach and apply net purchase ratio as a measure of insider trading activity.

The third objective is to empirically test and to bridge tournament incentives, M&A, and behavioural finance literature with the insider trading literature. Therefore, the thesis not only contributes to the insider trading literature, but it also enhances these three different streams of literature. Corporate insiders are the tournament contenders in the tournament incentives model, yet no research exists that has studied the effect of losing CEO tournaments on the losers' trading behaviour. Similarly, the existing M&A literature has predominantly focused on insider trading behaviour in either the acquiror or the target firm, yet insider trading's informativeness has largely been overlooked. Equally, research on anchoring bias has mainly focussed on non-informed investors, not so much on insiders who know better than the market their firm's prospects.

1.2 Overview and Main Findings of the Study

In chapter 2, I focus on the non-CEO director's insider trading activity around the CEO turnover event. I analyse the drivers of trading profitability of non-CEO managers who remain with their firm after losing their CEO promotion opportunity. The tournament incentives model implies that high-ranking non-CEO managers are willing to accept compensation contracts below the optimal level for their effort, as they incorporate the expected value of future promotional prospects into their contract. The CEO position is their only promotion destination in their firms; thus, they only have one opportunity to win during the CEO tournament. Consequently, the model predicts that these tournament losers will be under-compensated for their efforts, due to the drastic decline in the expected value of their future promotion. I document that such tournament losers trade on their private information opportunistically, profitably, and aggressively with the aim of compensating themselves for the forgone pay rise linked to the CEO position. I observe that these non-promoted executives will trade in the CEO turnover year in 63% of my CEO promotion sample, and 92% of these insider transactions are sell trades, significantly higher than the unconditional sell transaction proportion of 82%. I use their personal characteristics to conclude that their true motivation for making such informed transactions is the forgone CEO promotion, as opposed to stock mispricing. These insiders primarily make more informed sell, although not purchase, transactions, because they trade against the newly appointed CEO's noisy buy trades. I find that they trade on their firm's future declining performance, increase in its cost of capital, in addition to investors' sentiments. I adopt a two-stage least square estimator to show how this insider trading opportunity weakens the well-documented positive relationship between tournament incentives and firm performance. A large pay disparity between the CEO and other non-CEO executives will not incentivise these non-CEO executives to exert effort to the extent that the literature documents, because they have the outside option to narrow the gap independently.

In this chapter, I contribute to the literature from three different perspectives. One is that it is the first empirical analysis bridging the two relatively different streams of research, insider trading and tournament incentives. I document that the realisation of their tournament incentives affects insiders' trading. In addition, this is the first study to show the substitution effect between the insider trading opportunity and promotion opportunity. I show that if tournament contenders trade on their material information aggressively prior to a tournament, they are less likely to win the promotion opportunity. However, if their promotion opportunity is gone, they will use their insider trading opportunity to compensate themselves. The finding suggests that simply having a large pay gap between CEO and other senior executives is not as effective as the compensation committee reckoned because executives can always use their private information to compensate themselves for the forgone tournament incentives *ex-post*. The committee should have an internal insider trading restriction if they want to incentivise contenders to exert effort to win the CEO promotion incentive is large.

Second, I contribute to the tournament incentives literature by documenting an unintended consequence of holding a CEO tournament, namely, it causes more aggressive insider trading activities. Kini and Williams (2012) show that the intra-organisational CEO promotion tournaments are like long call options, in which the downside loss is limited but the upside gain is infinite. Therefore, corporate executives will increase firm risks to have better firm performance by following riskier policies. Unlike Kini and Williams (2012), I specifically focus on those tournament losers and show that the unintended effect of holding CEO promotion tournament is long-lasting and will persist up to two years after the CEO turnover. Third, I contribute to the insider trading literature by documenting a further non-previously documented corporate event through which insiders systematically incorporate private information into their trading decisions, with the goal of achieving higher abnormal returns. I show that insider trading opportunity also complements future unrealised compensation, with insiders adjusting their trading strategies according to their career concerns and the forgone pay rise; this is an unexplored area within the insider trading literature. My results imply that companies would benefit from reducing the pay gap between CEO and top-ranked executives and that regulation should not focus on only CEO trading. Additionally, I show that insiders do not always purchase stocks to reap abnormal profit, they can avoid incurring large losses by timing their sell transactions. The result directly challenges the existing findings in the literature that insider sell transactions are less informed than purchase transactions, on average.

Chapter 3 uniquely concentrates on the changes to insider trading activity and profitability around the announcement of their competitor or supply-chain firms having become the target in a deal. I document that corporate insiders systematically engage in less selling when their competitors or customers have become the target in an M&A deal. No significant change arises when their suppliers have become the target. This reduced selling pressure is correlated with a higher abnormal return in the future, indicating that these insider transactions are more informative. I investigate the informational content underpinning these informed transactions. I identify that these insiders trade on the improvement in both operating and purchasing efficiency hypotheses, the two well-documented sources of gain in the M&A literature. Furthermore, these informed insider transactions enable prediction of deal competition probability, in addition to the probability of their firm becoming a target.

Chapter 3 contributes to both the insider trading and M&A literatures. The former has predominately argued that insiders generate abnormal returns due to their superior access to their proper firms' future fundaments. I build on Alldredge and Cicero (2015) which solely focuses on customer relationship, and I extend their results to the competitors and supplier relationships using a significantly larger sample. I show that insiders' ability to better understand the public information not only exists for their customers, but also competitors. Moreover, the existing M&A literature is primarily concerned with insider trading activity, either in the acquiring or target firms (Agrawal and Nasser, 2012; Fidrmuc and Xia, 2021). This paper is the first to focus on insider trading activity in a firm that is indirectly involved in an M&A deal. I show that M&A announcements do not just significantly change the insider trading activity in the acquiring and target firms, but they alter insider trading activity in a firm in the target organisation's supply chain. The aggregate investor will not fully incorporate the impact of the M&A deal announcement into the prices of firms in the target organisation's supply chain due to the limited attention constraint. The short-term misevaluation will provide profitable trading opportunities for corporate insiders in these firms, and these informed agents will actively exploit the temporary mispricing as they are not suffering from the constraint. Lastly, I document that the source of gains behind the informed trading is the improvement in both operating and purchasing efficiencies resulting from the deal, and these corporate insiders can reap abnormal returns without exacerbating their litigation risk as the news is public.

Chapter 4 focuses on the intersection between the behavioural finance and insider trading literatures. The former proposes that informed investors should not adopt a contrarian trading strategy to sell (buy) at the 52-week high (low), due to these two historical price levels being fundamentally irrelevant to the company's future performance. Nevertheless, literature has identified outside uniformed investors to adopt contrarian strategies unprofitably by selling (buying) shares at 52-week high (low), and even some corporate insiders, who are informed investors, systematically sell at the 52-week high, while stock prices carry on rising. In this thesis, I present original evidence to propose that these corporate insiders are not suffering from the 52-week high and low bias. Their ability to time the market and thwart outside investors enables them to sell at the 52-week high and still generate abnormal returns, but they are more likely to buy (sell) profitably when their firms' share prices reach their 52-week low (high) at the expense of uninformed investors.

Chapter 4 contributes to the literature by revising the existing finding that corporate insiders suffer from the 52-week high and low biases. My results indicate that opportunistic insiders are not subject to the 52-week high anchoring bias. Moreover, in contrast to Cen, Hilary and Wei (2013) as well as Clarkson, Nekrasov, Simon and Irene's (2020) claim that financial analysts suffer from anchoring bias, I provide evidence that corporate insiders are unlikely to be subject to such behavioural predisposition, in line with Lee and Piqueira (2017) and Kelly and Telock (2017).

1.3 Overall Contribution of the Study and Policy Implications

In summary, this thesis contributes to the current literature in four ways. First, this research increases our standing of the informational content behind insider transactions. The existing insider trading studies perceive that the main motivation behind informed insider transactions is to support stock price or signaling stock misevaluation. The market reaction to the insider purchase transaction is, on average, positive, and corrects the stock misevaluation shortly. I contribute to the past vast literature by showing that insiders make informed transactions when there are substantial changes in their career prospect and in their firms' future operating efficiency and when there are uninformed investors trading their firms' stocks in the wrong direction. My results show that price support or past misevaluation play secondary roles in these corporate events. This thesis is also an effort to examine the insider trading behaviour in many theoretical contexts. I provide evidence that is consistent with the predictions of the tournament incentive model proposed by Lazear and Rosen (1981), the industry growth hypothesis suggested by Eckbo (1983), the higher acquisition probability hypothesis proposed by Song and Walking (2000) and the 52-week high behaviour bias explanation documented by George and Hwang (2004). I construct a unique dataset on supply chain by using Factset Revere and manually bridge insider trading dataset with Execucomp to conduct these large sample studies. As far as I am aware, this is the first insider trading study to employ Factset Revere, and to provide one of the largest link tables between the insider trading dataset and Execucomp.

Second, the thesis links the role of 1) CEO promotion opportunity 2) firm supply chain and 3) the 52-week high/low, with insider trading literature. I focus on the insider trading informativeness around these three corporate events not covered in the past literature. This thesis provides additional evidence to show that their superior timing ability is also one of the main reasons that insiders can reap abnormal returns in these three contexts. I show that although these three corporate events will not induce a significant stock misevaluation, corporate insiders time their transactions better and trade on their private information to generate abnormal returns. Lakonishok and Lee (2001) and Cohen *et al.* (2012) argue that corporate insiders can generate abnormal returns mainly because they have superior access to the material information. My result on the superior timing skills is complementary to the private information channel.

Third, the study contributes to the insider trading literature by showing that insider sell transactions are more informative than purchase transactions in many corporate events. The majority of the insider trading studies after Lakonishok and Lee (2001) have agreed to the notion that corporate insiders mainly generate abnormal returns by purchasing shares. Nevertheless, my research has shown that insiders will make more informed sell transactions when they have forgone promotion opportunities, and when their stock prices recently dropped to the 52-week low. In the former scenario, their purchase transactions are not as informed as their sell transactions, suggesting that insiders have various options to generate abnormal returns, not only by purchasing shares.

Lastly, the study embeds profound policy implications. The results suggest that if the board would like to incentivise managers to exert effort by creating large pay disparity between the CEO and other non-CEO senior managers, firms should impose more restrictive internal insider trading policies to prevent those CEO candidates from compensating themselves. Moreover, my results indicate that insiders frequently make sell transactions to reap loss-averting abnormal returns at the expense of outside investors. SEC and market regulators should impose more rigours insider sell transactions' rules to protect uninformed investors from these insiders sell trades.

1.4 Limitations of the Study

Like any social science study, I recognise that my empirical work is likely to be subject to the following set of limitations, which I may not have able to resolve fully.

1) The causality between the three events I focussed on and the change in insider trading may not have been effectively and fully established. Endogeneity is consistently a major issue in social science in general and in insider trading research, in particular, because the genuine motivation underpinning insider transaction is not observable. Moreover, Hillier, *et al.* (2015) show that insiders' personal attributes also affect their trading performance which further induce omitted variable bias. I employ various identification strategies in these three chapters to mitigate the impact of endogeneity. For example, I use diff-in-diff regression, two-stage least square estimator and instrumental variables. Nevertheless, in some circumstances, the outstanding omitted variable bias deters me from claiming a causal relationship.
2) This study does not investigate other insider trading regulation systems, apart from the US. In general, regulations on insider trading are relatively common across countries. For example, the European Union (EU) adopted similar rules in 2014 under the Criminal Sanctions for Market Abuse Directive. Therefore, I expect my results to apply also in non-US institutional setting. However, the legislations on insider trading across the world may differ in their scope and implementations. For example, Sturc *et al.* (2012) contrast insider trading rules in the US and the UK to show that one insider trading event in the UK would have been considered in the US. Bhatacharya and Daouk (2002) document that insider trading rules existed in only 34 countries out of the 103 countries they studied, in the pre-1990 period, rising to 87 in the post 1990s, but their enforcement, as measured by prosecutions, has taken place in only 38 of them. Hauck (2015) reports that the EU Criminal Sanctions for Market Abuse Directive lacks competence of legislation across the EU member states and the wordings of the directives are not as strong as the US's.
3) I do not attempt to evaluate other corporate announcements around these three events, given the substantial sample size and the data unavailability in machine-readable form.
4) Corporate insiders are only obliged to report their transactions up to 6 months after leaving the firm. Chapter 2 reports that managers do not profitably trade on their shares prior to leaving the firm. It is not feasible to analyse whether they delay their informed trading once they have left the firm due to data unavailability. The extent to which these limitations will alter or confirm my US results is the subject of further research.

Chapter 2

Tournament incentives and insider trading[2]

Abstract

I analyse the drivers of trading profitability of non-CEO managers who remain in their firm after losing their CEO promotion opportunity. Consistent with the implication of the tournament incentive models, I show that they trade intentionally on their private information opportunistically, profitably, and aggressively to compensate themselves for the forgone pay rise associated with the CEO position. They exert less effort and trade on their firm's future declining performance, increase in its cost of capital, and investors' sentiments. Using instrumental variable to address the reverse causality concern, I conclude that this trading opportunity weakens the well-documented positive relationship between tournament incentives and firm performance.

Keywords: Insider Trading; Tournament Incentives; Manager Compensation; Career Outcome

JEL Classification: G14; G11; G12; G40; G41

[2] I thank Ian Marsh, Onur Tosun, Massimiliano Barbi, Lilian Ng, Patrick Verwijmeren, Masatoshi Kurusu, Tse-Chun Lin, Omrane Guedemi and seminar participants at Bayes Business School, City, University of London, UTS Business School, University of Technology Sydney, University of Sussex Business School, CICF 2022, FMA Europe 2022, EFMA 2022, AFS 2022 for their helpful comments. Any errors remain my own responsibility.

2.1 Introduction

On 1st November 2016, The Toro Company (NYSE: TTC) internally promoted Richard M. Olson to be the next CEO, replacing the eleven-year incumbent Michael J. Hoffman, with a subsequent increase in his total compensation package from $1.5 million to $4 million. The other three internal CEO candidates who missed the promotion and the remuneration awards stayed with the firm. The following year, they executed several loss-avoiding sell trades with an average yearly abnormal buy-and-hold return of -13.78% and generated 40.43% (41.89%) lower yearly abnormal returns than their sell transactions executed one year (two years) before the CEO decision was made.

I investigate why such non-promoted managers' transactions become drastically more informative after losing the CEO promotion opportunity. I consider that the loss of future promotion opportunity and the forgone rise in compensation associated with the CEO position motivate them to exploit their informational advantage by trading on their private information aggressively. I base my argument on the intersection between tournament incentives and insider trading literature.

The former has established that firms hold promotion tournaments by making several top employees compete for a single more senior position promotion-based prize, which is the increase in compensation (DeVaro, 2006; Kale, Reis and Venkateswaran, 2009). Cvijanovic, Gantchev and Li (2021) show that 83.6% of S&P 1500 firms do not have a formal CEO succession plan and hold open CEO tournaments for competition. Employees are willing to accept contracts that offer them explicit incentives such as annual salary and bonuses below the optimal levels for their effort, because they value the chance of future promotion; they incorporate into their contracts the expected increase in the explicit incentives associated with the promotion (Lazear and Rosen, 1981; Main, O'Reilly and Wade, 1993). At the highest level of the corporate hierarchy, the CEO position and pay are the only promotion destination and ultimate tournament prize that incentivize senior non-CEO managers to exert efforts to win. Kale, *et al.* (2009) find a positive relationship between firm performance and the pay increase non-CEOs expect to receive if they successfully realize the promotion-based incentives.

However, senior managers who lose the first CEO promotion tournament during their time in the firm see a significant reduction in their likelihood of winning the next round of CEO tournament in the same firm. Consequently, there is a drastic decline in the overall value of these tournament losers' contracts because the value of their implicit promotion-based incentives is much lower, if not foregone completely. Since firms are restrained from adjusting their contracts to compensate them for the forgone compensation opportunity and restoring the explicit incentives to the optimal level even after paying retention bonus (Chan, Evans and Hong, 2022), more competent managers leave the firm to participate in other firms' tournaments rather than face compensation contract below the optimal level. This contributes to the high turnover rate among senior managers observed empirically following the appointment of a new CEO (Chan, *et al.* 2022; Gregory-Smith and Wright, 2019).

I hypothesize that non-promoted managers who choose to stay with the firm, and costly to layoff, will be motivated to compensate themselves for the forgone promotion opportunity by exploiting their private information aggressively because their contracts are now worth less, and the explicit incentives are below the optimal level. One strategy is to trade on price-sensitive private information to generate higher abnormal returns, as they are closely involved with their firm's daily operation and have superior access to price-sensitive information, which allows them to trade profitably without attracting the market regulator's attention (Ali and Hirshleifer, 2017).[3] Empirical evidence has unanimously documented that corporate insiders actively trade on their private information regarding their firms' future to generate excess returns, resulting in return predictabilities following both insider purchase and sell transactions (Lakonishok and Lee, 2001; Cohen, Malloy and Pomorski, 2012; Biggerstaff, Cicero and Wintoki, 2020). Their transactions become drastically more informative before some specific corporate events, such as the release of quarterly earnings announcement (Ali and Hirshleifer, 2017), around M&A rumor (Davis *et al.* 2020), when there is a worsening in the industry level information environment (Contreras and Marcet, 2021), and if they narrowly miss their

[3] In a conventional insider trading model, an informed agent's trading aggressiveness α is increasing in his risk tolerance (Cespa, 2008). Since there is a decrease in insider's overall compensation value, her risk tolerance should become higher because the expected loss of losing her job is lower if regulators prosecute them for illegal insider trading. Consequently, I hypothesize that non-promoted managers will tolerate higher litigation risk and trade on their private information more aggressively.

performance-based bonus (Gao, 2019). This evidence suggests that insiders will intentionally trade on their private information aggressively when the expected gain is large enough to outweigh the associated litigation risk and to maximize their private benefits. I extend this evidence by assessing the extent to which the gains from their trades will compensate non-promoted managers for the foregone CEO promotion opportunity.

I use a sample of 165,705 insider transactions undertaken by 21,723 US non-CEO executives between 1996 and 2019 to assess whether non-promoted managers trade on their private information with greater aggressiveness after losing the CEO promotion opportunity. One main concern in the literature is endogeneity, as the true motivations behind insider trading, including private information, personal liquidity need and portfolio diversification, are not directly observable, leading to random post-trades' returns, and the omitted variable bias will subsequently result in inconsistent estimates. I use two approaches to mitigate this problem. Firstly, I specify a diff-in-diff regression based on matched sample to isolate the losing CEO tournament effect within event years (-2, +1). I match my test firms with a control group without CEO turnover by total assets, average insider trading profitability and book-to-market ratio one year before my test firms' CEO turnover. To test the appropriateness of my matching algorithm, I follow Angrist and Pischke (2009), Cengiz *et al.* (2019) and Baker, Larcker and Wang (2021) and conduct an event-study type diff-in-diff regression to show the parallel trend assumption. Second, I apply two-stage least square (2SLS) estimator by using the age of former CEO as instrumental variable (IV) to further generalize the finding outside my event window. The former CEO's age is a publicly available information, not correlated with the firm's future fundamental that insiders are exploiting because former CEO has left the firm on average six years ago, but it empirically embeds predictive power for the future CEO turnover. I informally test the exclusion restriction of my IV by showing that former CEO's age contains little predictive power for non-CEO insider trading profitability outside the CEO turnover event, further stressing the exclusion restriction plausibility.

I find that non-promoted managers are significantly more likely to sell than to purchase shares in their own company after losing the tournament. I find a significant increase in the more intense selling pressure only after the tournament because their winning probabilities is likely to be adversely affected if they executed more opportunistic sell transactions before the tournament. These results may suggest that they unwind previously accumulated equity positions following non-promotion to reduce their undiversified portfolio and probably to bypass regulatory constraints as Lakonishok and Lee (2001) argue that insiders sell a stock for a variety of reasons, but the main motivation to purchase a stock is to seek profit. However, I find that their trades are not random. They are significantly more profitable in the year they lose their CEO promotion than they would have generated without CEO turnover. Their loss-averting sell trades persist one year after the CEO turnover and are significantly more profitable than their peers who left the firm, reinforcing my hypothesis that they trade to cover their opportunity cost.

I use various proxy variable to support my arguments. I expect the losing tournament effect to be weaker for firms with planned CEO successor prior to the tournament, as the assignment of a CEO successor would depress the discontent among non-promoted managers. I also expect insiders with larger pay gap with their CEO before the tournament outcome to trade on their private information more aggressively because of the higher opportunity loss. In the same logic, the trading profitability should be higher for younger insiders because they have a higher expected value on the promotion-based components in their remuneration contracts as their career horizons are longer. In contrast, older and closer to retirement insiders should have placed less importance on the future promotion opportunity. Insiders who have stayed in the firm for a long time but never won a CEO tournament should trade with lower aggressiveness because they are unlikely to win any future CEO tournament. Similarly, I conjecture that short investment horizon sellers have shorter career horizons because they frequently reverse their previous buy positions to reduce their ownerships (Akbas, Jiang and Koch, 2020). Managers with higher probability of becoming CEO but failed to be promoted should trade on their private negative information more aggressively because they have higher expected value of implicit promotion-based incentives. Managers who receive a larger retention bonus after losing the tournament should trade on their private information less aggressively as their forgone incentives is lowered (Armstrong, Blackburne and Quinn, 2021). Lastly, their trading profitability is decreasing with the board conservatism. My results support these hypotheses and suggest that insiders sell on negative insider information for personal gains.

To test for the firm-level informativeness, I follow Tucker and Zarowin (2006) and construct the future earnings response coefficient, and Piotroski and Roulstone (2004) to calculate the return synchronicity. I expect insiders' sell trades to be less profitable when the future earnings response coefficient is lower, and their buy trades do not vary with these two firm-level informativeness measures. I find no significant relationship between the return synchronicity and insider transaction profitability. I show that the change in insider trading profitability is robust to the inclusion of these two proxies, suggesting that trading on their firm's stock misevaluation contributes to the increase in their trading profitability, but also is a way of compensating themselves for the forgone CEO promotion opportunity. I investigate the informational content behind these more informed insider transactions to show that unobservable stock and market movement do not randomly drive the higher abnormal profit. I find their sell trades systematically predict future decreases in both return on asset and investor sentiment, and an increase in the future cost of capital, but this is not the case for their relatively rare purchases. These results suggest that insiders will exert less effort and trade on the worsening in future firm performance for personal gains, and probably to undermine the performance of the newly promoted CEO.

Inspired by these results, I investigate the possibility that the positive causal effect between the tournament incentives and firm performance is not as high as documented by Kale *et al.* (2009) since insiders have outside options to trade on their private information to compensate themselves for the forgone incentives. To investigate this possibility, I first replicate the results of Kale *et al.* (2009). I show that the positive causal relationship between tournament incentives and firm performance persists in my sample period. Following Kim and Lu (2011), I further use the sum of the maximum marginal federal and state long-term capital gain tax rates as my IV for the total non-promoted insider trading transactions. I find a weaker causal relationship between the tournament incentives and firm performance when non-CEO insiders execute more transactions, further confirming my hypothesis. Moreover, I find that the historical average insider trading profitability and the board conservatism can significantly predict the scale of post-tournament turnover among non-promoted directors, implying these tournament rejectees will assess the abnormal profit they can generate from the future informed insider trading activity and make their decisions to leave or to stay.

I further consider the possible reverse causality induced by the possibility that tournament losers are more likely to be insiders who trade on their private negative information more aggressively. I employ 2SLSa 2SLS estimator to generalize the results outside the CEO turnover event window and investigate whether the increase in insider trading profitability is significantly higher than their unconditional return predictabilities. I show that the increase in the return predictability embedded in both insider purchase and sell trades following the CEO turnover persists when I take insider transactions outside the CEO turnover event window into consideration. The more negative abnormal return predictability embedded in insider sell transactions persists two years after losing the CEO promotion opportunity. Their sell, but not their buy, trades yield more negative abnormal returns when the newly appointed CEO increases her holdings. I question why their buy trades, which involves lower litigation risk, are rare. Inspired by the finding of Armstrong *et al.* (2021) that newly appointed CEOs are likely to be noisy traders, I find that non-promoted managers sell trades are loss-averting because they trade against uninformed CEO purchases, which result in short-term inflated stock prices but lower long term returns. I find that they dissimulate their private negative information by making sequential sell transactions and randomly mixing with uninformative purchase transactions to thwart outsiders and market regulators. I show that the losing CEO competition effect becomes stronger after accounting for these strategies. Lastly, I show the share offloading trades of exiting executives does not drive my results.

My results are robust when I use different return proxies and include another fourteen control variables that proxy for the possible channels in which the age of a former CEO can indirectly affect the firm's future value. They are also similar when I control for performance-induced CEO turnover, exclude tournament competitors that are not the top two highest paid non-CEO managers in the firm or older than 60, include 10b5-1 transactions, exclude firms that retain former CEOs, exclude firms that promote outsider as CEO, and when I remove firms with a COO prior to the tournament and CFO trades. I construct pseudo-CEO turnovers to show the robustness of my diff-in-diff regression and conduct 1,000 placebo tests for diff-in-diff and 2SLS regression separately to rule out the possibility that these significant results are due to luck.

I contribute to the literature from three aspects. First, I focus on two streams of literature, tournament incentives and insider trading, which although both study the managers' behaviors, the ongoing investigations in these two domains are largely parallel and do not intersect. To the best of my knowledge, this is the first empirical analysis that bridges these two streams of literature. I show that the realization of their tournament incentives affects insiders' trading. Second, I contribute to the tournament incentives literature by documenting an unintended consequence of holding a CEO tournament that is causing more aggressive insider trading activities. I report that insider trading opportunity weakens the positive effect of tournament incentives on firm performance documented by Kale *et al.* (2009). My results imply that compensation committees must consider insider trading on private information when setting out optimal tournament incentives, as the non-promoted executives' *ex-post* trading opportunity on private information mitigates their effectiveness. Unlike many tournament incentives studies, I follow Chan *et al,* (2022) to uniquely focus on these "rejectees", and I shed light on losing competitors' investment decisions to show that their career concern affects their trading decisions. Finally, I contribute to the insider trading literature by documenting one more corporate event in which insiders systematically incorporate private information into their trading decisions to seek higher abnormal returns. Roulstone (2003) and Gao (2019) show that insider trading profits can complement explicit forms of compensation, such as annual salary and performance-based bonus. I show that insider trading opportunity also complements future unrealized compensation, and insiders adjust their trading strategies depending on their career concerns and the forgone pay rise, an unexplored area in the insider trading literature.

The remainder of the paper proceeds as follows. In Section 2.2, I review the relevant literature. Section 2.3 describes my sample and the construction of the variables, justifies the exclusion and relevance conditions of my IV and specifies my regressions. Section 2.4 presents the empirical results and revisits the results of Kale *et al.* (2009) by accounting for the role of insider trading opportunity. Section 2.5 presents the 2SLS estimation results, robustness, and placebo tests. The conclusions are in Section 2.6.

2.2 Literature Review and Hypotheses Development

A CEO promotion tournament involves a contest amongst senior executives to become the firm's next CEO. The winner will receive the corresponding promotion-based monetary rewards, such as remuneration, benefits, and other privileges. The increase in the winner's compensation package, referred to as the tournament incentives, is possibly the largest in her lifetime. The losers, if not laid off by the board to avoid conflicts but at a cost, can stay in the same firm and wait for the next chance for advancement, or leave to participate in tournaments in other firms (Lazear and Rosen, 1981; Gibbs, 1995; DeVaro, 2006). Boards hold promotion tournaments to encourage agents to exert effort, identify the most suitable senior manager for the CEO position, and improve firm performance.

Theorists have supported the logic behind the tournament-type CEO succession. Lazear and Rosen (1981), Gibbons and Murphy (1992) and Main, O'Reilly and Wade (1993) developed model on tournament incentives where senior executives endure pay below the optimal market rates because they not only value the explicit incentives such as the regular increase in their salaries, stock options and annual bonuses but incorporate the implicit value of the future promotion opportunity. The implicit value of the future promotion opportunity depends on both the promotion subjective probability and the subsequent increases in their compensation packages if they eventually win it (Kale *et al,* 2009). Gibbons and Murphy (1992) show that an optimal incentive contract must optimize the combination of employee's career concern regarding future promotion opportunity and the current explicit incentives. Thus, if the employee is close to her retirement, the subjective probability of future promotion becomes lower, which attributes to the lower expected promotion-based incentives. Consequently, the manager will largely place more importance on explicit incentives and not value the future promotion opportunity. In the same logic, Holmstrom and Milgrom (1994), and Baker, Gibbs and Holmstrom (1994) have documented the complementarity between explicit and implicit incentives components in designing the optimal remuneration contract. Ederhof (2011) studies the pay structure of a multinational firm in a single year and shows that firms adjust the pay structures of their mid-level managers with fewer promotion levels to reach in the corporate hierarchy by substituting the weaker promotion-based incentives with higher bonus-based incentives, a form of explicit incentives. In the same vein, Gibbs (1995) argues that the tournament prize must rise at an increasing rate when executives are moving up to the corporate hierarchy because principles need to maintain a large enough incentive for the senior executives who already receive relatively high compensations. This pronounces the most the pay disparity between the CEO and other non-CEO senior executives[4], reflecting the strongest implicit incentives at the top level of the hierarchy and justifying the largest compensation gap between the CEO and other senior managers observed in real life.

I argue that an additional implication of these tournament incentives models is the behaviour of the promotion rejectees, as the loss of a CEO tournament lowers drastically the promotion-based component in their contract, resulting in a decrease in their overall value of their compensation plan, because of, at least, the following four reasons. First, the timing and the outcome of the next round of the tournament is uncertain (DeVaro, 2006). This is because the higher the hierarchical level of the non-promoted manager, the fewer the promotion opportunities, as the only promotion destination is the CEO position, a long-tenure job[5]. Second, the negative image of a previous tournament loser will further lower the probability for the senior manager's promotion to the CEO position in the next tournament, further lowering the expected value of promotion opportunity in their contracts, and, consequently, their contracts' overall value.[6] Third, there is a fundamental difference between implicit promotion-based and explicit performance-based awards, as the former is only possible to realize with the occurrence of a promotion, unlike the explicit incentives such as annual salary increases or bonuses which are recurring and relatively predictable incomes that managers will receive without promotion (DeVaro, 2006). Becoming the next CEO in the firm is the ultimate victory and is the only way to realize fully the CEO promotion prize. The uncertainty about the timing of the next promotion opportunity jointly with the lower probability of winning the next promotion leads to a lower value of promotion-based incentives. Finally, firms will not adjust the explicit

[4] For example, Adamson, Canavan and Ziemba (2020) report that CFOs make one-third of CEO pay, and have relatively lower compensation increases and a smaller proportion in the form of stocks and LTIPs.
[5] My data shows an average of 9 years, close to 7.6 years in UK (Gregory-Smith and Wright, 2019).
[6] Chan *et al.* (2022) estimate a probit model to show the expected probability of winning a future CEO tournament significantly decreased from 27.4% to 9.4% after managers lose their first tournament while there is no significant increase in the number of competitors in the future tournament.

incentives to compensate the non-promoted managers for losing the tournament because of high adjustment costs of restructuring the incentive plan at the end of a tournament. This causes a suboptimal equity ownership level in managers' incentive contract (Morck, Shleifer and Vishny, 1988) and leading firms to always have misaligned incentives because their transaction costs overweight the benefits of a properly aligned incentive (Core, Guay and Larcker, 2003).

Empirically, several studies show that firms do not adjust their incentive plans to compensate non-promoted managers because the high adjustment cost curbs firms to compensate the tournament losers *ex-post*, weakening the *ex-ante* tournament incentives (Chan *et al.* 2022). This lack of adjustment of compensation contracts leads also to a lower overall incentive plan and a gradual decline in tournament losers' performance rating (Gibbs, 1995). Bushman, Dai and Zhang (2016) show high adjustment costs associated with issuing equity constrain firms' abilities to restore the optimal pay-performance sensitivity. Kale *et al.* (2009) find that firms will systematically provide a higher-level tournament incentive proxied by the larger pay gap between the CEO and the executive team's median compensation following a new CEO's appointment. The uncertainty regarding the future CEO promotion lowers the non-promoted managers' subjective probabilities of successfully realizing the implicit promotion-based incentives in the next tournament.

However, previous studies assume a rather passive role of the tournament losers, who either accept the loss and the subsequent decrease in their compensation contract's overall value or leave the firm to participate in tournaments in other firms. My data shows that 68% of them stay with the firm two years after the tournament. I argue that they have incentives to stay to exploit their informational advantage more assertively by conducting insider trading with greater aggressiveness. Since the promotion-based incentive represents an unrealized part of senior managers' remuneration contracts, they can materialize their private information regarding the firm's true future valuation to gradually make up the discrete losses in the valuation of their positions. The existing tournament incentives studies overlooked this strategy, but it is plausible because all CEO tournament competitors are high-ranked managers closely involved in their firms' daily operations, and they are privy to price-sensitive information, which they can trade on. Although the SEC prohibits corporate insiders from trading on any material private information, anecdotal evidence and empirical studies in insider trading literature have shown that corporate insiders trade profitably (Lakonishok and Lee, 2001; Cohen, *et al.* 2012). Their trades are based on future earnings (Piotroski and Roulstone, 2005), future cash flows (Jiang and Zaman, 2010) or in the month before quarterly earnings announcements (Ali and Hirshleifer, 2017), violating the regulation as the expected monetary gain outweighs any litigation risk. The profitability embedded in insider trades persists from the 80s until today, even though insider trading regulation became tighter after the Sarbanes-Oxley act in 2002 implementation (Beneish and Markarian, 2019).[7]

Roulstone (2003) finds that firms set up internal policies to restrict insider trading activity and offer their managers a premium for their forgone insider trading opportunity, as managers, *de-facto*, consider their trading opportunities as a way of compensating themselves. Bourveau, Brochet, Ferri, and Sun (2021) report that the mandatory adoption of say-on-pay increases executives' incentives to engage in insider trading to offset the regulatory-induced increase in compensation risk. Gao (2019) uses a regression discontinuity to find that managers who marginally missed their relative performance goals and lost their performance-based bonuses trade more profitably than their counterparts who narrowly met the goals and received the bonuses, suggesting that they intentionally trade on their private information more aggressively to compensate themselves for the forgone bonuses. Overall, I expect promotion rejectees to trade more aggressively and profitably on inside information to make up for the decreases in the overall valuation of their positions, as they are "under the shadow" relative to the CEO who is exposed to public visibility through the media, market regulators and investors scrutiny, the key determinants of insider trading profitability (Sabherwal and Uddin, 2019).

[7] Sarbanes-Oxley act came into force in 30 July 2002. Gayle, Li and Miller (2022) argue that SOX discourages managers from breaking the law, thereby strengthening the property rights of shareholders, and mitigated the agency conflicts between shareholders by affecting incentives that motivate law-abiding managers to act in the firm's interest but did not affect CEOs' attitude toward risk taking. It also shortens the reporting deadline to SEC from 10 to 2 days after the end of the month in which insiders executed the transactions. At the same time, the SEC adopted Rule 10b5-1 to allow insiders to set up planned pre-announced trades, executed by their brokers, generally at a fixed time interval, without allegations of illegal insider trading. However, Larcker *et al* (2021) report opportunistic use of 10b5-1, particularly plans with a short cooling-off period, and those adopted just before that quarter's earnings announcement. Franco and Urcan (2021) find that insiders trade profitable by using equity deferrals to circumvent Rule 10b-5 trading restrictions through the timing and content of corporate disclosures around these trades.

2.3 Sample and Variable Construction

I follow prior literature (Kale *et al.* 2009; Kini and Williams, 2012) to identify CEO turnover event and collect manager's compensation data from Execucomp, which covers S&P 1500 firms from 1996 to 2019, with the first CEO turnover event occurring in 1997. My initial sample consists of 269,456 manager-year observations with 4,838 CEO turnover events. I use the annual CEO flag (*ceoann*) to identify the historical CEO changes. Throughout the study, my event window is (-2, 1) relative to CEO turnover year 0, as I assume that the tournament begins in year -2, and the losing tournament effect will gradually decay outside my event window. I additionally restrict that there is only one CEO turnover in the window (-2, 2) to remove confounding event. I use CEO promotion and CEO turnover interchangeably to denote the change of CEO position and solely refer to non-CEO managers whenever I mention insiders, managers, or promotion rejectees unless specified otherwise.

I define tournament competitors as those covered by Execucomp but are not CEOs in their firms (Kale *et al.* 2009; Kini and Williams, 2012). These filters select tournament competitors relatively properly because Execucomp mainly covers the top five highest-paid managers in a firm; their only promotion destination is the CEO position. I reckon the total compensation package that a manager receives better measures her seniority within the firm than her job title. I exclude from the tournament competitor category insiders not covered by Execucomp in years (-2, -1) but gained coverage in years (0, 1) as they are either new joiner or low-rank managers who did not participate in the CEO tournament but covered by Execucomp after the tournament. I also exclude ex-CEOs in the firm and remain with the firm after stepping down from their position, like Microsoft's Bill Gates, but have both lower probability and fewer incentives to become the next CEO, and founders identified by using the job title (*titleann*). The median (mean) number of tournament competitor is 4 (3.8) in my final sample.[8]

[8] My results are robust if event window is extended to (-3,3), narrowed to (-1,1), restricted to cases with only one turnover in (-4,2), includes all confounding events and the three types of non-CEO managers I exclude, or I only keep the top two highest paid non-CEO managers. I do not restrict other event years than the turnover year in the event window of other CEO turnover events as this effectively implies one turnover in ten years. In unreported results, I employ the insider transaction samples reported by those who are not covered by Execucomp, I cannot observe the same increase in trading profitability for both insider purchase and sell samples.

To construct the tournament incentive measure, I first use the item total compensation (*tdc1*), adjusted to account for the regulatory change of Financial Accounting Standards Board (FASB) 123R revision, as detailed in Appendix 2.1, following Coles, Daniel and Naveen (2006) and Walker (2009). The adjusted total compensation reflects the true managers' annual compensation. I then take the logarithm of the difference between the CEO's total compensation and the median total compensation of other non-CEO managers (Kini and Williams, 2012; Coles *et al.* 2014). I follow Kini and Williams (2012) and remove former CEO who remains in the firm as an executive when identifying the median non-CEO manager pay. I collect my instrumental variable, the former CEO's age in the last fiscal year (*age*), from Execucomp, or BoardEx or Factiva if data is missing. I extract accounting and financial data from Compustat, and stock prices and holding period returns data from CRSP, excluding non-common shares (*shrcd* is not 10 or 11) and stocks priced under $2 at the beginning of a calendar year. Appendix 2.2 shows the sample sizes across my databases.

I compile all U.S. insider transactions from January 1996 to August 2019 from Smart Insider Ltd[9]. I keep all insider open market transactions in Form 4. I exclude transactions with less than 100 shares, in line with previous studies (Lakonishok and Lee, 2001; Cohen *et al.* 2012), and any 10b5-1 pre-scheduled trades, as their information content is likely to be trivial, but include them in robustness test since Larcker *et al.* (2021) and Franco and Urcan (2021) find that insiders exploit them. I aggregate these insider trades at the insider-day level. To measure the direction of insider trades, I compute the net purchasing value (NPV) as the dollar value of the purchase transaction minus that of the sell transaction over the total dollar value[10]. If *NPV* is greater (less) than zero, the insider is net buying (selling) on a given day. I exclude the 0.3% cases where *NPV* is 0 from my final sample.

I match Execucomp's unique manager identifier *execid* to Smart Insider's non-unique insider identifier *personid*. I use BoardEx to crosscheck the validity of my *execid-personid* match. For 48,429 distinct *execid* in Execucomp, I match 43,952 (90.8%) of them with 44,187

[9] This database (https://www.smartinsider.com/) is the same as Thomson Reuters. It gathers data from Form 5, the annual statement of change in beneficial ownership and reports any exempt trades not reported on Form 4.
[10] Some studies use net purchasing ratio, NPR, the ratio of the number of shares bought over the total traded as an alternative measure of insider trading direction (Lakonishok and Lee, 2001). I find same results using NPR.

personid. I match 42,358 of 46,720 (90.7%) distinct *execid* for non-CEO managers. *I* discard the unmatched *execid* from my sample, as they have not reported any transactions on Form 4. After removing 29% cases with confounding events, I construct a sample of 3,428 CEO turnover events with 2,636 (77%) internal promotions, close to the 72% reported by Cziraki and Jenter (2020).[11] I find 1,259 (37%) firms did not report any insider trades in year 0, leaving 2,169 events in my final sample. I find 152,273 matched sell trades but only 13,022 purchases, representing 8% of the total trades, significantly lower than the 37% reported by, say, Lakonishok and Lee (2001), or the 20% in my full database, indicating a higher propensity to sell by non-promoted insiders. The details are in Appendix 2.3.

I use the CRSP value-weighted market index return to adjust the holding period return and compute the buy-and-hold (BHAR) abnormal return for holding period *t* as follow:

$$BHAR_{i,t} = \prod_{i=1}^{t}\left(1 + \mathrm{return}_{\mathrm{i,t+i}}\right) - \prod_{i=1}^{t}(1 + \mathrm{mkt}_{\mathrm{t+i}}) \tag{1}$$

where $\mathrm{return}_{\mathrm{i,t+i}}$ is the stock's *i* holding period return, and $\mathrm{mkt}_{\mathrm{t+i}}$ is the value weighted CRSP index. I measure BHAR one day after insider transaction date to 365-calendar day holding period as "short-swing profit" rule in Section 16(b) of the 1934 Security Act prohibits insiders from profiting from short-term price movements. I require at least 243 trading days in the holding period as in Agrawal and Nasser (2012). Appendix 2.5 shows details of my variables.

2.3.1 Endogeneity Concern and Identification Strategy

One major concern in insider trading literature is endogeneity because the true motivation behind insiders' trading decisions is not observable. The omitted variable bias will lead to an inconsistent OLS estimate for the losing tournament effect. I use an extensive set of explanatory variables to control for insider trading return and include firm and month fixed effects to proxy for time-invariant unobservable variables to eliminate potential endogeneity[12].

Nevertheless, I recognize that these approaches do not completely solve the endogeneity issue. I specify a diff-in-diff regression based on a matched sample as my baseline

[11] My results are robust to the inclusion of the confounding events.
[12] My results are robust when I replicate all diff-in-diff regressions with firm and year fixed effects.

regression to eliminate the concern that unobservable market anticipation will bias my results. I match my test firms with control firms with no CEO turnover in (-2, 2) and shortest Mahalanobis distance on the average insider purchase/sell profitability, logarithm of the total asset, and the book-to-market ratio in the year *t-1*. I match one treated firm with one control firm to minimize the biasedness. I successfully match 192 out of 547 (35%) firm-year observations with at least one insider purchase transaction in the CEO turnover event year, and 1,331 of 1,775 (75%) for firms with at least one insider sell transaction[13]. My sample size varies depending on the availability of the *execid-personid* link table and the different control variables included. The comparative analysis of the subsequent insider trading profitability across these two samples can better disentangle the incremental change solely attributable to the loss of CEO turnover within my event window. I estimate the following diff-in-diff regression to study whether the return predictability of insider purchase (sell) trades remains systematically the same or increases (decreases) in and/or after the CEO events by focusing on my event window only:

$$\text{BHAR\_m\_365}_{i,t} = \alpha + \beta_1 \text{Post}_{i,t} + \beta_2 \text{Treat}_{i,t} + \beta_3 \text{Post}\times\text{Treat}_{i,t} + \beta_4 \text{CEO\_IT}_{i,t} + \text{controls} + \gamma + \rho + u_i \quad (2)$$

where the treatment dummy, $\text{treat}_{i,t}$, is equal to one for my treated firms, and the post-treatment period dummy, post_t, is equal to one for two years from 0 to +1 post-CEO tournament outcome, depending on the specific focus period. I expect β_3 to be positive if the buy trades are profitable and negative if the sell trades are loss-avoiding, after losing the CEO tournament. I also include $\text{CEO\_IT}_{i,t}$ to proxy for the CEO trading direction and to capture the trading strategy that non-CEO insiders time their transactions based on the current CEO's trading activity. Armstrong *et al.* (2021) show that newly appointed CEOs are more likely to make noisy purchase transactions to signal their commitments to improve the firm's performance, not necessarily to seek a profit, but to prolong their tenure even if they underperform, yet the market reacts positively, overvaluing the firm. These buy trades systematically generate low long-term abnormal returns, leading non-promoted insiders to

[13] Many firms do not report insider purchase transactions in years (-2, -1). I tried various schemes to match on their past insider trading profitability, matching on year -1 yields the most suitable results.

adopt contrarian strategies by selling overvalued shares and increasing their trading profitability.[14] To account for this strategy, I first compute the net insider trading value of a CEO in the year *t* as the difference between the aggregated value of insider sell and buy trades, which I then divide into annual quintiles to get $CEO\_IT_{i,t}$ as the quintile number. If the CEO is not trading in year t, the selling and buying values are zero, but the lower the $CEO\_IT_{i,t}$, he more shares the CEO has purchased in the year *t*.

I include various control variables in my regression to account for firm and insider personal characteristics (Lakonishok and Lee, 2001; Gregory, Tharyan and Tonks, 2013; Cohen *et al.* 2012). I compute a dummy equal to one for firms that promoted an outsider CEO, and a dummy equal to one if the CEO succession was planned in (-2, -1) to assess whether such appointment reduces insiders' intensity of exploiting their private information advantage. I measure the tournament incentive at the firm level by computing the natural logarithm of the difference between the adjusted CEO total compensation and the median adjusted total compensation of other insiders. At manager level, I use a dummy equal to one for high incentive managers whose total difference in the adjusted total compensation between CEO and managers is in the top three in their companies, given that the median and mean ranks are three, and zero otherwise[15]. I control for the firm's recent and long-term stock price momentum, growth, profitability, size, innovation level using last year research and development cost, the Amihud (2002) illiquidity measure, and the financial analyst coverage that controls the firm's information environment. To control for some personal characteristics that can affect insiders' trading returns, I include personal wealth risk (Beneish and Markarian, 2019) by following Core and Guay (2002) to calculate the performance-based incentives as a dollar change in manager *i*'s wealth associated with a 1% change in the firm's stock price (in $000). As in Coles, Daniel and Naveen (2006), I calculate the risk-taking incentives as a dollar change in manager *i*'s wealth associated with a 0.01 change in the standard deviation of the firm's stock returns

[14] Armstrong *et al.* (2021) show that the market reaction to the purchase transactions executed by CEO who successfully (failed to) prolonged her tenure in the next year is positive (negative). Since I removed all the confounding events in my sample, all the CEOs in my post-tournament period prolonged their tenures.
[15] This measure proxies for the potential increase in remuneration packages if promoted to be the next CEO. In some rare cases, some non-CEO managers have higher compensation than CEO, such as Bill Gates (*execid*: 00635) continued to be compensated significantly more than Steven Ballmer, who took over Gates' CEO position. I restrict the difference in total compensation to be zero and my result is robust with or without those outliers.

(in \$000). Finally, I control for firm's financial health using the yearly industry average S&P long-term rating, which summarizes industry risk and can predict forced CEO turnover. I include γ and ρ as firm and month fixed effects, respectively. I cluster my standard errors at the firm-month level as Alldredge and Blank (2019) show that insiders cluster their trades with their colleagues. Subscripts *t, d* and *m* are for fiscal year, trading day and month, respectively. I match the time dimension of the control variables on the insider transaction date instead of the CEO turnover event.[16]

Table 2.1 shows the summary statistics of insiders and firm characteristics. Panel A reports that the profitability embedded in non-promoted insiders' buy trades before the CEO tournament (-2, -1) is 5.9%, rising significantly to 30.4% in the post-event window (0, +1), suggesting that they trade on their private information while their average *total_compensation* declines significantly from \$1.403 million to \$1.07 million. The momentum, *mom*, a proxy for long term stock returns is significantly higher after the tournament, suggesting that they often buy to support the price when their stocks perform poorly. Panel B shows that their sell trades in the event period generate significantly lower abnormal returns than the pre-event period[17]. They are more likely to adopt contrarian strategies by buying (selling) when the long-term and short-term momentum stock return, as proxied by *mom*, and *ret30*, are lower (higher) and book to market higher (lower) in line with previous evidence (Lakonishok and Lee, 2001; Cohen *et al.* 2012). They tend also to buy (sell) in smaller firms and those with lower (high) *pay_gap_firm* and *total_compensation*, *ROA*, and sell-side analyst coverage, and in less (more) liquid firms. The BHARs, not reported, are more pronounced for non-promoted insiders and depend on whether the promoted CEO is an external, the CEO succession is planned, and the incentives are high. I account for these factors in my regressions.

One drawback of my diff-in-diff estimator in this research setting is that I only compare the post-tournament insider trading profitability in year (0, 1) with pre-tournament insider trading profitability in year (-2, -1). To generalize the results outside this event period, and to

[16] My results remain robust if I match the time dimensions of these control variables by using the end of last month figure in the last fiscal year. My results also remain unchanged if I include both the one-fiscal year lagged control variables and one-month lagged control variables in my regression.
[17] Appendix 2.4 reports the post-transaction return for CEO and Other Directors. The lower abnormal return is not observed for these groups of insiders.

control for potential endogeneity, and compare the post-tournament insider trading profit with their unconditional ones outside the event window, I employ a 2SLS estimator. The IV should embed predictive power for the CEO turnover event one year after the event to satisfy the relevance condition, should not correlate with insiders' trades abnormal returns, which proxy for their private information regarding the firm's future fundamentals to meet the exclusion restriction. I select the former CEO age in year *t-1* as a suitable IV in my setting. Peters and Wagner (2014), Cziraki and Jenter (2020) and Jenter and Lewellen (2021) show that the CEO's age embeds significant predictive power for CEO turnover in addition to the CEO tenure and firms' performance. Inspired by these results, I hypothesize that the age of the former CEO also embeds predictive power for the future CEO turnover because the former CEO age is positively correlated with the time distance between the current year and the previous CEO turnover event[18]. The former CEO's age embeds predictability not only for the year of CEO turnover, but for one year after the CEO turnover. I expect the recently left CEOs to be systematically younger than other former CEOs. In Table 2.9 I test the relevance condition. Although the exclusion condition is not formally testable, it is less of a concern, as the average time distance between year *t* and the year that the former CEO left the firm of six years is relatively long to affect the firm's future value and corporate policies decision making[19]. Moreover, since former CEO's age is a public information, and insiders trade on the firm's future value that has not been fully incorporated into the current stock price (Lakonishok and Lee, 2001), I expect my IV to satisfy the exclusion restriction. I employ the 2SLS estimator to study insider's trading propensity after losing the CEO turnover. I conduct additional tests to rule out the possible channels that my IV can influence the insiders' private information in the robustness test to further show the exclusion restriction's plausibility. I run two first-stage regressions to overcome endogeneity in my interaction variable:

$$NPED_{i,t} = \alpha + \beta_1 age\_ceo_{i,\,t-1} + \beta_2 (age\_ceo_{i,\,t-1} \times CEO\_IT_{i,t}) + \beta_3 CEO\_IT_{i,t} + control + u_i \quad (3)$$

[18] The use of former CEO age discards all observations in my entire sample before the first CEO turnover, reducing my sample size. With the current CEO's age, the sample size is larger. The correlation between the two measures is 0.25. I recognize that the former measure is more exogenous than the current CEO age. The correlation between former CEO age and current CEO tenure is 0.39. With the current CEO tenure in my 2SLS in robustness test, all coefficients remain robust but weaker.

[19] These decisions include governance changes (Nelson, 2005), firm's cash holding (Feng and Rao, 2018), total risk and idiosyncratic risk (Cen and Doukas, 2017), and performance (Palia, 2001; Bhagat and Bolton, 2013).

$$(\text{NPED}_{i,t} \times \text{CEO\_IT}_{i,t}) = \alpha + \beta_1 \text{age\_ceo}_{i,\,t-1} + \beta_2 (\text{age\_ceo}_{i,\,t-1} \times \text{CEO\_IT}_{i,t}) + \beta_3 \text{CEO\_IT}_{i,t} + \text{control} + z_i \qquad (4)$$

where $\text{NPED}_{i,t}$ is a dummy equal to one for insider buy/sell trades executed in the post turnover year *t,* and zero for other years. $\text{age\_ceo}_{i,t-1}$, the interaction term between my IV $\text{age\_ceo}_{i,t-1}$, and the moderator variable $\text{CEO\_IT}_{i,t}$ are my first and second joint IV to predict the $\text{NPED}_{i,t}$ and $\left(\text{NPED}_{i,t} \times \text{CEO\_IT}_{i,t}\right)$.

In the second-stage regression, I replace $\text{NPED}_{i,t}$ and $(\text{NPED}_{i,t} \times \text{CEO\_IT}_{i,t})$ by the estimated $\widehat{\text{NPED}}_{i,t}$, a continuous variable representing the predicted probability that a given insider purchase or sell transaction executed in the post-tournament year *t*, and $(\text{NPED}\widehat{\times \text{CE}}\text{O\_IT})_{i,t}$ as follows:

$$\text{BHAR\_m\_365}_{i,(d+1,d+365)} = \beta_1 \widehat{\text{NPED}}_{i,t} + \beta_2 (\text{NPED}\widehat{\times \text{CE}}\text{O\_IT})_{i,t} + \beta_3 \text{CEO\_IT}_{i,t} + \text{control} + \varepsilon_i \qquad (5)$$

If managers exploit their informational advantage to compensate themselves for losing the CEO tournament, β_1 should be positive (negative) for buy (sell) trades. If they increase their selling activities when the CEO is increasing their holdings to prolong her tenure, I expect β_2 to be positive and significant for insider sell transactions. I include the same set of control variables and fixed effects.

Table 2.1: Summary Statistics

This table reports the summary statistics for the main sample with matched firm. Panel A (B) reports the sample averages for the non-CEO insider purchase (sell) trades around CEO turnover event. *OutsiderD*$_{j,t}$ is a dummy equal to one if the promoted CEO is an outsider. *GOOD*$_{j,t}$ is a dummy equal to one if the CEO succession was planned in $(-2,-1)$. *pay_gap_firm* is the natural logarithm of the difference between the adjusted CEO total compensation (*tdc1*) and the median adjusted total compensation of non-CEO insiders, deflated to 2010 CPI. *ret30* and Mom are days -30 to -1 and -364 to -31 stock price momentum. *bm*, *ROA*, *rd*, and *marketcap* proxy for growth, profitability, research and development cost, and size of the firm, respectively. *illiq*$_{j,m-1}$ is the Amihud (2002) illiquidity measure. *numest*$_{j,m-1}$ is financial analyst coverage. *delta*$_{i,t-1}$ is dollar change in manager *i*'s wealth associated with a 1% change in the firm's stock price (in \$000). *vega*$_{i,t-1}$ is the dollar change in manager *i*'s wealth associated with a 0.01 change in the standard deviation of the firm's returns. *rating*$_{i,t-1}$ is the yearly industry average S&P long-term rating from Compustat, assigning AAA a value 2 to CC a value of 23, and then scaled by dividing by 9, so one unit in the increase in the scaled rating corresponding to an increase in rating from AAA to BBB and an increase in rating from BBB to CCC. CEO_IT_Net_Value$_{i,t}$ is the net insider trading value of the current CEO. *high_incentiveD*$_{i,t-1}$ is equal to one for high (in the top three) incentive managers and zero otherwise; Appendix 2.5 details the variables. N is for observations. ***, **, * (^{a}, ^{b}, ^{c}) indicate the sample mean (differences in means and medians) between the pre- (-2, -1) and post- (0, 1) event is statistically different at the 99%, 95% and 90% confidence level, respectively. All variables except insider purchase size and shares are winsorised at the top 99% and the bottom 1% level.

	Event Window (-2, -1)			Event Window (0, 1)			Event Window (-2, -1)			Event Window (0, 1)		
Variable	Mean	Median	N	Mean	Median	N	Mean	Median	N	Mean	Median	N
	Panel A: Non-CEO Insider Purchase transactions						Panel B: Non-CEO Insider Sell Transactions					
BHAR_m_365	0.059^{**}	-0.059	834	0.304^{***a}	0.119^{a}	818	0.057^{***}	0.012	17,137	0.026^{***a}	-0.005^{a}	12,676
pay_gap_firm (\$000s)	$1{,}560^{***}$	696	742	$2{,}079^{***a}$	674	832	$3{,}507^{***}$	2,183	16,194	$3{,}340^{***a}$	$2{,}147^{a}$	13,019
Non-CEO compensation (\$000s)	$1{,}403^{***}$	893	834	$1{,}070^{***a}$	681^{a}	832	$2{,}308^{***}$	1,400	17,153	$2{,}1434^{***a}$	$1{,}346^{a}$	13,062
illiq (000s)	0.271^{***}	0.042	831	0.576^{***a}	0.087^{a}	832	0.049^{***}	0.007	17,146	0.032^{***a}	0.005^{a}	13,062
marketcap (\$million)	$2{,}425^{***}$	834	834	$1{,}765^{***c}$	545^{a}	832	$12{,}092^{***}$	2,751	17,153	$14{,}112^{***a}$	$3{,}361^{a}$	13,062
Mom	0.059^{***}	0.050	801	0.000^{b}	0.042	831	0.320^{***}	0.264	16,798	0.288^{***a}	0.240^{a}	13,059
ret30	-0.067^{***}	-0.056	717	-0.021^{***a}	-0.029^{a}	709	0.059^{***}	0.053	14,452	0.056^{***a}	0.048^{a}	11,048
bm	0.787^{***}	0.597	833	0.883^{***b}	0.752^{a}	832	0.419^{***}	0.334	17,143	0.418^{***}	0.337^{a}	13,062
numest	7.753^{***}	6.000	834	5.905^{***a}	5.000^{a}	832	12.497^{***}	11.000	17,153	12.492^{***}	11.000	13,062
ROA	0.029^{***}	0.025	834	-0.009^{**a}	0.005^{a}	832	0.064^{***}	0.062	17,150	0.061^{***a}	0.060	13,062
rd	0.028^{***}	0.000	834	0.034^{***}	0.001^{a}	832	0.058^{***}	0.000	17,153	0.078^{***a}	0.005^{a}	13,062
delta (in \$000)	174^{***}	16	805	25^{***a}	11^{a}	767	229^{***}	66	16,295	154^{***a}	57^{a}	12,345
vega (in \$000)	19^{***}	6	803	11^{***a}	5	760	49^{***}	18	16,293	48^{***}	16^{a}	12,342
OutsiderD$_{it}$	0.000	0.000	834	0.369^{***a}	0.000^{a}	832	0.000	0.000	17,153	0.295^{***a}	0.000^{a}	13,062
COOD$_{i,j}$	0.000	0.000	834	0.133^{***a}	0.000^{a}	832	0.000	0.000	17,153	0.186^{***a}	0.000^{a}	13,062
high_incentiveD$_{i,t-1}$	0.388^{***}	0.000	834	0.453^{***a}	0.000^{a}	832	0.537^{***}	1.000	17,153	0.562^{***a}	1.000^{a}	13,062
rating$_{i,t-1}$	1.325^{***}	1.353	825	1.319^{***}	1.366	821	1.380^{***}	1.431	17,069	1.392^{***a}	1.439^{a}	12,645
CEO_IT_Net_Value$_{i,t}$ (\$000s)	-819^{***}	0.000	834	300^{***a}	-42^{a}	832	$-15{,}509^{***}$	-3,498	17,153	$-2{,}581^{***a}$	$0{,}000^{a}$	13,062
Average Number of Shares traded	$12{,}255^{***}$	2,882	834	$10{,}176^{***}$	$2{,}000^{a}$	832	$33{,}382^{***}$	11,191	17,153	$27{,}781^{***a}$	$10{,}000^{a}$	13,062
Average Value of Shares traded (\$000s)	156^{***}	38	834	163^{***}	19^{a}	832	$1{,}039^{***}$	355	17,153	944^{***a}	327^{a}	13,062
Average No of Observations		417			416			8,576			6,531	

2.4 Empirical results

2.4.1 Insider Trading Propensity around CEO tournament

Table 2.2 Panel A reports the results of matching my test firms with control firms. I first account for the pre-event period performance using changes in stock returns during the pre-event period, ΔBHAR_m_365$_{(-2,-1)}$, as a proxy, as firms that replace their CEOs are more likely to be underperforming. I find no statistical significance in size, book to market, momentum, and profitability, which I do not use in my matching, indicating my matching procedure is appropriate. However, the average purchase transaction for the treated firm is statistically larger than that of control firms, and the non-CEO managers from treated firms receive 7% higher total compensation than their counterparts from control firms for sell sample, but I do not expect these significant differences to affect my results as, economically, they are relatively small.

Panel B reports that the difference in BHAR_m_365 between test and control firms for both insider purchase and sell samples are statistically indifferent from zero in the years (-2, -1), indicating my matching strategy is successful, and rejecting the hypothesis that there is a parallel trend returns between control and treated firms. Furthermore, the test firms generate higher (lower) BHAR_m_365 in year 0 (1) than control firms in purchase sample and yield lower returns in year 0 and 1 in sell sample, further supporting my hypothesis. I conduct a formal parallel trend assumption test following Angrist and Pischke (2009), Cengiz *et al.* (2019) and Baker *et al.* (2021). The coefficient of Pre$_{-1}$ is statistically insignificant in both purchase and sell samples. This means that the trend in (-2, -1) between control and treated firm is parallel after controlling for firm characteristics that can explain insider trading profitability suggesting that the post-tournament results are not driven by the matching algorithm's inappropriateness to obtain the control group and the use of the diff-in-diff estimator. If I use year -1 as the base year, the parallel trend still holds. Appendix 2.6 reports the full results.

I then investigate the consequence of executing opportunistic sells and purchase transactions before the CEO turnover. I classify insider transactions into opportunistic and routine traders, in line with Cohen *et al.* (2012). The former trades are executed by insiders who regularly trade in a clear pattern, which I define as trades in the same calendar month in the past three years, and the latter are discretionary trades that embed higher return predictability and more private information on average. I re-classify each insider at the beginning of each calendar year based on her past three years' trading history, excluding those with no trades in the past three consecutive years. I conjucture that if non-CEO executives execute a large number of opportunistic sell (purchase) transactions, the probability of them winning the CEO promotion is lower (higher). I focus on CEO turnover year (0,0) and estimate a logit model and a linear probability model with firm and year fixed effects at insider-firm level. The dependent variable is a dummy variable equal to one for newly promoted CEO, and zero for other non-promoted managers who were competing in the turnover. The main variables with interests are the total numbers of opportunistic insider purchase and sell transactions in year -1 and year -2. I control for manager's age, tenure, total compensation, delta and vega and other firm-level characteristics all calculated at the end of year -1. Table 2.2 Panel C reports the regression results. These result show that insiders who make more opportunistic purchase (sell) transactions are more (less) likely to win the CEO competition, and the conclusion is robust using a linear probability model, in line with the substitution hypothesis. If I include all transactions in year -1 and year -2, the results for sell transaction remain robust, but there is no significant signaling effect for purchase transaction using linear probability model[20]. The signaling effect is consistent with the finding in Armstrong *et al.* (2021).

Next, I assess whether non-promoted insiders are more likely to execute opportunistic transactions after losing the CEO tournament. I estimate Equation (2) using the matched sample and $opp\_D_{i,t}$ a dummy equal one for opportunistic transactions and zero for routine transactions as the dependent variable. Panel D, Columns (1) to (2) show that the coefficient of the interaction term $(\text{Treat}\times\text{Post})_{i,t}$ is insignificant, suggesting that there is no significant change in the propensity of executing opportunistic buy transactions in years 0 and +1. In contrast, columns (3) to (4) show that the coefficients of $(\text{Treat}\times\text{Post})_{i,t}$ and $CEO\_IT_{i,t}$ for the sell trades are positive and significant. This suggests that non-promoted executives increase their propensity to sell opportunistically in year (0,1), and they do so if the newly appointed CEO is

[20] I do not find significant results using all transactions, including routine transactions. Appendix 2.7 displays the result.

also trading. I find, but not report, that the coefficient of the control variable momentum is positive and statistically significant, suggesting that insiders adopt contrarian strategies by selling when the stock return are high, and $bm_{j,m-1}$ and $size_{j,m-1}$ are negative and significant implying that their opportunistic selling is more pervasive in small and growth stocks. The sign and significance of the remaining control variables are consistent with the existing literature (e.g., Lakonishok and Lee, 2001).

Overall, these results suggest that insiders are more likely to make opportunistic sell transactions in year (0,1) after losing the CEO competition, which are more informative than an average sell trades suggested by Cohen *et al.* (2012). In an unreported logit regression, I find that insiders are more likely to execute opportunistic sell, than buy, trades after they have lost the promotion, consistent with my hypothesis. These findings are consistent with my hypothesis that insiders mainly incorporate private information into their sell transactions to compensate themselves for losing the CEO competition. Furthermore, these results provide preliminary evidence that non-promoted insiders strategically time their transactions based on the trading activity of the newly appointed CEO.

Table 2.2: Insider trading propensity after losing the CEO competition

Panel A reports the summary statistics at firm level for both the treated firms and control firms in the pre-CEO turnover period (-2, -1) and Panel B shows summary statistics of BHAR in event window (-2, +1). Firms that have CEO turnover event in year *t* are matched with firms on the average insider purchase/sell profitability, logarithm of the total asset and the book-to-market ratio in the fiscal year *t-1* using Mahalanobis distance. Column (3) and (6) reports the t-test results by assuming unequal variance between treated and control firms for insider purchase and sell transaction, respectively. Panel C reports the logit and linear probability models estimating the likelihood of a manager *I* becoming CEO in year *t.* The dependent variable is one for CEO, and zero otherwise. I estimate regressions using all tournament competitors defined previously and for CEO turnover year *t* only. Sample is at manager-firm level. Variables $no\_buy_{i,t-1}$ and $no\_sell_{i,t-1}$ represent the number of opportunistic insider purchase and sell transactions made by insiders *I* in year *t-1*. Variables $no\_buy_{i,(t-2,t-1)}$ and $no\_sell_{i,(t-2,t-1)}$ represent the number of opportunistic insider purchase and sell transactions made by insiders *I* in years between *t-2* and *t-1*. Other independent variables included but omitted are $ret30_{j,t-1,(d-1,d-30)}$, $mom_{j,\,t-1,(d-31,d\,-364)}$, $bm_{j,t-1}$, $illiq_{j,t-1}$, total $asset_{j,t-1}$, $roa_{j,t-1}$, tobin's $Q_{j,t-1}$, $leverage_{j,t-1}$. Standard errors in Panel C are clustered by firm in brackets. Panel D reports the linear probability regression output. The dependent variable is $opp\_D_{i,t}$ equal to one for insider transactions executed by opportunistic traders, and zero otherwise. I identify opportunistic traders by following Cohen *et al.* (2012). Standard errors reported in parentheses in Panel D are computed based on robust standard errors clustered at the firm-month level. Appendix 2.5 defines all control variables in the table. ***, **, and * denote significance at the 99%, 95% and 90% confidence level, respectively. All variables are winsorised at the top 99% and the bottom 1% level.

Panel A: Summary Statistics in Pre-Treatment Period (-2, -1) at firm level						
	Insider Purchase Transactions			Insider Sell Transactions		
	(1)	(2)	(3)	(4)	(5)	(6)
	Treated Firms	Control Firms	Difference (1)-(2)	Treated Firms	Control Firms	Difference (4)-(5)
ΔBHAR_m_365$_{(-2,-1)}$	0.124	0.111	0.013	-0.055	-0.058	0.003
	(0.030)	(0.033)	(0.045)	(0.005)	(0.005)	(0.008)
total $asset_{j,t-1}$	7.322	7.238	0.083	8.000	7.943	0.056
	(0.085)	(0.081)	(0.118)	(0.029)	(0.028)	(0.040)
$mom_{j,\,t,(d-31,d\,-364)}$	0.148	0.184	-0.036	0.176	0.192	-0.015
	(0.025)	(0.020)	(0.033)	(0.007)	(0.007)	(0.010)
$bm_{j,m-1}$	0.634	0.634	0.000	0.492	0.488	0.003
	(0.019)	(0.022)	(0.029)	(0.007)	(0.007)	(0.010)
$roa_{j,t-1}$	0.027	0.033	-0.006	0.053	0.055	-0.002
	(0.001)	(0.000)	(0.007)	(0.002)	(0.002)	(0.003)
Non-CEO total comp ($000s)	1,231	1,325	-94.04	2,115	1,971	144***
	(59.62)	(92.52)	(110.06)	(20.24)	(17.69)	(26.89)
Transaction Value	156,920	89,887	67,032***	1,004,076	1,039,358	35,285
	(16,169)	(19,477)	(25,314)	(18,873)	(20,050)	(27,535)
N Matched Firm-Year	192	192		1331	1331	
N Transactions.	834	889		17,153	17,804	
Panel B: Summary Statistics of BHAR in pre- and post-event period						
BHAR_m_365$_{(t=-2)}$	-0.017	-0.002	-0.015	0.069	0.070	-0.001
	(0.029)	(0.022)	(0.037)	(0.004)	(0.004)	(0.006)
BHAR_m_365$_{(t=-1)}$	0.085	0.115	-0.030	0.047	0.040	0.007

	(0.029)	(0.021)	(0.036)	(0.004)	(0.004)	(0.006)
BHAR_m_365$_{(t = 0)}$	0.405	0.213	0.192^{***}	0.032	0.043	-0.011^{*}
	(0.032)	(0.026)	(0.041)	(0.004)	(0.006)	(0.007)
BHAR_m_365$_{(t = +1)}$	0.075	0.279	-0.204^{***}	0.014	0.038	-0.024^{***}
	(0.038)	(0.050)	(0.062)	(0.004)	(0.004)	(0.006)

Panel C: Opportunistic insider trading and the probability of winning CEO promotion

	Logit		Linear Probability Model	
	$CEOD_{i,t}$	$CEOD_{i,t}$	$CEOD_{i,t}$	$CEOD_{i,t}$
$age_{i,t-1}$	-0.030^{**}	-0.031^{**}	-0.003	-0.003
	(0.015)	(0.015)	(0.002)	(0.002)
$tenure_{i,t-1}$	0.046^{*}	0.040	0.006	0.005
	(0.026)	(0.026)	(0.004)	(0.004)
$COOD_{j,t-1}$	2.992^{***}	2.996^{***}	0.400^{***}	0.400^{***}
	(0.194)	(0.192)	(0.034)	(0.035)
no_buy$_{j,t-1,}$	0.341^{***}		0.046^{*}	
	(0.103)		(0.027)	
no_sell$_{j,t-1}$	-0.118^{**}		-0.013^{***}	
	(0.051)		(0.005)	
no_buy$_{j,(t-2,t-1)}$		0.178^{**}		0.022
		(0.070)		(0.015)
no_sell$_{j,(t-2,t-1)}$		-0.057^{**}		-0.006^{**}
		(0.026)		(0.003)
$delta_{i,t-1}$(×0.01)	0.029	0.038	0.005	0.006
	(0.037)	(0.038)	(0.005)	(0.005)
$vega_{i,t-1}$(×0.01)	0.068	0.066	0.106^{***}	0.103^{***}
	(0.157)	(0.161)	(0.033)	(0.033)
$lncompen_{i,t-1}$(×0.01)	0.029^{***}	0.029^{***}	0.006^{***}	0.006^{***}
	(0.005)	(0.005)	(0.001)	(0.001)
Other Control	Yes	Yes	Yes	Yes
Fixed Effect			Firm,Year	Firm,Year
Sample	1,466	1,466	1,364	1,364
R^2	0.38	0.37	0.43	0.42

Panel D: Opportunistic Insider trading propensity after losing the CEO competition

	Insider Purchase Transactions	Insider Sell Transactions

Year *t*	(0,0)	(1,1)	(0,0)	(1,1)
$Post_{i,t}$	-0.050**	-0.073	-0.025***	-0.066***
	(0.023)	(0.054)	(0.008)	(0.011)
$Treat_{i,t}$	-0.064**	-0.107**	-0.006	-0.015
	(0.027)	(0.044)	(0.010)	(0.010)
$(Treat \times Post)_{i,t}$	0.043	-0.024	0.025**	0.047***
	(0.029)	(0.084)	(0.012)	(0.016)
$CEO\_IT_{j,t}$	-0.025*	0.031**	0.008***	0.006**
	(0.013)	(0.015)	(0.003)	(0.003)
Constant	0.674	1.668*	1.295***	1.391***
	(0.614)	(0.942)	(0.100)	(0.111)
Control Variables	Yes	Yes	Yes	Yes
Sample	987	715	30,879	28,462
Within R^2	0.17	0.22	0.36	0.37
Fixed Effect	Firm, Month	Firm, Month	Firm, Month	Firm, Month

2.4.2 Diff-in-Diff regression results

Table 2.3 reports the diff-in-diff estimation result. In column (2), the coefficient of the interaction term $(Treat \times Post)_{0,0}$ is statistically significant, implying that the buy trades executed by insiders after losing a CEO turnover tournament yields a 24.5% higher BHAR_m_365 that those generated without CEO turnover, *ceteris paribus*. However, it is insignificant in the remaining buy trades columns. Column (5) to (6) indicate that, the sell trades in treated firm systematically generate more negative BHAR_m_365 of between 3.0% in years (0,0) and 4.8% in year (1,1), than those of the control firms, as the coefficients of the interaction term $(Treat \times Post)_{i,t}$ are negative and statistically significant. Using the average sell transaction value in year 0 and year 1, non-promoted insiders' sell transactions would yield \$28,209 (\$45,567) more profit if their transactions are made in the year 0 (year 1) than other non-CEO managers. The dollar profit is higher than the average profit of \$12,000 reported by Cziraki and Gider (2021) between 1986 and 2013. Additionally, the abnormal dollar profit accounts for 2.1% (3.3%) of the average non-CEO manager total compensation in year 0 (year 1), higher than the average 1.2% reported by Cziraki and Gider (2021) for all non-CEO managers covered by Execucomp.

The losing tournament effect is weaker for insiders who stay with firms with CEO successor prior to the tournament because the coefficients of $COOD_{j,t}$ are in the opposite signs to the coefficients of $(Treat \times Post)_{i,t}$ for both insider purchase and sell samples. This evidence shows that a pre-assigned successor will serve to depress the discontent among managers effectively. Thus, they will react to the loss of CEO tournament with less intensity because their sell transactions do not generate as negative returns as their counterparts from a firm that did not have a CEO successor. Moreover, insiders mainly make sell transactions to compensate themselves because the losing tournament effect persists until year +1 in the insider sell sample. In contrast, the effect solely exists in the year of CEO turnover in the insider purchase sample. The short-term and long-term momentum variables, $ret_{j,t,(d-1,d-30)}$, and $mom_{j,t,(d-31,d-364)}$ are both negative and mostly statistically significant for insider sell sample, but $mom_{j,t,(d-31,d-364)}$ is negative and significant only in column (1) for buy trade sample, suggesting that worst performing firms generate higher subsequent returns. Overall, the significance and signs of my control variables are consistent with other insider trading studies Gregory, Tharyan and Tonks, (2013), Cohen *et al.* (2012), Beneish and Markarian (2019) and Contreras and Marcet (2021).

2.4.3 Motivations behind more informed insider transactions

In this section, I assess whether insiders intentionally trade to compensate themselves for the forgone CEO promotion, referred as *forgone incentives hypothesis*, or to exploit the stock misevaluation after a major corporate change, referred as *stock misevaluation hypothesis*. In the former I expect a stronger increase (decrease) in the BHAR_m_365 of transactions submitted by insiders whose tournament prizes are larger. Although I control for the pay disparity in the last fiscal year using high_incentive$D_{i,t-1}$ as a proxy in my previous results, the historical pay disparity in year -1 is a more relevant measure for their tournament prizes had they won the tournament. A larger tournament prize indicates a larger opportunity loss, and they should trade on their private information more aggressively.

I further re-specify my diff-in-diff regression with a triple interaction term $(\text{Post}\times\text{Treat}\times\text{Pay\_rank})_{i,t}$, which I expect to be negative (positive) for insider purchase (sell) trades, if managers with high tournament prizes compensate themselves for the forgone promotion-based opportunity with greater intensity than other insiders. I also include $\text{Pay\_rank}_{i,t}$, $(\text{Post}\times\text{Pay\_rank})_{i,t}$ and $(\text{Treat}\times\text{Pay\_rank})_{i,t}$.I report the results in Table 2.4 Panel A. I include the same set of control variables but omit their coefficients for brevity. The coefficient of $(\text{Post}\times\text{Treat}\times\text{Pay\_rank})_{i,t}$ is statistically insignificant in the buy trade sample. However, it is positive and statistically significant in the sell trade sample, suggesting that non-promoted insiders with higher tournament incentives compensate themselves for the forgone promotion opportunity by selling on negative private information with greater aggressiveness.

Another method to reaffirm the *forgone incentives hypothesis* is to check the age effect. Gibbons and Murphy (1992) show that managers close to their retirement age will place less importance on the promotion-based incentives. Consequently, I hypothesize that older managers will react to the loss of tournament with less intensity, i.e., the subsequent changes in their abnormal returns will be less dramatic than those of younger managers. To test this

Table 2.3: Difference-in-difference regression output

The dependent variable is BHAR_m_365. $(Post \times Treat)_{I,t}$ is a dummy variable equals to one for firms that have a CEO turnover in year *t*, and zero otherwise. Other variables are described in Table 2.1 and Appendix 2.5. I only include sample in pre-CEO turnover period (-2, -1) and post-CEO turnover period (t, t+i). Standard errors in parentheses are based on robust standard errors clustered at the firm-month level. ***, **, and * denote significance at the 99%, 95% and 90% confidence level, respectively. All variables are winsorised at the top 99% and the bottom 1% level. All regressions include control variables and firm and month fixed effects.

	Insider Purchase			Insider Sell		
Year *t*	(0,1)	(0,0)	(1,1)	(0,1)	(0,0)	(1,1)
	(1)	(2)	(3)	(4)	(5)	(6)
$Post_{i,t}$	0.105	-0.002	0.152	0.021***	0.007	0.042***
	(0.073)	(0.051)	(0.181)	(0.008)	(0.009)	(0.011)
$Treat_{i,t}$	-0.320***	-0.349***	-0.342**	0.017*	0.011	0.008
	(0.108)	(0.117)	(0.133)	(0.010)	(0.010)	(0.010)
$(Treat \times Post)_{i,t}$	0.082	0.245**	-0.177	-0.038***	-0.030**	-0.048***
	(0.110)	(0.101)	(0.256)	(0.013)	(0.015)	(0.017)
$CEO\_IT_{i,t}$	0.036	0.015	0.108**	0.010***	0.009***	0.013***
	(0.029)	(0.024)	(0.044)	(0.003)	(0.003)	(0.003)
$COOD_{i,j}$	-0.442***	-0.421***	-0.440*	0.060***	0.069***	0.054**
	(0.135)	(0.145)	(0.227)	(0.018)	(0.021)	(0.025)
$ret30_{j,t,(d-1,d-30)}$	-0.811**	-0.333**	-0.963**	-0.171***	-0.185***	-0.131***
	(0.317)	(0.152)	(0.447)	(0.032)	(0.032)	(0.036)
$mom_{j,t,(d-31,d-364)}$	-0.182***	-0.102	-0.105	-0.035***	-0.039***	-0.036**
	(0.070)	(0.079)	(0.100)	(0.012)	(0.012)	(0.014)
$size_{j,m-1}$	-0.909***	-0.766***	-0.764***	-0.275***	-0.263***	-0.276***
	(0.159)	(0.116)	(0.243)	(0.012)	(0.011)	(0.014)
$delta_{j,t-1}(\times 0.01)$	0.002***	0.135***	0.129**	0.002**	0.001*	0.002**
	(0.000)	(0.051)	(0.053)	(0.001)	(0.001)	(0.001)
$vega_{j,t-1}(\times 0.01)$	-0.257***	-0.240***	-0.201*	-0.015***	-0.007**	-0.009**
	(0.092)	(0.087)	(0.119)	(0.004)	(0.003)	(0.004)
$lncompen_{i,t-1}$	0.018	0.033	0.027	0.032***	0.026***	0.035***
	(0.035)	(0.029)	(0.035)	(0.007)	(0.006)	(0.007)
$rating_{j,t-1}$	3.996***	3.207***	3.963***	-0.100	0.011	-0.147*
	(0.950)	(0.596)	(1.375)	(0.076)	(0.078)	(0.084)
Sample	2,126	1,833	1,328	45,776	36,829	33,658
Within R^2	0.38	0.37	0.39	0.15	0.15	0.14

hypothesis, I employ the natural logarithm of the current age of managers as the moderator variable. Table 2.4 Panel B shows that the coefficient of $(\text{Post}\times\text{Treat}\times\text{lnage})_{i,t}$ is insignificant in buy sample, but positive and significant in sell sample, in line with my previous findings that older managers will trade on their private information to compensate themselves for the forgone promotion-based incentives with higher aggressiveness. They did not place much implicit value on their future promotion opportunities because their career horizons are shorter, in line with Gibbons and Murphy (1992). In the same vein, I employ the natural logarithm of the current tenure of managers as the moderator variable. I report the regression output in Table 2.4 Panel C. The coefficients of the $(\text{Post}\times\text{Treat}\times\text{lntenure})_{i,t}$are all statistically significant and negative for the buy sample, but positive and significant in sell sample. The result is in line with the finding that executives who stay longer in a firm are less likely to be competing in a subsequent CEO tournament because more competent non-CEO executives are more likely to leave the firm after losing the first tournament (Chan *et al.* 2022).

I then employ insider personal investment horizons to proxy for insiders' career horizons and further confirm the *forgone incentives hypothesis*. Akbas, *et al.* (2020) show that short horizon (SH) insider sellers frequently reverse their previous buy positions to avoid overconcentration of their personal portfolios in their firms. Consequently, these insiders have shorter career horizon in their firms. I hypothesize that SH sellers will trade on their private information with lower aggressiveness to compensate themselves for the forgone CEO promotion because a shorter career horizon indicates a lower expected value for the forgone CEO incentives. I modify the investment horizon measure proposed by Akbas, *et al.* (2020) to identify SH sellers, as detailed in Appendix 2.1. I find only 2.3% (9.2%) of my buy (sell) trades were by short-horizon insider sellers, suggesting that SH sellers are less likely to trade after they have lost the tournament. I create short-horizon dummy variable $SHD_{i,t}$ equals to one for SH insiders, and zero otherwise. I employ $SHD_{i,t}$ as the moderator and report the results in Table 2.4 Panel D. The coefficient of $(\text{Post}\times\text{Treat}\times\text{SHD})_{i,t}$ is significantly positive in sell sample, suggesting that insiders who frequently unload their ownerships in their firms will trade on their private information with lower aggressiveness.

I further compute the subjective probability of insiders becoming CEO, $Probability_{i,t-1}$, by estimating a cross-section regression using only firms that had a CEO turnover in the year, and employ the probability in year -1 as the moderator and report the results in Table 2.4 Panel E. I explain the estimation of the variable in Appendix 2.1. Consistent with the *forgone incentives hypothesis*, non-promoted executives with higher subjective probability of becoming CEO exploit their private negative information more aggressively in their sell trades. There is no significant effect for insider purchase transactions. Next, I consider the possibility that the board will retain executives by awarding them a large retention bonus (Armstrong *et al*, 2021). Executives who have received a larger retention bonus, which compensates them for their forgone incentives, should trade on their private information less aggressively. I create the dummy variable $BA_{i,t-1}$ equals to one if the change in a manager *i*'s bonus is higher than the sample median among all managers in the same firms in the same year, otherwise zero. I employ the $BA_{i,t-1}$ as moderator and report the results in Table 2.4 Panel F. Non-promoted executives with larger bonus increases exploit their private negative information less aggressively in their sell trades. There is no significant effect for insider their purchase transactions[21]. Finally, I focus on the likelihood of the board allowing non-promoted executives to trade on their private information because Armstrong *et al* (2021) suggest that the board actively monitors the motivation behind insider transactions. I hypothesize that this board's monitoring role depends on its level of conservatism, as conservative boards are associated with higher litigation risk (Khan and Watts, 2009), higher likelihood of real earnings management which boosts managers' short-term compensation (Chung, Collins and Song, 2022), and lower motivation for insiders to trade to compensate themselves, and, consequently, lower insider trading profitability. To proxy for the board conservatism, I follow Khan and Watts (2009) and construct *C_score*, as detailed in Appendix 2.1. Table 2.4 Panel G reports the results. The coefficients of the interaction term are significantly negative for the buy, and positive for insider sell trades. In Panel H, I follow Kacperczyk and Pagnotta (2021) to define industries with high likelihood of having illegal insider trading investigation[22]. The results

[21] In unreported results, I also create dummy variable for sample after 2011, the year in which the unbinding Say-on-Pay law was passed. I did not find the implementation of Say-on-Pay law plays a significant result.
[22] Industries with two-digit SIC code of 28, 73, 36, 38, 35, 87, 60, 99, 20, 48 are more likely to receive illegal insider trading investigate from the SEC.

show that non-promoted directors are less likely to trade on their private negative informaiton in year 1 in these high litigation risk industries, there is no significant result for other event years. Overall, these results further reaffirms that the forgone CEO promotion opportunity motivates insiders to trade. Overall, these results further reaffirms that the forgone CEO promotion opportunity motivates insiders to trade.

Table 2.4: Insider heterogeneity and their trading intensity

This table reports the fixed effect regression output. The dependent variable is BHAR_m_365. In Panel A, the moderator variable is $Pay\_rank_{i,t}$, the rank of non-promoted manager sorted by their total compensation in year -1 among all tournament competitors. In Panel B, the moderator variable is $Lnage_{i,t}$, the natural logarithm of the age of the insider *i* in year *t*. In Panel C, the moderator variable is $Lntenure_{i,t}$, the natural logarithm of the tenure of the insider *i* in year *t* in firm *j*. In Panel D, the moderator variable is $SHD_{i,t}$, a dummy variable equals to one for short-horizon insiders identified by following Akbas *et al* (2020), and zero otherwise. In Panel E, the moderator variable is $Probability_{i,t-1}$, the estimated subjective probability of insider becoming the CEO estimated using his personal characteristics. In Panel F, the moderator variable is $\mathrm{BA}_{i,t-1}$, the bonus award in t-1. In Panel G, the moderator variable is $\mathtt{C\_quint}_{j,t}$, the quintile number based on the board conservatism for all firms in the same industry in each year. The board conservatism is measured by following Khan and Watts (2009). In Panel H, the moderate variable is $riskD_j$, a dummy variable equal to one if the firm is in high illegal insider trading industry, as outlined in Kacperczyk and Pagnotta (2021), and zero otherwise. I include firm and month levels and control variables described in Table 2.1 and main level of moderators. Moderator construction is detailed in Appendix 2.5. Standard errors in parentheses are based on robust standard errors clustered at the firm-month level. ***, **, and * denote significance at the 99%, 95% and 90% confidence level, respectively. All variables are winsorised at the top 99% and the bottom 1% level.

	Insider Purchase		**Insider Sell**	
Year t	(0,0)	(1,1)	(0,0)	(1,1)
	Panel A: Tournament Prize			
$(\text{Treat}\times\text{Post})_{i,t}$	0.248*	-0.072	-0.076***	-0.091***
	(0.150)	(0.363)	(0.022)	(0.027)
$(\text{Post}\times\text{Treat}\times\text{Pay\_rank})_{i,t}$	-0.007	-0.083	0.018***	0.019***
	(0.031)	(0.078)	(0.006)	(0.007)
Sample	1,590	1,100	34,883	28,988
	Panel B: Age Effect			
$(\text{Treat}\times\text{Post})_{i,t}$	-1.988	0.634	-0.743**	-1.032***
	(1.412)	(2.459)	(0.322)	(0.384)
$(\text{Post}\times\text{Treat}\times\text{lnage})_{i,t}$	0.556	-0.133	0.183**	0.250***
	(0.356)	(0.631)	(0.081)	(0.096)
Sample	1,415	1,074	32,158	29,552
	Panel C: Tenure Effect			
$(\text{Treat}\times\text{Post})_{i,t}$	0.370***	0.758***	-0.096**	-1.444***
	(0.122)	(0.268)	(0.038)	(0.050)
$(\text{Post}\times\text{Treat}\times\text{lntenure})_{i,t}$	-0.151*	-0.443***	0.043**	0.057***
	(0.087)	(0.166)	(0.019)	(0.025)
Sample	1,833	1,328	36,829	33,658
	Panel D: Investment Horizon			
$(\text{Treat}\times\text{Post})_{i,t}$	0.167***	0.177*	-0.034**	-0.053***
	(0.074)	(0.104)	(0.016)	(0.017)
$(\text{Post}\times\text{Treat}\times\text{SHD})_{i,t}$	-0.177	0.090	0.070**	0.080*
	(0.252)	(0.541)	(0.035)	(0.044)
Sample	1,833	1,328	36,829	33,658
	Panel E: Predicted probability of becoming CEO			
$(\text{Treat}\times\text{Post})_{i,t}$	0.039	0.080	0.051**	0.029
	(0.162)	(0.545)	(0.024)	(0.027)
$(\text{Post}\times\text{Treat}\times\text{Probability})_{i,t}$	-0.443	1.655	-0.158***	-0.185***
	(0.639)	(1.084)	(0.057)	(0.070)
Sample	715	625	24,689	24,356
	Panel F: Bonus award effect			
$(\text{Treat}\times\text{Post})_{i,t}$	0.153*	0.093	-0.041***	-0.068***
	(0.081)	(0.118)	(0.015)	(0.017)
$(\text{Treat}\times\text{Post}\times\text{BA})_{i,t}$	0.145	0.101	0.103***	0.128***
	(0.106)	(0.178)	(0.029)	(0.032)
Sample	1,593	1,103	35,154	31,969
	Panel G: Board Conservatism			
$(\text{Treat}\times\text{Post})_{i,t}$	0.652***	0.074	-0.741***	-0.105***
	(0.200)	(0.536)	(0.026)	(0.003)
$(\text{Treat}\times\text{Post}\times\text{C\_quint})_{j,t}$	-0.150**	-0.113	0.262***	0.024**
	(0.065)	(0.140)	(0.010)	(0.011)
Sample	1,833	1,328	36,829	33,658

	Panel H: High illegal insider trading industry			
$(\text{Treat}\times\text{Post})_{i,t}$	0.089	0.213	-0.023	-0.041**
	(0.128)	(0.149)	(0.018)	(0.020)
$(\text{Treat}\times\text{Post}\times\text{riskD})_{j,t}$	0.198	-0.417*	-0.021	0.069**
	(0.159)	(0.238)	(0.026)	(0.034)
Sample	1,833	1,328	36,829	33,658

I investigate whether *stock misevaluation hypothesis* plays a role in the insider trading decision, I employ two proxies to measure the stock informativeness: the Future Earnings Response Coefficient (FERC) proposed by Tucker and Zarowin (2006) and the return synchronicity suggested by Piotroski and Roulstone (2004). I explain the constructions of these two proxies in details in Appendix 2.1. For FERC, I create binary variable $FERC_{i,t}$ equal to one for the top quintile of stocks whose current prices contain the most future earnings information and zero otherwise. As for return synchronicity, I create a binary variable $Synch_{I,t}$ that equals to one for the top quintile of stocks whose current prices contain less firm-specific information and co-move strongly with the current and lagged market and industry returns, and zero otherwise. I then employ $FERC_{i,t}$ and $Synch_{i,t}$ as the second moderator variables separately. I hypothesize that when the firm's share price is less (more) informative for the firm-specific information, insider trading returns will be higher (lower) as suggested by Wang (2019). The significance and the sign of the coefficient of $(Treat{\times}Post)_{i,t}$ should be robust to the inclusions of these two firm information environment measures because insiders' motivation to trade is not only to correct the mispricing but to compensate themselves for the forgone CEO promotion opportunity.

I find, but not report, that for the buy trades, the coefficient of $(Post{\times}Treat{\times}FERC)_{i,t}$ is insignificant suggesting that insider purchase profitability after the CEO turnover is not affected by the level of stock price informativeness for future earnings. However, for the sell trades, it is positive and statistically significant. This implies that insiders' sell transaction generate returns that are more negative when the current stock price reflects lower future earnings information in year 0. I also employ $Synch_{i,t}$ as the moderator variable. Although the sign and significance of $(Treat{\times}Post)_{i,t}$ remain consistent, the coefficient of $(Post{\times}Treat{\times}Synch)_{i,t}$ is statistically insignificant in all columns, suggesting that insiders' trading profitability does not depend on the level of co-movement between current firm return and the current and lagged market and industry returns, i.e., when stock price contains firm-specific information. The results are in Appendix 2.8. In conclusions, the significant roles of age, historical pay rank, personal investment horizon, *ex-ante* promotion probability and change in bonus further lend stronger support to the *forgone incentives hypothesis*.

2.4.4 Informational content embeds in insider transactions

I examine the informational content of insider trading after losing the CEO competitions to confirm that the unobservable firm characteristics do not drive these more informed insider transactions. The loss of promotion opportunity will lower their total compensation packages to a suboptimal level for their effort. Although they will trade to compensate themselves, these more informed transactions cannot fully adjust their packages to the optimal level, otherwise they would not have enough incentives to compete in the tournament *ex-ante*. Therefore, they will exert less effort and their sell transactions should predict the worsening in future firm performance. I focus on three non-mutually exclusive possibilities: insiders may trade on future operating performance changes, exploit the change in investor sentiments, and base on the future change in the cost of capital.

I compute the 2-year change in ROA from (t, t+2) with year *t* being the insider transaction year to estimate the former, denoted as ΔROA[23]. *I* explain the constructions of the change in investor sentiments and change in the cost of capital in details in Appendix 2.1. To measure the change in investor sentiment denoted as $\Delta \mathrm{Sentiment}$, I compute the market-to-book ratio decomposition of Rhodes–Kropf, Robinson and Viswanathan (2005). Cziraki, Lyandres and Michaely, (2021) argue the method can separate the firm-specific sentiment from industry-level sentiment and is appealing to insider trading studies because insiders are more likely to possess private information on the former than on the latter (Wang, 2019). I follow Cziraki *et al.* (2021) and measure the change in sentiment $\Delta \mathrm{Sentiment}_{t-1,t+1}$ between (t-1, t+1) with year *t* as insider trading year. To measure the change of cost of capital $\Delta r_{t,t+2}$, I follow Cziraki, *et al.* (2021) and estimate a modified Fama and French (1993) three-factor model. I re-estimate the difference-in-difference regression by separately substituting $\Delta \mathrm{ROA}_{t,t+2}$, $\Delta \mathrm{Sentiment}_{t-1,t+1}$ and $\Delta r_{t,t+2}$ for the dependent variable BHAR_m_365. I control the same set of control variables and report the regression results in Table 2.5

Panel A, where the dependent variable is $\Delta \mathrm{ROA}_{t,t+2}$, shows that insider sell transaction can significantly predict a decrease in ROA in the next three years. Insider sell transactions predict a 2%, and 1.1% decrease in $\Delta \mathrm{ROA}_{t,t+2}$ in year 0 and 1, respectively, unlike insider purchase transactions as column (1) and (2) show that $(\mathrm{Post}\times\mathrm{Treat})_{i,t}$ is not significant. Similarly, in Panel B, where the dependent variable is $\Delta \mathrm{Sentiment}_{t-1,t+1}$, insider purchase

[23] My results remain robust if I use the change in ROA from $(t, t+1)$ with insiders' trade in year t.

transactions do not significantly predict future changes in investor sentiment in year 0, while insider sell transactions in years 0 and 1 predict a 5.4% and 6.2% additional decrease in the firm's market value that fundamentals do not explain. In Panel C, $\Delta r_{t,t+2}$ is the dependent variable. I can observe that insider purchase sample does not predict the future decrease in the cost of capital in year 0 whereas insider sells predict 0.1% increases in the cost of capital in both year 0 and 1. The coefficient of $(\text{Post}\times\text{Treat})_{i,t}$ is statistically significant at the 95%, and 90% in column 3 and 4, respectively. Overall, these results highlight that the higher return predictability embedded in the insider sell transactions is not random. Insiders exploit the worsening in future firm performance, the lower investor sentiment, and an increase in the future cost of capital to yield higher negative returns in sell transactions. However, there is no clear result for insider purchases.

Chan *et al.* (2022) show that more competent managers are more likely to leave the firm because a higher explicit compensation contract does not comepensate the permanent loss in their implicit promotion-based incentives. If non-promoted insiders are trading on the talent losses rather than their private information, I expect their sell transactions contain little predictability for future performance. I split my sample depending on whether there is non-CEO director leaves the firm in the next year and repeat the regression in Table 2.5. Appendix 2.9 reports the results. My results remain overall robust, meaning insiders are trading on their private information regarding the firm’s future performance rather than the simple talent loss. Moreover, these results also suggest that these tournament losers will exert lower level of effort to improve the firm performance because their total compensation packages have drastically lower value.

Table 2.5: Post CEO turnover insider trading and changes in firm and investor features

This table reports the fixed effect regression output based on matched sample in Table 2.4. In Panel A, the dependent variable is the change in return on asset between year t and year t+2. In Panel B, the dependent variable is the change in investor sentiment measured as firm-specific component from the market-to-book decomposition of Rhodes–Kropf, *et al.* (2005). The change in investor sentiment $\Delta\text{Sentiment}_{-1,1}$ is measured between year t-1 to year t+1. In Panel C, I obtain the $\Delta r_{t,t+2}$ by following Cziraki *et al.* (2021) to estimate a modified Fama and French (1993) Three-Factor model. I include the control variables in Equation (2), omitted for brevity. Standard errors reported in parentheses are computed based on robust standard errors clustered at the firm-month level. ***, **, and * denote significance at the 99%, 95% and 90% confidence level, respectively. All variables are winsorised at the top 99% and the bottom 1% level. All regressions include control variables and firm and month fixed effects.

	Insider Purchase		**Insider Sell**	
	(1)	(2)	(3)	(4)
Year *t*	(0,0)	(1,1)	(0,0)	(1,1)
	Panel A: Future Firm Performance			
Dependent Variable	$\Delta ROA_{t,t+2}$	$\Delta ROA_{t,t+2}$	$\Delta ROA_{t,t+2}$	$\Delta ROA_{t,t+2}$
$\textbf{Post}_{i,t}$	-0.001	0.015	-0.001	-0.003
	(0.012)	(0.012)	(0.003)	(0.003)
$\textbf{Treat}_{i,t}$	-0.087***	-0.069***	0.015***	0.019***
	(0.022)	(0.019)	(0.004)	(0.004)
$\textbf{(Post×Treat)}_{i,t}$	0.007	-0.018	-0.020***	-0.011**
	(0.015)	(0.025)	(0.005)	(0.005)
Within R-square	0.15	0.19	0.07	0.06
Sample	1,727	1,271	35,582	32,628
	Panel B: Investor Sentiment			
Dependent Variable	$\Delta\text{Sentiment}_{t-1,t+1}$	$\Delta\text{Sentiment}_{t-1,t+1}$	$\Delta\text{Sentiment}_{t-1,t+1}$	$\Delta\text{Sentiment}_{t-1,t+1}$
$\textbf{Post}_{i,t}$	-0.086	-0.284**	-0.003	0.037**
	(0.064)	(0.113)	(0.014)	(0.017)
$\textbf{Treat}_{i,t}$	0.038	0.104	0.034**	0.034**
	(0.134)	(0.137)	(0.016)	(0.017)
$\textbf{(Post×Treat)}_{i,t}$	0.046	0.038*	-0.054**	-0.062**
	(0.121)	(0.219)	(0.023)	(0.026)
Within R-square	0.07	0.18	0.07	0.10
Sample	1,728	1,288	35,894	31,232
	Panel C: Change in Cost of Capital			
Dependent Variable	$\Delta r_{t,t+2}$	$\Delta r_{t,t+2}$	$\Delta r_{t,t+2}$	$\Delta r_{t,t+2}$
$\textbf{Post}_{i,t}$	-0.000	0.007**	-0.000	-0.000
	(0.013)	(0.003)	(0.000)	(0.000)
$\textbf{Treat}_{i,t}$	-0.085***	0.008***	-0.001	-0.001
	(0.022)	(0.002)	(0.000)	(0.000)
$\textbf{(Post×Treat)}_{i,t}$	0.005	-0.004***	0.001**	0.001*
	(0.016)	(0.003)	(0.000)	(0.001)
Within R-square	0.14	0.21	0.05	0.05
Sample	1,727	1,334	37,001	33,727

2.4.5 Insider trading activities for existing managers

I expect non-promoted executive who increase opportunistic trading to stay with the firm, as they will view the overall level of compensation as sufficient to maintain employment. To test this hypothesis, I first use the same diff-in-diff regression. Table 2.6 reports the results. In column (1) and (3), the dependent variable is $\text{ExitD}_{i,j}$, a dummy variable equals to one for exiting executives who are leaving the firm in the (0, 2), and zero otherwise. I include the same set of control variables. The results indicate that the coefficients of $(\text{Post}\times\text{Treat})_{i,t}$ for both samples do not explain executives' exiting probability, suggesting that exiting managers do not abnormally purchase or offload their positions in their firms before they leave. In column (2) and (4), I compare the post-transaction return between exiting and staying managers by interacting the dummy variable $\text{LastD}_{i,t}$ with the interaction term $(\text{Post}\times\text{Treat})_{i,t}$. $\text{LastD}_{i,t}$ is a dummy equal to one if the manager *i* is staying in the firm for the last year, and zero otherwise. While there is no significant difference between staying and exiting managers in the purchase sample, the interaction variable is positive and significant for sell sample suggesting that exiting managers cannot generate as high abnormal return as staying managers, and thus, they are more likely to leave the firm. On the other hand, a higher trading profitability compensates managers for their forgone CEO promotion incentives and aligns managers' compensation levels closer to the optimal level, causing them less likely to leave.

Panel B reports the results based on insider matched sample. For each exiting manager who are leaving in year (0, 2), I select a control manager in year *t-1*, which is one year before CEO turnover by matching on their total compensation, average insider trading profitability and total shares traded. I require there is no CEO turnover event occurred for my control sample within years (-3, 3). The coefficient of $(\text{Post}\times\text{Treat})_{i,t}$ is negative and statistically significant for both purchase and sell samples but the post-trade profitability is not significant, as reported in columns (2) and (4). These results suggest that exiting insiders systematically make less purchase and sell transactions that are not informative.[24]

[24] Under SEC rule 16a-2(b) executives need to file their trades for six months after they have left their firms.

Table 2.6: Insider trading after CEO turnover for exiting managers

This table reports the fixed effect regression output for exiting managers who are leaving the firm in year (0,2). The dependent variable in column (1) and (3) is $\text{LeaveD}_{i,t}$, a dummy variable equal to one for managers that leave the firm in the next year, and zero otherwise. The dependent variable in column (2) and (4) is BHAR_m_365 as defined before. The moderator variable in column (2) and (4) is $\text{LastD}_{i,t}$a dummy variable equal to one if a manager is staying in the firm for the last year, and zero otherwise. In Panel A, I employ the same matched sample as Table 2.4. In Panel B, I match each exiting managers using their total compensation, average insider trading profitability and total shares traded in year *t-1* with a manager from firms that do not have CEO turnover in year (-3,3) using the shortest Mahalanobis distance. I include the control variables in Equation (2), omitted for brevity. I include all observations between event year (-2, 1). Standard errors reported in parentheses are computed based on robust standard errors clustered at the firm-month level. ***, **, and * denote significance at the 99%, 95% and 90% confidence level, respectively. All variables are winsorised at the top 99% and the bottom 1% level.

Panel A: Firm Matched Sample				
	Insider Purchase		Insider Sell	
	(1)	(2)	(3)	(4)
Year *t*	(0,1)	(0,1)	(0,1)	(0,1)
Dependent Variable	$\text{ExitD}_{i,j}$	BHAR_m_365	$\text{ExitD}_{i,j}$	BHAR_m_365
$\textbf{Post}_{i,t}$	0.044	0.120	0.038***	0.026***
	(0.029)	(0.075)	(0.007)	(0.008)
$\textbf{Treat}_{i,t}$	-0.057	-0.323**	0.012	0.024**
	(0.045)	(0.109)	(0.009)	(0.010)
$\textbf{(Post×Treat)}_{i,t}$	-0.011	0.088	0.008	-0.027**
	(0.042)	(0.114)	(0.013)	(0.013)
$\textbf{LastD}_{i,t}$		-0.137		0.023*
		(0.013)		(0.013)
$\textbf{(Post×Treat×LastD)}_{i,t}$		-0.128		0.049**
		(0.163)		(0.025)
Other Control Variable	Yes	Yes	Yes	Yes
Within R-square	0.04	0.39	0.02	0.17
Fixed Effect	Firm, Month	Firm, Month	Firm, Month	Firm, Month
Sample	2,134	2,126	46,002	45,773
Panel B: Insider Matched Sample				
	Insider Purchase		Insider Sell	
Year *t*	(0,1)	(0,1)	(0,1)	(0,1)
Dependent Variable	$\text{ExitD}_{i,j}$	BHAR_m_365	$\text{ExitD}_{i,j}$	BHAR_m_365
$\textbf{Post}_{i,t}$	0.228***	0.186***	0.287***	0.030***
	(0.041)	(0.071)	(0.011)	(0.010)
$\textbf{Treat}_{i,t}$	0.995	-0.189	0.888***	0.038**
	(0.057)	(0.154)	(0.019)	(0.017)
$\textbf{(Post×Treat)}_{i,t}$	-0.316***	-0.070	-0.250***	-0.027
	(0.072)	(0.123)	(0.019)	(0.019)
Within R-square	0.36	0.35	0.35	0.18
Fixed Effect	Firm, Month	Firm, Month	Firm, Month	Firm, Month
Sample	949	947	17,442	17,389

2.4.6 Firm level characteristics for high turnover firms

I further compare firms that have many non-promoted directors leave in year (0, 1) with firms that have less directors leave. The sample median for the proportion of exiting directors is 0.4, I define dummy variable High_TurnoverD equal to one if firm *j* if there are more than 40% of their tournament contenders leaving the firm in the next two years, and zero otherwise. I additionally include many control variables. I compute the average BHAR_m_365 for firm *j* with and without CEO transactions in the year (-3, -2). I time the BHAR_m_365 for sell transaction by -1 to correct for the direction. I include $tobin's\ Q_{j,t-1}$, $capital\_intensity_{j,t-1}$, $leverage_{j,t-1}$, and $dividend\text{-}yield_{j,t-1}$ to control for firm level characteristics, I include $cash\_flow\_vol_{j,t-1}$ and $skt\_ret\_volatility_{j,t-1}$ to control for firm risk taking incentives. For corporate governance, I control for $institutional\_ownership_{j,q-1}$, $independent\_managers_{j,t-1}$, $independent\_committee_{j,t-1}$ which is the proportion of independent managers on the compensation committee and include the $C\_score_{j,t-1}$ to proxy for the board conservatism. Following Dang *et al.* (2021), I include $analyst\_talent_{j,t-1}$, which significantly lowers the insider trading profitability, to proxy for the average talent of sell-side analysts following the firm *j* in the last fiscal year and to control for industry-level informativeness[25]. Appendix 2.5 details the construction of my variables. I estimate both logit and fixed effect regressions by including year dummy variable. I use robust standard error for logit and cluster standard error at year-industry level for fixed effect regression.

Table 2.7 reports the regression results. I observe that those tournament losers are more likely to leave value firms (high book-to-market value), have higher analyst coverage, are smaller, have high research and development cost, have high stock return and cash flow volatilities and there are more independent managers on the board.

More importantly, the coefficients of historical average insider profitability remain negative and statistically significant, indicating if insider trading profitability is high in the past, those non-promoted directors are less likely to leave the firm in the future. Moreover, the coefficient of $\mathrm{C\_score}_{\mathrm{j,t-1}}$ is positive and significant, implying that the more conservative the

[25] I am grateful to Dr Li for making the analyst talent data available.

board is, the more likely these tournament rejectees will leave the firm. These results indicate that non-promoted directors will assess their ability of compensating themselves using their private information after the tournament. If their firms' boards are more conservative in terms of allowing insiders to generate abnormal return, these non-promoted directors are more likely to leave these firms. The finding is consistent with my hypothesis that there will be a higher non-promoted director turnover rate among firms that have more rigorous insider trading regulation.

Table 2.7: Firm-level characteristics and the scale of non-CEO director turnover

This table reports the firm level Logit and Linear Probability regression results. The dependent variable High_TurnoverD is a dummy equal to one if firm j has more than 40% of their tournament contenders leave the firm in year (0, 1), and zero otherwise. Other independent variables are $illiq_{j,t-1}$, $roa_{j,t-1}$, tobin's $Q_{j,t-1}$, dividend-yield$_{j,t-1}$, leverage$_{j,t-1}$, capital_intensity$_{j,t-1}$, institution_ownership$_{j,t-1}$, independent_committee$_{j,t-1}$, and analyst_talent$_{j,t-1}$. I omit their coefficients for brevity. (Mean_BHAR_with_CEO)$_{j,(t-3,t-2)}$ is the average BHAR for 365 holding period with CEO trades between year (-2, -1). I time the BHAR for sell transactions by -1 to correct the direction. Standard errors reported in parentheses are computed based on robust standard errors for logit regression and clustered at the year-industry level for fixed effect regression. Control variable construction is detailed in Appendix 2.5. ***, **, and * denote significance at the 99%, 95% and 90% confidence level, respectively. All variables are winsorised at the top 99% and the bottom 1% level.

	Logit		**Linear Probability Model**	
	High_TurnoverD	High_TurnoverD	High_TurnoverD	High_TurnoverD
(Mean_BHAR_with_CEO)$_{j,(t-3,t-2)}$	-1.169***		-0.253***	
	(0.191)		(0.046)	
(Mean_BHAR_without_CEO)$_{j,(t-3,t-2)}$		-1.089***		-0.238***
		(0.205)		(0.049)
C_score$_{j,t-1}$	0.003***	0.003*	0.001**	0.001**
	(0.001)	(0.002)	(0.000)	(0.000)
mom$_{j,(d-364,d-31),t-1}$	0.354**	0.274	0.074*	0.058
	(0.181)	(0.192)	(0.045)	(0.047)
bm$_{j,t-1}$	0.566***	0.687***	0.126***	0.152***
	(0.169)	(0.183)	(0.040)	(0.043)
numest$_{j,t-1}$	0.023**	0.027***	0.005**	0.006**
	(0.010)	(0.010)	(0.002)	(0.003)
size$_{j,t-1}$	-0.162***	-0.173***	-0.035**	-0.037***
	(0.058)	(0.062)	(0.014)	(0.015)
rd$_{j,t-1}$	1.807**	1.963**	0.402**	0.435**
	(0.782)	(0.889)	(0.178)	(0.192)
skt_ret_volatility$_{j,t-1}$	9.684**	11.088**	2.233**	2.505**
	(4.661)	(4.984)	(1.083)	(1.195)
cash_flow_vol$_{j,t-1}$	10.999***	12.889***	2.524***	2.943***
	(3.649)	(4.084)	(0.881)	(0.940)
independent_manager$_{j,t-1}$	1.169***	1.416***	0.252***	0.300***
	(0.394)	(0.423)	(0.096)	(0.097)
Other Control	Yes	Yes	Yes	Yes
Sample	1,953	1,764	2,016	1,814
Year Dummy/Year Fixed Effect	Yes	Yes	Yes	Yes

2.4.7 Insider trading and the effect of the tournament incentives

In this section, I revisit the empirical finding in Kale *et al.* (2009) by considering insider trading opportunity as an additional factor to consider. I investigate whether the presence of insider trading opportunity weakens the positive effect of tournament incentives on firm performance because the tournament prize is not as high as it appears. To measure the total non-CEO insider trading activity, I construct the variable $\text{all\_IT}_{j,t}$ which is the total number of insider transactions executed by non-CEO managers for firm *j* in year *t*. The higher $\text{all\_IT}_{j,t}$, the more prevailing the insider trading activity in firm *j*. Furthermore, I use the following refined fixed effect regression version of Kale *et al.* (2009) using Tobin's Q and ROA to proxy for the firm performance.

$$\begin{aligned}\text{firm\_performance}_{j,t} = \alpha &+ \beta_1\text{pay\_gap}_{j,t} + \beta_2\text{rd}_{j,t} + \beta_3\text{sale}_{j,t} + \beta_4\text{sale}^2_{j,t} + \beta_5\text{capital-to-sale}_{j,t} + \\ &\beta_6\text{advertising-to-sale}_{j,t} + \beta_7\text{dividend-yield}_{j,t} + \beta_8\text{leverage}_{i,t} + \\ &\beta_9\text{lnage}_{j,t} + \rho + \delta + \varepsilon_i \qquad (6)\end{aligned}$$

where $pay\_gap_{j,t}$ proxies for tournament incentives as previously specified. ρ is firm fixed effect, and δ is year fixed effect. I cluster the standard error at the firm level. Appendix 2.5 defines the remaining variables. $pay\_gap_{j,t}$ represents the tournament incentives, and β_1 should be statistically significant and positive according to Kale *et al.* (2009) because the higher tournament incentives, the better the firm performs. Unlike Kale *et al.* (2009), I correct the CEO compensation figure for FASB 123R revision. I estimate a 2SLS regression with two first-stage regressions. Kale *et al.* (2009) applied the median value of tournament incentives for firms in the same sales quintiles and the same two-digit SIC industry as the firm as their instrumental variable because it is a significant determinant of the amount of each firm's tournament incentives. Since compensation structures depend also on the firms' size, I use the median value of tournament incentives in the same size, proxied by sales, and industry as my IV. My second stage regression is as follows:

$$\text{firm\_performance}_{j,t} = \alpha + \beta_1\widehat{\text{pay\_gap}}_{j,t} + \beta_2\widehat{\text{pay\_gap} \times \text{all\_IT}}_{j,t} + \beta_3\text{all\_IT}_{j,t} + \text{control} + \varepsilon_i \qquad (7)$$

If the presence of high insider trading activity weakens the positive relationship between the tournament incentives and the firm performance, β_2 will be negative and statistically significant. The above regression specification implicitly assumes that $all\_IT_{j,t}$ is exogenous. One source of endogeneity is reverse causality as insiders may purchase (sell) more in outperforming (underperforming) firms, as they understand their firms' future valuation. Thus, simply using one IV for the tournament incentives is not sufficient to conclude the causal relations. I use an additional IV to proxy for the $all\_IT_{j,t}$ to relax this assumption. I follow Kim and Lu (2011) and use the sum of maximum state and federal marginal personal income tax rates (hereafter called tax rate) as my second instrumental variable. Kim and Lu (2011) argue that personal income taxes may affect the personal portfolio composition and the timing of stock transactions and option exercises as, *ceteris paribus*, managers in a high tax state may prefer more tax-exempt securities to stock, thus causing lower stock ownership. I expect tax changes to also lead to changes in share ownership as managers may sell (hold) more shares when they anticipate a tax increase (decrease). Moreover, the variation in state tax laws across states and years is exogenous to a firm's future performance. I collect the sum of maximum state and federal marginal long-term capital gain tax rates from Feenberg and Coutts (1993)[26] from 1997 until 2019, assuming a married representative taxpayer with joint filing and top tax bracket in her state. Insiders are subject to capital gains tax on any capital return from trading stocks, and high rates will reduce their propensity to trade.

Table 2.8 reports the results. For brevity, I omit the first-stage regression result and report only the first-stage F statistics. In column (1) and (2), I replicate the finding in Kale *et al.* (2009). The coefficient of $pay\_gap_{j,t}$ is positive and statistically significant at the 99% confidence level in both columns, indicating that tournament incentives' positive effect on the firm performance persists in my sample period. In column (3) and (4), I employ the median industry tournament incentive as the IV and interact the insider trading intensity with the predicted tournament incentive. The coefficient of $\widehat{pay\_gap}_{j,t}$ is positive and statistically significant. The result further highlights the finding in Kale *et al.* (2009) that there is a causal relationship between tournament incentives and firm performance. A higher pay disparity between the CEO and other managers will motivate them to exert higher effort to compete for the next CEO position

[26] I thank Prof. Feenberg for updating these data regularly and making these data publicly available. https://users.nber.org/~taxsim/state-rates/

and consequently improve the firm performance. More importantly, the interaction term's coefficient is negative and statistically significant, suggesting that that insider trading opportunity weakens tournament incentives' positive effect on the firm performance. In column (5) and (6), I employ the tax rate as my IV to predict the number of insider transactions $all\_IT_{j,t}$. The significance of Sanderson-Windmeijer F statistics which test the null hypothesis of under-identification of each endogenous variables as I have three endogenous variables in the first stage regression, implies that all three endogenous variables are identified. In an unreported result, I separately check the explanatory power of tax rate on insider trading transactions by including the tax rate as the only IV to explain the $all\_IT_{j,t}$ in the first-stage regression. The tax rate coefficient is negative and statistically significant at the 99% confidence level with 11.4 first-stage F statistics[27], meaning a higher tax rate is associated with fewer insider transactions. The coefficient of $\widehat{\mathrm{pay\_gap}}_{j,t}$ is positive and statistically significant, in line with Kale *et al.* (2009). Moreover, the interaction term's coefficient is negative and statistically significant and its magnitude is around a third of the coefficient of $\widehat{\mathrm{pay\_gap}}_{j,t}$, suggesting that the tournament incentive's effect on firm performance will be overestimated by a third if the possibility that managers can trade on their private information to realize their implicit promotion-based compensation is overlooked. The coefficient of the $all\_IT_{j,t}$ is also positive and statistically significant, suggesting that insider trading transactions improve firm's performance, mitigating agency problems by aligning managers' and shareholders' interest. Overall, my results confirm that insider trading opportunity weakens the positive effect of tournament incentive on firm performance and that insiders consider their unrealized promotion prize when they trade, consistent with my previous findings.

[27] Stock and Yogo (2005) weak identification test also supports my conclusion that the tax rate can explain the variation in insider transaction number.

Table 2.8: Insider trading and tournament incentives

The data covers all firm-year observations in Execucomp in 1996-2019. The control variables in all six columns are $rd_{j,t}$, $sales_{j,t}$, $capital\text{-}to\text{-}sales_{j,t}$, $advertising\text{-}to\text{-}sales_{j,t}$, $dividend\text{-}yield_{j,t}$, $lnage_{i,t}$, and $skt\_ret\_volatility_{j,t}$. The regression specification is a shorter version of Kale *et al.* (2009). Appendix 2.5 defines all variables in the table. In column (1) and (2), I regress Tobin's Q and ROA on all control variables with firm and year fixed effects, respectively. In column (3) to (6), I conduct a 2SLS regression with two first-stage regressions. My endogenous variables are $pay\_gap_{j,t}$ and the interaction term between $pay\_gap_{j,t}$ and my insider trading intensity measure which is $all\_IT_{i,t}$. In the first stage regression, I employ the median $pay\_gap_{j,t}$ in the same sales quintiles and the interaction term between the $all\_IT_{i,t}$ and $pay\_gap_{j,t}$ as my two IVs in column (3) and (4). In column (5) and (6), I use the sum of the maximum federal and state long-term capital gain tax rates as the IV for $all\_IT_{i,t}$, and use the product between the tax rate and median $pay\_gap_{j,t}$ as the IV for the endogenous interaction term. In the second stage, I regress the Tobin's Q and ROA on all control variables with predicted $\widehat{pay\_gap}_{j,t}$, $\widehat{all\_IT}_{j,t}$ and predicted interaction term. I cluster my standard error at firm level and report it in the parentheses. ***, **, and * denote significance at the 99%, 95% and 90% confidence level, respectively. All variables are winsorised at the top 99% and bottom 1% level. All columns include firm and year fixed effects.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	Fixed Effect		2SLS-Second Stage			
			One IV		Two IVs	
Dependent Variable	Tobin's $Q_{j,t}$	$ROA_{j,t}$	Tobin's $Q_{j,t}$	$ROA_{j,y}$	Tobin's $Q_{j,t}$	$ROA_{j,y}$
$\mathbf{pay\_gap_{j,t}}$	0.014^{***}	0.001^{***}				
	(0.005)	(0.000)				
$\mathbf{\widehat{pay\_gap}_{j,t}}$			0.084^{***}	0.002^{*}	0.168^{**}	0.015^{**}
			(0.016)	(0.001)	(0.086)	(0.007)
$\mathbf{\widehat{pay\_gap\times all\_IT}_{j,t}}$			-0.008^{***}	-0.003^{***}	-0.037^{*}	-0.005^{**}
			(0.002)	(0.000)	(0.022)	(0.002)
$\mathbf{all\_IT_{j,t}}$	0.021^{***}	0.002^{***}	0.088^{***}	0.004^{***}		
	(0.002)	(0.001)	(0.014)	(0.001)		
$\mathbf{\widehat{all\_IT}_{j,t}}$					0.383^{**}	0.029^{*}
					(0.179)	(0.015)
Other Control Variable	Yes	Yes	Yes	Yes	Yes	Yes
First-Stage F- $\mathbf{\widehat{pay\_gap}_{j,t}}$ only			334.37^{***}	345.28^{***}	209.57^{***}	209.60^{***}
Sanderson-Windmeijer F- $\mathbf{\widehat{pay\_gap}_{j,t}}$					11.04^{***}	11.14^{***}
Sanderson-Windmeijer F- Interaction					10.37^{***}	10.46^{***}
Sanderson-Windmeijer F - $\mathbf{\widehat{all\_IT}_{j,t}}$					9.06^{***}	9.11^{***}
Sample	35,806	35,822	35,806	35,822	34,258	34,274

2.5 Robustness Test

2.5.1 Reverse causality concern

I subject my results to various robustness checks. I have shown that tournament competitors systematically avoid trading on their private negative information when competing for the CEO position in year (-2, -1) because their trading decisions adversely affect their winning probabilities as their sell trades would be seen as a lack of belief in their firm. In the same vein, insiders who frequently trade on their private information have lower probability of promotion to the CEO position. This possible reverse causality will induce endogeneity and further questions my results. In addition, these informed sell transactions after the outcome of CEO tournament may not generate significantly lower abnormal returns compared with their transactions outside the event window which will result in a weaker external validity.

Moreover, my results show that non-promoted executives predominantly make sell, not buy, transactions to compensate themselves for the forgone promotion opportunity, even though buy trades are subject to, in general, lower litigation risk and are more profitable (Skinner, 1994; Lakonishok and Lee, 2001). Inspired by the finding of Armstrong *et al.* (2021), I hypothesize that they trade against the nosiy transactions of the newly promoted CEO to reap higher abnormal return because CEO's transactions embed strong signal for stock valuation, and the market adjusts the stock price based on CEO's transactions even when the signal is false (Wu, 2019).

I estimate the 2SLS using the last fiscal year's former CEO age as my IV based on the universal sample to generalize my results outside the tournament period to further reaffirm that my results are not affected by the potential endogeneity, are robust to the alternative estimation method, and do not hinge on the underlying matched sample. I compare non-promoted managers' transaction profitability with their unconditional return to investigate whether their post-tournament transaction return is significantly different from their transaction returns outside a CEO turnover event before tournament began. I focus on the isolated CEO turnover and exclude transactions in year +2 to have a cleaner sample with no confounding events to be consistent with diff-in-diff regression, even though my results are robust to their inclusion. I further conduct a test on the predictive power of insider trading on tournament outcome to alleviate further the reverse causality concern. I find, but not report for brevity reasons, that the coefficients of $age\_ceo_{j,t-1}$ in all first-stage regressions are statistically significant with the expected signs, indicating that $age\_ceo_{j,t-1}$ is an appropriate instrumental variable for CEO turnover event. It is positive and statistically significant for periods (0,0), suggesting that the older the former CEO, the higher the likelihood of a CEO turnover in the next fiscal year, in line with my hypothesis. For periods (1,1), the coefficients of $age\_ceo_{j,t-1}$ become negative and statistically significant, suggesting that the recently left CEO is younger than the average former CEO age among all firms covered by Execucomp. The first stage F statistics, computed without the interaction term $\widehat{NPED\times CEO}\_IT_{i,t}$ reported at the bottom of Panel A Table 2.9, are all above 10, which is the minimum value to alleviate the weak instrument concern[28], providing significant support for the relevance condition. The Anderson-Rubin F-statistic rejects the null hypothesis and indicates that the endogenous regressor $NPED_{i,t}$ is statistically significant. The result indicates that, after losing the CEO competition, insiders indeed incorporate more private information into their transactions. The Anderson-Rubin F-statistic is robust to the presence of weak instrumental variable (Andrews, Stock and Sun, 2019) and thus reaffirm my findings. In unreported result, I also check for a potential weak instrument using the Stock and Yogo (2005) test and the Shea Partial R-squared values. I find that my IV does not suffer from weak instrument problem in my study. The Difference-in-Sargan *C*-statistic rejects the null hypothesis that the $NPED_{i,t}$ is exogenous to insider transactions' profitability. Since I have only one endogenous variable and one instrumental variable, the *Difference-in-Sargan C-test* is equivalent to a *Hausman* test comparing 2SLS estimates with fixed effect (FE) estimates. The significant *C*-statistics confirm the need to apply 2SLS rather than the FE estimator.

[28] The first stage F-statistics are all relatively large for my insider sell sample because of the large sample size and the two fixed effects and/or the high predictive power embedded in my IV for my endogenous variable. If my IV and endogenous variable are high predictable, then the amount of exogenous variation left for the second-stage regression will be small. To address this concern, I separately estimate all the first-stage regression and check the within R-squared whenever the first stage F-statistics is larger than 200. After using the firm and month fixed effects, the within R-squared in the first-stage regression is generally around 0.4, making my IV suitable.

Table 2.9 Panel A reports the second-stage regression results. For insider purchase sample, I omit to report the coefficient of $NPED \times CEO\_IT_{i,t}$, which is insignificant, suggesting that when non-promoted managers make purchase transactions, they do not consider the current CEO trading activity. The coefficient of $\widehat{NPED}_{i,t}$ is positive and statistically significant in period (0,0). The results indicate that every 1% increase in the probability of the occurrence of CEO turnover event in year 0 leads to a 0.626% increase in the BHAR_m_365. The results are consistent with my diff-in-diff regression result suggesting that insiders who lost the CEO competition incorporate more positive private information into their purchase transactions, but this is only in event year (0,0). The coefficients of $\mathrm{OutsiderD}_{\mathrm{I,j}}$ is negative and significant, suggesting that the trades executed by insiders from firms that hired an outsider CEO will trade on their private information with relatively lower aggressiveness.

The endogeneity problem is likely to be more severe in insiders' sell than buy trades, because many insiders do not sell to seek profit. The coefficients of $\widehat{NPED}_{i,t}$ are negative and statistically significant, suggesting that insiders incorporate more private negative information into their sell transactions to compensate themselves for the forgone promotion-based incentives. The interaction term's coefficient is positive and statistically significant in both year 0 and +1, indicating that their sell trades are systematically loss averting when the newly appointed CEO increases her holding, suggesting that managers strategically time their sell trades against the current CEO's noisy transactions. For an otherwise-average insider sell trade, a 1% increase in the predicted probability of the transaction in year 0 leads to a decrease in returns by 1.117% (= 2.911%-1.794%) in (0,0) and by 0.6% if the 1% increase is in year 0 and +1. $(\widehat{NPED \times CEO\_IT})_{i,t}$ is larger in year 0, implying that the CEO trading direction plays a more prominent role in insiders' trading decision-making process in year 0 and 1. The coefficient of $COOD_{i,j}$ is positive and significant in year 1 for the sell sample, suggesting that non-promoted insiders from firms with a CEO successor prior to the tournament trade on their private negative information with less aggressiveness than their counterparts from firms with no pre-assigned CEO successor.

The asymmetry effect of CEO trading activity proxied by $CEO\_IT_{i,t}$ in the insider purchase and sell sample is due to the finding that newly-appointed CEO often makes noisy purchase transactions to prolong their contracts, instead of making abnormal return, as suggested by Armstrong *et al.* (2021). CEO purchase transactions embed a strong signaling effect for the stock undervaluation and the outside investors will adjust the stock price upward even if the signal is false (Wu, 2019). The short term buying pressure from these uninformed investors will temporarily boost the stock price, setting up a premise for the non-promoted executives to sell their sharess at an inflated price. The price will be gradually corrected in the long term making their sell trades loss-avoiding. Insiders will not benefit greatly from trading against CEO's sell transactions to cover their purchase transactions as it is rare that new CEO will be selling the shares in the first year of appointment. Thus, the interaction term is insignificant in unreported results for insider purchase sample.

I investigate whether the return profitability of CEO purchase transaction will decrease to negative in long term as suggested by Wu (2019). In Appendix 2.11, I estimate a fixed effect regression using the regression specification of equation (5) without $COOD_{i,j}$, $Outsider_{i,j}$, and $high\_incentiveD_{i,t-1}$. I find no signficant change in CEO buy trades in year 0 return profitabilities in 30-day holding period, but the return predictability is 11.1% significantly lower than their average buy trades in 365-day holding period. The return reversal is clearer in year 1. CEO purchases generate a statistically significant 2.2% higher abnormal return in 30-day period, indicating their buy trades boosted stock prices. However, these buy trades yield significant 10.4% lower profits confirming that these CEO buy trades are nosiy, and the market corrects the inflated prices to a lower level. My results confirm that non-CEO managers adopt contrarian strategies by trading profitably against their CEO.

Overall, the diff-in-diff estimation results are in line with my hypothesis that non-promoted managers make more informative purchase and sell transactions after losing the CEO promotion. The 2SLS results show insiders incorporate more negative private information into their sell transactions in all post-event years, consistent with the diff-in-diff regression results. Additionally, I apply the 2SLS estimator with the same IV based on the matched insider sell sample. Appendix 2.10 reports the results. Like my previous finding, the last fiscal year's former CEO age remains a valid predictor for CEO turnover because the first stage F statistics are all above 10, highlighting that my IV's relevance condition is valid in the smaller sample.

The signs and levels of significance of the coefficient $\widehat{\mathrm{NPED}}_{\mathrm{I,t}}$ are overall consistent with the 2SLS estimates obtained using the universal sample. Insiders incorporate more negative information into their sell transactions in all two post-event years. For the insider purchase sample, there are only 770 observations with a valid non-missing former CEO age. The coefficient is insignificant, and I omit the regression output.

2.5.2 Insider sequential sell transactions around dissimulation strategy

Huddart, Hughes and Levine (2001) argue that the implementation of the U.S security law increases the market scrutiny of insiders' transactions and reduces insider dealing profitability by strictly regulating corporate insiders to disclose publicly their transactions two days after execution. Despite a potential lessening of their returns by as much as a half because of the improved market efficiency, trading on private information remains a profitable strategy. To mitigate their litigation risk, insiders will dissimulate their private information by randomly trading in a manner inconsistent with their informational agent role. If their private information is long-lived,[29] they will intentionally make noisy transactions to thwart outsiders who intend to follow them. Biggerstaff *et al.* (2020) report that insiders incorporate their private negative information into multiple/sequential sell trades, executed at most 30 days apart, to minimize the price impact. They show that, on average, the return of the last transaction in a sequence is more negative than isolated sell trades. The dissimulation strategy is only effective to disguise the negative private information embedded in sell trades, not the positive one in buy trades.

Inspired by these results, I test whether the losing tournament effect persists after accounting for the possibility that insiders intentionally split their private negative information into many sell transactions and randomly mix with purchase transactions. I define transactions are in the same sequence when they are executed within ten, fifteen, or thirty calendar days. When a sequence contains both purchase and sell transactions, I aggregate the trading value to compute the sequence's trading direction. If the total value is negative, I define all transactions in the sequence as sequential sells. Other sell transactions not in a sequence are isolated sells.

Furthermore, I adjust the BHAR_m_365 for all transactions in a sequence using the BHAR_m_365 from the last transaction in a sequence, or by extending the holding period from

[29]Insiders with short-lived information, which is revealed quickly to the market, cannot adopt this strategy.

the beginning to the 365 calendar days after the last transaction. I implicitly assume insiders will close all her positions 365 days after the last transaction. In un-tabulated univariate statistics, 48.9% of all sell transactions are sequential sell transactions. A typical sell sequence will last for 23 days, consists of eight transactions on average. Out of these sequential sells, only 7% contains both purchase and sell transactions. I expect the result because the short-swing rule prevents insiders from realizing profit from two offsetting transactions in the first six months after the first transaction. All my results are robust if I remove purchase transactions and solely focus on sequential sell transactions. I re-estimate Equation (5) with the adjusted BHAR_m_365 based on all sequential and isolated sell transactions. In un-tabulated results, I substitute the BHAR_m_365 from the last transaction in a sequence for all sequential transactions in the same sequence. The coefficients of $\widehat{\mathrm{NPED}}$ are negative and statistically significant, providing further robustness to my results. Furthermore, I extend the holding period for sequential sells from 1 day after the first transaction to 365 days after the last transaction. Since the holding horizon varies depending on the sequence length, I compute the daily average BHAR_m_365×252, the median number of trading days in a 365-calendar day holding period. I report the coefficients of $\widehat{\mathrm{NPED}}$ in Table 2.9 Panel B. My overall results remain unchanged, but the coefficients of $\widehat{\mathrm{NPED}}$ become more negative in all two post-event years for sells, implying the losing tournament effect is stronger after controlling for insider dissimulation strategy.

2.5.3 Additional tests for IV exclusion restriction

One of the main assumptions behind my results is that my IV, the last year former CEO's age and the private information that non-CEO managers are exploiting are not correlated. The former CEO's age *per se* will not affect a firm's valuation as it bears no impact on its future cash flow, but I recognize the possibility that former CEOs may affect her firm's future valuation through the adaption of corporate decisions with long-lasting effect. Although there is no reason to believe that the preference for a long-last policy is systematically related to manager age, this possible violation of exclusion restriction will lead to an inconsistent estimate and weakens my conclusions. I alleviate this potential concern by including a set of proxy variables for corporate performance in my 2SLS regression.

In the first robustness test, I add to Equation (5) fourteen additional control variables that embed predictive power for the firm's future fundamental and are possibly determined by the personal preferences of CEOs in different age groups to better demonstrate the validity of the exclusion restriction and the robustness of my results. Appendix 2.5 details the construction of my variables. I include *tobin's* $Q_{j,t-1}$, $capital\text{-}to\text{-}sales_{j,t-1}$, $advertising\text{-}to\text{-}sales_{j,t-1}$, $capital\_intensity_{j,t-1}$, $leverage_{j,t-1}$, and $dividend\text{-}yield_{j,t-1}$ to control for firm level characteristics. I compute the segment sales-based Herfindahl index denoted as $firm\_focus_{j,t-1}$ as to control for firm diversification. *I* include $cash\_flow\_vol_{j,t-1}$ and $skt\_ret\_volatility_{j,t-1}$ to control for firm risk taking incentives, and $institutional\_ownership_{j,q-1}$, $independent\_managers_{j,t-1}$, and $independent\_committee_{j,t-1}$, the proportion of independent managers on the compensation committee, to control for corporate governance. I also control for the natural logarithm of the current age of non-CEO managers denoted as $lnage_{i,t}$. Following Dang *et al.* (2021), I include $analyst\_talent_{j,t-1}$, which significantly lowers the insider trading profitability, to proxy for the average talent of sell-side analysts following the firm *j* in the last fiscal year and to control for industry-level informativeness. Lastly, I include $CEO\_tenure_{i,t-1}$ to control for the tenure of CEO in the last fiscal year to show that my IV is not simply capturing the current CEO tenure. Table 2.10 Panel A reports the result without the interaction term $\widehat{\mathrm{NPED}\times\mathrm{CEO\_IT}}_{i,t}$ for the insider purchase sample which is insignificantly. In column (1), the coefficient of $\widehat{\mathrm{NPED}}_{i,t}$ is 1.448 and significant at the 95% confidence level. For insider sell samples, the sign and significance of $\widehat{\mathrm{NPED}}_{i,t}$ and $\widehat{\mathrm{NPED}\times\mathrm{CEO\_IT}}_{i,t}$ are consistent with my previous results. I find, but do not report, similar results when firm characteristics above are at the end of the year that the former CEO left the company.

Table 2.9: 2SLS regression result for purchase and sell transactions

Panel A reports the output of the 2SLS regression. The dependent variable in the first stage regression is $NPED_{i,t}$, a dummy variable equal to one for the non-promoted managers' buy/sell trades in the tournament year (0,0) and (1,1), zero for years outside the event window and (-2, -1). I exclude transactions in year +2 to remove confounding events and CEO observations and insider transactions conducted by non-competitors. Appendix 2.5 details the variables. The instrumental variable is the last fiscal year's previous CEO age. I calculate *ret30, mom, bm, numest, illiq* and *size* at the end of last month relates to the insider transaction date that will be used in the second stage of IV regression. Panel B extends the holding period for sequential sells from 1 day after the first transaction to 365 days after the last transaction, using the daily average BHAR_m_365×252, the median number of trading days in a 365-calendar day holding period. Standard errors reported in parentheses are based on robust standard errors clustered at the Firm-Month level. ***, **, and * denote significance at the 99%, 95% and 90% confidence level, respectively. I do not report the coefficients of the control variables $rating_{j,t-1}$, $delta_{i,t-1}$, and $roa_{j,t-1}$; they are all insignificant. All variables are winsorised at the top 99% and the bottom 1%.

	Insider Purchase Trades		Insider Sell Trades	
Year *t*	(0,0)	(1,1)	(0,0)	(1,1)
Panel A Second Stage - *Dep Variable is BHAR_m_365, Endogenous Variables are (NPED)$_{i,t}$ and (NPED×CEO_IT)$_{i,t}$*				
$\widehat{NPED}_{i,t}$	0.626*	-0.790	2.911**	-0.793***
	(0.369)	(0.538)	(1.332)	(0.259)
$\widehat{NPED\times CEO\_IT}_{i,t}$			1.794***	0.193**
			(0.695)	(0.079)
$CEO\_IT_{j,t}$	0.069***	0.080***	-0.038	-0.012
	(0.022)	(0.028)	(0.023)	(0.008)
$OutsiderD_{j,t}$	-0.244**	0.032	0.944*	0.367***
	(0.102)	(0.193)	(0.570)	(0.104)
$COOD_{j,t}$	0.017	-0.109	-0.008	0.110***
	(0.032)	(0.083)	(0.012)	(0.042)
$high\_incentiveD_{i,t-1}$	-0.011	0.024	-0.010	0.025***
	(0.028)	(0.053)	(0.012)	(0.004)
$pay\_gap_{j,t-1}$	-0.001	-0.011	0.022**	0.003
	(0.022)	(0.030)	(0.010)	(0.003)
$ret30_{j,t,(d-1,d-30)}$	-0.470***	-1.110***	-0.171***	-0.151***
	(0.119)	(0.366)	(0.050)	(0.033)
$mom_{j,t,(d-31,d-364)}$	-0.156***	-0.485***	-0.006	-0.011
	(0.055)	(0.160)	(0.023)	(0.014)
$bm_{j,m-1}$	0.130	-0.146	0.060	0.047**
	(0.089)	(0.219)	(0.042)	(0.023)
$numest_{j,m-1}$	-0.010	-0.015	-0.001	0.002**
	(0.007)	(0.011)	(0.002)	(0.001)
$illiq_{j,m-1}$	0.044	0.112	-0.132**	-0.026
	(0.028)	(0.089)	(0.067)	(0.052)
$size_{j,m-1}$	-0.358***	-0.800***	-0.285***	-0.247***
	(0.060)	(0.186)	(0.025)	(0.012)
$vega_{i,t-1}$(×0.01)	-0.094**	-0.018	0.003	-0.011**
	(0.047)	(0.070)	(0.007)	(0.005)
$rd_{j,t-1}$	-1.459*	-2.839**	-0.323	0.090
	(0.777)	(1.352)	(0.380)	(0.185)
$lncompen_{i,t-1}$	0.070**	0.149**	0.034**	0.053***
	(0.035)	(0.062)	(0.015)	(0.008)
Sample	2,416	2,630	37,554	40,606
Fixed Effect	Firm, Month	Firm, Month	Firm, Month	Firm, Month
Difference in Sargan C (χ^2)	3.31*	2.067	58.08***	26.94***
First-Stage F-$\widehat{NPED}_{I,t}$	27.42***	25.20***	101.78***	508.45***
Anderson-Rubin Wald Test, F statistic	3.68*	2.27	29.93***	11.51***
Panel B: Dissimulation Strategy Results: t+1 after the first and t+365 after the last transaction				
$\widehat{NPED}_{i,t}$	0.623*	-0.428*	-2.945**	-0.979**
	(0.367)	(0.236)	(1.331)	(0.427)
Control Variables	Yes	Yes	Yes	Yes

As the second robustness test, I consider that former CEO's age will only affect non-CEO's trading profitability through CEO turnover. Therefore, if I regress the BHAR_m_365 on former CEO's age by using years other than years 0 and 1, the coefficient of CEO's age should be statistically insignificant if the exclusion restriction holds. In un-tabulated results, I re-estimate the regression in Table 2.10 by substituting the former CEO's age for the $\widehat{\mathrm{NPED}}_{i,t}$ with the same set of control variables. I find that the coefficient of the former CEO's age is statistically insignificant for both insider purchase and sell samples, strengthening the plausibility of exclusion restrictions further. I recognize that some firms retain their former CEOs on the board after they left their role. I argue that the possible retention does not affect the irrelevance condition because Evans, Nagarajan and Schloetzer (2010) show that the CEO retention does not affect firm's future stock return, and only 11.67% of my insider trading sample was made in a CEO retention year. Nevertheless, I replicate my 2SLS regression by excluding firms that retain the former CEO after the turnover. I lost 5% (2.6%) of insider purchase and 3.8% (2.6%) of insider sell in year 0 (year 1). In unreported results, all my conclusions remain robust.

2.5.4 Other robustness tests

In the third robustness test, I refine my year 0 sample into the transactions-day level. I have shown that managers are more likely to incorporate more positive (negative) private information into their purchase (sell) transactions in year 0. The conclusion hinges crucially on the assumption that I do not mis-specify the insider transactions prior to the tournament outcome as post-tournament transactions. I rely on Execucomp item *becomeceo* to identify the specific date for the CEO turnover. For the *becomeceo* date that is one calendar year apart from the fiscal year, I manually check and correct it by crosschecking BoardEx. I reclassify the transactions before the succession of the new CEO as pre-tournament transactions and re-estimate Equation (5). In an un-tabulated result, the coefficients of $\widehat{\mathrm{NPED}}_{i,t}$ are 0.733 and -3.078 and are statistically significant at the 90% and 95% confidence level for insider purchase and sell samples in year 0, respectively.

I also employ for robustness alternative holding periods and Fama-French Four-Factor model (Fama and French, 1993) to compute alpha over 30-, 180- and 360- calendar holding periods, as alternative measures of abnormal returns using Kenneth French's Data Library[30] as follows:

$$\mathrm{return}_{j,t} - \mathrm{rf}_t = \alpha + \beta_1(\mathrm{MKT}_t - \mathrm{rf}_t) + \beta_2\mathrm{SMB}_t + \beta_3\mathrm{HML}_t + \beta_4\mathrm{MOM}_t + \epsilon_t \qquad (8)$$

α, the risk-adjusted return is estimated from one day after the transaction date over the next 30/180/365 calendar days. $return_{j,t}$ is the daily return adjusted for dividend, rf_m is the risk-free rate proxied by the one-month T-bill rate. MKT_t is the CRSP value-weighted market index. I time the daily α by 22, 126, and 252 for these 3 holding periods. Additionally, I report the raw cumulative return $ret_{t+1,t+i}$ and the NYSE value-weighted size-decile adjusted return $BHAR\_size\__j$. Table 2.10 Panel B reports only the coefficient of $\widehat{\mathrm{NPED}}_{i,t}$ for brevity from re-estimating Equation (5). For the buy trades, $\widehat{\mathrm{NPED}}_{i,t}$ is mainly insignificant. In contrast, for the sell trades, it is mainly negative and significant, suggesting that these trades are loss avoiding for the 180 and 365 holding periods. The remaining results did not change.

In the fourth robustness test, I only keep the top two highest paid managers in each year for each firm. I recognize that the likelihood of them competing in an CEO turnover is the highest, and I re-estimate the diff-in-diff regression and 2SLS regression. From Table 2.10 Panel C, I observe that my conclusions remain robust despite I lose more than half of my sample. The results show that my conclusions do not hinge on the assumption that all top 4 highest paid non-CEO managers are tournament contenders. My results remain robust if I additionally impose that tournament contenders must be younger than 60. In the fifth robustness test, I include all 10b5-1 transactions because Larcker *et al.* (2021) and Franco and Urcan (2021) find that managers actively use the 10b5-1 exemption as a safe harbour to trade on private information. All my results remain robust in unreported result. The sixth robustness test investigates the probability that performance-induced turnover or planned succession drives the increase in insider trading profit. To proxy for the former, I create underperforming dummy variable equals one for the bottom quintile of firms divided by the raw annual stock return in the last fiscal year in the same two-digit SIC industry among all S&P 1500 firms, zero

[30] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. I thank Professor French for making these data publicly available.

otherwise. I follow the same specification in Equation (5) with the additional underperforming dummy as the moderator. In un-tabulated results, I find that the interaction term between the underperforming dummy variable and $\widehat{\mathrm{NPED}}_{\mathrm{i,t}}$ remains statistically insignificant in all post-event years for both buy and sell samples, suggesting that performance-induced turnover does not drive my results. The seventh robustness tests the validity of my diff-in-diff regression results over a $(-2, +1)$ period around pseudo-CEO turnovers, which are arbitrarily set as three years before or after the actual CEO turnover. I use the same pair of treated and matched firms obtained early in the study but remove the firms that had a CEO turnover in the pseudo-event window. I re-estimate Equation (2). I find, but not report for brevity, that the coefficient of the interaction term $\mathrm{Post}{\times}\mathrm{Treat}_{\mathrm{I,t}}$ remains statistically insignificant for both insider purchase and sell samples, supporting the validity of the parallel trends assumption and the credibility of my diff-in-diff design. I also exclude all external CEO promotion samples and re-estimate Table 2.3 to Tale 2.5, all results remain robust.

Finally, to confirm that unobservable market and firm conditions do not affect my findings, I re-estimate Equation (5) using 1,000 placebo tests for insider purchase and sell samples separately. Although the use of 2SLS estimator has greatly eliminated the probability that chance drives my results, I conduct the placebo tests to reaffirm the robustness of my results and my IV validity. Each test entails randomly selecting 400 firm-year observations with at least one insider purchase transaction and 1,600 firm-year observations with at least one insider sell transaction considered as CEO turnover year for insider purchase and sell sample, respectively. These two numbers are the nearest hundreds for the actual numbers of distinct CEO turnover firm-year observations, which are 386 and 1,601 in year 0 for purchase and sell samples, respectively. I remove the firm-year observations with actual CEO turnover event and the following two years from my sample. For each of the firm-year observations, I match the insider trading transactions in the given year and set $\mathrm{NPED}_{\mathrm{i,t}}$ to be one for all insider transactions in the year. I replicate Equation (5) without $Outsider_{j,t}$ and $COOD_{j,t}$ and report the coefficient of $\widehat{\mathrm{NPED}}_{\mathrm{i,t}}$ and the first-stage F statistics in Table 2.10 Panel C. If my results are due to chance or unobservable factors, a relatively large proportion of my placebo tests report will have a higher first-stage F statistics and the coefficients of $\widehat{\mathrm{NPED}}_{\mathrm{i,t}}$ will be statistically positive (negative) for insider purchase (sell) sample, respectively. Column (1) shows that, the mean coefficient for the insider buy sample is statistically indifferent from zero. The distribution of coefficient of $\widehat{\text{NPED}}_{i,t}$ is right-skewed. For the insider sell sample, the mean coefficient is positive and statistically insignificant with a right-skewed distribution. On the right-hand side of the panel, I report the percentage of the placebo sample with both a positive (negative) significant coefficient of $\widehat{\text{NPED}}_{i,t}$ and a first-stage F-statistics larger than 10 for insider purchase (sell) sample. There is no single test for insider purchase samples with both a significant positive coefficient at the 95% confidence level and a valid first stage F-statistics.

For insider sell sample, I find only 8 cases, out of 1,000 placebo tests, that report a significantly negative coefficient of $\widehat{\text{NPED}}_{i,t}$ at the 95% confidence level and an F-statistics larger than 10. Relying on a one-sided binomial test-statistic, none of the proportions is statistically different from the corresponding theoretical levels of 1%, 5% and 10%. I also find 34 tests that report a first-stage F-statistics larger than 10 with a maximum of 19 and a negative significant coefficient at the 90% confidence level. In Panel A, my first-stage F is generally larger than 10, indicating my IV will not randomly be significant, and it does not contain predictive power outside CEO turnover event.

I also conduct 1,000 placebo tests for my diff-in-diff regression. I first randomly select 1,000 firm-year observations without CEO turnover and not in any CEO turnover window. I then match these treated firms with one control firm with placement in the same year *t* using the same matching algorithm. I assume year *t* to be the event year. I estimate a diff-in-diff regression by using the observations of matched sample for year (t-2, t). I conduct placebo tests for insider purchase and sell samples separately. I restrict the treated firm cannot match to itself in the last year. I report the placebo test results in Table 2.10, Panel D. The average coefficient of the interaction term is negative (positive) for insider purchase (sell) sample. In column (5) to (7), I report the percentage of placebo tests with statistically significant and positive (negative) coefficient for purchase (sell) sample. As in Panel C, no proportion is statistically different at any significance level based on a one-sided binomial test-statistic. Overall, these results indicate that if I use a randomly selected sample of firms without CEO turnover events, I cannot replicate my main findings obtained from both diff-in-diff regression and 2SLS. The placebo tests further indicate that my IV is only relevant to explain years close to the CEO turnover, and it is extremity unlikely that I will obtain a significantly positive (negative) $\widehat{\mathrm{NPED}}_{i,t}$ for buy (sell) trades while satisfying my IV relevance condition. The profitability of an average insider transaction embedded in purchase (sell) transactions is unlikely to increase (decrease) without a CEO turnover.

Lastly, Goodman (2010) reports that Chief Finance Officers (CFOs) are less likely to become the next CEOs because these two roles required different skills. To test that CFO trading does not drive my results, I remove all CFO transactions in my pre-turnover window, which accounts for 9% of both the insider purchase and sell transactions sample. In unreported results, I re-estimate the results in Table 2.3 and the coefficient of $(\mathrm{Treat}\times\mathrm{Post})_{i,t}$ for insider sell in year +1 becomes weakly significant at the 90% confidence level, and the sign and significance of all other results remain robust. I further drop 10% observations within year $(-2, 1)$ from firms with a COO prior to the CEO turnover and re-estimate both the diff-in-diff and 2SLS regression, all my results remain robust.

2.5.5 Non-promoted manager future promotion opportunity and sample selection

I recognize that the non-promoted managers may stay with the firm after losing the CEO competition because they target other higher-ranking positions within the firm with an attractive increase in the salary, which mitigates their incentives to compensate themselves for the forgone CEO promotion. This possibility is trivial because Execucomp mainly reports the top four highest-paid managers whose career path is already at the top of the corporate hierarchy. Therefore, any increase in their compensation package will not be as significant as the CEO promotion reward. To rule out this possibility, I focus on isolated CEO promotion from year 0 to 7. I rank managers by their total compensation package in their firms. For example, if a manager's pay rank is 1, her total compensation package is the highest among all CEO competitors. Then, I compare their pay rank and total compensation package between years -1 and 4. I find, but not report, that non-promoted manager's pay rank decreases by 1.4 from year -1 to 4. The pay rank decrease is 0.6 in the same 5-year period without losing CEO turnover for control firms.

Table 2.10: Robustness Test

In Panel A, I extend the control variables in Equation (5) and report the 2nd stage of 2SLS regressions. Panel B reports the coefficients of $\widehat{NPED}_{I,t}$ using alternative holding returns measures including raw cumulative return $ret_{t+1,t+i}$ and the 4-factor αs multiplied by the median number of trading days of 22, 126, 252 in the three holding periods, respectively, calculated by running regression $r_{it} - r_{ft} = \alpha_{it} + \beta_1(r_{crsp,t} - r_{ft}) + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 UMD_t + \varepsilon_t$ from the day after insider transaction day to 3/6/12 month. $r_{crsp,t}$ is CRSP value-weighted market index and UMD_t is up-minus-down factor (momentum). For buy trades, the interaction term $\widehat{NPED \times CEO\_IT}_{I,t}$ is omitted as it is insignificant. I report the cluster standard errors at the firm-month level parentheses. ***, **, and * denote significance at the 99%, 95% and 90% confidence level, respectively. All variables are winsorised at the top 99% and the bottom 1% level. In Panel C, I only keep two top highest paid non-CEO managers for each firm in each year. Panel D reports the 1,000 placebo test results for the average coefficient of $\widehat{NPED}_{i,t}$, its standard error and its skewness. Columns (4) to (6) report the percentage of placebo test with positive (negative) coefficient of $\widehat{NPED}_{i,t}$ for purchase (sell) sample and first-stage F statistics larger than 10. Column (7) reports the percentage of sample with a first-stage F statistics larger than 10. Panel E reports the 1,000 placebo test results for the diff-in-diff regression coefficient of the interaction term, and in columns (5) to (7) the percentage of my placebo test with positive (negative) coefficient of the interaction term for purchase (sell) samples and is statistically significant at the 99%, 95% and 90% confidence level, respectively. In Panel D and E none of the proportions are statistically different from the corresponding theoretical level using a binomial one-sided test-statistic. All columns include control variables and firm and month fixed effects. In Panel A, I do not report the coefficients of advertising-to-$sale_{j,t-1}$, dividend-$yield_{j,t-1}$, and $lnage_{i,t}$ as they are insignificant.

Panel A: Extended Set of Control Variables

	(1)	(2)	(3)	(4)
	Insider Purchase		Insider Sell	
	(0,0)	(1,1)	(0,0)	(1,1)
2nd Stage ***-Dep Variable is BHAR_m_365, Endogenous Variables are $(NPED)_{i,t}$ and $(NPED \times CEO\_IT)_i$***				
$\widehat{NPED}_{i,t}$	1.448**	-7.027	-0.531*	-0.780*
	(0.574)	(7.323)	(0.316)	(0.473)
$\widehat{NPED \times CEO\_IT}_{i,t}$			0.324**	0.249**
			(0.146)	(0.119)
$CEO\_IT_{j,t}$	0.089*	0.148	-0.004	-0.012
	(0.046)	(0.113)	(0.007)	(0.012)
tobin's $Q_{j,t-1}$	-0.074	0.380	0.012	-0.009
	(0.103)	(0.510)	(0.010)	(0.013)
capital-to-$sale_{j,t-1}$	-0.410**	-0.607**	-0.019	-0.056***
	(0.201)	(0.301)	(0.022)	(0.020)
$leverage_{j,t-1}$	-0.694	-0.047	-0.135**	-0.102*
	(0.490)	(1.456)	(0.062)	(0.053)
$skt\_ret\_volatility_{j,t-1}$	17.409*	16.884	-0.208	-0.848
	(9.555)	(21.345)	(0.643)	(0.694)
$capital\_intensity_{j,t-1}$	4.162*	-0.745	-0.003	-0.018
	(2.123)	(4.691)	(0.209)	(0.222)
$firm\_focus_{j,t-1}$	0.268	-1.504	-0.075***	-0.015
	(0.262)	(1.795)	(0.028)	(0.035)
$cash\_flow\_vol_{j,t-1}$	-1.695	-18.148	-0.585	-0.641
	(4.830)	(20.125)	(0.535)	(0.573)
$institution\_ownership_{j,q-1}$	0.648	0.007	-0.024	-0.001
	(0.451)	(0.956)	(0.048)	(0.051)
$independent\_director_{j,t-1}$	-0.880	-0.765	0.092*	0.164***
	(0.574)	(1.457)	(0.054)	(0.060)
$independent\_committee_{j,t-1}$	0.252	0.877	0.200***	0.145***
	(0.234)	(0.723)	(0.038)	(0.042)
$analyst\_talent_{j,t-1}$	0.492	2.288	-0.220***	-0.209***
	(0.690)	(2.652)	(0.052)	(0.050)

CEO_tenure$_{j,t-1}$		0.116^{***}		-0.291	0.015^{***}		-0.001
		(0.044)		(0.352)	(0.003)		(0.011)
Sample		1,104		1,169	23,872		25,399
First-Stage F-$\widehat{NPED}_{j,t}$		34.31^{***}		1.23	266.55^{***}		34.54^{***}
Anderson-Rubin Wald F Test		6.13^{***}		5.60^{***}	14.43^{***}		3.19^{**}
Panel B: The coefficient of $\widehat{NPED}_{I,t}$ using Alternative Return Measure							
BHAR_m_30		-0.054		-0.041	-0.236		-0.060
		(0.065)		(0.059)	(0.175)		(0.057)
BHAR_m_180		0.197		-0.079	-2.026^{**}		-0.379^{**}
		(0.213)		(0.145)	(0.881)		(0.171)
$\alpha_{t+1,t+30}$(×22)		0.041		-0.147^{*}	-0.293		-0.035
		(0.074)		(0.077)	(0.207)		(0.068)
$\alpha_{t+1,t+180}$(×126)		0.066		0.016	-1.812^{**}		-0.124
		(0.165)		(0.135)	(0.763)		(0.157)
$\alpha_{t+1,t+365}$(×252)		0.088		-0.045	-1.765^{*}		-0.466^{**}
		(0.214)		(0.160)	(0.923)		(0.208)
$ret_{t+1,t+30}$		-0.116		-0.059	-0.316		-0.079
		(0.096)		(0.083)	(0.218)		(0.069)
$ret_{t+1,t+180}$		0.269		-0.199	-2.929^{**}		-0.374^{**}
		(0.340)		(0.236)	(1.211)		(0.191)
$ret_{t+1,t+365}$		0.903		-0.845	-3.436^{**}		-0.472^{*}
		(0.815)		(0.557)	(1.740)		(0.278)
BHAR_size_30		-0.016		-0.092	-0.335^{*}		-0.072
		(0.082)		(0.075)	(0.201)		(0.059)
BHAR_size_180		0.427		-0.226	-2.104^{**}		-0.415^{**}
		(0.324)		(0.228)	(0.923)		(0.174)
BHAR_size_365		0.952		-0.840	-2.647^{*}		-0.744^{***}
		(0.781)		(0.557)	(1.373)		(0.257)
Panel C: Alternative numbers of tournament contenders (two non-CEO managers)							
Diff-in-Diff regression							
(Post×Treat)$_{i,t}$		0.239^{*}		-0.289	-0.047^{**}		-0.038^{*}
		(0.133)		(0.363)	(0.023)		(0.023)
Sample		657		504	16,301		15,323
2SLS							
$\widehat{NPED}_{i,t}$		0.467		-0.553	-3.162^{*}		-1.050^{**}
		(0.940)		(1.047)	(1.906)		(0.424)
Sample		813		957	17,047		18,597
Panel D: Placebo Test for 2SLS							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				% significant coefficient with valid IV significance first-stage F (>10)			
	Mean	Median	SD	Skewness	1%	5%	10%
$\widehat{NPED}_{i,t}$ -Buy	6.007	158.87	28.904	0.00	0.00	0.00	0.40
$\widehat{NPED}_{i,t}$ -Sell	2.174	135.57	11.848	0.20	0.40	0.80	3.40
Panel E: Placebo Test for Diff-in-Diff regression							
				% significant positive (negative) for buy (sell)			
	Mean	Median	SD	Skewness	1%	5%	10%
(Post×Treat)$_{i,t}$-Buy	-0.049	-0.038	0.218	-0.328	0.70	3.20	5.80
(Post×Treat)$_{i,t}$-Sell	0.132	0.123	0.126	0.428	0.60	1.00	1.40

The difference is statistically significant. I find non-promoted managers receive a \$0.73 million pay rise in a 5-year time after losing the CEO turnover, compared to \$0.57 million if they have not lost the CEO competition. The \$0.16 million difference is statistically significant, but economically small.

I estimate a fixed effect regression with manager, firm, and year fixed effects. The dependent variable is the change in the natural logarithm value of the total compensation in one or two-years. I focus on a dummy variable that equals to one for year (0, 4) and zero otherwise. I control for manager's age, tenure, delta and vega, firm's size, leverage, book-to-market ratio, ROA, and Tobin's Q. I find, but not report, no significant change in the total compensation of non-promoted manager in both one- and two-years' time after they have lost the CEO promotion, in line with Kale, *et al.* (2009) and Chan *et al.* (2022), suggesting that losers are not compensated for the dimmer career prospects.

2.6 Conclusion

Corporate managers' remuneration contracts consist of both the explicit payment component such as annual salary, bonus and the implicit promotion-based component that provides them with the promotion opportunity and the chance to receive a pay rise from their higher job position known as the tournament incentive. For the high-rank managers, their only promotion destination is the CEO position. An unsuccessful CEO promotion lowers drastically or forgoes completely the likelihood of winning future CEO competitions. Consequently, the overall value in her remuneration contract is lower because the expected value of their implicit promotion-based component has decreased. To compensate themselves for the overall decrease in her compensation contract, non-promoted managers may more aggressively trade on their private information. I investigate the causal relationship between losing the CEO promotion opportunity and the manager trading profitability. I eliminate the endogeneity by using a matched sample to specify a diff-in-diff regression. I show that losing the CEO competition causes an increase (decrease) in the abnormal returns of the non-promoted managers' purchase (sell) transactions. The results indicate that managers indeed trade on their private information more aggressively and incorporate more positive (negative) private information into their purchase (sell) transactions. While the profitability of their sell transactions persists until one year after losing the tournament, that of their buy trades is limited to the year of losing CEO promotion competition.

Moreover, insiders with higher implicit promotion-based component incorporate more negative private information into their sell transactions, supporting the argument that they trade to compensate themselves for the forgone promotion opportunity. These changes in trading profitability are in addition to the profitability changes attributed to the different level of firm-level price information informativeness. My results remain the same if I use the former CEO's age as my IV and estimate a 2SLS regression to eliminate the endogeneity. Managers are more sophisticated when selling their shares than buying shares due to the asymmetric litigation risk embedded in these two types of transactions. They will incorporate more negative information into their sell transactions and execute more opportunistic sells when the newly appointed CEO increases their holdings. I do not find the same trading strategy when managers buy shares. Lastly, I revisit the findings in Kale *et al.* (2009) and show that the insider trading opportunity weakens the positive relationship between the tournament incentives and firm performance because insiders use their transactions to realize the tournament incentives prior to the tournament.

My results may be affected by other factors I have not considered in my analysis. Non-promoted executives could be trading just before material news is announced. They could also sell shares in their own company for liquidity and portfolio diversification reasons. While data on news announcements is not available in machine readable form and I tried to control indirectly for the other potential effects, further research is required to assess whether my results are robust to these outcomes. Moreover, the true motivation behind their informed transactions is not directly observable. I have used their personal and company characteristics to identify the group of non-CEO executives who are more likely to trade on their forgone CEO incentives. Nevertheless, it would be better to find an exogenous shock that will affect their personal career horizon only[31]. These shocks will allow researchers to better eliminate endogeneity.

[31] I have investigated the possibility to use the sudden death of current CEO as an exogenous shock. However, the sample is too small to conduct any meaningful analysis.

Appendix 2.1: Data Cleaning Process Details and Variable Construction

Walker (2009) and Coles, Daniel and Naveen (2014) point out that Execucomp's total compensation figure is not comparable before and after 2006 because of the passage of Financial Accounting Standards Board (FASB) 123R revision to the stock and options accounting and an expanded compensation disclosure requirement regarding the manager compensation disclosure. I follow Coles *et al.* (2014), Kini and Williams (2012) and Brockman, Lee and Salas (2016) to correct my pre- and post-2006 total compensation item *tdc1*[32]. Specifically, the stock option was valued using the Black-Scholes formula for the pre-2006 period but reported its fair value for the post-2006 period. A small number of firms still report their proxy statements in the old reporting format in 2006, I use the reporting flag to identify (*old_datafmt_flag*) these firms. Then, I correct the post-2006 period option value using the same set of Black-Scholes assumption that Execucomp used for the pre-2006 period. The following are the Black-Scholes assumptions I used:

1. Strike price per share is specified in its proxy statement. (*expric*)
2. Market price per share is equal to the strike price per share unless specified in its proxy statement. (*mktprice*)
3. Option grant terms: Options are assumed to be granted on July 1st of the particular year for which data were reported. The option's nominal term is the period between July 1st of the year of grant and the expiration date (*exdate*) reported in its proxy statement. I further round the nominal term is to the nearest year figure. However, the option's term was reduced to 70% of its nominal term as managers rarely hold her stock option until its expiration year. The expiration date is not available on Execucomp for post-2006 reporting format. Therefore, I follow Kini and Williams (2012) to assume all options have seven years until expiration.
4. Risk-free rate corresponding to the option's maturity is the historical annual series of treasury constant maturity with 7-year term downloaded from the Federal Reserve[33].
5. Stock price volatility: Individual stock price volatility is the annualised volatility calculated using the last 60 months. The stock volatility of all companies is winsorised at the top and bottom 5%. To calculate the volatility, Execucomp requires at least 12-month return data. For stocks that are traded less than 12 months, Execucomp the average volatility value for the firms in the S&P 1500 index.

[32] My results remain robust if I do not correct for the FSBA change and use raw figures reported by Execucomp.
[33] https://www.federalreserve.gov/datadownload/Choose.aspx?rel=H15

6. Future dividend yield. Execucomp uses the average dividend yield in the last three years to calculate the estimated future dividend yield. It is then winsorised at the top and bottom 5%.

Using these assumptions, I replicate the Black-Sholes option value for 2005, and the correlation between my Black-Sholes value and the Black-Sholes value calculated by Execucomp is 95.9%[34]. I further recalculate all option awards for both pre- and post-2006 period by using the same set of Black-Sholes assumptions to ensure consistency. Secondly, I follow Brockman *et al.* (2016) to value the ex-ante value of stock awards. I multiply the number of performance shares granted to the CEO (*shrtarg*) by the firm's fiscal year-end stock price (Compustat *prcc_f*). Finally, I recalculate the *tdc1* for all firm-year observations that reported in the pre-2006 old format (item *old_datafmt_flag=1*) by summing salary (*salary*), to bonus (*bonous*), other annual compensation (*othann*), restricted stock grant (*rstkgrnt*), all other total (*allothtot*), the fair value of stock awards (*shrtarg*×*prcc_f*) and Black-Scholes value of option grant (*option_awards_blk_value*). For *tdc1* reported in post-2006 new format (item *old_datafmt_flag=0*), I sum salary (*salary*), bonus (*bonous*), non-equity incentive plan compensation (*noneq_incent*), fair value of stock awards (*stock_awards_fv*), all other compensations (*othcomp*), deferred earnings (*defer_rpt_as_comp_tot*) and Black-Scholes value of option grant.

To build a link table between Execucomp and Smart Insider, I first obtain all historical cusip codes using the CRSP/Compustat link table. Second, for a given manager in Execucomp, I match the manager with all the managers who have traded the security with the same cusip. Third, I calculate the Damerau-Levenshtein (DL) distance and vectoral decomposition (VD) of texts with single gram and root weighting scheme between the name of the manager provided by Execucomp and reported by Smart Insiders. I sort these matches by DL distance and VD score to manually verify each pair of *execid-personid* match.

To identify short horizon seller, I modify the investment horizon measure proposed by Akbas, *et al.* (2020). Firstly, I define HOR as:

$$\mathrm{HOR}_{\mathrm{i,j,t}} = \frac{\sum_{\mathrm{Year-}}^{\mathrm{Year-}} \mathrm{NPV}_{\mathrm{t}}}{\mathrm{N}}$$

That is, for each year, I compute the annual NPV for each insider *i* in firm *j* in year *t* in the last eight calendar years. Then, I compute the average NPV by summing the annual NPV and divide

[34] Kini and Williams (2012) report a correlation of 96.8% for 2005. The difference is possibly due to different risk-free rate sources, which they do not report.

by the number of calendar years that an insider has traded in the last eight calendar years. HOR can only take a value between -1 and +1, which are the bounds of the NPV. If an insider only sold (bought) in the last eight years, then each of its NPV is -1 (1), and therefore, the average will be -1 (1) as well. I define SH sellers as those whose $\mathrm{HOR}_{i,j,t}$ is negative but larger than the median $\mathrm{HOR}_{i,j,t}$ after excluding the $\mathrm{HOR}_{i,j,t}$ of -1 which accounts for more than 50% of the insider sell sample. I restrict SH sellers must have traded at least in three different years in the past eight years.

I estimate the probability of becoming CEO from a cross-section regression. In each year *t,* I obtain a list of firms that have a CEO turnover event and keep all insiders except the former founders/co-founders, former CEOs and new joiners. I then estimate the following cross-section regression:

$$\begin{aligned}\mathrm{CEOD}_{i,t} = {} & \alpha + \beta_0 \mathrm{lncompen}_{i,t\text{-}1} + \beta_1 \mathrm{age}_{i,t\text{-}1} + \beta_2 \mathrm{tenure}_{i,t\text{-}1} + \beta_3 \mathrm{exp}_{i,t\text{-}1} + \beta_4 \mathrm{maleD}_i \\ & + \beta_5 \mathrm{COO}_{j,t\text{-}1} + \beta_6 \mathrm{COO\_firm}_{j,t\text{-}1} + \beta_7 \mathrm{bm}_{j,t\text{-}1} + \beta_8 \mathrm{momentum}_{j,t\text{-}1} + \beta_9 \mathrm{roa}_{j,t\text{-}1} \\ & + \beta_{10} \mathrm{outsider}_{j,t} + e_t\end{aligned}$$

The dependent variable is a dummy variable one for the manager who became CEO in the year, and zero for insiders who failed to become CEO. $\mathrm{lncompen}_{j,t\text{-}1}$ is the adjusted total compensation in the year before, $\mathrm{tenure}_{i,j,t\text{-}1}$ is the number of year the manager worked for the firm. $\mathrm{exp}_{i,t\text{-}1}$ is the number of year the manager has worked for any firm in the entire Execucomp. maleD_i is a dummy variable equal to one for male, and zero for female $\mathrm{COO}_{j,t\text{-}1}$ is a dummy variable equal to one for COO as identified using manager's title, and zero otherwise. $\mathrm{COO\_firm}_{j,t\text{-}1}$ is a dummy variable equal to one if the firm had a COO before the turnover, and zero otherwise. Other variables are as defined before. $\mathrm{outsider}_{j,t}$ is a dummy equal to one if the firm hired an external CEO in year *t*, and zero otherwise. I use the estimated coefficient to calculate the estimated probability $\mathrm{Probability}_{i,t}$ of a given insider *i* in the same year *t* to become the CEO. I re-estimate the cross-section every year using only the firm that had a CEO turnover in the year.

I follow Tucker and Zarowin (2006) and Wang (2019) to construct the FERC by first estimating the following equation:

$$\mathrm{R}_{j,t} = \alpha + \beta_0 \mathrm{X}_{j,t-1} + \beta_2 \mathrm{X}_{j,t} + \beta_3 \left(\mathrm{X}_{j,t+1} + \mathrm{X}_{j,t+2} + \mathrm{X}_{j,t+3}\right) + \beta_3 \mathrm{R}_{j,t+3} + \varepsilon_{j,t}$$

where $X_{j,t}$ is the basic annual earnings per share excluding extraordinary items (*epspx*), adjusted for stock splits and stock dividends and deflated by the stock price at the beginning of the fiscal year *t*. $R_{j,t}$ is the firm's annual return beginning at the fiscal year *t*. $R_{j,t+3}$ is a three-year future return for the firm from fiscal year *t+1* to *t+3*. The coefficient of the sum of the future three-year earnings per shares β_3 is the FERC. I truncate all variables at the top and bottom 1%. A higher β_3 means the current stock return impounds more future earnings information and is more informative for future earnings and *vice versa. I* follow Wang (2019) to estimate a rolling panel regression using the trailing 36 months across each two-digit SIC industry. I restrict that there are at least 8 (24) months in $R_{j,t}$ ($R_{j,t+3}$) for a stock to be included in the regression and create binary variable FERC that is one for the top quintile of the β_3 and zero otherwise.

I follow Piotroski and Roulstone (2004) and estimate the stock return synchronicity from the following equation:

$$\mathrm{FirmRET}_{j,t} = \alpha + \beta_1 \mathrm{MktRET}_{j,t} + \beta_2 \mathrm{MktRET}_{j,t-1} + \beta_3 \mathrm{IndRET}_{k,t} + \beta_4 \mathrm{IndRET}_{k,t-1} + \varepsilon_{i,t}$$

where $\mathrm{MktRET}_{j,t}$ is the market return proxied by the CRSP value-weighted buy-and-hold market return in year t. $\mathrm{IndRET}_{k,t}$ is the value-weighted average industry buy-and-hold return identified using the two-digit SIC code in year *t*. I estimate the regression for each firm-year observation with weekly return data and restrict a minimum of 45 weekly observations each year. The synchronicity is measured as $\ln\left(\frac{R^2}{1-R^2}\right)$. The R^2 is the R square of the above regression. A higher $\mathrm{Synch}_{i,t}$ indicates the current firm return comove strongly with the current and lagged market and industry returns, which further indicates the stock price contains less firm-specific information.

To measure the change in investor sentiment denoted as $\Delta\mathrm{Sentiment}$, I compute the market-to-book ratio decomposition of Rhodes–Kropf, Robinson and Viswanathan (2005) defined as the residual from the following regression

$$\ln(\mathrm{market\_value})_{j,t} = \alpha + \beta_{1z,t}\ln(\mathrm{book\_value})_{j,t} + \beta_{2k,t}\ln(\mathrm{net\_income})^{+}_{j,t} + \beta_{3k,t} I_{(<0>)} \ln(\mathrm{net\_income})^{+}_{j} + \beta_{4k,t}\mathrm{leverage}_{j,t} + \varepsilon_i$$

where subscript *k* indexes for Fama-French 12 industries, *j* for firms and *t* for year. I estimate the regression for each industry-year. $I_{(<0>)}$ is a dummy variable equal to one for loss-making firms, and zero otherwise. The firm-specific residual obtained from the regression is the part of the firm's market value not explained by fundamentals or by changes in the market valuation common across firms in the same industry. I follow Cziraki *et al.* (2021) to measure the change in sentiment between $(t-1, t+1)$ with year *t* as insider trading year.

To measure the change of cost of capital, I estimate the following modified Fama and French (1993) three-factor model by following Cziraki, *et al.* (2021)

$$r_{j,t}-r_{f,t}=\alpha_{-j}+\alpha_{\Delta j}D_t+b_{-j}(r_{m,t}-r_{f,t})+b_{\Delta j}D_t(r_{m,t}-r_{f,t})+s_{-j}SMB_t+s_{\Delta j}D_tSMB_t+h_{-j}HML_t+h_{\Delta j}D_tHML_t+e_t$$

where $r_{j,t}$ is the monthly stock return, $r_{f,t}$ is the return on 1-month U.S Treasury bill, $r_{m,t}$ is the CRSP value-weight market index, SMB_t and HML_t are the returns on the size and book-to-market ratio portfolios. D_t is a dummy variable that equals one if the year is in $(0,1)$, and zero for years in $(-3,-1)$. I use years $(-3,2)$ to estimate the cost of capital prior and after the CEO turnover. The expected change of cost of capital is obtained using the estimated coefficient of $\hat{\alpha}_{\Delta i}$ plus the product between $\hat{b}_{\Delta j}$, $\hat{s}_{\Delta j}$, $\hat{h}_{\Delta j}$ and the corresponding average factor premium estimated using all firms in CRSP database between 1993 and 2019[35].

$$\Delta r_{t,t+2} = \hat{\alpha}_{\Delta j}+\hat{b}_{\Delta j}\overline{(r_{m,t}-r_{f,t})}+\hat{s}_{\Delta j}\overline{SMB}_t+\hat{h}_{\Delta j}\overline{HML}_t$$

To measure the board conservatism, I follow the Khan and Watts (2009) to compute the C_Score, which is based on Basu (1997). I first estimate the annual cross-sectional regression model as follows:

$$\begin{aligned}X_i = \beta_1 + \beta_2 D_j + R_j\left(\mu_1 + \mu_2 Size_j + \mu_3 MB_j + \mu_4 Lev_j\right) \\ + D_jR_j\left(\lambda_j + \lambda_2 Size_j + \lambda_3 MB_j + \lambda_4 Lev_j\right) \\ + \left(\delta_1 Size_j + \delta_2 MB_j + \delta_3 Lev_j + \delta_4 D_j Size_j + \delta_5 D_j MB_j + \delta_6 D_j Lev_j\right) + \varepsilon_j\end{aligned}$$

X_i is the income before extraordinary items (*ib*) scaled by the lagged market value of equity (*csho*prcc_f*). D_j is a dummy variable equals one for firm-years with negative cumulative returns, zero otherwise. R_j is the 12-month cumulative abnormal return for the firm in the same fiscal year. $Size_j$ is the natural log of market value of equity. MB_j is the ratio of market value of equity to book value of equity (*ceq*) at the end of the year. Lev_j is the leverage, defined as long-term debt (*dltt*) plus short-term debt (*dlc*) over the market value of equity. After estimating the regression, I calculate the C_Score as following:

$$C\_Score = \hat{\lambda}_1 + \hat{\lambda}_2 Size_i + \hat{\lambda}_3 MB_i + \hat{\lambda}_4 Lev_i$$

[35] The average factor premium in my sample is 0.007 for $\overline{(r_{m,t}-r_{f,t})}$, 0006 for $\overline{SMB_t}$ and 0.002 for $\overline{HML_t}$

I further sort all firms in Compustat in the same industry into quantiles in each year to construct the moderator variable $\mathrm{C\_quint}_{j,t}$ that representing the quantile number.

Appendix 2.2: Sample size across different database

	Unique *execid*	Unique *personid*	Sample Size
Raw Execucomp Sample	48,429		269,456
Match with *execid-personid* link table	43,952	44,187	277,113
Match with CRSP both insider purchase and sale, including CEO	26,570	26,617	257,033
Match with CRSP both insider purchase and sale, excluding CEO	24,275	24,310	188,960
Remove new joiner, previous CEO, co-founders/founders	21,723	21,764	165,705
Valid insider purchase sample for Non-Promoted Manager in (0,0)	536	537	860
Valid insider purchase sample for Non-Promoted Manager in (0,1)	844	845	1,492
Valid insider sell sample for Non-Promoted Manager in (0,0)	3,107	3,110	7,935
Valid insider sell sample for Non-Promoted Manager in (0,1)	4,527	4,532	15,443

Appendix 2.3: CEO Turnover Summary

The table shows a summary of CEO turnover event, insider transactions in different fiscal years. I use Execucomp historical annual CEO flag (*ceoann*) to identify CEO turnover events. In column (2), I report the number of internal promotions after removing the confounding events. I define an external CEO promotion if the incoming CEO has not worked for the firm within the event window of (-5, -2). In column (4), I report the number of CEO Turnover after removing confounding events. In column (5) to (8), I exclude all CEO transactions and transactions occurred in the confounding events. In column (7) and (8), I report the yearly average insider transaction value. I aggregate insider purchase and sell transactions at the daily frequency by using the closing price at the transaction day times the number of shares bought/sold to compute the individual transaction value.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Fiscal Year	No. Isolated CEO Turnover	No. Isolated internal Promotions	No. Isolated Non-CEO Manager	Isolated CEO Turnover with Insider Trading	Matched non-CEO Insider Purchase Sample	Matched non-CEO Insider Sell Sample	Average non-CEO Insider Purchase Value ($000)	Average non-CEO Insider Sell Value ($000)
1996			10,045		711	4,011	138.23	1,408.52
1997	136	65	10,184	65	840	5,468	156.54	910.07
1998	146	31	10,586	95	1,170	5,277	113.10	964.49
1999	122	23	9,951	87	1,188	5,061	109.77	1,322.45
2000	160	34	9,269	104	988	6,297	181.07	1,517.59
2001	179	33	9,250	112	559	6,786	94.05	867.65
2002	113	23	9,451	73	708	5,700	75.42	686.37
2003	137	25	9,677	87	503	7,922	93.61	910.97
2004	131	24	8,766	82	327	8,923	150.71	960.54
2005	147	29	7,281	97	294	7,603	345.33	1,043.40
2006	132	33	8,765	88	329	9,267	278.93	987.41
2007	170	46	10,488	119	646	9,960	221.14	923.73
2008	197	54	10,046	122	1,001	6,287	161.35	825.85
2009	153	29	9,506	93	588	5,811	63.87	608.25
2010	123	32	9,289	77	298	7,125	123.84	736.35
2011	150	24	9,132	89	566	8,035	238.71	792.32
2012	164	32	9,006	110	485	8,672	81.88	876.73
2013	160	45	8,918	107	248	9,644	531.51	966.48
2014	152	47	8,805	107	296	7,208	171.67	1,068.98
2015	150	40	8,448	104	399	5,129	301.97	1,087.62
2016	162	31	8,052	110	282	3,889	176.48	1,005.09
2017	144	40	7,588	96	214	4,125	254.86	1,057.52
2018	142	18	7,311	53	72	1,328	175.32	1,232.57
2019	158	34	6,550	92	310	2,745	259.11	1,204.34
All	3,428	2,636	216,364	2,169	13,022	152,273	162.88	969.29

Appendix 2.4: Post-transaction returns of other directors

This table reports the BHAR_m_365 for CEO and Others insider transaction sample. For each treated firm, I collect the CEO transactions and all other directors' transactions excluding tournament competitors. I compute and report the post-transaction return proxied by BHAR_m_365, I winsorised the BHAR_m_365 at the top 99% and the bottom 1% level.

	Purchase Sample				Sell Sample			
Event Year	-2	-1	0	1	-2	-1	0	1
CEO	0.069	0.079	0.254	0.028	0.091	0.041	0.034	0.042
No.	128	202	281	84	3,963	4,515	1,139	1,222
Others	0.142	0.233	0.106	0.120	0.067	0.044	0.054	0.054
No.	585	1,153	1,049	762	4,919	8,483	8,238	5,897

Appendix 2.5: Definition of Variables

Variable Notation	Data Source	Definition
$BHAR\_m\_365_{(d+1,\ d+365)}$	CRSP	365-calendar day Buy-N-Hold return adjusted by using the CRSP value-weighted market index. Defined as the following: $BHAR_{m_n} = \prod_{t=1}^{d}[1 + R_{jt}] - \prod_{t=1}^{d}[1 + R_{mt}]$
$NPV_{i,d}$	Smart Insider	Net purchasing value for insider transactions in day *t* executed by insider *i*, calculated as the ratio of the net dollar amount of insider transactions over the total dollar amount of insider transactions. If *NPV_i* is greater (less) than 0, I recognize that the insider *i* is net buying (selling) on a given day *d*.
$opp\_D_{i,t}$	Smart Insider	Dummy variable equal to one for opportunistic insider transactions, and zero otherwise. I identify opportunistic transactions by following Cohen *et al.* (2012), that is the transaction executed by insiders who had made at least one transaction in the same calendar year in the past three consecutive years. Other insiders are routine traders. I reclassify each insider at the beginning of each calendar year.
$NPED_{i,t}$	Execucomp	Dummy variable equals one for insider purchase or sell transactions executed by non-promoted manager in the event year *t* zero for years other than *t*. *t* takes the value of 0, 1 in the study.
$pay\_gap_{j,t-1}$	Execucomp	The natural logarithm of the difference between the CEO total compensation (*tdc1*) and the median total compensation of other non-CEO managers covered by Execucomp in firm *j* in the last fiscal year. *tdc1* is adjusted by following Coles *et al.* (2014) and Brockman *et al.* (2016).
$lncompen_{j,t-1}$	Execucomp	The natural logarithm of *tdc1* adjusted by following Coles *et al.* (2014) and Brockman *et al.* (2016).
$rating_{j,\ t-1}$	Compustat	The average monthly S&P long-term issuer credit rating of firms in the same Fama-French 48 industry in the last fiscal year. Following Peters and Wagner (2014), I assign AAA a value 2 to CC a value of 23, then scale them by 9, so that a unit increase in the scaled rating corresponds to a change in rating from AAA to BBB or BBB to CCC.
$high\_incentiveD_{i,t-1}$	Execucomp	A dummy variable that is equal to one for high incentive managers, and zero otherwise. High incentive managers are defined as those managers *i* whose compensation differences between their CEOs and themselves are the largest three in firm *j* in year *t-1*.
$pay\_rank_{i,t-i}$	Execucomp	The rank of non-promoted manager sorted by their total compensation in year -1 among all tournament competitors in the same firm.
$mom_{j,(d-31,d\ -364)}$	CRSP	The cumulative raw return from (d-395, d-31), insider transaction occurs in day d. If there are less than 243 trading days in the event window, the variable is set to be missing.
$ret30_{j,(d-1,d-30)}$	CRSP	The cumulative raw return from (d-30, d-1), insider transaction occurs in day d. If there are less than 20 trading days in the event window, the variable is set to be missing.
$bm_{j,m-1}$	CRSP, Compustat	The book-to-market ratio calculated as the ratio of last fiscal year's 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 stockholder equity + deferred taxes and investment tax credit (Compustat: txditc, zero if missing) −preferred stock value. Stockholder equity is parent stockholder equity (Compustat: seq), or total common equity (Compustat: ceq) plus total preferred stock capital (Compustat: pstk) or the difference between the total

		asset (Compustat: at) and total liability (Compustat: lt), in that order, as available. Preferred stock value is the 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. The ratio is calculated for firm *j* at the end of the last month.
leverage$_{j,t}$	Compustat	Long term debt plus debt in current liability) over the total assets $$\frac{(\mathrm{dltt} + \mathrm{dlc})}{\mathrm{at}}$$
illiq$_{j,m-1}$	CRSP	Amihud's (2002) measure of illiquidity for firm *j* at the end of the last month. The measure is calculated as the monthly average of the daily ratio of absolute stock return to dollar volume.
size$_{j,m-1}$	CRSP	The logarithm of market capitalisation defined as adjusted stock price times adjusted shares outstanding for firm *j* at the end of the last month. The number is reported in a million.
roa$_{j,t-1}$	Compustat	Return on asset calculated as the net income (Compustat: ni) after taking out preferred dividend (Compustat: dvp), over the total asset (Compustat: at) for firm *j* at the end of the last fiscal year.
age_ceo$_{j,\,t-1}$	Execucomp	In the fiscal year *t-1, I* identify the former CEO of firm *j*. The variable is her age in year *t-1*. If Execucomp does not report the age of manager in a given year, I use the age of the same manager in other years to complete the age of the manager in the year.
numest$_{j,m-1}$	I/B/E/S	Analyst coverage is defined as the number of analysts that report a forecast for the next 1-fiscal year earnings per share for firm *j* at the end of the last month. If there is no earning forecast, the analyst coverage is set to be zero.
rd$_{j,t-1}$	Compustat	Research and development expense calculated as the research and development expense (Compustat: xrd) over sales (Compustat: sale) for firm *j* at the end of the last fiscal year. If Compustat reports missing research and development expense, it is set to be zero.
delta$_{i,t-1}$	Execucomp	Dollar changes in wealth associated with a 1% change in the firm’s stock price (in $000) for manager *i*. Calculated according to Coles *et al.* (2013).
vega$_{i,t-1}$	Execucomp	Dollar changes in wealth associated with a 0.01 change in the standard deviation of the firm’s returns (in $000) for manager *i*. Calculated according to Coles *et al.* (2013).
OutsiderD$_{j,t}$	Execucomp	If the new CEO had not been working in the company in the (-5, -2) of the CEO turnover window, the CEO is defined as outsiders. The dummy takes the value of one for insider transactions for firms with outside CEO appointment during the year $(0, 1)$, and zero otherwise.
COOD$_{j,t}$	Execucomp	If the firms had a COO and the COO is younger than the current CEO before the CEO tournament, the firm is defined as COO firm. The dummy takes the value of one for non-promoted insider transactions for COO firms during the year $(0, 1)$, and zero otherwise. I define COO is the manager who is younger than the incumbent CEO and whose job title (*titleann*) contains *chief operating office* or *chief operation officer* or *chief operations officer* or *chf operations officer* or *chf operation officer* or *che operating officer* or *coo* or *president* or/and *pres*

CEO_IT$_{j,t}$	Execucomp, Smart Insider	The number of quintiles of the net CEO selling value for firm *j* in year *t*. Net CEO selling value is the total value of selling transaction minus the total value of buying transaction executed by CEO in year *t* for firm *j*. If there is no CEO insider transaction in year *t*, the number is set to be 0.
lnage$_{i,t}$	Execucomp	The natural logarithm of the current age of the manager *i* in year *t*.
total asset$_{j,t-1}$	Compustat	Logarithm of the total asset (Compustat: at) in the last fiscal year. The variable is only used to conduct the matching only.
FERC$_{j,t}$	CRSP, Compustat	It is a dummy variable equal to one for firms in the top quantile of future earnings response coefficient calculated according to Tucker and Zarowin (2006), and zero for other firms.
Synch$_{j,t}$	CRSP	It is a dummy variable equal to one for firms in the top quantile of return synchronicity calculated according to Piotroski and Roulstone (2004), and zero for other firms.
tobin's Q$_{j,t-1}$	Compustat	Market value of equity plus book value of debt-deferred tax over book value of total assets. $$\frac{(\text{at} + \text{csho} \times \text{prcc\_f} - \text{ceq} - \text{txdb})}{\text{at}}$$
capital-to-sale$_{j,t-1}$	Compustat	Net fixed asset (Compustat: ppent) to sales (Compustat: sale).
advertising-to-sale$_{j,t-1}$	Compustat	Advertising expenditure (Compustat: xad) to sales (Compustat: sale). It is assumed to be zero if firms do not report advertising expenditure.
dividend-yield$_{j,t-1}$	Compustat	The dividends per share by ex-date divided (Compustat: dvpsx_f) by the close price for the fiscal year (Compustat: prcc_f).
all_IT$_{j,t}$	Smart Insider	The total number of non-CEO insider transaction for firm *j* in year *t*. If there is no non-CEO insider transaction in year *t*, the number is set to be 0.
sale$_{j,t-1}$	Compustat	The natural logarithm of the sale (Compustat: sale).
skt_ret_volatility$_{j,t-1}$	CRSP	Variance of 60 monthly returns preceding the sample year *t-1*
capital_intensity$_{j,t-1}$	Compustat	Capital expenditure (Compustat: capx) over total asset (Compustat: sale)
firm_focus$_{j,t-1}$	Compustat-Segment	Firm focus is computed as the segment sales-based Herfindahl index. I use Compustat segment file to identify a firm's segment sales according to their four-digit SIC code. Firm focus is equal to one if the firm operates only in one segment and decreases as the firm diversifies. (Kini and Williams, 2012)
cash_flow_vol$_{j,t-1}$	Compustat-Quarterly	It is the seasonally adjusted standard deviation of cash flows over assets for a five-year window (*t, t+4*). I require there are at least a three-year data to compute this variable. Quarterly cash flows over assets is defined as the EBITD (Compustat: saleq- cogsq- xsgaq) over total asset (Compustat: atq). For each of the four quarters in the year, I compute the mean values across the five-year window and then subtract these quarterly mean values to obtain the seasonally adjusted cash flows. I then compute the standard deviation of these adjusted cash flows over assets over the period *t* to *t+4*. (Kini and Williams, 2012)
institution_ownership$_{j,q-1}$	Thomson Reuter 13F Holding	Percentage of shares owned by institution investors over total shares outstanding in the last quarter.
independent_manager$_{j,t-1}$	Boardex	Percentage of independent managers on the company board.

independent_committee$_{j,t-1}$	Boardex	Percentage of independent managers on the company compensation committee.
analyst_talent$_{j,t-1}$	I/B/E/S	The average talent of financial analysts that cover firm *j* in the last fiscal year. It is the innate ability of sell-side analysts measured by the analyst fixed effect from the regression on analysts' forecast accuracy. Calculated according to Dang *et al.* (2021)
$\boldsymbol{\alpha}_{\mathbf{t+1,t+i}}$	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).
CEO_tenure$_{j,t-1}$	Execucomp	Computed as the difference between year *t* and the year the manager became CEO (Execucomp:*becameceo*). If the *becameceo* is missing, it is the number of yearly observations the manager has become CEO.

Appendix 2.6: Test on Parallel Trend Assumption

I follow Angrist and Pischke (2009) and Cengiz *et al.* (2019) to conduct an event-study type diff-in-diff regression and formally test on the parallel trend assumption. Variable Pre_t equals to 1 for treated firms in year *t,* and zero otherwise. Year *t* refers to the year in my event window with year *0* as the CEO turnover occurred. Variable Post_t is defined with the same logic. The coefficients of Pre_{-1} should be statistically insignificant for the parallel trend assumption to hold. I drop one pre-treated period to avoid perfect multicollinearity. Column (1) and (2) focuses on insider purchase and sell transactions, respectively. I control for firm, year, and cohort fixed effects. Standard errors are clustered at the firm-month level. ***, **, and * denote significance at the 99%, 95% and 90% confidence level, respectively. All variables are winsorised at the top 99% and the bottom 1% level.

	Purchase Transactions		**Sell Transactions**	
	(1)	(2)	(3)	(4)
	BHAR_m_365	BHAR_m_365	BHAR_m_365	BHAR_m_365
Pre_{-2}		-0.120		0.030
		(0.073)		(0.019)
Pre_{-1}	0.108		-0.030	
	(0.080)		(0.019)	
Post_0	0.211^{*}	0.171^{**}	-0.061^{**}	-0.031^{*}
	(0.119)	(0.072)	(0.026)	(0.018)
Post_1	0.079	0.048	-0.082^{***}	-0.052^{**}
	(0.151)	(0.080)	(0.032)	(0.025)
Control	Yes	Yes	Yes	Yes
Sample	2,309	2,309	47,094	47,094
Within R^2	0.38	0.38	0.30	0.30

Appendix 2.7: Insider trading and the probability of becoming CEO

This table reports linear probability models estimating the likelihood of a manager *i* becoming CEO in year *t*. The dependent variable is one for CEO, and zero otherwise. I estimate regressions using all tournament competitors defined previously and for CEO turnover year *t* only. Sample is at manager-firm level. Variables $no\_buy_{i,t-1}$ and $no\_sell_{i,t-1}$ represent the number of insider purchase and sell transactions made by insiders *i* in year *t-1*. $age_{i,t-1}$ and $tenure_{i,t-1}$ represent the age and tenure of insiders *i* in year *t-1*, respectively. $COOD_{i,t-1}$ is equal to one if the manager *i* is chief operating officer or president in year *t-1,* and otherwise zero. I define all other variables in Appendix 2.5 and winsorised at the 1% level. I include firm and year fixed effects. I report clustered standard errors by firm in brackets. ***, **, and * significant at the 99%, 95% and 90% confidence level, respectively.

	$CEOD_{i,t}$	$CEOD_{i,t}$
$age_{i,t-1}$	-0.005^{**}	-0.004^{**}
	(0.002)	(0.002)
$tenure_{i,t-1}$	0.006^{*}	0.006^{*}
	(0.003)	(0.004)
$COOD_{j,t-1}$	0.435^{***}	0.434^{***}
	(0.032)	(0.032)
$no\_buy_{j,t-1}$	0.044	0.041
	(0.027)	(0.028)
$no\_sell_{j,t-1}$	-0.006	-0.005
	(0.004)	(0.005)
$no\_buy_{j,t-2}$		0.009
		(0.033)
$no\_sell_{j,t-2}$		-0.000
		(0.006)
$delta_{i,t-1}(\times 0.01)$	0.012^{**}	0.012^{**}
	(0.006)	(0.006)
$vega_{i,t-1}(\times 0.01)$	0.062^{**}	0.061^{**}
	(0.031)	(0.031)
$lncompen_{i,t-1}$	0.000^{***}	0.000^{***}
	(0.000)	(0.000)
$ret30_{j,t-1,(d-1,d-30)}$	0.522^{***}	0.525^{***}
	(0.167)	(0.167)
$mom_{j,t-1,(d-31,d-364)}$	0.036	0.036
	(0.054)	(0.054)
$bm_{j,t-1}$	0.132^{*}	0.131^{*}
	(0.075)	(0.075)
$illiq_{j,t-1}$	0.038	0.040
	(0.076)	(0.076)
$total\ asset_{j,t-1}$	-0.118^{***}	-0.118^{**}
	(0.046)	(0.046)
$roa_{j,t-1}$	-0.113	-0.113
	(0.213)	(0.212)
$tobin's\ Q_{j,t-1}$	0.017	0.017
	(0.020)	(0.021)
$leverage_{j,t-1}$	0.059	0.057
	(0.130)	(0.130)
Constant	0.880^{**}	0.880^{**}
	(0.401)	(0.404)
Sample	1,364	1,364
Within R^2	0.45	0.45

Appendix 2.8: Insider trading and price informativeness around the CEO turnover

This table reports the fixed effects regression output based on the matched sample. The dependent variable is BHAR_m_365 in year (0,0) in columns 1 and 3 and (1,1) in 2 and 4. I match each treated firm with CEO turnover event in year *t* with one control firm using Mahalanobis distance on the average insider purchase/sell profitability, logarithm of the total asset and the book-to-market ratio in the fiscal year *t-1*. I restrict that the control firm sample does not have any CEO turnover in (-2, 2). In Panel A, the moderator variable is future earnings response coefficient (FERC) calculated according to Tucker and Zarowin (2006) and the $NPED_{i,t}$. $FERC_{i,t}$ is a dummy variable equals to one for firms in the top quantile of $FERC_{i,t}$ in year *t,* and zero otherwise. In Panel B, the moderator variable is the return synchronicity (Synch) calculated according to Piotroski and Roulstone (2004). $Synch_{i,t}$ is a dummy variable equals to one for firms in the top quantile of $Synch_{i,t}$ in year *t* in the same two-dig sic industry, and zero otherwise. Appendix 2.5 defines all variables in the table. I include the same set of control variables as in Equation (2). I report in parentheses the robust standard errors clustered at the firm-month level. ***, **, and * denote significance at the 99%, 95% and 90% confidence level, respectively. I winsorise all variables at the top 99% and the bottom 1% level.

	Insider Purchase		Insider Sell	
	Panel A: Future Earnings Response Coefficient			
	(1)	(2)	(3)	(4)
$Post_{i,t}$	0.125	0.037	0.016	0.037***
	(0.055)	(0.085)	(0.011)	(0.013)
$Treat_{i,t}$	-0.337***	-0.196	0.002	-0.002
	(0.113)	(0.121)	(0.012)	(0.012)
$(Treat\times Post)_{i,t}$	0.163*	0.196	-0.036**	-0.034*
	(0.095)	(0.124)	(0.018)	(0.020)
$FERC_{i,t}$	-0.117	0.057	-0.029	-0.013
	(0.115)	(0.112)	(0.020)	(0.023)
$(Post\times Treat\times FERC)_{i,t}$	-0.011	-0.095	0.099***	0.029
	(0.186)	(0.179)	(0.036)	(0.047)
Sample	1,400	1,079	30,879	28,415
	Panel B: Return Synchronicity			
$Post_{i,t}$	0.005	0.119	0.014*	0.031**
	(0.069)	(0.126)	(0.011)	(0.013)
$Treat_{i,t}$	-0.311***	-0.215*	0.016	0.012
	(0.114)	(0.116)	(0.013)	(0.012)
$(Treat\times Post)_{i,t}$	0.234**	0.011	-0.031**	-0.038**
	(0.103)	(0.170)	(0.019)	(0.019)
$Synch_{i,t}$	0.040	0.001	0.021	-0.013
	(0.084)	(0.080)	(0.013)	(0.017)
$(Post\times Treat\times Synch)_{i,t}$	-0.142	0.222	0.028	0.014
	(0.136)	(0.191)	(0.033)	(0.040)
Sample	1,828	1,323	31,131	28,542

Appendix 2.9: Insider trading informativeness based on the number of exiting directors

This table reports the fixed effect regression output based on matched sample in Table 2.4. In Panel A, the dependent variable is the change in return on asset between year t and year t+2. In Panel B, the dependent variable is the change in investor sentiment measured as firm-specific component from the market-to-book decomposition of Rhodes–Kropf, *et al.* (2005). The change in investor sentiment $\Delta \text{Sentiment}_{-1,1}$ is measured between year t-1 to year t+1. In Panel C, I obtain the $\Delta r_{t,t+2}$ by following Cziraki *et al.* (2021) to estimate a modified Fama and French (1993) Three-Factor model. I include the control variables in Equation (2), omitted for brevity. I split the sample base on whether the firm has at least one non-CEO director that is leaving in the next year. Standard errors reported in parentheses are computed based on robust standard errors clustered at the firm-month level. ***, **, and * denote significance at the 99%, 95% and 90% confidence level, respectively. All variables are winsorised at the top 99% and the bottom 1% level.

	Insider Sell (No Exiting)		**Insider Sell (With Exiting)**	
	(1)	(2)	(3)	(4)
Year *t*	(0,0)	(1,1)	(0,0)	(1,1)
	Panel A: Future Firm Performance			
Dependent Variable	$\Delta ROA_{t,t+2}$	$\Delta ROA_{t,t+2}$	$\Delta ROA_{t,t+2}$	$\Delta ROA_{t,t+2}$
$Post_{i,t}$	0.003	0.000	-0.005	0.004
	(0.005)	(0.005)	(0.004)	(0.005)
$Treat_{i,t}$	0.008**	0.019***	0.039***	0.040***
	(0.004)	(0.004)	(0.011)	(0.010)
$(Post \times Treat)_{i,t}$	-0.014**	-0.015*	-0.014**	-0.026***
	(0.007)	(0.008)	(0.007)	(0.008)
Other Control	Yes	Yes	Yes	Yes
Within R-square	0.11	0.08	0.07	0.10
Fixed Effect	Firm, Month	Firm, Month	Firm, Month	Firm, Month
Sample	18,424	15,647	17,023	16,426
	Panel B: Investor Sentiment			
Dependent Variable	$\Delta \text{Sentiment}_{t-1,t+1}$	$\Delta \text{Sentiment}_{t-1,t+1}$	$\Delta \text{Sentiment}_{t-1,t+1}$	$\Delta \text{Sentiment}_{t-1,t+1}$
$Post_{i,t}$	-0.028	0.104***	0.047**	0.041*
	(0.022)	(0.024)	(0.018)	(0.024)
$Treat_{i,t}$	0.087***	0.077***	0.060**	0.026
	(0.025)	(0.026)	(0.026)	(0.027)
$(Post \times Treat)_{i,t}$	-0.039	-0.100**	-0.124***	-0.064*
	(0.035)	(0.042)	(0.036)	(0.038)
Other Control	Yes	Yes	Yes	Yes
Within R-square	0.11	0.11	0.15	0.17
Fixed Effect	Firm, Month	Firm, Month	Firm, Month	Firm, Month
Sample	18,612	15,766	16,765	16,172
	Panel C: Change in Cost of Capital			
Dependent Variable	$\Delta r_{t,t+2}$	$\Delta r_{t,t+2}$	$\Delta r_{t,t+2}$	$\Delta r_{t,t+2}$
$Post_{i,t}$	-0.001***	-0.002**	0.000	0.001***
	(0.000)	(0.001)	(0.000)	(0.001)
$Treat_{i,t}$	-0.001	-0.001	-0.001	-0.001**
	(0.001)	(0.001)	(0.001)	(0.001)
$(Post \times Treat)_{i,t}$	0.002***	0.002**	0.001**	0.001
	(0.001)	(0.001)	(0.000)	(0.001)
Other Control	Yes	Yes	Yes	Yes
Within R-square	0.05	0.05	0.14	0.08
Fixed Effect	Firm, Month	Firm, Month	Firm, Month	Firm, Month
Sample	19,038	16,804	17,485	16,789

Appendix 2.10: 2SLS regression result for matching sample

The table reports the regression output of 2SLS regression on sample obtained by nearest neighbour matching. The dependent variable in the first stage of the regression is $NPED_{i,t}$, a dummy variable equals to one for the purchase/sell transactions of promotion rejectees in (0,0) and (1,1) with year 0 the CEO turnover event depending on the year *t* and zero for years outside the event window and (-2, -1). I state the year t at the top of the table. In all columns, I obtain the sample by the nearest neighbour matching using Mahalanobis distance. I match firms with CEO turnover event in year *t* with firms on the average insider purchase/sell profitability, logarithm of the total asset and the book-to-market ratio in the fiscal year *t-1*. I match each treated firm with one control firm. I restrict that the control firm sample does not have any CEO turnover in (-2, +2). My instrumental variable is the previous CEO's age in the last fiscal year. I include the same set of control variables as in Equation (2). I report the robust standard errors clustered at the firm-month level in parentheses. ***, **, and * denote significance at the 99%, 95% and 90% confidence level, respectively. All variables are winsorised at the top 99% and the bottom 1% level.

	Insider Sell	
	(1)	(2)
	First Stage	
Year *t*	(0,0)	(1,1)
Dependent Variable	$NPED_{i,t}$	$NPED_{i,t}$
$age\_ceo_{j,t-1}$	0.019^{***}	-0.023^{***}
	(0.002)	(0.002)
Control Variable	Yes	Yes
	Second Stage	
Dependent Variable	BHAR_m_365	BHAR_m_365
Endogenous Variable		
$\widehat{NPED}_t$	-0.543^{*}	-1.132^{**}
	(0.309)	(0.467)
$\widehat{NPED \times CEO\_IT}_{i,t}$	0.564^{***}	0.331^{**}
	(0.200)	(0.157)
Control Variables		
$CEO\_IT_{j,t}$	0.004	-0.024
	(0.011)	(0.016)
Other Control Variable	Yes	Yes
Sample	18,368	18,831
Fixed Effect	Firm, Month	Firm, Month
Difference in Sargan *C* (χ^2)	37.23^{***}	18.35^{***}
First-Stage F-$\widehat{NPED}_{i,t}$	163.75^{***}	225.09^{***}
Anderson-Rubin Wald Test, F-Statistics	20.82^{***}	8.71^{***}

Appendix 2.11: CEO purchase transaction trading profitability after CEO turnover

The dependent variable is Buy-N-Hold abnormal return calculated for 30, 180 and 365-calenday holding periods, respectively. The variable with interest $yearD_{i,t}$ is a dummy variable equals to one for focal year, and zero otherwise. I only include CEO purchase transaction in the table. Standard errors in parentheses are based on robust standard errors clustered at the firm-month level. ***, **, and * denote significance at the 99%, 95% and 90% confidence level, respectively. All variables are winsorised at the top 99% and the bottom 1% level. All regressions include control variables and firm and month fixed effects. Control variables that are omitted for brevity are $bm_{j,m-1}$, $numest_{j,m-1}$, $roa_{j,t-1}$, $vega_{i,t-1}$, $rd_{j,t-1}$. Appendix 2.5 defines all control variables in the table.

	Year 0			**Year 1**		
	BHAR_m_30	BHAR_m_180	BHAR_m_365	BHAR_m_30	BHAR_m_180	BHAR_m_365
$yearD_{i,t}$	-0.014	-0.029	-0.111^{**}	0.022^{**}	-0.011	-0.104^{**}
	(0.012)	(0.034)	(0.055)	(0.011)	(0.030)	(0.043)
$pay\_gap_{j,t-1}$	0.006^{**}	0.021^{***}	0.016	0.006^{**}	0.022^{***}	0.021^{*}
	(0.003)	(0.007)	(0.012)	(0.003)	(0.007)	(0.012)
$ret30_{j,t-1,(d-1,d-30)}$	-0.008	0.050	0.363^{**}	-0.018	0.001	0.394^{**}
	(0.040)	(0.106)	(0.175)	(0.035)	(0.099)	(0.178)
$mom_{j,\ t-1,(d-31,d\ -364)}$	-0.028^{**}	-0.048	-0.112^{**}	-0.029^{**}	-0.051	-0.114^{**}
	(0.012)	(0.034)	(0.047)	(0.011)	(0.033)	(0.052)
$illiq_{j,m-1}$	0.012	0.234^{***}	0.423^{***}	0.011	0.233^{***}	0.408^{***}
	(0.015)	(0.047)	(0.066)	(0.015)	(0.048)	(0.067)
$size_{j,m-1}$	-0.042^{***}	-0.223^{***}	-0.392^{***}	-0.038^{***}	-0.231^{***}	-0.390^{***}
	(0.011)	(0.032)	(0.051)	(0.011)	(0.036)	(0.051)
$delta_{i,t-1}(\times 0.01)$	0.001^{*}	0.004^{***}	0.008^{***}	0.001^{**}	0.004^{***}	0.008^{***}
	(0.000)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
$lncompen_{i,t-1}$	0.017^{**}	0.064^{***}	0.144^{***}	0.017^{**}	0.066^{***}	0.108^{***}
	(0.008)	(0.021)	(0.042)	(0.008)	(0.021)	(0.030)
$rating_{j,\ t-1}$	0.079	0.332^{*}	0.612^{**}	0.111	0.449^{**}	0.875^{***}
	(0.075)	(0.193)	(0.269)	(0.075)	(0.200)	(0.283)
Constant	0.038	0.434	0.701	-0.035	0.332	0.535
	(0.114)	(0.307)	(0.481)	(0.112)	(0.311)	(0.462)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Sample	4193	5116	5061	4193	5116	5086
Fixed Effect	Firm,Month	Firm,Month	Firm,Month	Firm,Month	Firm,Month	Firm,Month
Within R^2	0.029	0.114	0.174	0.027	0.158	0.160

Chapter 3

Insider trading through supply-chain M&A event[36]

Abstract

I document that corporate insiders significantly alter their trading activities and make more informed transactions when their competitors or customers firms in their supply chain become an M&A target. I argue that these insiders have a better understanding of the impact of the deal on their firms than the aggregate market. Consistent with the prediction of the operating and purchasing efficiency hypotheses, the main sources of gain behind these more informed transactions are the changes in future operating and in innovation efficiencies, and a higher probability of being acquired in the future. I show that these more informed transactions are more likely to be based on public information rather than the conventional private information channels.

[36] The chapter is co-authored with Lasfer Meziane and Lijuan Xie. Lijuan is with Nanjing University. I thank seminar participants at Bayes Business School, City University of London. Any errors remain my own responsibility.

3.1 Introduction

The limited attention constraint theory stipulates that financial markets cannot efficiently incorporate the information of a firm into the stock prices of its supply-chain partners because of the information acquisition cost and the market segmentation (Huang and Liu, 2007; Hong, Torous and Valkanov, 2007; Cohen and Frazzini, 2008). This constraint implies that aggregate investors systematically react to the shock on a supply chain with a delay and there will be a temporary mispricing for firms on the supply chain. The information will diffuse gradually through the supply chain, leading to a cross-section return predictability. Informed investors are not, however, affected by this constraint. Some, such as financial analysts, display this constraint (Cohen and Lou, 2012), while others, including mutual fund managers, do not and actively exploit the limited constraint of the aggregate market to maximise their portfolio gains (Cohen and Frazzini, 2008; Huang and Kale, 2013).

Alldredge and Cicero (2015) focus on corporate insider trading decisions based on their supply chain partners. They compare post-transaction profitability across insiders of firms that report at least one major customer and others from firms without a major customer. They show that the former group systematically generate higher abnormal returns and exploit the limited attention constraint to maximise their personal gains. However, their study is a general examination of insider trading profitability without conditioning on any specific corporate event or public information announcement. They also do not test for endogeneity to assess whether insiders are trading on their private or public information.

I build on Alldredge and Cicero (2015) to better identify the changes in insider trading activity and profitability by focusing on M&A announcement of their economically linked firms, a public information. I select this specific corporate event for three reasons. First, it allows me to better differentiate the information channel insiders are considering in their trading decision. Second, M&A is a major corporate event that will make a substantial impact on all firms on the supply-chain even when they are not directly involved in the deal. Yet, the empirical evidence on its impact on economically linked firms is mixed, mainly because previous studies predominantly focus on the stock returns around the deal announcement date which are biased given the market limited attention constraint.[37] Third, M&A deals systematically motivate target firms' insiders to alter their trading decisions to maximise their

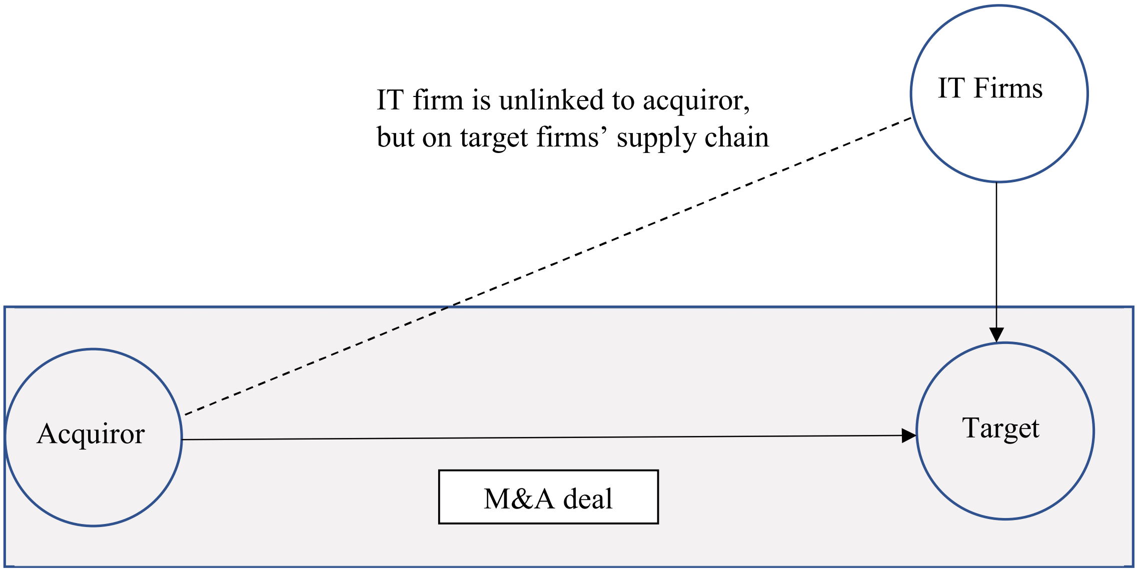
[37] See, for example, Fee and Thomas (2004); Shenoy (2012); Gaur, Malhotra and Zhu (2013); Bradley, Desai and Kim (1988); Eckbo (1983); Akhigbe, Borde and Whyte (2000). Shenoy (2012) and Davis *et al.* (2021) provide a general review of the predominant theories regarding the source of merger gains.

personal gains without taking too much litigation risk by systematically selling less (more) before (after) M&A announcement to reap the M&A premium, a practice known as passive trading strategy (Agrawal and Nasser, 2012; Fidrmuc and Xia, 2021; Davis *et al.* 2021).[38] I argue that corporate insiders are likely to better understand the implication of M&A deals in their supply chain for their firms because they have superior knowledge about the nature, the stability, and the condition of their supply chains. Moreover, the limited attention of the aggregate investors who are unable to fully understand the impact of the deal on the supply chain, will provide an opportunity for insiders to profitably trade the stock of their own firm, which is not involved in the deal, without any potential litigation risk. Figure 3.1 summarises my research design. I focus on the trading by insiders in IT firms when their supply chain firms, which are either their competitors, suppliers or customers become targets.

I collect a sample of 685 U.S domestic deals announced between 2003 and 2020[39]. I then identify 1106 competitors, 812 customers and 598 supplier companies that are linked to the target firm. I focus on the legal corporate insider transactions for these linked firms in the next three months since the M&A announcement month to assess whether these insiders systematically alter their trading activities to make more informed transactions. One main concern in the insider trading literature is endogeneity, as the true motivations behind insider transactions, including private information, personal liquidity need and portfolio diversification, are not directly observable, leading to random post-transaction returns, and inconsistent estimates. To mitigate this potential bias, I specify a difference-in-difference regression based on a matched sample firm to isolate the M&A announcement effect within months (-12, 2). I match my treated firms with a group of control firms that were also target firms over months (-12, 12), but without any commercial links to my test firms. I base my matching on the last six-month returns, book-to-market ratio, and the logarithm of market capitalisation at the end of month -1 using the shortest Mahalanobis distance. I also consider the possible reverse causality that the M&A deal is induced by changes in the treated firm's fundaments by employing a two-stage least square (2SLS) estimator with the mutual fund hypothetical sales proposed by Edmans, Goldstein and Jiang (2012) and Dessaint *et al.*(2019) as an instrumental variable (IV) to eliminate any potential bias.

[38] M&A is a corporate event that attracts the attention of market regulator with SEC devoting more resources to catch illegal insider trading, which account for more than half the investigations, placing insiders under high market scrutiny, and reducing their aggressive trading (Agrawal and Jaffe, 1995; Kacperczyk and Pagnotta, 2021).
[39] My sample size is limited by data availability from supply-chain database Factset Revere.

Figure 3.1: Research setting illustration



Target Firm is IT firms' 1.Competitor 2.Customer 3.Supplier

I find that insiders abnormally sell less shares in their companies after their competitors or customers have become the target in a M&A deal, indicating these insiders recognise their firms will benefit from the M&A deal, there is no significant effect if their supplier firms become target. These insiders will sell $223,523 and $570,957 less worth of shares in each month of the next months if their competitors or customer firms have become the target, respectively. The treatment effect is stronger when the target firm is likely producing homogeneous products, when the target firms have a more complicated supply chain which is measured using the number of suppliers. Moreover, these more informed transactions will systematically yield higher abnormal return, implying insiders incorporate more informational contents into the current stock price. These results also indicate the aggregate market indeed suffers from the limited attention constraint and cannot efficiently incorporate the M&A announcement into the prices for all firms on the supply chain. My results suggest that insiders from these non-focal firms trade on the temporary mispricing of their firms to maximize their personal gains.

To understand the informational content behind these informed insider transactions, I focus on operating efficiency hypothesis and purchasing efficiency hypothesis, two none-mutually exclusive and commonly accepted sources of gain in M&A deals. The former suggests that if insiders sell less (more) shares, their firms will perform better (poorer). I proxy future performance by using future changes in return on asset, earnings surprise, and in sales growth. I find strong evidence to support the operating efficiency hypothesis. The purchasing efficiency hypothesis predicts the larger demand of the merging firm will lower the price of their input materials and the purchasing efficiency will be enjoyed by their competitors and suppliers, the former can also enjoy lower input price and the latter can possibly lower the price of their input resources due to the larger downstream demand. Using change in the cost of goods sold to measure the input cost, I find evidence to support this hypothesis.

Additionally, I examine two non-mutually signaling hypotheses, industry growth hypothesis suggested by Eckbo (1983) and higher acquisition probability hypothesis proposed by Song and Walking (2000). The former implies the merging firms will reveal innovation that allows rivals to similarly replicate. I employ the unit cost of developing a patent and show that insider transactions can predict the lower cost of developing a patent when their competitors have become the target. The signaling higher acquisition probability hypothesis conjectures that markets infer from the deal that the industry is undervalued, or the deal will reveal innovations that allow rivals to similarly replicate efficiency but only upon being acquired. Using cross-section regressions, I find that the more these insiders purchase after the M&A announcement, the higher the likelihood of their firms to be taken over, in favour of this signaling hypothesis.

I rule out the possibility that insiders are trading on their own firm's private information than their better understanding of the M&A deal. I expect that insider trading activity should vary with the firm-specific price informativeness if they simply trade on the firm-specific mispricing. To proxy for the firm-level informativeness, I follow Tucker and Zarowin (2006) and construct the future earnings response coefficient, and Piotroski and Roulstone (2004) to calculate the return synchronicity. My results do not vary with the firm-level informativeness. Moreover, I find that the cumulative abnormal return of the target firm around the M&A announcement date can predict the insider trading activity, the predictability is not seen in the abnormal return of their own firms. The abnormal insider trading activity and the higher return predictability remain robust when I predict treated firms use my IV to eliminate the reverse-causality concern and cannot be replicated in a sample of incomplete deal and 1000 placebo tests. These results suggest that the main information source for their abnormal trading profits is their better understanding of the deal of their supply chain firm.

My paper contributes to both the insider trading, supply chain, and M&A literatures. Insider trading literature has predominately argued that insiders generate abnormal profits because they have superior access to their firms' future fundaments. Alldredge and Cicero (2015) is the first to show that insiders have better understanding of the public information about their customers firms than the aggregate market. I build on Alldredge and Cicero (2015) to extend their results to the competitors and supplier relationships in addition to the customer relationship. I eliminate the endogeneity bias by showing that insiders' ability to better understand the public information not only exists for their customers, but also competitors. Moreover, the existing M&A literature mostly focuses on the insider trading activity either in the acquirer or target firms (Agrawal and Nasser, 2012; Fidrmuc and Xia, 2021; Davis *et al.* 2021). I believe that I am the first to focus on insider trading activity in a firm that is not directly involved in the M&A deal. I show that corporate insiders alter significantly their trading activity following M&A announcement of the supply chain firms. They trade on the deals' operating and purchasing efficiencies gains for their personal gains without exacerbating their litigation risk as the news is public. Their trades signal to the market potential bids of their firm.

The remainder of the paper proceeds as follows. In Section 3.2, I review the relevant literature and develop my hypotheses. Section 3.3 describes my sample and the constructions of variables, explains the matching algorithm and specifies my difference-in-difference regression. Section 3.4 presents the empirical results and Section 3.5 presents the and placebo tests. The conclusions are in Section 3.6.

3.2 Literature review and hypotheses development

Theorists first model that the financial market is unable to efficiently incorporate the public information of a firm into the stock price of its economically linked firms on the supply-chain. Huang and Liu (2007) show that it is rational for investors to obtain value-relevant information with limited frequency and accuracy because of the high information acquisition costs. The limited accurancy will directly lead to a cross-section return predictability[40]. Consistent with the model, Cohen and Frazzini (2008) is the first paper to empirically show that there is a significant return predictability embedded in the supply-chain information. The study proposes that aggregate investors cannot immediately incorporate all the public announcements of customer firms into supplier firms' stock prices. The delay in the

[40] The psychologist literature also sets up the foundations of limited attention theories. See, for example, Egeth and Kahneman (1975), and Fiske and Taylor (1991).

information processes will directly lead to stock misvaluation of supplier firms, leading stock returns of principle customer firms that account for more than 10% of their supplier firms' annual revenue to embed return predictability for supplier firms' stock returns. They show that a long-short equity trading strategy based on sorting of the principal customer's return predicts supplier's return up to twelve months, and yields monthly alphas of over 150 basis points. The stock return predictability is weaker (stronger) when the instiutional ownership in the supplier firms is higher (lower), suggesting that these informed institutional investors are particualy attentative to the public information and trading on it to generate abnormal returns. In the same vein, Hong *et al.* (2007), Menzly and Ozbas (2010), and Lee *et al.* (2019) argue that aggregate investors are limited in their abilities to understand the full impact of complicated public information due to their specialisation and market segmentation. Consequently, value-relevent public information diffuses slowly in financial markets, leading to a return predictability.

A common finding in these early empirical asset pricing literature is that informed investors, such as institutional investors and financial analysts, are less subject to the limited attention constraint, as they incorporate complex information into stock prices. For example, Huang and Kale (2013) find that mutal fund managers who invest in serveral related industries perform better than those who invest a disproportionately large portion of their portfolio in one industry . They actively exploit the misvalution due to outside investors' limited attention through the supply-chain information. They are more attentative to the public announcement of firms in related industries, and better understand the impact of the announcement on their peers than outside investors. They trade on the peer firms to fully incorporate the public information into their stock prices.

In contrast, some studies show that analysts are subject to the limited attention bias. Cohen and Lou (2012) focus on two sets of firms, those that require a straightforward analysis to update their prices, and another in need of a more sophisticated and comprehensive financlial analysis to accureatly incorporate the same value-relevant information into their prices. They document a strong return predictability from the former to the latter set of firms. In the same vein, Ali and Hirshleifer (2020) has shown that sell-side analysts incorporate news about linked firms sluggishly. They ague that financial analysts are also subject to the attention constraint because their forecast revision in the former set of firms will predict their subsequent revision in the latter set of firms. The effect becomes strong if the linkage between firms is more complex and indirect, in line with the limited attention bias predictions.

However, the existing literature has overlooked the trading decision of corporate insiders who are commonly recognised as informed investors in response to the public information that will substantially impact their firms. Insider trading literature has presented robust evidence to support that corporate insiders frequently trade on their private information for personal gain (Seyhun, 1986, 1992; Lakonishok and Lee, 2001). Their transactions become drastically more informative before some specific corporate events, such as the release of quarterly earnings announcement (Ali and Hirshleifer, 2017), around M&A rumour (Davis *et al.* 2020), when there is a worsening in the industry level and/or firm-specific information environment (Wang, 2019; Contreras and Marcet, 2020), and if they narrowly miss their performance-based bonuses (Gao, 2019). Although the SEC in the US and regulators in other countries prohibit corporate insiders from trading on any material private information, anecdotal evidence and empirical studies in insider trading literature have shown that corporate insiders can systematically earn abnormal return followings their transactions (Seyhun, 1986, 1992; Lakonishok and Lee, 2001; Cohen, *et al.* 2012), mainly because insider trading rules are not binding (Bhattacharya and Daoud, 2002). Lakonishok and Lee (2001) and Wu (2019) have showed that one of the main motivations for insiders to trade their own firms is that their transactions embed a strong signal to the market. If their firms are undervalued by outside investors, corporate insiders will be motivated to buy shares of their firms to profitably support the price. Alldredge and Cicero (2015) is the only study to focus on the insider trading through supply-chain. They find that corporate insiders from firms that report at least one principal customer systematically yield lower abnormal returns when they sell compared to their counterparts that did not report any principal customer. They attribute the higher return predictability to the closer attention paid by insiders to the public announcement of their economically linked firms. They conclude that insiders are less subject to the attention constraint because they only focus on the value-relevant information for their firms rather than the entire market or industry. Moreover, insider trading literature has commonly accepted that insiders time the market to trade profitably, particularly before some corporate announcements such as share repurchases, seasonal equity offerings, earnings announcements and other price sensitive corporate news announcements (Cziraki, Lyandres and Michaely, 2021; Ali and Hirshleifer; 2017; Cohen, *et al.* 2012). The literature has employed the post-transaction return to gauge the private information embedded in insider transactions (Lakonishok and Lee, 2001; Cohen, *et al.* 2012; Alldredge and Cicero, 2015; Ali and Hirshleifer, 2017). In the same logic, I expect insiders to have informational advantage when their economically linked firms become targets in M&A deals. If insiders better understand the implication of the public announcement of their economically linked firms than the outside investors and trade on it, I expect higher returns predictability associated with these abnormal transactions. Therefore, I propose two complementary hypotheses.

H_1: *Insiders will systematically alter their trading activities and trade profitably to exploit their firm's mispricing after M&A announcement of a target firm in their supply chain.*

I propose two none-mutually exclusive hypotheses, the *productive efficiency hypothesis* and the *purchasing efficiency hypothesis* to explain the informational channels behind informed insider transactions following the M&A announcement. Fee and Thomas (2004) focus on the CAR of corporate customer, suppliers, and rivals of the firms that initiate horizontal mergers to find that merging firms improve their operating efficiency, marketing, or distribution activities, but not their purchasing decisions. These efficiency gains benefit their competitors, suppliers as well as customers. Shenoy (2012) finds similar evidence to support the efficiency enhancing rational. Other studies focus on *acquisition probability hypothesis* as a complement to the *productive efficiency hypothesis* to show that mergers will positively impact the target firm's industry if the deal reveals innovations that would allow competitors to similarly replicate these efficiency gains, but only upon being required (Song and Walkling, 2000; Akhigbe *et al.* 2000; Becher, Mulherin and Walkling, 2012; Cai, Song and Walkling, 2011; Davis *et al.* 2021). However, the industry is likely to be unnecessary for the competitors to be acquired to replicate the efficiency gain as there is a efficiency-spillover effects after the M&A deal (Gaur, Malhotra and Zhu, 2013; Bradley, Desai and Kim, 1988; Eckbo, 1983; Akhigbe, Borde and Whyte, 2000). Fee and Thomas (2004) develop the *purchasing efficiency hypothesis*. They show that the merging firm will gain purchasing efficiency because of their larger demand for input resources, and the efficiency gain will be passed onto their rivals and customers to benefit the entire industry as well as downstream industry. The source of gain is distinct to the production channel because there is no innovation in the source. I summarise these two main hypotheses in Table 3.1.

I propose the insider trading activity of corporate insiders should unbiasedly reflect the change in future business performance due to the M&A deal. Cziraki *et al.* (2021) show that insiders frequently trade on the future change in return on asset to generate abnormal return, Alldredge and Cicero (2015) and Ali and Hirshleifer (2017) show that one of the main sources of insider trading gains is the earnings surprise and Boehm and Sonntag (2021) report that the sales of a firm will be directly affected by the M&A deal of their linked firms. Inspired by these finding, I propose that insiders, through their informed trades, will predict future changes in several accounting measures if they better understand the impact of the deal on their firms. Previous studies also show that managers will systematically increase (reduce) their selling before initiating (receiving) a deal (Akbulut, 2013; Agrawal and Nasser, 2012). This evidence demonstrate that corporate insiders have better understanding of the M&A environment than outside investors, and they actively trade on it. Therefore, I propose my second hypothesis.

H_2: *Insiders' transactions after an announcement that their supply chain firm became a target will predict both the future change in their business performance and the probability of receiving or initiating a bid.*

3.3 Sample and Variable Construction

I combine five different datasets for my empirical analysis: I use SDC Platinum to collect M&A deal announcements, I employ Factset Revere to form supply-chain and competitor relationships, I collect insider transactions from Smart Insider, and I obtain financial and accounting information from CRSP and Compustat.

I first collect a list of US domestic M&A deals with public US target firms from 2003 to 2020, from the SDC Platinum Mergers and Acquisitions database. database. The first year of the M&A deal used in this study is 2003, corresponding to the availability of supply-chain data from Factset Revere. I exclude the deal types of exchange offers, repurchases, spin-off, minority stake purchase, recapitalisation, acquisitions of remaining interest, privatisation, restructuring, reverse takeover, acquisition of certain assets and buybacks to be consistent with the previous M&A literature (Suk and Wang, 2021). To ensure that the economic impact of the acquisition is nontrivial, I exclude deals with values of less than $1 million, where the acquiror already held more than 50% of the target companies' shares prior to the announcement, and when the acquiror did not seek to own more than 50% of the target shares after the deal. I also exclude deals for the same target firm announced within 730 calendar days to ensure a clear treatment effect. The final M&A sample consists of 4,388 deals.

Table 3.1:Hypothesis development and predicted effect

Hypothesis	Competitor	Customer	Supplier	Proposed and supported by
Productive Efficiency: Merging firm will improve their operating efficiency, marking or distribution activity, but excluding purchasing. The improved operating efficiency may be originated from the deal synergy, or the innovation revealed by the deal or both.	**Positive:** Rivals could replicate the efficiency gain. Signaling higher. acquisition probability (Song and Walking, 2000): The market infers from the deal that the industry is undervalued, or the deal will reveal innovations that allow rivals to similarly replicate efficiency through future merge of their own. Signaling industry growth (Eckbo, 1983): the deal will reveal innovations that allow rivals to similarly replicate without being acquired. **Negative:** If rival is not able to replicate the efficiency, they will face comparative disadvantage	**Unaffected or Positive:** IT firm can directly benefit from the downstream efficiency. As Fee and Thomas (2004) explained, the merging target firm can gain a comparative advantage to their competitors, leading to a greater demand for suppliers, and increase suppliers' sales.	**Unaffected or Positive:** The efficiency gain will be passed to their customers, resulting in a cheaper in-put price.	Akhigbe *et al.* (2000); Song and Walking (2000); Fee and Thomas (2004); Cai *et al.* (2011); Becher *et al.* (2012); Shenoy (2012); Akbulut (2013); Davis *et al.* (2021).
Purchasing Efficiency: Merging firm can switch to a cheaper supplier or buy input at a large scale to reduce the cost of goods sold or both. Merging firm's supplier can also realise economies from serving a larger customer.	**Positive:** Rivals can benefit from the cheaper industry-wise input price. **Negative:** Comparative disadvantage if these rivals cannot benefit from the cheaper input price	**Positive:** Although input price might be lower, the larger merged customer will have higher demand and lead to a lower input price for suppliers. **Negative：** Lower input price will lower the earnings for supplier.	**Unaffected or Positive:** The cheaper input-price can be passed to the customers	

I collect the supply-chain and competitor network data from Factset Revere[41], a specialized dataset that describes around 1 million vertical and horizontal relationships of large and mostly listed US and foreign firms between 2003 and 2020. Factset uses its proprietary research method to collect these relationships annually through companies' 10-K fillings, investor presentations, websites, news reports and press releases. The coverage on the supply-chain relationship is much broader than Bloomberg and Compustat Customer file used in Alldredge and Cicero (2015). I compare the Factset with the Compustat Customer file which solely records the principal customer disclosed on the firms' 10-K filling and find that around 97% of the customer relationship reported by Compustat has been included in Factset. I complete the Factset dataset by including the remaining 3% of the relationship in Compustat to make my dataset coverage noticeably broader than the Compustat Customer File which has been the common source for identifying customer and supplier relationships (Fee and Thomas, 2004; Alldredge and Cicero, 2015).

Each Factset relationship has a start date, an end date, relationship type and the identifiers of the source and target firms. Factset reports thirteen different types of relationships, and I follow Boehm and Sonntag (2021) to summarise these relationships into three main categories, competitor, customer, and supplier. If the target company is the source company's (i) manufacturing partner (ii) distribution partner (iii) marketing partner (iv) in-licensing partner (v) product licensing partner, and/or (vi) technology partner, then the target company is deemed as the supplier of the source company. If the target company is the source company's out-licensing partner, then the target company is deemed as the customer of the source company. I discard the relationship type of (i) equity investment (ii) investor (iii) joint venture (iv) integrated product offering, and (v) research collaborator. I further annualise the relationship data: when the distance between the start date and end date is longer than one calendar day, I recognise these two firms are linked in the year. I combine the relationship dataset with my SDC deal list using *cusip* code and keep the 1,266 deals in which the target firm has at least one linked firm in the year of the M&A announcement. I refer to the target firm in the M&A deal as the linked firm and firms linked to the target firms as insider trading firms (IT firms), making IT firm as the target firm's competitor, supplier, and/or customer. I exclude deals if the IT firm is also linked to the acquiror or has more than one of its linked

[41] Factset Revere is available on WRDS. The dataset has been successfully accepted in finance and economics literature such as Gofman and Wu (2022), Ding *et al*. (2021) and Boehm and Sonntag (2021) and widely applied in supply-chain management literature such as Son, Chae and Kocabasoglu-Hillmer (2020). Boehm and Sonntag (2021) and Ding *et al.* (2021) provide a detailed discussion on its coverage and structure.

firms become the target firm in the same year, or the deal is eventually not completed. After this merge, the M&A list drops to 955 deals.

I compiled all insider transactions from Smart Insider Ltd for these IT firms in the sample period[42]. I keep all insider open market transactions in Form 4 and exclude transactions with less than 100 shares, transactions for non-common shares, in line with insider trading literature (Lakonishok and Lee, 2001; Cohen *et al.* 2012), and any pre-scheduled trades, known as 10b5-1 trades, because the information content embedded is likely to be trivial[43]. I only keep the transactions submitted by the CEO, CFO, COO, chairman of the board and president because these top managers have the best access to the most price-sensitive private information, and they actively trade on it for personal gains (Cohen *et al.* 2012; Cziraki *et al.* 2021). Additionally, I follow Cohen *et al.* (2012) to identify "routine" traders. At the beginning of each year, I classify "routine" traders as insiders who have been trading in the same calendar month, in the same direction in the past three calendar years. These insiders follow a clear trading pattern and the true motivations behind their transactions are less likely to be trading on private information for reaping abnormal returns. Thus, I exclude all their transactions in the year from my sample. I further collect financial data from CRSP and accounting data from Compustat and only focus on the common shares with the share class code of 10 or 11. I collect analyst coverage data from I/B/E/S and institutional ownership from Thomson Reuters Institutional Holdings File.

I report the screening details in Appendix 3.1 Panel A. My final sample consists of 685 M&A deals undertaken by 559 distinct acquirors for 681 distinct targets with 1,413 distinct IT firms and 2,669 distinct insiders who trade at least once in the months (-12, 2). Appendix 3.1 Panel B and C show the annual and industry distribution of my sample. There is a clear upward trend in the M&A sample included in the study because Factset keeps improving its coverage

[42] This database (https://www.smartinsider.com/), formerly known as Directors Deal Ltd, gathers information from Form 5, the annual statement of change in beneficial ownership and reports any and exempt transactions not reported on Form 4. Previous studies, including (Fidrmuc, Korczak and Korczak, 2013; Goergen, Renneboog and Zhao, 2019) used it.

[43] To minimise the impact of insider transaction on the stock price, SEC allows insider to pre-announce their transaction plan before the actual transaction date. Insiders will relinquish insider control over the plan and allow their brokers to execute their pre-announced transactions on the pre-determined date without allegations of illegal insider trading. As an example, Bill Gates has a long-term 10b5-1 plan and has been regularly selling more than 2 million common shares of Microsoft each year over the last 20 years. However, recently, Larcker *et al* (2021) show that insiders do use 10b5-1 plans to trade opportunistically mainly by setting them with a short cooling-off period and adopting them just before that quarter's earnings announcement. Franco and Urcan (2022) find that insiders trade profitable by using equity deferrals to circumvent Rule 10b-5 trading restrictions through the timing and content of corporate disclosures around these trades. In my sample, these plans are relatively trivial, I excluded them in my analysis.

on large US firms. More than 50% of the M&A sample occurred after 2015. I include 75 deals in 2017 and only 12 in 2003. The industry distributions of IT and target firms linked as competitors are similar because firms in the same industry are more likely to be competing. The industry "Machinery and Business Equipment" accounts for the second most of the IT firm samples under all three types of relationship. The distribution of IT firms in the Fama-French 17 industry is overall consistent with Alldredge and Cicero (2015).

Agrawal and Nasser (2012), Suk and Wang (2021) and Fidrmuc and Xia (2021) have shown that insiders from the target firm in an M&A deal tend to adopt a passive trading strategy that they sell much less than they did one year before the deal announcement because of the high litigation risk involved with actively trading prior to M&A announcement. To control for this possible trading strategy, I aggregate these insider transactions at the insider-firm-month level and compute the net purchasing value (NPV) as the purchase transaction dollar value minus sell transaction dollar value over the total dollar value[44] to measure insider trading direction (Lakonishok and Lee, 2001). If *NPV* is greater (less) than 0, I recognise that the insider is net buying (selling) in each month.

$$\mathrm{NPV}_{\mathrm{i,j,m}} = \frac{\$\mathrm{purchase}_{i,j,m} - \$\mathrm{sell}_{i,j,m}}{\$\mathrm{purchase}_{i,j,m} + \$\mathrm{sell}_{i,j,m}}$$

My main empirical analysis is to investigate whether insiders' transactions in IT firms following an M&A announcement of their linked firms generate higher abnormal returns, proxied using the buy-and-hold (BHAR) abnormal return for holding period *t* as follow:

$$BHAR_{i,j,m} = \prod_{k=1}^{30}(1 + return_{j,t+k}) - \prod_{k=1}^{30}(1 + mkt_{t+k})$$

where $return_{t+k}$ is the log raw return generated by the IT firm *j* over the over the holding period t+k and mkt_{t+k} is the corresponding benchmark return. I measure BHAR from one day after the transaction date to the next 30-calendar days, in line with Cohen and Frazzini (2008), Cohen *et al.* (2012) and Alldredge and Cicero (2015) because the stock mis-valuation through the supply-chain caused by limited attention of uninformed investors is mainly in the short term. As the first proxy, I use the CRSP value-weighted market index return to adjust the

[44] In literature, net purchasing ratio, which is the ratio of 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, I repeat all regression by using NPR as well, and the result is virtually unchanged because the correlation between NPR and NPV is generally around 0.93.

holding period return, and the abnormal return is denoted as $BHAR\_m\_30_{i,d}$. For the second proxy, denoted as $BHAR\_ff\_30_{i,d}$,we employ the appropriate size decile portfolio of firms based on NYSE size breakpoints (Alldredge and Cicero, 2015)to control for the unobservable market-related risk that affects all firms with similar size during the same 30-day holding period[45]. A valid $BHAR_{it}$ must have at least 20 trading days in the holding period as suggested by Agrawal and Nasser (2012). Appendix 3.2 presents the constructions of all the variables.

One major concern in insider trading literature is endogeneity induced by omitted variable bias because the true motivation behind insider transactions is not observable. Insiders can make purchase transactions to support the stock price when there is an increase in short interests (Wu, 2019) when their firms are undervalued (Lakonishok and Lee, 2001). In the same vein, insiders will sell their firms' stock, some of which are stock options, for personal liquidity need, gradually unwind their share positions to diversify (Huddart and Ke, 2007), or for personal gains (Contreras and Marcet, 2021). The omitted variable bias will lead to an inconsistent OLS estimate for estimating the treatment effect. I use an extensive set of explanatory variables to control insider trading return and include firm, insider, and month-year fixed effects to proxy for time-invariant unobservable variables to eliminate potential endogeneity[46].

Nevertheless, I recognise that these approaches do not completely solve the endogeneity issue. I follow Cziraki *et al.* (2021) to specify a diff-in-diff regression based on a matched sample as my baseline regression to eliminate the concern that unobservable market anticipation will bias my results. I match each IT firm with a control firm in the same month by restricting that the control firm is not linked to the same linked firm in Factset. Furthermore, the control firm does not have any linked firms become the target in a deal in the last and next 12 calendar months. I select control firms by matching my IT firms with a single firm with the shortest Mahalanobis distance on the cumulative return in the last six months, the logarithm of the total asset and the book-to-market ratio at the month *t-1.* I match each treated firm with only one specific control firm to minimize any biasedness. I specify baseline diff-in-diff regression as follows:

[45]http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. I thank Professor French for making these data publicly available.
[46] In unreported results, I replicate all diff-in-diff regressions with firm, insider, and year fixed effects, all my results remain robust.

$$NPV_{i,j,m} = \alpha + \beta_1 Post_{i,t} + \beta_2 Treat_{i,t} + \beta_3 Post \times Treat_{i,t} + controls + \tau + \gamma + \rho + u_i$$

Where τ, γ and ρ are firm, insider and month-year fixed effect, respectively. I cluster my standard errors at the firm-month level as Alldredge and Blank (2019) show that insiders cluster their trades with their colleagues. The main independent variables include treatment dummy $treat_i$ that equals to one for firms that have their linked firms become the target, the post-treatment period dummy $post_t$ that equals one for month (0,2) with month 0 as the M&A announcement month, and their interaction $treat \times post_t$. I focus on three months from 0 to 2 post-M&A announcements because the stock misevaluation caused by the market attention constraint is mainly a short-term phenomenon (Cohen and Frazzini, 2008). I use samples in month (-12, 2) to estimate the baseline diff-in-diff regression. If there is a systematic increase (decrease) in the insider transactions after the M&A announcement, β_3 should be positive (negative) and statistically significant.

To capture the incremental increase in insider trading predictability solely attributed to the M&A announcement of their linked firms rather than the firm performance, I include various control variables in my regression to account for the insider trading activity explained by the firm and insider personal characteristics (Lakonishok and Lee, 2001; Cohen *et al.* 2012; Akbulut, 2013). Other control variables are the logarithm of the market capitalization at the end of each month $Ln(makt\_cap)_{j,m}$, momentum $mom_{j,m,(d-1,d-365)}$, book-to-market ratio $bm_{j,m-1}$, percentage of shares owned by institutional investors $insti\_hold_{j,q}$, Herfindahl index based on the number of institutional investors $insti\_HI_{j,q}$, Amihud (2002) illiquidity measure $illiq_{j,m-1}$, sell-side analyst coverage $numest_{j,t-1}$, return on asset $roa_{j,t-1}$, research and development cost $rd_{j,t-1}$, leverage $lever_{j,t-1}$, the total normalised trading volume $vol_{j,(-90,-1)}$, annualised standard deviation of stock return $sd_{j,(-365,-1)}$, the change in standard deviation $delta\_sd_{j,(m-3,m-1)}$. I proxy the age of insiders as the time distance between their first occurrence in Smart Insider and the insider trading day, and I proxy the tenure using the distance between their first occurrence in the same firm and the insider trading day. I also include $competitor_{j,t}$, $customer_{j,t}$ and $supplier_{j,t}$ that is dummy variable equals one if the acquiror is a competitor, customer or supplier of the target firm, respectively, and zero otherwise. Appendix 3.2 provides further details.

3.4 Empirical Results

3.4.1 Univariate Evidence

I present the descriptive statistics in Table 3.2. In Panel A, I report the monthly average of all variables included in the regression for these three types of relationship separately. The average total asset is \$17.5 billion, \$14.6 billion, and \$53 billion for the competitor, customer and supplier, respectively. IT firms that have their suppliers become the target are larger than other IT firms because firms with major suppliers are more likely to be in the asset-intense industry and produce at a larger scale, and therefore, expected to have more assets. In contrast, the differences between their market capitalisations are relatively smaller. IT firms that have their competitor, customer or supplier becomes the target are on average worth \$14.2 billion, \$16.6 billion, and \$26.0 billion, respectively. The relatively smaller difference in market capitalisation is also reflected in the similar book-to-market value. IT firms' average book-to-market ratio is 0.416 for the competitors, close to the 0.424 of the IT firm for the customer, but smaller than the 0.47 for the supplier. The suppliers of IT firms have also a relatively larger sell-side analysts followers, but the age and tenure of the insiders are relatively homogeneous across the three types of relationships.

I have observed at least one competitor relationship between IT and target firms in 457 deals, customer relationship in 287 deals and supplier relationships in 318 deals. There are 1,106 competitor relationships, and only 305 out of 1,106 have IT and target firms in the same four-digit SIC industry. The four-digit SIC industry has been the primary way to identify competitors in the literature (Fee and Thomas, 2004; Davis *et al.* 2021), but Factset's proprietary research method will enable me to identify a larger number of competitor relationships between firms in different industries[47]. More than 80% of these M&A deals are diversification deals, where the acquiror is unrelated to the target in the Factset dataset mainly because of my restriction that the IT firm is unlinked to the acquiror. If the acquiror is linked to the target, the likelihood that the acquiror is also linked to the IT firm is high. The average market value of the customer target firm is \$4.4 billion, and the average deal value of the customer target firm is \$6 billion, are both the largest among these three relationships because

[47] It is far from reality that firms only compete with peers in the same four-digit SIC industry. For instance, Amazon (gvkey: 064768) which has primary SIC code 5961(Catalog and Mail-Order Houses) is competing with Oracle (gvkey: 012142) which is in the SIC industry 7372 (Pre-packaged Software) over their cloud computing and storage services since 2016. Also, Compustat Segment file would not correctly identify the competitor relationship. Factset identifies the competitor relationship, but the conventional four-digit SIC code method does not. The competitor relationship has been reported by Oracle on its website. https://www.oracle.com/cloud/oci-vs-aws/

major customers are larger firms that produce at a larger scale. However, the average bid premium of these three types is similar, ranging from 34% to 37%. I also report the insider trading activity measured between month (-6, -1). The average NPV for all three types is negative and ranges from -0.50 for the competitor to -0.63 for the customers. The negative NPVs are consistent with the insider trading literature because insiders are frequently rewarded free shares in the form of stock options from the compensation committee to align CEOs' interests with the shareholders (Lakonishok and Lee, 2001).

In Panel B, I report the cumulative abnormal return (CAR) for the M&A announcement effect for all acquiror, target and IT firms. I use the standard event study methodology to calculate CAR. The market model parameters are estimated over the 200 trading day period starting at day -240 relative to the M&A announcement date. I employ the CRSP value-weighted index as the market return and require at least 100 trading days over the estimation window for a firm to be included in the sample. Notably, I compute and report the CAR for IT firms even if they do not report any insider transactions in my focus period. I report three different event windows that are around day (-1,1), (-3,3) and (2,30) for all three relationships. The target firm CAR (-1,1) is 27.1%, 25.5% and 25.9% for competitor, customer, and supplier relationship, respectively, while the respective acquiring firms' CARs are -1.1%, -1.3% and -1.5%, in line with previous empirical literature. The IT firms generate some excess returns over the event periods, but they are not all significant and their magnitude is much smaller. Although the competitor relationship is identified using a different method, the positive CAR is consistent with the Fee and Thomas (2004) and Davis *et al.* (2021). The relatively small scale of CAR (-1,1) provides an opportunity for insiders to time the market because insiders have a better understanding of the impact of the M&A deal on their companies. Cohen and Frazzini (2008) and Alldredge and Cicero (2015) have shown that the limited attention of outside investors will lead to an insufficient price adjustment, leading insiders to trade on the public announcement for personal gains.

Table 3.2: Descriptive statistics

This table Panel A reports the summary statistics for the insider trading firms around month (-12, 2), M&A announcement is in month 0, I aggregate all insider transactions at monthly level. The row "Competitor", "Customer" and "Supplier" mean the M&A target firm is the competitor, customer or supplier of the insider firm, respectively. Panel B reports the cumulative abnormal return around the M&A announcement for deal target, acquiror and insider trading firms. The CAR is computed by using the market model over the 200 trading days period starting at day -240 relative to the M&A announcement date. I require at least 100 trading days over the estimation window for a firm to be included in the sample. I use CRSP value weighted market index as the market return. All firms reported in Panel B are not conditioning on there is at least one insider transactions in month (-12, 2). Appendix 3.2 details all the variables. ***, **, * indicate the sample mean is statistically different at the 99%, 95% and 90% confidence level, respectively. ***, **, and * denote significance at the 99%, 95% and 90% confidence level, respectively. All variables are winsorised at the top 99% and the bottom 1% level.

Panel A: Summary statistics for insider trading firms

	Competitor			**Customer**			**Supplier**		
	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD
IT firm characteristics around month (-12, 2)									
$total\_asset_{j,t-1}$($m)	17,542	2,016	73,235	14,573	1,170	50,596	53,099	8,131	155,649
$mkt\_cap_{j,m}$($m)	14,235	2,834	31,136	16,595	2,022	37,755	26,053	10,789	42,042
$momentum_{j,m(d-365,d-1)}$	0.416	0.314	0.380	0.424	0.311	0.395	0.470	0.346	0.409
$illiq_{j,m-1}$	0.003	0.000	0.013	0.004	0.000	0.016	0.001	0.000	0.007
$bm_{j,m-1}$	0.416	0.314	0.380	0.424	0.311	0.395	0.470	0.346	0.409
$numest_{j,t-1}$	13	10	10	12	9	9	17	17	9
$Insti\_hold_{j,q}$	0.722	0.800	0.256	0.730	0.795	0.242	0.752	0.808	0.224
$Insti\_HI_{j,q}$	93.030	25.229	465.226	71.835	27.177	300.985	103.457	14.130	563.220

$roa_{j,t-1}$	0.014	0.045	0.161	0.010	0.039	0.143	0.039	0.044	0.100
$rd_{j,t-1}$	0.123	0.010	0.347	0.101	0.034	0.210	0.061	0.000	0.188
$leverage_{j,t-1}$	0.210	0.165	0.210	0.207	0.174	0.192	0.263	0.240	0.204
$age_{i,d,m}$	11.458	11.008	7.348	10.850	10.074	7.551	11.784	11.121	7.699
$tenure_{i,j,d,m}$	7.989	6.455	6.560	7.473	5.427	6.707	8.341	6.984	6.809
$vol_{j,(d-90,d-1)}$	0.652	0.472	0.574	0.620	0.456	0.536	0.705	0.509	0.618
$sd_{j,(d-365,d-1)}$	0.451	0.387	0.227	0.487	0.431	0.235	0.395	0.337	0.205
$delta\_sd_{j,(m-3,m-1)}$	-0.004	-0.007	0.169	-0.007	-0.012	0.180	-0.009	-0.011	0.144
Observations	2,862			1,709			2,189		
Deal and Relationships Characteristics									
No. Deals	457			287			318		
No. Relationships	1,106			598			812		
IT and target in the same 4-digit SIC	305(28%)			43(7%)			32(10%)		
IT and target in the same 2-digit SIC	683(62%)			133(22%)			145(18%)		
Diversification Deal (Bidder unrelated to Target)	385(84%)			252(88%)			270(84%)		
Target Market Cap 4-weeks ago ($m)	2,494	609	6,639	4,415	1,090	8,964	2,690	533	6,774

Deal Value ($m)	3,329	800	9,006	6,001	1,557	12,123	3,578	687	8,929
Tender Offer	0.178	0	0.383	0.133	0	0.341	0.192	0	0.395
Bid premium (%)	37.5	30.18	34.83	34.05	28.13	32.86	37.00	31.5	33.10
Insider trading measure between month (-6,-1)									
NPV	-0.505	-1	0.857	-0.545	-1	0.833	-0.634	-1	0.767
Distinct Director	1,397			794			1029		
Distinct Firms	875			480			566		

Panel B: CAR around M&A announcement unconditional on insider trading

	Competitor			**Customer**			**Supplier**		
	$CAR_{(-1,1)}$	$CAR_{(-3,3)}$	$CAR_{(2,30)}$	$CAR_{(-1,1)}$	$CAR_{(-3,3)}$	$CAR_{(2,30)}$	$CAR_{(-1,1)}$	$CAR_{(-3,3)}$	$CAR_{(2,30)}$
Target Firm	0.271***	0.279***	-0.006	0.255***	0.266***	-0.002	0.259***	0.270***	-0.004
	(0.013)	(0.013)	(0.005)	(0.013)	(0.014)	(0.005)	(0.013)	(0.013)	(0.005)
Sample	481	481	480	395	395	395	384	384	385
IT Firm	0.007***	0.008***	-0.005*	0.002*	0.004**	-0.000	0.000	0.003**	0.002
	(0.001)	(0.001)	(0.003)	(0.001)	(0.002)	(0.003)	(0.000)	(0.001)	(0.002)
Sample	3,251	3,251	3,249	1,762	1,762	1,754	2,725	2,725	2,725
Acquiror Firm	-0.011*	-0.009	-0.017*	-0.013**	-0.012	-0.031***	-0.015**	-0.012*	-0.025**
	(0.006)	(0.006)	(0.010)	(0.006)	(0.007)	(0.010)	(0.006)	(0.007)	(0.011)
Sample	221	221	221	177	177	177	165	165	165

Table 3.3 Panel A reports the summary statistics between my treated and control IT firms during the pre-treated period. The results show that the difference between the treated and control firm in the $Sum\_NPV_{(-6,-1)}$ and $Sum\_NPV_{(-12,-1)}$, which represent the aggregate insider trading pressure calculated for the corresponding period at the beginning of month 0, is not statistically significant, highlighting the appropriateness of my matching algorithm, even though I do not match on these two variables. Similarly, my treated and matched firms have similar book-to-market ratios, $bm_{j,m-1}$, and 6-month return, $ret6_{j,m,(d-1,d-180)}$, but my treated firms are marginally larger than the matched firms competitors and suppliers. To better understand the impact of the difference, I investigate the scale of the difference in market capitalisation between treated and control firms. I find that the difference for competitor relationship is on average 7.7% and 17.8% of the standard deviation computed using all CRSP firms in the month -1 for competitor and supplier, respectively. Furthermore, if I divide all firms into deciles according to their market capitalisation at the end of month -1, all pairs of treated and control firms are in the same size decile and the difference is on average 43% and 72% of the standard deviation computed in the size decile for competitor and supplier, respectively. These two differences are statistically significant but economically small, and therefore I recognise that my matching algorithm remains appropriate. In addition to these variables that have been employed in the matching algorithm, other variables remain mostly insignificant between treated and control firms. Treated firms have a lower return on asset than control firms for competitor relationship, and lower insider trading profitability than control firms for supplier relationships.

In Panel B, I focus on the difference between treated and control firms in the post-announcement period. Insiders in the treated firms systematically sell less shares than control firms for competitor and customer relationships but sell more for supplier relationship after their linked firms have become the target in a deal. More remarkably, insiders from treated firms systematically incorporate more private information into their transactions because their trades are more profitable than their counterparts' from the control firms. Their purchase transactions generate higher abnormal returns for customer and supplier relationships. In contrast, their sell transactions yield lower abnormal returns which is a gain for sell transactions for competitor and customer relationships. The increase in the return predictability remains significant when the abnormal return is measured by $BHAR\_m\_30_{i,d}$.

Table 3.3: Summary statistics around M&A announcement

This table Panel A reports the summary statistics for the nearest neighbour matching. Appendix 3.2 details all the variables. Firms that have either their competitor, customer or supplier becomes the target in a M&A deal in month 0 are matched with one firm on the cumulative return in the last six months, the book-to-market ratio and the logarithm of market capitalisation at the end of month -1. The distance is calculated by using Mahalanobis distance. I restrict that the control firm will not have any of its competitor, customer or supplier became the target in the month (-12, 12) with month 0 as the M&A announcement month. $Sum\_NPV_{(-6,-1)}$ is the NPV calculated by aggregating all insider transactions for a given insider between month (-6, -1). Column (3), (6) and (9) report the t-test results by assuming unequal variance between treated and control firms for insider purchase and sell transaction, respectively. Panel B compares the monthly insider trading activities between treated and control firms.

Panel A: Summary statistics for treated and control firms

	Competitor			Customer			Supplier		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Treated	Matched	Diff	Treated	Matched	Diff	Treated	Matched	Diff
$Sum\_NPV_{(-6,-1)}$	-0.478	-0.486	0.008	-0.570	-0.591	0.021	-0.641	-0.629	-0.123
	(0.026)	(0.021)	(0.033)	(0.031)	(0.025)	(0.040)	(0.028)	(0.022)	(0.036)
$Sum\_NPV_{(-12,-1)}$	-0.504	-0.511	0.007	-0.575	-0.605	0.031	-0.694	-0.661	-0.032
	(0.023)	(0.020)	(0.030)	(0.028)	(0.024)	(0.037)	(0.023)	(0.021)	(0.031)
$bm_{j,m-1}$	0.492	0.477	0.015	0.474	0.457	0.016	0.499	0.496	0.003
	(0.012)	(0.010)	(0.015)	(0.015)	(0.012)	(0.019)	(0.014)	(0.011)	(0.018)
$ret6_{j,m,(d-1,d-180)}$	0.067	0.081	-0.014	0.090	0.095	-0.005	0.068	0.078	-0.009
	(0.008)	(0.007)	(0.010)	(0.010)	(0.009)	(0.013)	(0.007)	(0.006)	(0.009)
$Ln(makt\_cap)_{j,m}$	7.454	7.296	0.158**	7.493	7.382	0.111	8.806	8.430	0.376***

	(0.049)	(0.048)	(0.069)	(0.067)	(0.057)	(0.088)	(0.075)	(0.065)	(0.099)
$roa_{j,t-1}$	-0.028	-0.009	-0.019*	0.006	-0.000	0.007	0.032	0.032	0.001
	(0.009)	(0.005)	(0.010)	(0.005)	(0.008)	(0.009)	(0.005)	(0.005)	(0.007)
BHAR_m_$30_{i,d}$	0.005	-0.001	0.006	0.004	0.001	0.003	-0.012	0.002	-0.010*
	(0.005)	(0.002)	(0.006)	(0.006)	(0.003)	(0.007)	(0.005)	(0.002)	(0.006)
BHAR_ff_$30_{i,d}$	0.001	-0.001	0.002	0.002	-0.000	0.002	-0.020	-0.002	-0.018***
	(0.005)	(0.002)	(0.006)	(0.005)	(0.003)	(0.006)	(0.005)	(0.002)	(0.006)

Panel B: Insider trading around supply chain firms' M&A announcement month (0,2)

	Competitor			Customer			Supplier		
	Treated	Matched	Diff	Treated	Matched	Diff	Treated	Matched	Diff
NPV	-0.488	-0.550	0.061**	-0.581	-0.673	0.091*	-0.731	-0.608	-0.123***
BHAR_m_$30_{i,d}$(Buy)	-0.004	-0.006	0.002	0.051	0.005	0.047***	0.032	-0.009	0.041**
BHAR_m_$30_{i,d}$(Sell)	-0.006	0.001	-0.007*	-0.007	0.003	-0.010*	0.002	0.002	0.00
BHAR_ff_$30_{i,d}$(Buy)	0.016	-0.008	0.024**	0.045	-0.000	0.045***	0.026	-0.009	0.035***
BHAR_ff_$30_{i,d}$(Sell)	-0.006	0.001	-0.007*	-0.008	0.002	-0.010*	0.001	0.003	-0.002

Their purchase transactions generate higher abnormal returns for customer and supplier relationships. In contrast, their sell transactions yield lower abnormal returns which is a gain for sell transactions for competitor and customer relationships. The increase in the return predictability remains significant when the abnormal return is measured by $\mathrm{BHAR\_m\_30}_{i,d}$. The univariate evidence is consistent with Alldredge and Cicero (2015) which reports that insiders' sell trades are loss averting when firms report major customers.

I further conduct a formal parallel trend assumption test following Angrist and Pischke (2009), Cengiz *et al.* (2019) and Aktas *et al.* (2021). I define variable pre_m **(**Post_m) equal to 1 for treated firms in pre- (post-) M&A announcement month 0, and zero otherwise. If the parallel trend assumption holds, most of the pre_m should remain statistically insignificant. I control for the same set of control variables as in my baseline diff-in-diff regression and present the result in the Appendix 3.3. The coefficients of Pre_m are mostly statistically insignificant for all three relationships and for all three different dependent variables, meaning the trend in month (-12, -1) between control and treated firm is parallel after controlling for firm characteristics that can explain insider trading activity and return. The regression output alleviates the concern that the post-announcement results are driven by the matching algorithm's inappropriateness to obtain the control group and the use of the diff-in-diff estimator. Remarkably, I do not directly match on the insider trading activity in the pre-announcement period, but there is no significance difference in monthly average NPV between treated and control firms from month (-6, -1), implying the probability of M&A information leakage is low or it is likely that insiders are not trading on the upcoming M&A information before the public announcement.

3.4.2 Insider trading activity around the M&A announcement

I report the regression output for my baseline diff-in-diff regression in Table 3.4 and only report the coefficients of a selected range of control variables for brevity. I estimate the regression for competitor, customer, and supplier separately and report regression results in column (1), (3) and (5), respectively. The results show that the coefficients of $(\mathrm{Post}\times\mathrm{Treat})_{I,t}$ are 0.044 and 0.062 when targets are competitor and customer in the supply chain, respectively, both statistically significant at the 95% confidence level, but not significant if the target is the supplier. If an IT firm's competitor or customer has become the target in an M&A deal, the expected net purchase ratio will increase by 4.4% and 6.2% for competitor and customer, respectively. If I use the average insider trading value between month (0, 2) to compute the economic impact, insiders will buy an additional \$223,523 and \$570,957 worth of shares for the competitor and customer relationship, respectively. However, the previous univariate evidence indicates that the average NPV remains negative after the M&A announcement, and therefore these results support my hypothesis that the M&A announcements for their competitor and supplier systematically motivate insiders to sell less than they would otherwise do. The higher net purchase ratio implies that the outside investors fail to incorporate all the information of the M&A deal through the supply chain. Therefore, these IT firms remain mispriced even two months after the announcement month. Insiders from IT firm consider their firm to be undervalued as the full impact of the M&A deal announcement has not been incorporated into its stock prices. Consequently, they keep their positions for a longer period to generate a higher abnormal return for personal gain.

The coefficients of $\mathrm{Ln(makt\_cap)}_{j,m}$ and $\mathrm{mom}_{j,m.(d-1,d-365)}$ are all negative and significant across all three types relationships, suggesting that insiders are more likely to sell their shares when their firm is large and its stock returns are high, in line with previous literature that documents that these two factors are the major determinants of insider trading activity (Lakonishok and Lee, 2001; Cohen *et al.* 2012). I include $\mathrm{Competitor}_{j,t}$, $\mathrm{Customer}_{j,t}$, and $\mathrm{Supplier}_{j,t}$ to control for the relationship between the acquiror and target firms. For competitor relationship, if the focal acquiror is the competitor with the target firm, insiders from a non-focal competitor will reduce their selling with a greater intensity as evident by the significant and positive coefficient of the $\mathrm{Competitor}_{j,t}$. On the other hand, insiders are less likely to reduce their selling when the deal is a vertical integration, meaning the target firm is already the supplier of the acquiror before the announcement date. In unreported results, I find that the coefficients of the other control variables are mostly insignificant and thus omitted.

The coefficients of institutional holding $\mathrm{insti\_hold}_{j,q}$ and the Herfindahl index $\mathrm{insti_HI}_{j,q}$are mostly insignificantly, highlighting that the trading decision of insiders is not affected by the presence of institutional investors. The results suggest that the informational content embedded in corporate insider trading is complementary to that obtained by other informed investors, such as mutual fund managers, consistent with the finding that insiders generally trade on different informational contents with other informed investors (Fishman and Hagerty, 1992; Hsieh *et al.* 2019; Wang, 2019).

Table 3.4: Insider trading activity around M&A announcement

This table report the diff-in-diff regression result. The dependent variable is $NPV_{i,m}$ computed at the monthly level. $(Post\times Treat)_{i,t}$ is a dummy variable equals to one for firms that have a linked firms become the target in a M&A deal in month *m*, and zero otherwise. In column (2), (4) and (6), I exclude the top quintile samples and their corresponding control firms with the most competitor, customer and supplier, respectively. $Competitor_{j,t}$,$Customer_{j,t}$,$Supplier_{j,t}$ is dummy equal to one if the target firm is acquiror's competitor, customer or supplier, respectively Appendix 3.2 details all the variables. I include sample in pre-announcement month (-12,-1) and post-announcement period (0,2). Standard errors reported in parentheses are computed based on robust standard errors clustered at the firm-month level. ***, **, and * denote significance at the 99%, 95% and 90% confidence level, respectively. All variables are winsorised at the top 99% and the bottom 1% level.

	Competitor		**Customer**		**Supplier**	
	All	No top quintile	All	No top quintile	All	No top quintile
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	NPV	NPV	NPV	NPV	NPV	NPV
$TreatD_{i,j}$	0.085**	0.080*	0.105**	0.102	0.062	0.068
	(0.037)	(0.048)	(0.052)	(0.063)	(0.040)	(0.045)
$PostD_{i,j}$	-0.001	0.012	-0.001	-0.026*	0.041***	0.044***
	(0.010)	(0.012)	(0.011)	(0.013)	(0.015)	(0.016)
$(Post \times Treat)_{i,t}$	0.044**	0.045**	0.062**	0.072**	-0.016	-0.018
	(0.021)	(0.023)	(0.024)	(0.031)	(0.023)	(0.026)
$Ln(makt\_cap)_{j,m}$	-0.201***	-0.208***	-0.163***	0.065	-0.125**	-0.094
	(0.040)	(0.046)	(0.057)	(0.059)	(0.058)	(0.063)
$mom_{j,m.(d-1,d-365)}$	-0.128***	-0.102***	-0.085**	-0.115***	-0.112***	-0.116***
	(0.034)	(0.034)	(0.035)	(0.030)	(0.037)	(0.041)
$Competitor_{j,t}$	0.043**	0.067***	0.020	0.037	-0.131	-0.008
	(0.017)	(0.021)	(0.016)	(0.029)	(0. 011)	(0.013)
$Customer_{j,t}$	0.081	0.072	-0.031	-0.034	0.046	0.041
	(0.051)	(0.055)	(0.024)	(0.024)	(0.045)	(0.055)
$Supplier_{j,t}$	-0.100***	-0.132***	0.002	0.001	0.041*	0.037
	(0.034)	(0.048)	(0.015)	(0.014)	(0.025)	(0.027)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Insider FE	Yes	Yes	Yes	Yes	Yes	Yes
With-in R^2	0.07	0.07	0.05	0.04	0.05	0.06
Sample	7,276	6,399	4,240	3,103	5,122	4,351

I further remove IT firms with many linked firms because losing one of them is unlikely to substantially impact the business prospects. The exclusion of these treated firms should not weaken my results, and this refined sample will serve as a robustness test for the regression. In each month, I divide all IT firms of each relationship type into quintiles in accordance with the number of linked firms. I remove the top quintile and their corresponding control firms from the sample and re-estimate these baseline regressions. I report the results in columns (2), (4) and (6). The coefficients of $(\text{Post} \times \text{Treat})_{i,t}$ remain positive and statistically significant at the 95% confidence level for competitor and customer, but still insignificant for the supplier, implying that my previous results are robust to the exclusion. Overall, these results support my hypothesis that insiders trade on the M&A announcement of their economically linked firms.

3.4.3 Target firm heterogeneity

In this section, I further explore the target firm heterogeneity. Although I cannot directly support the productive efficiency and purchasing efficiency hypotheses, the heterogeneity analysis will shed additional light on the plausibility of these two hypotheses. I first focus on the specificity of the target firms. I assume that if they produce homogeneous products, then insiders from IT firms are likely to sell less with greater intensity because it is easier for merging firm to obtain the purchasing efficiency as the demand for the input resource of homogeneous product is larger. Consequently, the purchasing efficiency is easier to be passed onto their competitors and customers, but the effect is unclear for their suppliers as suggested in Table 3.1.

I follow Barrot and Sauvagnat (2016) and use two proxies to identify target firms that produce homogeneous products. I first borrow the industry classification from Rauch (1999)[48] who classifies 1,189 four-digit SITC Rev.2 system industry codes into homogeneous and differentiated product industry. The classification scheme recognises that products sold on an organised exchange or are reference priced are more likely to be homogeneous products, and other products are differentiated products. I use Feenstra (1996)[49] to link the SITC code with SIC code, and code industry that is on an organised exchange as 0, in the reference priced industry as 1 and producing differentiated product as 2. Since one SITC code can correspond to several SIC code, I compute the average for a SIC code, and classify a SIC industry is producing homogeneous product if it lies below the median along this dimension (Barrot and

[48] I thank Professor Rauch to make the data public https://econweb.ucsd.edu/~jrauch/rauch_classification.html
[49] I thank Professor Feenstra to make the data public https://cid.econ.ucdavis.edu/usix.html

Sauvagnat, 2016). I create a dummy variable $homo_{i,j}$ equal to one for firms in the homogeneous product industry and zero otherwise. For the second measure, I employ the number of patent that a firm receives to proxy its specificity. I hypothesise that firms that receive more patents are specialised. I collect the number of patents from USPTO, and use the link table provided by Arora, Belenzon and Sheer (2021) to match the firm with their patents granted prior to 2015. For those granted after 2015, I manually match the name, state and city of assignees using fuzzy matching algorithm. I further consider firms in the top quintile portfolio formed according to the number of patents granted in a year to be innovative, and assigned a dummy $innov_{i,j}$ equal to one and zero otherwise.

I employ these two moderators in the diff-in-diff regression and report the regression in Table 3.5 Panel A and B. I control for all the main levels of interaction variables and omit their outputs for brevity. From Panel A, I observe that insiders will significantly reduce their selling with greater intensity when the target firm is producing homogeneous products for competitor and supplier relationships. The result is consistent with Panel B in which I proxy differentiated product producer using the number of patents. Insiders reduce their selling with lower intensity when the target firm is innovative firm for competitor and supplier relationship. These results support the purchasing efficiency hypothesis that the merging firm can increase their purchasing power to lower the input price, and the efficiency gain will be shared with their industry peers and customer firms. The result is insignificant for customer relationship because the overall effect on the IT firm is not significant. The lower input price is a negative news for IT firms, but the merging firm will have a larger demand, and consequently, the net effect is zero for IT firms.

Table 3.5: M&A target firm heterogeneity

This table report the diff-in-diff regression result by interacting five moderators with Post×Treat$_{i,j}$. The regression specification is the same as in Table 3.3. The dependent variable is NPV$_{i,m}$ computed at the monthly level. (Post×Treat)$_{I,t}$ is a dummy variable equals to one for firms that have a linked firms become the target in a M&A deal in month *m*, and zero otherwise. In Panel A, the moderator variable is homo$_{i,j}$, an dummy variable equal to one for industry that is not selling differentiated goods as defined by Rauch (1999), zero otherwise. In Panel B, the moderator variable is innov$_{i,j}$, an dummy variable equal to one for the top quantile of firms that receive most of USPTO patent each year, zero otherwise. In Panel C, D, E, F and G, the moderator variable is top, a dummy variable equal to one for the top quantile of firms that have most competitors, supplier and customers, the highest bid premium and the highest percentage of stock financing, respectively, and zero otherwise. These moderators are calculated for the target firm in the M&A deal. I include all control variables and all main and interaction terms, but omit their coefficients for brevity. Appendix 3.2 details all the variables. I only include sample in pre-announcement month (-12,-1) and post-announcement period (0,2). I control for firm, month-year and person fixe effects in all panels. Standard errors reported in parentheses are computed based on robust standard errors clustered at the firm-month level. ***, **, and * denote significance at the 99%, 95% and 90% confidence level, respectively. All variables are winsorised at the top 99% and the bottom 1% level.

	Panel A: Homogeneous product producer-Rauch (1999)		
	Competitor	Customer	Supplier
	All	All	All
	(1)	(2)	(3)
Dependent Variable	NPV	NPV	NPV
Post×Treat$_{i,j}$	0.028	0.063**	-0.018
	(0.021)	(0.026)	(0.023)
Post×Treat×homo$_{i,j}$	0.381**	-0.025	0.185**
	(0.188)	(0.062)	(0.081)
Control Variables	Yes	Yes	Yes
	Panel B: Innovative target firm-top quantile for patent received		
Post×Treat$_{i,j}$	0.051**	0.064**	-0.008
	(0.022)	(0.028)	(0.023)
Post×Treat×Innov$_{i,j}$	-0.224**	0.028	-0.239**
	(0.114)	(0.081)	(0.116)
Control Variables	Yes	Yes	Yes
	Panel C: Target firm with many competitors-top quantile for number of competitors		
Post×Treat$_{i,j}$	0.018	0.040	-0.041
	(0.022)	(0.027)	(0.026)
Post×Treat×top$_{i,j}$	0.087*	0.128**	0.088*

	(0.052)	(0.061)	(0.050)
Control Variables	Yes	Yes	Yes
	Panel D: Chain complexity-number of suppliers		
Post×Treat$_{i,j}$	0.052**	0.034	0.003
	(0.023)	(0.024)	(0.024)
Post×Treat×top$_{i,j}$	-0.117**	0.400***	-0.112*
	(0.057)	(0.130)	(0.063)
Control Variables	Yes	Yes	Yes
	Panel E: Target firm with many customers -top quantile for number of customers		
Post×Treat$_{i,j}$	0.020	0.013	-0.030
	(0.021)	(0.024)	(0.024)
Post×Treat×top$_{i,j}$	0.206*	0.243**	0.106*
	(0.107)	(0.113)	(0.059)
Control Variables	Yes	Yes	Yes
With-in R^2	0.07	0.06	0.05
Sample	7,276	4,240	5,122
	Panel F: Bid Premium		
Post×Treat$_{i,j}$	0.049**	0.079***	-0.018
	(0.022)	(0.030)	(0.025)
Post×Treat×top$_{i,j}$	-0.138**	-0.103*	0.009
	(0.062)	(0.056)	(0.048)
Control Variables	Yes	Yes	Yes
Sample	7,212	4,155	5,074
	Panel G: Percentage of consideration paid in stocks		
Post×Treat$_{i,j}$	0.009	0.075***	0.004
	(0.021)	(0.029)	(0.023)
Post×Treat×top$_{i,j}$	0.155**	-0.095	-0.113
	(0.075)	(0.058)	(0.077)
Control Variables	Yes	Yes	Yes
Sample	7,210	4,286	5,145

In Panel C, I create dummy variables for target firm that is in the top quintile of firms with the most competitor and employ the dummy variable as the moderator variable. From the regression results, I observe that insiders from IT firms are more likely to reduce their selling when their supplier firms have many competitors for all three relationships because the coefficient of $\mathrm{Post}\times\mathrm{Treat}^{*}\mathrm{top}_{i,j}$ is positive and statistically significant. These results are mostly consistent with my previous hypothesis that the purchasing efficiency will be gained for a merging firm in a large industry with many peer firms. Moreover, insiders are also reacting with greater intensity if their customers have many competitors, in line with both the productive efficiency and the purchasing efficiency as insiders recognise the increase in the efficiency for customers firms in a more competitive environment should be higher to gain comparative advantage, further boosting IT firms' turnover.

I use the number of suppliers to measure the complexity of the supply chain for the target firms. If the target firm has a large supply chain, the limited attention constraint should play a more significant role because it is more difficult for the market to understand the impact of the deal on all firms on the chain. Therefore, insiders from IT firms will have a larger informational advantage and should trade with greater intensity. The results in Panel D confirm my hypothesis. The coefficient of $\mathrm{Post}\times\mathrm{Treat}^{*}\mathrm{top}_{i,j}$ is positive and statistically significant for customer, and negative for competitor and supplier, meaning insiders will react to the M&A announcement with different intensity depending on the target firm supply chain complexity. The negative coefficient for competitor relationship is possibly attributed to the various differentiated input resources that the target firm require to produce their final products. There will be no significant decrease in the input price when competitors have many suppliers, and therefore, insiders from IT firms recognise they cannot replicate the efficiency gain and will have comparative disadvantage. On the other hand, insiders react positively to the announcement of their customers with many suppliers. The result reconciles with my findings that the net effect for suppliers is positive because the increase in demand outweighs the drop in price, and other competitors of the merging firm are unable to gain the same purchasing efficiency.

In Panel E, I sort firms in accordance with the number of customers they report, a proxy for their market shares, to find that insiders reduce their sell trades with greater intensity in such target competitors. The result indicates that insiders from IT firms expect the merging firm with many customers to gain both purchasing efficiency and productive efficiency, and these efficiencies gains will be passed onto their customers and competitors. Moreover, insiders from IT firm that is the supplier of the merging firm will also reduce selling with larger intensity, because the net effect for these suppliers is positive and the larger demand exceed the downward pressure on the output price.

In Panel F, I focus on the bid premium and create dummy variable equal to one for the top quintile of deals with the highest bid premium. I find that insiders systematically sell more when their competitors or customers have been offered a very high bid premium. Although I cannot infer insiders' motivation directly from these results, these insiders recognize that these high premium deals are value-destroying for the IT firms, and they are less likely to receive efficiency gains from these deals. The result is consistent with Malmendier and Tate (2008) who show that overconfident CEOs are more likely to initiate value-destroying deals and overpay bid premium. In Panel G, I focus on the percentage of consideration paid in stocks and show that insiders react more positively when their competitors are bought largely using acquiror's stock, in line with Di Giuli (2013) and Eckbo, Makaew and Thorburn (2018) who argue that more informed target managers use a larger fraction of stock financing. Target managers believe the deal is value-creation and will generate long-term positive effect on the merging firm, and therefore are willing to accept a high percentage of stock consideration. Consequently, insiders from IT firms will consider the percentage of stock financing as a signal and to trade the shares of their own firms accordingly. I do not find similarly evidence for customer and suppliers relationships. In unreported results, I further explore whether the deal is a tender offer or not, the industry relativeness between acquiror and target defined by their first three-digit SIC codes, the relative size ratio between acquiror and target, and the deal attitude. I do not find significant results and thus omit these outputs.

3.4.4 Insider trading profitability around the M&A announcement

Previous results have indicated that insiders will adapt a passive trading strategy by systematically selling less when either their competitors or customers have become the target in M&A deals, and they will not significantly alter their trading activities if their suppliers have become the target. In addition to the adaption of passive trading strategy, insiders may better time their transactions by selling (buying) more when their firms have become overpriced (underpriced). Their post-transaction returns will allow me to investigate the informativeness embedded in their transactions and to study whether they have better understanding of the impact of the deal on their own firms than outside investors. Alldredge and Cicero (2015) show that insiders from firms that report principal customers earn higher abnormal returns than their peers from firms that do not have principal customers without conditioning on any specific corporate event. The specific M&A setting allows me to extend their findings to the other two relation types to investigate whether insiders truly have better understanding of the public announcement than outsiders.

In Table 3.6, I use the $\text{BHAR\_m\_30}_{i,d}$ and $\text{BHAR\_ff\_30}_{i,d}$ as my dependent variables, and estimate my diff-in-diff regression. Since I have documented that insiders adapt passive trading strategy, I additionally interact $\text{Post}\times\text{Treat}_{i,j}$ with $\text{NPV}_{i,j}$ to see whether the return predictability is varying with insider net purchasing value, the approach has been successfully applied in Cziraki *et al.* (2021). I include all the control variables, but omit to report their coefficients for brevity. The coefficient of $\text{Post}\times\text{Treat}_{i,j}$ is positive and statistically significant for all three relationships regardless the abnormal return measures used, suggesting that insider transactions are systematically profitable after M&A announcements. On average, insider transactions will generate a 2.8%, 3.9% and 4.2% $\text{BHAR\_m\_30}_{i,d}$ if their competitors, customers and suppliers have become targets in M&A deals, respectively. The coefficient is slightly larger and remains significant if the dependent variable is $\text{BHAR\_ff\_30}_{i,d}$. These results provide support to my previous findings that insiders on average sell less after M&A announcements, and their firms yield higher excess returns following the announcement.

The coefficient of $\text{Post}\times\text{Treat}^{*}\text{NPV}_{i,j}$ is also positive and statistically significant for all three relationships regardless of the profitability measure. The result indicates that when insiders sell less which indicates higher NPV, their firms will yield higher abnormal returns. On the other hand, if insiders sell more after the announcement, their NPV will be lower, and these sell transactions will generate lower abnormal returns which indicate gains to the sellers. The result further reaffirms the finding that insiders have access to the private information regarding their firm's prospects and they actively trade on it for personal gains. The coefficients of other control variables are consistent with the past insider trading literature and thus omitted for brevity. In unreported results, I remove the top quintile IT firms that have most of linked firms as well as their corresponding control firms from the sample and re-estimate these baseline regressions. The coefficients of $\text{Post}\times\text{Treat}^{*}\text{NPV}_{i,j}$ remain to be positive and statistically significant across all three relationships and for both abnormal return measures. My results are robust to the exclusion of these firms.

Table 3.6: Insider trading return around M&A announcement

This table reports the diff-in-diff regression output. $(\text{Post}\times\text{Treat})_{i,m}$ is a dummy variable equals to one for firms that have a CEO turnover in year t, and zero otherwise. Appendix 3.2 details all the variables. I only include sample in pre-announcement month (-12,-1) and post-announcement period (0,2). I control for all main levels of interactions terms. Standard errors reported in parentheses are computed based on robust standard errors clustered at the firm-month level. ***, **, and * denote significance at the 99%, 95% and 90% confidence level, respectively. All variables are winsorised at the top 99% and the bottom 1% level.

	Competitor		Customer		Supplier	
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	$BHAR\_m\_30_{i,d}$	$BHAR\_ff\_30_{i,d}$	$BHAR\_m\_30_{i,d}$	$BHAR\_ff\_30_{i,d}$	$BHAR\_m\_30_{i,d}$	$BHAR\_ff\_30_{i,d}$
$TreatD_{i,j}$	-0.007	-0.006	-0.029	-0.023	0.011	0.011
	(0.010)	(0.011)	(0.021)	(0.024)	(0.012)	(0.011)
$PostD_{i,j}$	-0.011^{**}	-0.010	-0.018^{**}	-0.020^{**}	-0.002	-0.003
	(0.005)	(0.006)	(0.008)	(0.008)	(0.006)	(0.006)
$Post\times Treat_{i,j}$	0.028^{**}	0.032^{**}	0.039^{**}	0.042^{**}	0.042^{***}	0.042^{***}
	(0.013)	(0.013)	(0.015)	(0.017)	(0.014)	(0.014)
$Post\times Treat\times NPV_{i,j}$	0.029^{**}	0.034^{***}	0.039^{***}	0.046^{***}	0.028^{**}	0.027^{**}
	(0.013)	(0.013)	(0.015)	(0.017)	(0.014)	(0.013)
$NPV_{i,j}$	0.014^{**}	0.014^{**}	0.011	0.009	-0.000	0.000
	(0.007)	(0.007)	(0.012)	(0.014)	(0.008)	(0.008)
$Ln(makt\_cap)_{j,m}$	-0.048^{***}	-0.060^{***}	-0.071^{***}	-0.094^{***}	-0.068^{***}	-0.073^{***}
	(0.011)	(0.016)	(0.019)	(0.026)	(0.015)	(0.017)
$mom_{j,m.(d-1,d\ -365)}$	-0.043^{***}	-0.045^{***}	-0.039^{***}	-0.035^{**}	-0.039^{***}	-0.040^{***}
	(0.010)	(0.011)	(0.014)	(0.017)	(0.012)	(0.014)
$bm_{j,m-1}$	-0.032	-0.037	0.036^{*}	0.043^{*}	0.010	0.008
	(0.021)	(0.027)	(0.020)	(0.026)	(0.024)	(0.023)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
With-in R^2	0.05	0.06	0.08	0.08	0.08	0.08
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Insider FE	Yes	Yes	Yes	Yes	Yes	Yes
Sample	6,113	6,065	3,527	3,482	4,222	4,199

These results are consistent with Alldredge and Cicero (2015) that insiders have better ability to analyse the impact of public announcement on their firms than outsiders. Furthermore, their better understanding of public information is not only witnessed when IT firms report principal customers, but when IT firms also have competitor or suppliers.

My results are reconciling with Cohen and Frazzini (2008) which document that there is a delay in incorporating public information through supply-chain by outside investors as a whole because of their limited attention. I show that the limited attention will induce stock mispricing which further motivates insiders to trade on the public information and to reap abnormal returns.

Overall, these results support my hypothesis that insiders will actively trade on the mispricing of their firms caused by the public M&A announcement, and their transactions will generate higher abnormal returns following these more informed trades.

3.4.5 Reverse causality: Two-Stage Least Square Regression

My findings between a more informed insider trading in IT firm and the M&A announcement of linked firm may be driven by the change in the business prospects of the IT firms, which may reversely and adversely cause the linked firms to become more vulnerable to acquiror. If acquiror can anticipate the change, they may negotiate a deal with the affected firms in advance. For example, if the IT firm is the major competitor of linked firm and IT firm launches a major product that will substantially lessen the market share of the linked firm, linked firm will be worth less and become cheaper to be acquired.

I therefore apply an instrumental variable (IV) approach that exploits the exogeneous shocks that are outside the control of IT firms and will make IT firms more likely to become the treated firm in my sample, meaning they have a higher likelihood to have one of their linked firms become the target in a M&A deal. My instrument builds on Edmans *et al.* (2012), Dessaint *et al.* (2019), and has been successfully applied in Boehm and Sonntag (2018). These papers show that when large mutual funds fire-sell a part of their portfolio to fulfil the capital withdrawal request from their investors, the capital outflow will place a downward pressure on the share prices of firms in their portfolio and increase the likelihood of these firms to be acquired. The occurrence of the capital outflow is exogeneous to these firms that have been sold by mutual funds, and thus unrelated to their prospects.

I follow Edmans *et al.* (2012) and Dessaint *et al.* (2019) to construct the hypothetical shares sold by large US mutual funds in response to a sudden capital outflow. The shares sold is hypothetical not actual because mutual funds are not required to disclose the reasons behind their investment decisions. Therefore, I can only infer their motivations from their disclosed holdings in different firms' shares. The construction details for the hypothetical shares sales are described in Appendix 4. I further sort all firms into quintiles each year in accordance with the hypothetical number of shares that have been fire-sold by mutual funds, and I recognise firms at the bottom quintile are those experienced an extreme downward pressure on their stock prices. I create dummy variable $\mathrm{MFHSD}_{j,t}$ equals to one for firms that are at the bottom quintile, zero otherwise. Agrawal and Nasser (2012) and Boehm and Sonntag (2018) have shown that there is generally a one-year lag between M&A negotiation period and M&A announcement date, and therefore I include observations from month (-24, 2) to reflect the additional one-year lag between outflow event and M&A announcement. Finally, I compute my IV $\mathrm{MFHS}_{j,t}$, which is a continuous variable equals to the market capitalisation weighted average $\mathrm{MFHSD}_{j,t}$ of all linked firms in year *t* for a given relationship type. If control firm does not have any linked firm each year, the variable is set to be zero.

The IV is appropriate because it reflects an increase in the probability that a firm will be acquired, and thus can directly predict the probability of a firm becomes a treated IT firm in my setting. Thus, I recognise the IV relevance condition is satisfied, and I conduct formal test on the condition at a later stage. On the other hand, the exogeneous shock to the linked firm's stock price is unlikely to have any direct impact on both the linked firm's business operation and IT firm's business environment because the shock is nonfundamental and exogeneous (Dessaint *et al.* 2019), further highlighting the plausibility of the exclusion condition. Therefore, these shocks make a possible IV.

Table 3.7 panel A reports the results by using NPV as the dependent variable in the second stage regression. I exclude the control variables for brevity. I use the IV $\mathrm{MFHS}_{j,t}$ and the interaction term between the same IV and $\mathrm{PostD}_{i,j}$ denoted as $\mathrm{MFHS}^{*}\mathrm{PostD}_{i,j}$ to jointly predict the endogenous variable $\mathrm{TreatD}_{i,j}$, and the interaction term $\mathrm{Post}{\times}\mathrm{Treat}_{i,j}$ in two separate first-stage regressions. To better demonstrate the incremental predictive power of my IV on the $\mathrm{TreatD}_{i,j}$, I report the first-stage regression without the interaction term $\mathrm{MFHS}^{*}\mathrm{PostD}_{i,j}$ in column (1), (3) and (5) for competitor, customer and supplier, respectively. From these results, I can observe that the coefficients of $\mathrm{MFHS}_{j,t}$ are all positive and statistically significant at the 99% confidence level for all three relationships. The Kleibergen-Paap *F*-statistics are 41.17, 74.10 and 18.58 for these three relationships, respectively. The first stage F statistics are all above 10, which is the minimum value to alleviate the weak instrument concern, providing significant support for the relevance condition, indicating $\mathrm{MFHS}_{j,t}$ is an appropriate IV. If I include the interaction term $\mathrm{MFHS}^{*}\mathrm{PostD}_{i,j}$, the Kleibergen-Paap *F*-statistics are 19.19, 36.86 and 9.22 for these three relationships, respectively. The coefficients of $\mathrm{Post} * \widehat{\mathrm{Tre}}_{i,j}$ are 0.131 and 0.203 for competitor, customer, respectively, and are all statistically significant at the 95% confidence level, but insignificant for supplier. In addition, the unreported Anderson-Rubin *F*-statistic rejects the null hypothesis and indicates that the endogenous regressor $TreatD_{i,t}$ is statistically significant at the 95% confidence level for competitor and customer. The Anderson-Rubin F-statistic is robust to the presence of weak instrumental variable (Andrews, Stock and Sun, 2019) and thus reaffirm my previous findings that insiders from IT firms will systematically sell less shares after their competitor or customer firms have become the target in a M&A deal. In unreported result, I also check for a potential weak instrument using the Stock and Yogo (2005) test and the Shea Partial R-squared values, and I find that my IV does not suffer from weak instrument problem throughout the study. The Difference-in-Sargan *C*-statistic rejects the null hypothesis that the $TreatD_{i,t}$ is exogenous to the net purchase value. Since my 2SLS is just-identified meaning I only have one IV with one endogenous variable, the *Difference-in-Sargan C-test* is equivalent to a *Hausman* test comparing 2SLS estimates with fixed effect (FE) estimates. The significant *C*-statistics confirm the necessity of applying 2SLS rather than the FE estimator.

I further change the dependent variable of the second stage regression to $\mathrm{BHAR\_m\_30}_{i,d}$, and report the results in Table 3.7 panel B. $\mathrm{MFHS}_{j,t}$ remains a valid IV despite there is a decrease in the sample size. The coefficient of $\mathrm{MFHS}_{j,t}$ is quantitatively similar to the result in panel A and all Kleibergen-Paap *F*-statistics are well above 10 in the first stage when $\mathrm{MFHS}_{j,t}$ is the only IV included. The coefficients of $\mathrm{Post} * \widehat{\mathrm{Tre}}_{i,j}$ are 0.034, 0.054 and 0.040 for competitor, customer and supplier, respectively, and they are all statistically significant at the 90% confidence level. These results are consistent with my previous findings that insiders will better time their transactions after the M&A announcement to generate a higher abnormal return. Overall, my results remain robust when using 2SLS estimator, further emphasising that my conclusions were not driven by the endogeneity induced by the reverse causality.

Table 3.7: Two-stage least square regression for insider trading activity

This table reports the replications of Table 3.3 and Table 3.4 using two-stage least square estimator in Panel A and Panel B, respectively. I include the same set of control variables as in Table 3.3 and Table 3.4. I use $MFHS_{(j,t)}$ as my instrumental variable by following Boehm and Sonntag (2018). The construction of the IV is described in detail in Appendix 3.4. My endogenous variable is $TreatD_{(i,j)}$ and all the interaction terms between $TreatD_{(i,j)}$ and other variables. I only report the first-stage regression output without the inclusion of endogenous interaction terms to show the predictability of my IV for $TreatD_{(i,j)}$. I report the Kleibergen-Paap rk Wald F Statistic for the first stage regression at the bottom of each panel. *K-P Wald F ($TreatD_{(i,j)}$)* and *K-P Wald F (All)* denotes the first-stage regression by excluding and including the endogenous interaction term $\widehat{Tre} * PostD_{(i,j)}$, respectively. The coefficients of these control variables are omitted for brevity. Standard errors reported in parentheses are computed based on robust standard errors clustered at the firm-month level. ***, **, and * denote significance at the 99%, 95% and 90% confidence level, respectively. All variables are winsorised at the top 99% and the bottom 1% level.

	Panel A: Insider Trading Activity					
	Competitor		Customer		Supplier	
	First Stage	Second Stage	First Stage	Second Stage	First Stage	Second Stage
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	$TreatD_{(i,j)}$	NPV	$TreatD_{(i,j)}$	NPV	$TreatD_{(i,j)}$	NPV
$MFHS_{j,t}$	0.046***		0.205***		0.041***	
	(0.007)		(0.024)		(0.010)	
$PostD_{i,j}$		-0.029		-0.044**		0.002
		(0.019)		(0.020)		(0.022)
$\widehat{TreatD}_{i,j}$		-0.873		-0.296*		-0.501
		(0.535)		(0.169)		(0.559)
$Post\times\widehat{Tre}_{i,j}$		0.131**		0.203**		0.076
		(0.060)		(0.091)		(0.066)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Insider FE	Yes	Yes	Yes	Yes	Yes	Yes
K-P Wald F ($TreatD_{i,j}$ Only)	41.17***		74.10***		18.38***	
K-P Wald F (All)	19.79***		36.86***		9.22***	
Sample	11,771	11,771	6,876	6,876	8,545	8,545
	Panel B: Insider Trading Profitability					
	Competitor		Customer		Supplier	

	First Stage	Second Stage	First Stage	Second Stage	First Stage	Second Stage
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	$TreatD_{(i,j)}$	$BHAR\_m\_30_{i,d}$	$TreatD_{(i,j)}$	$BHAR\_m\_30_{i,d}$	$TreatD_{(i,j)}$	$BHAR\_m\_30_{i,d}$
$MFHS_{j,t}$	0.049***		0.145***		0.042***	
	(0.009)		(0.015)		(0.011)	
$PostD_{i,j}$		-0.013**		-0.016**		-0.009
		(0.006)		(0.008)		(0.007)
$\widehat{TreatD}_{i,j}$		-0.145		-0.017		0.293*
		(0.134)		(0.068)		(0.158)
$Post\times\widehat{Tre}_{i,j}$		0.034*		0.054*		0.040*
		(0.020)		(0.030)		(0.024)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Insider FE	Yes	Yes	Yes	Yes	Yes	Yes
K-P Wald F ($TreatD_{i,j}$ Only)	32.05***		28.04***		15.52***	
K-P Wald F (All)	15.50***		13.66***		7.94***	
Sample	9,446	9,446	5,518	5,518	6,798	6,798

3.4.6 The source of gain behind informed trading

The above results established that insiders systematically sell less when their linked firms have become the target in a M&A deal, and these transactions are more informed because they generate higher abnormal returns. The obvious next question is: what is the informational content behind their trades? Can these more informed transactions support the productive efficiency hypothesis or purchasing efficiency hypothesis or both? Are insiders trading on public or private information?

Insiders can generate abnormal return because they have superior access to the information that outside investors would not know at the time of the M&A announcement, known as *private information channel*. Existing insider trading literature has predominately argued that this is the main source of gain for informed insider transactions. However, Alldredge and Cicero (2015) propose a complementary explanation that insiders can generate abnormal return based on the public information because they better understand the implication of these public information for their firms than outside investors, known as *public information channel*. In the section, I first investigate the informational content behind these informed insider trading and examine whether the higher abnormal return is attributed to the conventional *private information channel* or *the public information channel*.

The impact of the linked firm's M&A announcement should reflect the IT firm's future efficiency gain and the improve in their business performance and thus can be examined using balance sheet items. To examine the productive efficiency hypothesis, I focus on five measures for the future business performance efficiency that are change in the return on asset between year 0 and year 2, the normalised earnings surprise measured by DellaVigna and Pollet (2009) between quarter 4 and quarter 5, the sale growth between year 0 and year 2, the change in the unit cost of a patent between year 0 and year 3 and the change in the cost of goods sold (COGS) between year 0 and year 2. I select these five items because they directly reflect the improvement in operating performance that were predicted by the operating efficiency hypothesis and existing literature has showed that these three items are sensitive to the supply-chain changes (Alldredge and Cicero, 2015; Cziraki *et al.* 2021; Boehm and Sonntag, 2021). I keep at least one-calendar year time lag from the deal announcement year for the deal to complete and fully exerts its impact on the IT firm's balance sheet.

I keep the same regression specification as my diff-in-diff regression and interact the $\mathrm{Post}{\times}\mathrm{Treat}_{i,j}$ with $\mathrm{NPV}_{i,j}$. If insiders are indeed trading on the change in their performance affected by the M&A deal, the coefficient of $\text{Post}\times\text{Treat}\times\text{NPV}_{i,j}$ should be positive and statistically significant. The less (more) insiders sell after the M&A announcement, the better (worse) their firms will perform in the future. In unreported results, I also conduct a parallel trend assumption test following Angrist and Pischke (2009) and Aktas *et al.* (2021) using these dependent variables to ensure the appropriateness of diff-in-diff regression specification. I confirm that the control and treated samples do not show different pre-trend before the M&A announcement and my diff-in-diff framework is appropriate in the setting.

Table 3.8 panel A reports the results where $\Delta\text{roa}_{t,j}$ is the dependent variable. The coefficient of $\text{Post}\times\text{Treat}\times\text{NPV}_{i,j}$ is positive and statistically significant at 90% and 95% for competitor and customer, respectively. The coefficient is insignificant for supplier. The result indicates that when insiders are selling less after the M&A announcement, their firms will have a higher increase in the return on asset. Moreover, if an IT firms have many suppliers or customers, losing one of them is unlikely to make a substantial impact on their business performance. I divide all IT firms into quintiles each year according to the number of linked firms they have, and I further remove the top quintile IT firms with their corresponding control firms from my sample and re-estimate the regression. If the source of gain is indeed the M&A announcement of their linked firms, the coefficient should become larger. In panel A column (4) to (6), I report the regression results. From the output, I can see that the coefficient of $\text{Post}\times\text{Treat}\times\text{NPV}_{i,j}$ increases from 0.015 to 0.021 for competitor, and the confidence level increases from 90% to 95%. The coefficient also increases from 0.019 to 0.025 for customer, remains insignificant for supplier. The larger coefficient after excluding the top quintile further reaffirms that insiders are indeed trading on the M&A announcement of their linked firms.

Table 3.8: Informational content behind insider transactions

This table reports the fixed effect regression output based on matched sample. In Panel A, the dependent variable is the change in return on asset between year t and year t+2. In Panel B, the dependent variable is the change in the earnings surprise between the quarter q+4 and the quarter q+5 proposed by DellaVigna and Pollet (2009). In Panel C, the dependent variable is the change in sale between year t and year t+2. In Panel D, the dependent variable is the change in the unit cost of a new patent scaled by research and development cost between year t and year t+3. In Panel E, the dependent variable is the change in the cost of goods sold scaled by sale between year t and year t+2. I include the same set of control variables as in Table 3.3. The coefficients of these control variables are omitted for brevity. I include firm, month-year and director fixed effects in all panels. Standard errors reported in parentheses are computed based on robust standard errors clustered at the firm-month level. ***, **, and * denote significance at the 99%, 95% and 90% confidence level, respectively. All variables are winsorised at the top 99% and the bottom 1% level.

	Panel A: Change in return on asset					
	Change in return on asset$_{(0,2)}$			Change in return on asset$_{(0,2)}$ (Excluding top quintile)		
	(1)	(2)	(3)	(4)	(5)	(6)
	Competitor	Customer	Supplier	Competitor	Customer	Supplier
$Post\times Treat_{i,j}$	0.018**	0.021**	-0.003	0.024**	0.026**	-0.002
	(0.008)	(0.009)	(0.009)	(0.010)	(0.011)	(0.011)
$Post\times Treat\times NPV_{i,j}$	0.015*	0.019**	0.005	0.021**	0.025**	0.009
	(0.008)	(0.009)	(0.009)	(0.010)	(0.012)	(0.011)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Sample	6,074	3,432	4,453	4,784	2,742	3,843
	Panel B: Earnings Surprise					
	Earnings Surprise$_{(q+4,q+5)}$			Earnings Surprise$_{(q+4,q+5)}$ (Excluding top quintile)		
	Competitor	Customer	Supplier	Competitor	Customer	Supplier
$Post\times Treat_{i,j}$	0.017	0.006	0.042	0.031*	0.012	0.061*
	(0.014)	(0.006)	(0.025)	(0.018)	(0.009)	(0.033)
$Post\times Treat\times NPV_{i,j}$	0.025*	0.010**	0.044*	0.043**	0.016**	0.062**
	(0.014)	(0.005)	(0.024)	(0.021)	(0.008)	(0.031)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Sample	6,722	3,861	4,952	5,270	2,787	4,100
	Panel C: Sale Growth					
	Sales Growth$_{(0,2)}$			Sales Growth$_{(0,2)}$(Excluding top quintile)		
	Competitor	Customer	Supplier	Competitor	Customer	Supplier
$Post\times Treat_{i,j}$	0.027	0.063**	-0.038	0.044**	0.059**	-0.042
	(0.020)	(0.031)	(0.023)	(0.019)	(0.030)	(0.031)

Post×Treat×NPV$_{i,j}$	0.039**	0.080***	-0.031	0.049***	0.092***	-0.039
	(0.020)	(0.031)	(0.023)	(0.019)	(0.030)	(0.030)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Sample	6,835	3,669	4,798	5,378	2,721	3,969
	Panel D: Change in the unit cost of a patent					
	Change in the unit cost of a patent$_{(0,3)}$			Change in the unit cost of a patent$_{(0,3)}$ (Excluding top quintile)		
	Competitor	Customer	Supplier	Competitor	Customer	Supplier
Post×Treat$_{i,j}$	-1.069**	-1.308	1.179*	-1.066*	-1.979	1.817*
	(0.545)	(1.162)	(0.693)	(0.629)	(1.418)	(0.938)
Post×Treat×NPV$_{i,j}$	-1.163**	-1.063	1.183*	-1.150**	-2.217	1.653*
	(0.536)	(1.195)	(0.702)	(0.576)	(1.476)	(0.948)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Sample	5,775	3,185	4,252	4,591	2,322	3,479
	Panel E: Change in the cost of goods sold					
	Change in COGS$_{(0,2)}$			Change in COGS$_{(0,2)}$ (Excluding top quintile)		
	Competitor	Customer	Supplier	Competitor	Customer	Supplier
Post×Treat$_{i,j}$	-0.015	-0.020	0.016	-0.040	-0.009	-0.013
	(0.056)	(0.017)	(0.022)	(0.076)	(0.019)	(0.015)
Post×Treat×NPV$_{i,j}$	-0.182***	-0.033*	0.006	-0.231**	-0.024	0.015
	(0.071)	(0.018)	(0.021)	(0.103)	(0.016)	(0.028)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Sample	6,216	3,763	4,586	4,875	2,771	3,772

Panel F: Less alternative suppliers in the same four-digit SIC industry (Supplier Only)					
	Δroa$_{(0,2)}$	Earnings Surprise$_{(q+4,q+5)}$	Δsale$_{(0,2)}$	Δcost of patent$_{(0,3)}$	ΔCOGS$_{(0,2)}$
Post×Treat$_{i,j}$	0.002	-0.007	-0.006	-0.441	0.031
	(0.005)	(0.009)	(0.019)	(0.571)	(0.036)
Post×Treat×NPV$_{i,j}$	0.010**	0.006	0.040**	-0.650	-0.074*
	(0.005)	(0.012)	(0.020)	(0.580)	(0.040)
Control Variables	Yes	Yes	Yes	Yes	Yes
With-in R^2	0.32	0.03	0.31	0.08	0.22
Sample	1,395	1,530	1,481	1,327	1,534

I follow DellaVigna and Pollet (2009) to construct the normalized earnings surprise as follows:

$$\mathrm{SUE}_{q,j} = \frac{\mathrm{actual\_earnings}_{q,j} - \mathrm{expected\_earnings}_{q,j}}{\mathrm{price}_{q,j}}$$

where $\mathrm{SUE}_{t,k}$ is the standardised unexpected earnings announced by firm j for quarter q, $\mathrm{actual\_earnings}_{q,j}$ is the actual earnings per share for firm j for quarter q, and $\mathrm{expected\_earnings}_{q,j}$ is the corresponding median of all analysts' earnings per share forecasts issued closest to in time to the earnings announcement date, but not more than 90 days prior to the fiscal period end. I normalize the $\mathrm{SUE}_{q,j}$ by $\mathrm{price}_{q,j}$ for firm *j* at the end of the quarter *q. I* calculate the change in $\mathrm{SUE}_{q,j}$ between quarter 4 and quarter 5, and use it as dependent variable in my regression. Table 3.8 panel B reports the regression output. The coefficients of $\mathrm{Post{\times}Treat{\times}NPV}_{i,j}$ are 0.025 and 0.044 for competitor and customer, respectively, both statistically significant at the 90% confidence level. The coefficient of $\mathrm{Post{\times}Treat{\times}NPV}_{i,j}$ for customer is 0.010 and statistically significant at the 95% confidence level. These coefficients all become larger and more significant for competitor and customers when I remove firms that have many linked firms. These stronger results further support my conclusions that the M&A deal will make an impact on IT firm's business performance, insiders better understand the impact than outsider and systematically trade on it. In panel C, I employ the $\Delta\mathrm{sale}_{t,j}$ as my proxy for business performance, and I obtain similar results. Insider transactions after the M&A announcement systematically predict the future sale growth for both competitor and customer relationships, and the coefficients become larger and more significant when I exclude firms with many competitors and customers. The coefficient is constantly insignificant for supplier. These results support the operating efficiency hypothesis that competitors and suppliers of the target firm will see an improvement in their firm performance attributed to the M&A deal.

Moreover, the signaling industry growth hypothesis predicts that competitor firms can replicate the innovation without being acquired by other firms. To investigate the hypothesis, I employ the change in the unit cost of a patent as the dependent variable between year t and t+3. I extend the period to the 3rd year after the M&A deal announcement because I use the patent grant date to match my main dataset and there is an additional one-year lag between the patent application date and patent grant date. I use the research and development cost divide by the number of patents granted in the same year to compute the unit cost of a patent and report the regression results in Panel D. I observe a negative and statistically significant coefficient for $\text{Post}\times\text{Treat}\times\text{NPV}_{i,j}$. For every 10% increase in the NPV, the unit cost for obtaining one more patent is 0.116 million lower after the M&A deal. The relationship is insignificant for customers and suppliers in the supply chain as IT firms are in the downstream and upstream and cannot benefit from the innovation revealed from the deal. These results are robust to the exclusion of top quintile sample and are consistent with the signaling industry growth hypothesis.

I investigate the purchasing efficiency using the change in the COGS normalized by sale as the moderator. The COGS is the most direct measure to gauge the input price. Panel E reports the regression results. I observe that the coefficient of $\text{Post}\times\text{Treat}\times\text{NPV}_{i,j}$ is negative and statistically significant for competitor and customer relationships, and insignificant for suppliers. These results imply that when insiders are buying more after the M&A announcement, their firms can enjoy the purchasing efficiency because of the larger industry-wise demand attributed to the merging deal of their competitors. Furthermore, a larger merging customer will have a larger demand for their input resource from suppliers, these suppliers can also benefit from the larger demand to lower their input prices, a prediction consistent with the purchasing efficiency hypothesis.

I further focus on the supplier relationship by excluding linked firms that have many peers in the same four-digit SIC industry each year, as IT firms can find alternative suppliers easily and thus alleviate the potential impact on their operating performance. In the entire Compustat file, I count the number of firms in a four-digit SIC industry each year and divide all four-digit SIC industries into deciles. I further remove deals in which the linked firms are the top decile each year, as well as removing the corresponding IT and control firms. I report the results in panel F. I observe that there is a significant drop in the same size, indicating that firms in the industry that has many peers are more likely to be acquired. Furthermore, the coefficient of $\text{Post}\times\text{Treat}\times\text{NPV}_{i,j}$ is 0.01, 0.04, and -0.074 when the proxy is $\Delta\text{roa}_{t,j}$, $\Delta\text{sale}_{t,j}$ and $\Delta\text{COGS}_{t,j}$, respectively, all statistically significant. The coefficient becomes insignificant for $\text{SUE}_{q,j}$, suggesting that analysts can correctly forecast their firms' earnings information when they do not have many alternative suppliers. The insignificant results for the change in the cost of patent further implies customer firms cannot gain innovation efficiency from the upstream M&A deal. In unreported results, I also remove the top decile for competitor and customer relationships and replicate all results in Table 3.8. For customer, I find the coefficients of $\text{Post}\times\text{Treat}\times\text{NPV}_{i,j}$ for $\Delta\text{roa}_{t,j}$, $\Delta\text{sale}_{t,j}$, and $\Delta\text{COGS}_{t,j}$ remain robust with the expected sign and insignificant when the dependent variable is $\text{SUE}_{q,j}$ and change in cost of a patent. For competitor, the coefficient is only significant with the expected sign when the dependent variable is change in cost of a patent. The coefficient is insignificant for all other proxies. The insignificant result for competitor further highlights that firms are not necessarily competing with their peers in the same four-digit SIC industry and the conventional method to identify competitor is inaccurate. On the other hand, the larger and more significant coefficients for customer and supplier justifies that using four-digit SIC code to identify alternative customers and suppliers is reasonable and firms that cannot easily find alternative customers or suppliers will have a more substantial effect on their performance. These more significant results reconcile with my findings that insiders from IT firms trade on the change in their firm's *future business performance* affected by the M&A deal, and these results supporting further both the operating efficiency hypothesis and purchasing efficiency hypothesis.

Although I have documented the informational content behind these informed insider transactions, it is unclear whether the higher predictability is originated from their superior access to the future fundamentals of firms that is the *private information channel* or their better understanding of the public M&A announcement that is the *public information channel*. To answer this question, I employ two proxies to measure the firm-specific stock informativeness: the Future Earnings Response Coefficient (FERC) proposed by Tucker and Zarowin (2006) and the return synchronicity suggested by Piotroski and Roulstone (2004). Wang (2019) has employed these measures to show that insider's transactions systematically yield higher abnormal returns when the firm-specific information environment is low. Wang (2019) argue that when the current stock prices poorly reflect the value of the firm, insiders will trade to correct the misevalution because they have superior access to the true fundamentals of their firms.

I follow these previous works to construct these two measures and explain the details in Appendix 3.5. For FERC, I further create binary variable $\text{FERC}_{i,t}$ that is one for the top quintile of stocks whose current prices contain the most future earnings information and zero otherwise, meaning these firms have better firm-specific information environment. As for return synchronicity, I create a binary variable $\text{Synch}_{i,t}$ that equals to one for the bottom quintile of stocks whose current prices contain more firm-specific information and comove weakly with the current and lagged market and industry returns, and zero otherwise. I then employ $\mathrm{FERC}_{i,t}$ and $\mathrm{Synch}_{\mathrm{i,t}}$ as the second moderator variables separately. I hypothesise that if insiders are trading on their private information rather than public information, the predictability of firm performance should vary with firm-specific stock informativeness. In the same logic, if the main source of gain is originated from the better understanding of the public M&A announcement, the predictability should not vary with the informativeness measure.

I replicate the Table 3.8 by using $\mathrm{FERC}_{i,t}$ and $\mathrm{Synch}_{\mathrm{i,t}}$ as the second moderator variables. I find, but not report, that for all panels, the coefficient of $(\mathrm{Post}\times\mathrm{Treat}\times\mathrm{FERC})_{\mathrm{i,t}}$ is constantly insignificant. I find similar insignificant results when using $Synch_{i,t}$ as the moderator variable. The coefficient of $(\mathrm{Post}\times\mathrm{Treat}\times\mathrm{Synch})_{\mathrm{i,t}}$ is statistically insignificant across all panels. To further confirm my findings, I replicate all results in Table 3.4 and Table 3.6 by using these two measures as moderator variables separately, and all results remain insignificant. Therefore, I conclude that insiders are indeed trading on the public M&A announcement because the change in their trading activity, the change in their abnormal return and the amount of information they incorporate into the current stock price are all invariant with the firm-specific price informativeness. They have better understanding of the M&A deal and its impact on their firm's business performance rather than their private information. The results are consistent with Alldredge and Cicero (2015) who show that insiders with major customers generate higher abnormal return because they pay more attention to the operating performance of their customers, a piece of public information that they understand better.

3.4.8 Insider trading and the propensity of future M&A activity

I focus on the signaling acquisition probability hypothesis, that is the increased insider trading activity is due to improved prospects of receiving and initiating takeover bids. Song and Walkling (2000) and Davis *et al.* (2021) show that there is an increasing probability for the competitor of a target firm to be acquired in the next one year because the preceding deal demonstrates an improved prospect of the industry. To the extent that insiders are correct at gauging such possibility, their trading activities should predict future M&A activity. I investigate this possibility by estimating a cross-section regression.

I aggregate all the insider trading activities in IT firm *j* between month (0,2) to construct the net purchasing value $\mathrm{NPV}_{\mathrm{j},(0,2)}$. Then, I define a dummy dependent variable $\mathrm{TargetD}_{\mathrm{j}}$ equal to one if the IT firm has become the target between months 3 and 14 after a bid for the supply chain firm, and zero otherwise. Similarly, I also set another dummy dependent variable

AcquirorD_j equal to one when IT firms initiate M&A deals in months 3 to 14, and zero otherwise. My sample includes 4,816 major M&A deals I collected from SDC. Appendix 3.1 provides the screen details. I follow David *et al.* (2021) to include a refined set of control variables representative of the various theories of M&A gains and management's motives to engage in M&As. I include the price run up 30 days from the end of month 0 denoted as $\text{runup}_{j,m,(d-30,d-1)}$, the total number of M&A deal announced in the same 4-dig SIC industry in the last 12 months $\text{ind\_activity}_{j,(m-1,m-12)}$ and other control variables are self-explanatory $\text{roa}_{j,t-1}$, total $\text{asset}_{j,t-1}$, $\text{illiq}_{j,m}$, $\text{bm}_{j,t-1}$, $\text{tobinq}_{j,t-1}$, $\text{roa}_{j,t-1}$, $\text{cash\_ratio}_{j,t-1}$, $\text{sale\_growth2y}_{j,t-1}$, $\text{rd}_{j,t-1}$, $\text{cash\_ratio}_{j,t-1}$, $\text{leverage}_{i,t-1}$, $\text{concentration}_{i,t-1}$, $\text{industryROA}\Delta_{i,j-1}$ and $\text{mom}_{j,m,(d-1,d-365)}$. Appendix 3.2 describes the construction of these variables.

Table 3.9 reports the regression results. I find that $\text{NPV}_{j,(0,2)}$ is positively and significantly correlated to the likelihood of receiving a takeover bid in the next twelve months for all three relationships. The result indicates that when insiders from IT firms are selling less after the M&A announcement of their linked firms, IT firms are more likely to receiving a bid. Since receiving a bid is associated with an increase in the stock price as evident by my previous evidence, insiders would have kept their ownership in their firms to avoid an opportunity loss. I also discover that when IT firm's supplier become the target, the $\text{NPV}_{j,(0,2)}$ is negatively correlated with the probability of IT firm initiating a bid, and the relationship is statistically significant at the 90% confidence level. Initiating a M&A deal usually leads to a decrease in the acquiror's stock price on average, insiders would avoid the opportunity loss by reducing their ownership in the firms in advance. These findings corroborate with the signaling hypothesis that when insiders trade after the M&A announcement of their linked firms, they will consider the further M&A activity of their firms. Other firm-level control variables are all insignificant and thus their coefficients are omitted for brevity.

Table 3.9: Propensity of IT firm's future M&A activity within one year

The table presents the coefficient estimates for a series of fixed effect regressions investigate the relationship between the net insider trading value between months (0,2) and the likelihood that their firm becomes a target or an acquiror between months 3 and 14, relative to a takeover bid of their supply chain firm. The binary dependent variables are equal to one if the IT firm becomes a target (column 1, 3 and 5) or a bidder (column 2,4 and 6), and zero otherwise. $\mathrm{NPV}_{j,(0,2)}$ is the NPV by aggregating all transactions from a given insider between months (0, 2), their linked firms become the target in a deal in month 0. Other control variables are insignificant and thus omitted for brevity: $\mathrm{roa}_{j,t\text{-}1}$, $\mathrm{sale\_growth2y}_{j,t\text{-}1}$, $\mathrm{rd}_{j,t\text{-}1}$, $\mathrm{leverage}_{i,t\text{-}1}$,$\mathrm{cash\_ratio}_{j,t\text{-}1}$, $\mathrm{concentration}_{i,t\text{-}1}$, $\mathrm{industryROA\Delta}_{i,j\text{-}1}$, $\mathrm{mom}_{j,m,(d\text{-}1,d\ \text{-}365)}$, $\mathrm{ind\_activity}_{j,(m\text{-}1,m\text{-}12)}$ and constant. Appendix 3.2 details all the variables. I control for month-year fixed effect in all columns. Standard errors reported in parentheses are computed based on Hubert-White robust standard errors. ***, **, and * denote significance at the 99%, 95% and 90% confidence level, respectively. All variables are winsorised at the top 99% and the bottom 1% level.

	Competitor		**Customer**		**Supplier**	
	$\mathrm{TargetD}_j$	$\mathrm{AcquirorD}_j$	$\mathrm{TargetD}_j$	$\mathrm{AcquirorD}_j$	$\mathrm{TargetD}_j$	$\mathrm{AcquirorD}_j$
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathrm{NPV}_{j,(0,2)}$	0.017**	-0.010	0.011**	-0.006	0.032***	-0.038*
	(0.007)	(0.016)	(0.005)	(0.023)	(0.012)	(0.021)
$\mathrm{total\ asset}_{j,t\text{-}1}$	0.003	0.018***	-0.003	0.011***	-0.008***	0.011*
	(0.002)	(0.004)	(0.002)	(0.004)	(0.003)	(0.006)
$\mathrm{runup}_{j,m,(d\text{-}30,d\ \text{-}1)}$	-0.052**	-0.016	-0.005	-0.024	0.030	-0.012
	(0.023)	(0.032)	(0.026)	(0.070)	(0.057)	(0.046)
$\mathrm{illiq}_{j,m}$	-0.039	0.081*	-0.004	0.097	-0.334*	-0.024
	(0.036)	(0.042)	(0.003)	(0.223)	(0.194)	(0.664)
$\mathrm{bm}_{j,t\text{-}1}$	0.004	-0.023**	-0.015	-0.005	0.002	-0.019
	(0.008)	(0.009)	(0.009)	(0.022)	(0.011)	(0.012)
$\mathrm{tobinq}_{j,t\text{-}1}$	-0.009***	-0.001	-0.003	0.001	-0.008*	-0.003
	(0.002)	(0.002)	(0.003)	(0.006)	(0.004)	(0.005)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Within R^2	0.026	0.031	0.018	0.022	0.030	0.013
Sample	1,342	1,342	821	821	974	974

3.4.9 Insider Trading on the CAR of linked firms

In this section, I further investigate the relationship between the insider trading decision and the CAR of linked firms around the M&A announcement. I argue previously that insiders mainly trade on the public M&A announcement rather than their private information, and therefore I hypothesis that the CAR around the M&A announcement of the target firm will predict the insider trading activities in IT firms in the subsequent three months. Insider trading literature has shown that insiders predominantly trade in a contrarian fashion that they will decrease (increase) their holdings when their firms' returns have been high (low) because they possess private information and trade against the market (Lakonishok and Lee, 2001; Cohen *et al.* 2012). It is unclear whether they also employ the same trading strategy when they trade on the public M&A announcement of their linked firms. I do not make a prediction because insiders can time the market and buy (sell) when the market has underreacted (overreacted).

I include the initial market return ($CAR_{(-3,3)}$) and the post-announcement returns ($CAR_{(4,14)}$) of both the target firms and IT firms in the regression. The dependent variable is $NPV_{j,(0,2)}$ and I use the same set of control variables as in Table 3.9. Table 3.10 reports the results and shows that insiders systematically trade on the $CAR_{j,(-3,3)}$ around M&A announcements of their linked firms. The coefficients of $NPV_{j,(0,2)}$ of 0.122, 0.241 and 0.182 for competitor, customer and supplier, respectively, are all statistically significant, suggesting that the higher the $CAR_{j,(-3,3)}$, the less insiders sell in the next three months. The coefficient of $CAR_{j,(4,15)}$ suggests that insiders trade up to 15 calendar days after the M&A announcement. On the other hand, insiders' do not consider the $CAR_{j,(4,15)}$ of their firms when they trade, except for customer relationship. The coefficient of $mom_{j,(d-1,d-365)}$ remains negative and statistically significant at the 99% confidence level for all firms, indicating that my results is not significantly different from the conventional insider trading literature. Insiders still employ the contrarian strategy to trade on average, but they will become a trend chaser when their economically linked firms have become the target in a M&A deal. Moreover, the previous univariate statistics have shown that the CAR of IT firms around the M&A announcement is significant but economically small. The small CAR explains the insignificant coefficients of $IT\_CAR_{j,(-3,3)}$ and $IT\_CAR_{j,(4,15)}$ in most of columns, and indicates that outside investors fail to fully adjust the value of IT firms and recognise that the M&A deal will not substantially affect the business performance of IT firms. Insiders trade in their own firm against these outside investors to correct the misevaluation and reap abnormal returns.

Table 3.10: Insider trading on the CAR of target firm around the announcement date

This table presents the coefficient estimates for a series of fixed effect regressions investigate the relationship between the net insider trading value between months (0,2) and the CAR of linked firms. I use the standard event study methodology to calculate CAR. The market model parameters are estimated over the 200 trading days period starting at day -240 relative to the M&A announcement date. I employ the CRSP value weighted index as the market return and require at least 100 trading days over the estimation window for a firm to be included in the sample. Other control variables refer to independent variables I omitted for brevity: $cash\_ratio_{j,t-1}$, $tobinq_{j,t-1}$, $bm_{j,t-1}$, $mom_{j,m.(d-1,d\ -365)}$, $roa_{j,t-1}$, $illiq_{j,m}$, $sale\_growth2y_{j,t-1}$, $rd_{j,t-1}$, $leverage_{i,t-1}$, $concentration_{i,t-1}$, $industryROA\Delta_{i,j-1}$ and constant. Appendix 3.2 details all the variables. Standard errors reported in parentheses are computed based on Hubert-White robust standard errors. ***, **, and * denote significance at the 99%, 95% and 90% confidence level, respectively. All variables are winsorised at the top 99% and the bottom 1% level.

	Competitor		**Customer**		**Supplier**	
	$NPV_{j,(0,2)}$		$NPV_{j,(0,2)}$		$NPV_{j,(0,2)}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$Target\_CAR_{j,(-3,3)}$	0.122***		0.241**		0.182*	
	(0.047)		(0.123)		(0.106)	
$Target\_CAR_{j,(4,15)}$		0.118***		0.302**		0.202**
		(0.045)		(0.123)		(0.098)
$IT\_CAR_{j,(-3,3)}$	0.207		-0.205		-0.424	
	(0.192)		(0.127)		(0.280)	
$IT\_CAR_{j,(4,15)}$		0.119		0.703***		-0.219
		(0.143)		(0.267)		(0.354)
$mom_{j,(d-1,d\ -365)}$	-0.101***	-0.103***	-0.194***	-0.190***	-0.251***	-0.247***
	(0.035)	(0.037)	(0.071)	(0.070)	(0.083)	(0.085)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
With-in R^2	0.09	0.08	0.11	0.16	0.07	0.08
Sample	902	902	420	420	636	639

These results further reaffirm that insiders primarily trade on the public information of their linked firms rather than the private information regarding their own firms. Insiders agree with the market as they trade in the same direction as the market, but they recognise the market has not fully incorporated the effect of the M&A deal into the stock price of the IT firm, so they increase (decrease) their holdings when the CAR is higher (lower).

3.4.10 Insider trading activities and profitability around M&A announcement of incomplete deals

My next exercise speaks to the possibility that the increase in both increase trading activity and insider trading profitability is driven by unobservable shocks. If the possibility is true, the shock must be correlated with the M&A announcement of their linked firms in order to explain the findings in my baseline regressions. For instance, the motivation of the acquiror to take over the target firm may not be observed by the market but known by insiders, and they may trade on the private information to generate abnormal returns

To account for the possibility, I follow Boehm and Sonntag (2018) to find IT firms that are comparable in terms of the shocks but do not eventually experience any impact on their business' performance. One possible sample is to use deals that have been announced but eventually withdrawn. If there are omitted variables motivating insiders to trade, I would expect the same positive and significant relationship using the same diff-in-diff regression specification. On the other hand, if my previous results are correct, insiders are indeed trading on the change in their firms' performance after the deal has been completed, I would expect an insignificant relationship using the announcement of these incomplete deals because the business prospects remain the same for those IT firms. I obtain a list of withdrawn deals from SDC by applying the same filters, and I end up with 187 deals, accounts for around one quarters of my complete M&A deal sample.

I replicate Table 3.4 and Table 3.6 using these withdrawn deals and report the regression results in Table 3.11 Panel A and Panel B, respectively. From the results, I can see that the coefficients of $\mathrm{Post{\times}Treat}_{i,j}$ in Panel A and the coefficients of $\mathrm{Post{\times}Treat{\times}NPV}_{i,j}$ in Panel B are inconsistent with my previous findings. In unreported results, I replicate Table 3.6 using these incomplete deals, and find none of the coefficients of $\mathrm{Post{\times}Treat{\times}NPV}_{i,j}$ is statistically significant. To the extent that incomplete deals are a good comparison group to the complete deals, the increases in insider trading activity and profitability are not likely to be driven by the unobserved shocks. Furthermore, the approach is like comparing of a placebo test with the actual treatment in a sense that these incomplete deals will not affect the future performance of IT firms, and therefore are not likely to motivate insiders to trade.

The explicit assumption behind these tests is that insiders from IT firms will have better insight regarding the probability of deal competition. Since these economically linked firms are closely involved in their daily operations, they may better predict the deal competition than the aggregate market. If my previous results are correct that insiders are trading on the future impact of the deal on their firms, they should be able to predict the deal completion probability as incomplete deals would not impact their firms. In the section, I re-specify a cross-section regression to explore the possibility.

First, I aggregate all the insider trading activities in IT firm *j* between month (0,2) to construct the net purchasing value $NPV_{j,(0,2)}$ which is the main variable with interest, the announcement of their linked firm is in month 0. For IT firms that have no insider trading transactions, the $NPV_{j,(0,2)}$ is set to 0. Then, I define the dependent variable CompletionD equals to one if the deal eventually completes and zero otherwise. To differentiate the deal completion probability estimated by corporate insiders and the market, I follow Fidrmuc and Xia (2021) which is built on Samuelson and Rosenthal (1986) and Fidrmuc, Roosenboom and Zhang (2018) to construct the market-measured deal completion probability denoted as Mkt_pro_t for target firm *t*. I compute two similar versions of Mkt_pro_t by following Samuelson and Rosenthal (1986) and Fidrmuc *et al.* (2018) separately. I report the result using the former but also use the latter measure to obtain the robust results. The construction details are in Appendix 3.6. The average Mkt_pro_t is 0.638 in my sample.

I follow Fidrmuc and Xia (2021) to include a refined set of control variables representative of the factors that will affect the probability of deal completion. I include $Ln(makt\_cap)_{j,m}$, $illiq_{j,m-1}$, $bm_{j,m-1}$, $mom_{j,m,(d-1,d-365)}$, $sd_{j,(d-365,d-1)}$, $delta\_sd_{j,(m-3,m-1)}$, all calculated based on the target firm in the M&A deal month *m* announcement date *d* rather than the IT firm.

Appendix 3.2 describes the construction of these variables. In addition, I include the 3-day CAR of target firms in my regression, and control for year and industry fixed effects (Fidrmuc and Xia, 2021).

Table 3.11: Insider trading activity and profitability around withdraw M&A announcement

The table Panel A and Panel B report the diff-in-diff regression output based on a list of M&A deal that has been announced but withdrawn. I replicate Table 3.3 in Panel A and Table 3.4 in Panel B. In both Panel A and B, I control for firm, month-year and director fixed effects. I control for the same set of control variables as in Table 3.3 and 3.4 but omit their coefficients for brevity. Standard errors are clustered at the firm-month level. Panel C reports the cross-sectional fixed effect regressions investigate the relationship between the net insider trading value between months (0,2) and the likelihood that the deal in which their economically linked firm has become the target will complete. The binary dependent variables are equal to one if the deal is complete, and zero otherwise. $NPV_{j,(0,2)}$ is the NPV by aggregating all transactions from a given insider between months (0, 2), their linked firms become the target in a deal in month 0. Mkt_pro_t is the probability of the deal completion calculated based on market reaction to the M&A announcement for target firm t calculated based on Samuelson and Rosenthal (1986) and Fidrmuc and Xia (2021). $Target\_CAR_{j,(-3,3)}$ is the seven day cumulative abnormal return (CAR) around the M&A announcement date for the target firm. I use the standard event study methodology to calculate CAR. The market model parameters are estimated over the 200 trading day period starting at day -240 relative to the M&A announcement date. I employ the CRSP value weighted index as the market return and require at least 100 trading days over the estimation window for a firm to be included in the sample. Other control variables refer to independent variables I omit for brevity: $Ln(makt\_cap)_{j,m}$, $illiq_{j,m-1}$, $bm_{j,m-1}$, $mom_{j,m,(d-1,d-365)}$, $sd_{j,(d-365,d-1)}$, $delta\_sd_{j,(m-3,m-1)}$ and constant. These control variables are calculated based on target firms with day *d* as the M&A announcement date. I control for IT firm and 2-dig SIC industry fixed effects. Appendix 3.2 details all the variables. Standard errors reported in parentheses are computed based on Hubert-White robust standard errors. ***, **, and * denote significance at the 99%, 95% and 90% confidence level, respectively. All variables are winsorised at the top 99% and the bottom 1% level.

			Panel A: Insider Trading Activity			
	Competitor		Customer		Supplier	
	All	No top quintile	All	No top quintile	All	No top quintile
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	NPV	NPV	NPV	NPV	NPV	NPV
$Tre^{*}PostD_{i,j}$	-0.052	-0.054	0.022	0.063	0.05	0.001
	(0.042)	(0.052)	(0.035)	(0.054)	(0.041)	(0.036)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
With-in R^2	0.051	0.056	0.068	0.080	0.102	0.010
Sample	2,061	1,661	1,846	1,325	1,734	1,466
			Panel B: Insider Trading Profitability			
	Competitor		Customer		Supplier	
Dependent Variable	$BHAR\_m\_30_{i,d}$	$BHAR\_ff\_30_{i,d}$	$BHAR\_m\_30_{i,d}$	$BHAR\_ff\_30_{i,d}$	$BHAR\_m\_30_{i,d}$	$BHAR\_ff\_30_{i,d}$
$Tre^{*}PostD_{i,j}$	-0.026	-0.021	0.029	0.005	-0.017	-0.008
	(0.022)	(0.019)	(0.043)	(0.053)	(0.027)	(0.031)

$Tre^{*}PostD^{*}NPV_{i,j}$	-0.039*	-0.052**	0.017	0.031	-0.016	-0.011
	(0.023)	(0.026)	(0.047)	(0.051)	(0.026)	(0.299)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
With-in R^2	0.085	0.069	0.103	0.128	0.11	0.126
Sample	1,680	1,671	1,513	1,510	1,432	1,416

Panel C: Insider Trading Activity and the probability of deal completion

	Competitor		Customer		Supplier	
Dependent Variable	CompletionD	CompletionD	CompletionD	CompletionD	CompletionD	CompletionD
$NPV_{j,(0,2)}$	0.053**		0.089**		-0.022	
	(0.026)		(0.040)		(0.029)	
$NPV_{j,(0,0)}$		0.053**		0.093**		-0.034
		(0.026)		(0.040)		(0.031)
$NPV_{j,(1,1)}$		-0.002		0.002		-0.041
		(0.029)		(0.046)		(0.032)
$NPV_{j,(2,2)}$		-0.002		0.012		0.025
		(0.029)		(0.046)		(0.032)
Mkt_pro_t	0.020***	0.020***	0.027***	0.027***	0.057***	0.057***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.012)	(0.012)
$Target\_CAR_{j,(-3,3)}$	0.311***	0.311***	0.329***	0.333***	0.321***	0.326***
	(0.047)	(0.047)	(0.086)	(0.088)	(0.057)	(0.057)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Industry Dummy	Yes	Yes	Yes	Yes	Yes	Yes
With-in R^2	0.067	0.067	0.106	0.106	0.101	
Sample	1,262	1,262	709	709	899	899

Table 3.11 Panel C shows that NPV can predict the future deal completion probability for competitors and customers both at the 95% confidence level, but not for suppliers. The results further confirm that when insiders buy more after the M&A announcement, they consider that the deal has higher probability of completion. On the other hand, when insiders do not significantly increase their NPV, the deal completion probability will be relatively lower. More importantly, the market-estimated probability is positive and statistically significant at the 99% confidence level for all three relationship types. The results are consistent with the previous findings that the aggregate market can correctly predict deal completion probability (Fidrmuc and Xia, 2021, Derrien *et al.* 2021). The significant predictive power embedded in the insider trading in the economically linked firm is in addition to the market-estimated probability, implying the informational content embedded in the insider trading activity is not the same as the aggregate market, further support my previous findings that insiders have better understanding about the deal completion than the market. The coefficient of the target firm's 7-day CAR is positive and statistically significant at the 99% confidence level, indicating the better the market reacts to the M&A announcement, the higher the probability that the deal will be eventually completed (Dessaint, Eckbo and Golubov, 2022). The results for the control variables are consistent with the previous findings and thus omitted for brevity. I also aggregate insider trading in each month rather than month (0,2) to investigate the timing of these informed insider trading. I report the results in column (2), (4) and (6). The coefficient of $\text{NPV}_{j,(0,0)}$ is quantitatively the same as $\text{NPV}_{j,(0,2)}$ for all three relationships, indicating that only insider trading in the M&A announcement month that embeds a strong predictive power for the future deal completion probability, while their trading decisions in the next two months contain little predictive power.

3.5 Robustness Test

To confirm that my findings are not due to chance and the inappropriateness of matching logarithm, I re-estimate my baseline diff-in-diff regression using 1000 placebo tests. I randomly select 840 firm-year observations to be considered as treated firms. I choose 840 pseud-event firms as I am focusing on the average number of treated firms across three types of relationships. To be comparable to the true event treatment effect and avoid biases due to the M&A announcement of economically linked firms, I restrict these pseud-event firms not to have any of their economically linked firms becoming a target of a M&A deal in the pre-event months (-12, 0). For each test, I repeat my matching algorithm to select one nearest neighbour in the same calendar month in terms of last six-month return, size and book-to-market ratio using the shortest Mahalanobis distance. For each of the 1000 tests, I replicate Table 3.4 and Table 3.6 and compute the test statistics associated with the two-tailed α significance level of the interaction term, $\mathrm{Post}\times\mathrm{Treat}_{i,j}$ and $\mathrm{Post}\times\mathrm{Treat}\times\mathrm{NPV}_{i,j}$.

Table 3.12 summarises the results of the test. The left-hand side shows that the average and median values of the interaction term $\mathrm{Post}\times\mathrm{Treat}_{i,j}$ are close to zero when replicating both Table 3.4 and Table 3.6. Although the coefficient $\mathrm{Post}\times\mathrm{Treat}_{i,j}$ is negative and statistically significant at the 99% confidence level, its scale is economically small, consistent with the observation that there is a decreasing trend in the NPV with the passage of time. The coefficient of $\mathrm{Post}\times\mathrm{Treat}\times\mathrm{NPV}_{i,j}$ remains statistically indifferent from zero when replicating Table 3.4. In the right-hand side of Table 3.12, I report the percentage of 1000 placebo tests. The coefficients of $\mathrm{Post}\times\mathrm{Treat}_{i,j}$ are statistically different from zero using a two-tailed t-test at the reported confidence level with a positive coefficient.

Table 3.12 indicates that my main findings are not driven by a random selected firms that do not have their economically linked firms become the target in a M&A deal. Relying on a binomial one-sided test, none of the proportions reported in the last three columns are statistically different from the theoretical threshold. Furthermore, none of the 1000 randomly selected samples produce both a statistically significant and positive coefficient of $\mathrm{Post}\times\mathrm{Treat}_{i,j}$ and $\mathrm{Post}\times\mathrm{Treat}\times\mathrm{NPV}_{i,j}$ when replicating Table 3.4 and Table 3.6, respectively. These placebo tests indicate that it is extremely unlikely to find a significant increase in the insider net trading value as well as a significant increase in the insider trading profitability at the same time without being affected by shocks.

Table 3.12: Robustness Test

The table Panel A reports the results of a placebo test on 1000 random samples of 840 firms drawn from the Smart Insider U.S company population after excluding firms whose economically linked firms become the target of a M&A deal. The left-hand side of the table reports the mean, median, standard deviation (SD) and skewness (Skew) of the distribution of the coefficients of the $Post \times Treat_{i,j}$ and $Post \times Treat \times NPV_{i,j}$, estimated using the same diff-in-diff regression specification in Table 3.3 and Table 3.5. I match the pseudo-treated firm with one control firms by matching on the last six-month return, size and book-to-market ratio in the same calendar month with the shortest Mahalanobis distance. The right-hand side of the table reports the percentage of 1000 random samples of 840 firms that reject the null hypothesis of the diff-in-diff coefficient is equal to zero at the 1%, 5% and 10% levels in favour of the alternative hypotheses of being significantly positive. Relying on a binomial one-sided test-statistics, none of the proportions are statistically different from the corresponding theoretical threshold. For the last two rows, I focus on the sample that report both statistically significant and positive coefficient for $Post \times Treat_{i,j}$ and $Post \times Treat \times NPV_{i,j}$, when replicating Table 3.3 and Table 3.4, respectively.

	Dependent variable	**Table that has been replicated**	**Coefficient**				**% statistically significant positive coefficient**		
			Mean	Median	SD	Skew	1%	5%	10%
$Post \times Treat_{i,j}$	NPV	3	-0.0014***	-0.001	0.015	-0.307	0.002	0.006	0.007
$Post \times Treat \times NPV_{i,j}$	$BHAR\_m\_30_{i,d}$	4	0.000	0.000	0.017	-0.067	0.005	0.036	0.060
$Post \times Treat \times NPV_{i,j}$	$BHAR\_ff\_30_{i,d}$	4	0.001	0.001	0.017	-0.048	0.007	0.039	0.060
$Post \times Treat_{i,j}$	$BHAR\_m\_30_{i,d}$	4	0.014	0.011	0.010	0.983	0.005	0.035	0.057
$Post \times Treat_{i,j}$	$BHAR\_ff\_30_{i,d}$	4	0.014	0.011	0.010	0.994	0.007	0.032	0.066
$Post \times Treat \times NPV_{i,j}$ and $Post \times Treat_{i,j}$ are both positive	NPV and $BHAR\_m\_30_{i,d}$	$Post \times Treat_{i,j}$ for Table 3.4 and $Post \times Treat \times NPV_{i,j}$ for Table 3.6					0.000	0.000	0.000
$Post \times Treat \times NPV_{i,j}$ and $Post \times Treat_{i,j}$ are both positive	NPV and $BHAR\_f\_30_{i,d}$	$Post \times Treat_{i,j}$ for Table 3.4 and $Post \times Treat \times NPV_{i,j}$ for Table 3.6					0.000	0.000	0.000

3.6 Conclusion

In this chapter, I document that corporate insiders systematically reduce their sell transactions in their own firm when their competitors or customers, but not their suppliers, in their supply chain become targets in M&A deals. Their transactions are uniformly profitable, indicating that corporate insiders better time their transactions when their firms are misvalued due to the limited attention constraint faced by the aggregate market.

I investigate the informational content behind these informed transactions and show that these more informed insider transactions can support both productive efficiency and purchasing efficiency hypotheses. I question the informational channel that these insiders are trading, I find that they trade on their better understanding about the public announcement of the M&A deal rather than the private information, the conventional motivation for their trades. Furthermore, insiders learn from the market reaction to the M&A announcement and they adjust their trading decisions based on the five-day CAR of the target firms, not the CAR of their own firms, the result reaffirms my findings that insiders are trading on the public rather than private information. I argue that if insiders are indeed trading in the future change in their business performance, I should not observe a significant change for M&A announcements that are eventually withdrawn. I subject my results to a battery of robustness test and find that incomplete M&A announcements do not lead to the significant change in both insider trading activity and profitability. Moreover, insider trading measure can predict the probability of the deal completion, and the predictive power is in addition to the market-estimated probability.

Lastly, I show that my results are robust to the exclusion of the insider firms with many linked firms, and to the exclusion of firms that have many peer firms in the same four-digit SIC industry. My results are unlikely to be driven by the inconsistency caused by reverse causality, and my conclusions cannot be replicated using 1000 placebo tests.

While my results hold after subjecting them to many robustness tests, I was not able to link their trades to news releases of their firms and their supply chain firms, because of data limitation. I also was not able to include corporate governance variables which may affect their trades and their supply chain firms agency conflicts which may drive the M&A bids, in addition to their stock price performance. The extent to which these and other factors will confirm or alter my results is the subject of further research.

Appendix 3.1: Sample composition

Panel A: Sample Construction

	Change in Sample Size	Sample Size
Total US domestic M&A deals from SDC (2003-2020)		169,298
Less		
Deal value under 1 million ($)	111,548	57,750
Nonpublic Target	39,517	18,233
Deal Type: Exchange Offers, Repurchases, Spin-off, Minority Stake Purchases, Recapitalization, Acquisitions of Remaining Interest, Privatization, Restructuring, Reverse Takeover, Acquisition of Certain Assets, Buyback	13,349	4,884
Percent of shares held at announcement <= 49.99%	4	4,880
Percent of shares acquiror is seeking to own after transaction: >=50%	64	4,816
Deals that are announced for the same target within 730 days	428	4,388
Deals in which target firms have no data on relationship in Factset Revere	3,122	1,266
Deals in which IT firms are also connected to the acquiror	37	1,229
Deals in which IT firms have more than one of their linked firms become target within 360 days	48	1,181
Deals that are not completed or partially completed	226	955
Deals in which linked firms have missing data or IT firms fail to match a control firm	261	694
IT firms that report no insider transactions in the entire history of Smart Insiders	9	685
Final sample		685

Panel B: M&A sample distribution by M&A announcement year

Announcement year	Number of Deals	% of Sample
2003	12	1.75
2004	13	1.90
2005	20	2.92
2006	21	3.07
2007	25	3.65
2008	13	1.90
2009	21	3.07
2010	30	4.38
2011	27	3.94
2012	26	3.80
2013	44	6.42
2014	66	9.64
2015	68	9.93
2016	75	10.95
2017	62	9.05
2018	62	9.05
2019	56	8.61

2020	41	5.99

Panel C: Industry classifications of IT and target firms %						
Fama-French 17 industry classification	Competitor		Customer		Supplier	
	IT	Target	IT	Target	IT	Target
Food	2.17	1.54	3.34	1.34	4.31	1.6
Mining and Minerals	0.45	0.09	0.33	0.00	0.25	0.86
Oil and Petroleum Products	2.90	2.53	3.18	3.35	2.96	1.6
Textiles, Apparel & Footwear	0.72	0.54	1.51	0.50	2.46	0.99
Consumer Durables	1.36	1.36	2.68	0.67	1.85	0.49
Chemicals	1.90	1.99	0.50	0.84	1.35	1.85
Drugs, Soap, Perfumes, Tobacco	5.16	7.78	5.52	3.02	4.68	3.69
Construction and Construction Materials	2.44	3.16	2.84	2.85	2.71	2.46
Steel Works Etc	0.81	0.72	1.00	1.17	0.99	1.23
Fabricated Products	0.54	0.54	0.84	0.17	0.49	0.37
Machinery and Business Equipment	13.85	11.3	20.74	8.54	12.07	14.29
Automobiles	1.54	1.45	0.67	1.17	2.71	0.86
Transportation	1.90	2.08	4.01	3.18	3.69	2.83
Utilities	2.35	2.98	2.17	4.52	6.53	2.59
Retail Stores	9.23	11.66	1.84	19.60	9.85	0.86
Banks, Insurance Companies, and Other Financial Institutions	9.68	8.86	5.52	6.53	10.34	3.82
Other	42.99	41.41	43.31	42.55	32.76	59.61

Appendix 3.2: Definition of Variables

Variable Notation	Data Source	Definition
total $\text{asset}_{j,t-1}$	Compustat	Logarithm of the total asset (Compustat: at) in the last fiscal year.
$\text{mkt\_cap}_{j,m}$	CRSP	Market capitalization value of a given stock at the end of day *d*.
$\text{Ln}(\text{mkt\_cap})_{j,m}$	CRSP	Logarithm of the market capitalization value of a given stock at the end of day *d*.
$\text{BHAR\_m\_30}_{i,d}$	CRSP	30-calendar day Buy-N-Hold return adjusted by using the CRSP value-weighted market index. Defined as the following: $BHAR_{m_n} = \prod_{t=1}^{d}[1 + R_{jt}] - \prod_{t=1}^{d}[1 + R_{mt}]$
$\text{BHAR\_ff\_30}_{i,d}$	CRSP, French's website	30-calendar day Buy-N-Hold return adjusted by using the NYSE size-decile portfolio.
$\text{NPV}_{i,m}$	Smart Insider	Net purchasing value for insider transactions in month *m* executed by insider *i*, calculated as the ratio of the net dollar amount of insider transactions over the total dollar amount of insider transactions. If *NPV_i* is greater (less) than 0, I recognise that the insider *i* is net buying (selling).
$\text{mom}_{j,m,(d-1,d-365)}$	CRSP	The cumulative raw return from (d-365, d-1), insider transaction occurs in day d.
$\text{ret6}_{j,m,(d-1,d-180)}$	CRSP	The cumulative raw return from (d-180, d-1) for firm *j* at the end of month m.
$\text{illiq}_{j,m-1}$	CRSP	Amihud's (2002) measure of illiquidity for firm *j* at the end of the last month. The measure is calculated as the monthly average of the daily ratio of absolute stock return to dollar volume.
$\text{bm}_{j,m-1}$	CRSP, Compustat	The book-to-market ratio calculated as the ratio of last fiscal year's book value over the market capitalization in the last trading day in December. Book value is computed as the following. Book value is equal to stockholder equity + deferred taxes and investment tax credit (Compustat: txditc, zero if missing) − preferred stock value. Stockholder equity is

		parent stockholder equity (Compustat: seq), or total common equity (Compustat: ceq) plus total preferred stock capital (Compustat: pstk) or the difference between the total asset (Compustat: at) and total liability (Compustat: lt), in that order, as available. Preferred stock value is the 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. The ratio is calculated for firm j at the end of the last month.
$numest_{j,t-1}$	I/B/E/S	Analyst coverage is defined as the number of analysts that report a forecast for the next 1-fiscal year earnings per share for firm j at the end of the last month. If there is no earning forecast, the analyst coverage is set to be zero.
$insti\_hold_{j,q}$	Thomson Reuter 13F Holding	Percentage of shares owned by institution investors over total shares outstanding.
$insti\_HI_{j,q}$	Thomson Reuter 13F Holding	Herfindahl index based on the number of institution investors invested in stock j. I divide the number by 100 for reporting clarity.
$roa_{j,t-1}$	Compustat	Return on asset calculated as the net income (Compustat: ni) after taking out preferred dividend (Compustat: dvp), over the total asset (Compustat: at) for firm j at the end of the last fiscal year.
$rd_{j,t-1}$	Compustat	Research and development expense calculated as the research and development expense (Compustat: xrd) over sales (Compustat: sale) for firm j at the end of the last fiscal year. If Compustat reports missing research and development expense, it is set to be zero.
$leverage_{j,t-1}$	Compustat	Long term debt plus debt in current liability) over the total assets $$\frac{(dltt + dlc)}{at}$$

$size_{j,m-1}$	CRSP	The logarithm of market capitalization defined as adjusted stock price times adjusted shares outstanding for firm *j* at the end of the last month. The number is reported in a million.
$age_{i,d,m}$	Smart Insider	The date difference between the first occurrence of director *i* in Smart insider database and the current transaction date *d* at the end of month *m*.
$tenure_{i,j,d,m}$	Smart Insider	The date difference between the date of the first transaction of director *i* in firm *j* in Smart insider database and the current transaction date *d* in the firm *j* at the end of month *m*.
$vol_{j,(d-90,d-1)}$	CRSP	The total normalized trading volume in the last 90 trading days. Daily trading volume is normalized using the total share outstanding times 1,000
$sd_{j,(d-365,d-1)}$	CRSP	Annualized standard deviation of stock return computed over day (-365, -181). Day 0 is the insider trading day
$delta\_sd_{j,(m-3,m-1)}$	CRSP	The change between standard deviation computed over day (-180, -1) and over day (-365, -181).
$competitorD_r$	Factset Revere, SDC	Dummy variable equals to one if acquiror is a competitor of target firm, zero otherwise.
$customerD_r$	Factset Revere, SDC	Dummy variable equals to one if acquiror is a customer of target firm, zero otherwise.
$supplierD_r$	Factset Revere, SDC	Dummy variable equals to one if acquiror is a supplier of target firm, zero otherwise.
$MFHSD_{j,t}$	Thomson Reuter and CRSP Mutual Fund	In each year, I divide all firms covered by both Thomson Reuter and CRSP mutual fund files according to their mutual fund hypothetical sales constructed by Edmans *et al.*(2012), Dessaint *et al.* (2019) and Boehm and Sonntag (2022) into quintiles. I create a dummy variable $MFHSD_{(j,t)}$ equal to one if the firm has been in the bottom quintile in year *t*, zero otherwise.
$MFHS_{j,t}$	Thomson Reuter and CRSP Mutual Fund	A continuous variable equals to the market capitalisation weighted average $MFHSD_{j,t}$ of all linked firms in year t for a given relationship type. If control firm does not have any

		linked firm in a given year, the variable is set to be zero.
tobin's $Q_{i,t-1}$	Compustat	Market value of equity plus book value of debt-deferred tax over book value of total assets. $\frac{(at + csho \times prcc\_f - ceq - txdb)}{at}$
$concentration_{i,t-1}$	Compustat	The ratio of sales of the largest four firms to the total three-digit SIC industry sales (Cornett *et al.* 2011 and Davis *et al.* 2021)
$industryROA\Delta_{i,j-1}$	Compustat	The change in the industry return on asset over the next 12 months following the announcement month of linked firm becomes target (Davis *et al.* 2021).
$cash\_ratio_{j,t-1}$	Compustat	The ratio between cash and short-term investments to the total asset (Cornett *et al.* 2011 and Davis *et al.* 2021). $\frac{che}{at}$
$sale\_growth2y_{j,t-1}$	Compustat	The change in the firm's sale over the previous 2 fiscal years (Cornett *et al.* 2011 and Davis *et al.* 2021).
$runup_{j,m,(d-30,d-1)}$	CRSP	The cumulative raw return from (d-30, d-1) at the end of month *m* for firm *j*.
$ind\_activity_{j,(m-1,m-12)}$	SDC	The total number of deal announcement in the same 2-dig SIC industry for firm j between month (-1,-12). If no deal is found, the value is zero.

Appendix 3.3: Event-type difference-in-difference regression

I follow Angrist and Pischke (2009) and Cengiz *et al.* (2019) to conduct an event-study type diff-in-diff regression and formally test on the parallel trend assumption. Variable pre_m **(**Post_m) is equal to 1 for treated firms in pre- (post-) month *m,* and zero otherwise. Month *m* refers to the month in my event window with month *0* as the M&A announcement month. The coefficients of Pre_m should be all statistically insignificant for the parallel trend assumption to hold. Pre_{-1} is omitted to avoid perfect multicollinearity. I control for firm, person, and month-year fixed effects. Standard errors are clustered at the firm-month level. ***, **, and * denote significance at the 99%, 95% and 90% confidence level, respectively. All variables are winsorised at the top 99% and the bottom 1% level.

	Competitor		Customer		Supplier	
	(1)	(2)	(3)	(4)	(5)	(6)
	NPV	$\mathrm{BHAR\_m\_30}_{i,d}$	NPV	$\mathrm{BHAR\_m\_30}_{i,d}$	NPV	$\mathrm{BHAR\_m\_30}_{i,d}$
pre_{-12}	0.006	-0.007	-0.013	-0.008	0.063	0.013
	(0.042)	(0.010)	(0.042)	(0.016)	(0.048)	(0.012)
pre_{-11}	0.021	0.014	0.023	0.002	0.020	0.015
	(0.050)	(0.012)	(0.056)	(0.018)	(0.045)	(0.011)
pre_{-10}	0.058	0.003	-0.003	0.010	-0.036	0.017
	(0.043)	(0.009)	(0.048)	(0.015)	(0.046)	(0.011)
pre_{-9}	0.044	-0.006	-0.012	0.014	-0.015	0.002
	(0.054)	(0.010)	(0.047)	(0.017)	(0.044)	(0.011)
pre_{-8}	0.038	0.016	0.014	-0.012	0.026	0.027^{**}
	(0.048)	(0.012)	(0.040)	(0.015)	(0.043)	(0.012)
pre_{-7}	-0.003	0.003	-0.019	0.000	0.020	0.018
	(0.046)	(0.010)	(0.041)	(0.016)	(0.043)	(0.011)
pre_{-6}	0.027	0.012	-0.013	-0.004	0.062	0.005
	(0.042)	(0.012)	(0.041)	(0.019)	(0.046)	(0.012)
pre_{-5}	0.054	-0.017	0.010	-0.001	0.052	0.012
	(0.048)	(0.011)	(0.043)	(0.015)	(0.049)	(0.013)
pre_{-4}	0.041	-0.004	0.036	-0.005	0.088	-0.002
	(0.041)	(0.010)	(0.038)	(0.013)	(0.066)	(0.011)
pre_{-3}	0.066	-0.008	0.020	-0.008	0.088	0.007
	(0.042)	(0.010)	(0.033)	(0.016)	(0.054)	(0.011)
pre_{-2}	0.051	-0.005	0.042	-0.021	0.016	0.017
	(0.045)	(0.010)	(0.039)	(0.016)	(0.048)	(0.013)
post_0	0.100^{**}	0.020^{**}	0.028	-0.014	0.072^{*}	0.033^{**}
	(0.048)	(0.010)	(0.037)	(0.015)	(0.040)	(0.013)
post_1	0.054	0.010	0.093^{*}	-0.025	0.049	0.029^{**}
	(0.047)	(0.012)	(0.051)	(0.019)	(0.053)	(0.014)
post_2	0.064	-0.013	0.102^{**}	0.033^{**}	0.062	0.023^{**}
	(0.040)	(0.010)	(0.046)	(0.015)	(0.044)	(0.011)
Other Control	Yes	Yes	Yes	Yes	Yes	Yes
Sample	7741	6503	4479	3806	5230	4133

Appendix 3.4: Construction of mutual fund hypothetical sales instrument

The instrumental variable (IV) used in the paper is the mutual fund hypothetical sales (MFHS). I follow the Appendix C of Dessaint *et al.* (2019) which is based on the Edmans *et al.* (2012). The IV has been successfully applied in Boehm and Sonntag (2018). I use both the CRSP mutual funds data and Thomson Reuter Mutual Fund data which is formerly known as the CDA Spectrum/Thomson to construct the IV.

First, I begin with the CRSP mutual funds data which reports the monthly return and total net assets by asset class *k*. I compute the weighted average return of fund *j* in month *m* of year *t* using the total net asset (TNA) by asset class as the weight.

$$Return_{j,m,t} = \frac{\sum_k (TNA_{k,j,m,t} \times Return_{k,j,m,t})}{\sum_k TNA_{k,j,m,t}}$$

where k indexs asset class. I compound these returns to obtain quarterly returns. Furthermore, I estimate the net inflow into fund *j* in quarter *q* of year *t,* as a fraction of its beginning-of-quarter net assets, as follows:

$$flow_{j,q,t} = \frac{TNA_{j,q,t} - TNA_{j,q-1,t} \times \left(1 + Return_{j,q,t}\right)}{TNA_{j,q-1,t}}$$

Second, I use Thomson Reuter to obtain the share holdings $shares_{j,i,q,t}$ of each fund *j* in firm *i* at the end of quarter *q* of year *t.* Finally, the hypothetical sales of fund *j*'s assets in firm *i* for all mutual funds for which $flow_{j,q,t} < -0.05$, I compute

$$MFHS_{i,q,t}^{dollars} = \sum_j (flow_{j,q,t} \times shares_{j,i,q-1,t} \times price_{i,q-1,t})$$

I obtain share price and trading volume from CRSP. This variable is the hypothetical net selling of stock i, in dollar value, by all mutual funds that subject to extreme capital outflows. I further normalise $MFHS_{i,q,t}^{dollars}$ by the dollar value of total trading volume in stock *i* in quarte *q* of year *t* as follows:

$$MFHS_{i,t} = \sum_{q=1}^{q=4} \frac{MFHS_{i,q,t}^{dollars}}{VOL_{i,q,t}}$$

Appendix 3.5: Construction of FERC and stock return synchronicity

I follow Tucker and Zarowin (2006) and Wang (2019) to construct the FERC by first estimating the following equation:

$$R_{i,t} = \alpha + \beta_0 X_{i,t-1} + \beta_2 X_{it} + \beta_3 \left(X_{i,t+1} + X_{i,t+2} + X_{i,t+3}\right) + \beta_3 R_{i,t+3} + \varepsilon_{i,t}$$

where $X_{i,t}$ is the basic annual earnings per share excluding extraordinary items (*epspx*), adjusted for stock splits and stock dividends and deflated by the stock price at the beginning of the fiscal year *t*. $R_{i,t}$ is the firm's annual return beginning at the fiscal year t and $R_{i,t+3}$ is a three-year future return for the firm from fiscal year *t+1* to *t+3*. The coefficient of the sum of the future three-year earnings per shares β_3 is the FERC. I truncate all variables at the top and bottom 1%. A higher β_3 means the current stock return impounds more future earnings information and is more informative for future earnings and *vice versa. I* follow Wang (2019) to estimate a rolling panel regression using the trailing 36 months across each two-digit SIC industry. I restrict that there are at least 8 (24) months in $R_{i,t}$ ($R_{i,t+3}$) for a stock to be included in the regression and create binary variable FERC that is one for the top quintile of the β_3 and zero otherwise.

I use the stock return synchronicity used by Piotroski and Roulstone (2004) estimated from the following equation:

$$\mathrm{FirmRET}_{i,t} = \alpha + \beta_1 \mathrm{MktRET}_{j,t} + \beta_2 \mathrm{MktRET}_{j,t-1} + \beta_3 \mathrm{IndRET}_{k,t} + \beta_4 \mathrm{IndRET}_{k,t-1} + \varepsilon_{i,t}$$

where $MktRET_{j,t}$ is the market return proxied by the CRSP value-weighted buy-and-hold market return in year t. $IndRET_{k,t}$ is the value-weighted average industry buy-and-hold return identified using the two-digit SIC code in year *t*. I estimate the regression for each firm-year observation with weekly return data and restrict a minimum of 45 weekly observations each year. The synchronicity is measured as $\ln\left(\frac{R^2}{1-R^2}\right)$. The R^2 is the R square of the above regression. A higher $Synch_{i,t}$ indicates the current firm return comove strongly with the current and lagged market and industry returns, which further indicates the stock price contains less firm-specific information.

Appendix 3.6: Construction of the deal completion probability

To differentiate the marginal predicative power of net insider trading in deal completion probability from the probability estimated by the aggregate market, I follow Fidrmuc and Xia (2021) estimate the market probability of deal completion which is based on Samuelson and Rosenthal (1986). Samuelson and Rosenthal (1986) argue that the market's assessment on the deal completion probability will reflect on the target stock prices after the M&A deal announcement because the larger the price difference between the target stock price on a day *d* and the offer price $\mathrm{p_{of}} - \mathrm{p_d}$, the higher the probability that the deal will be completed. If the stock price immediately jumps to the offer price, then the market reckons that the deal will be completed with certainty. On the other hand, a little change in price no higher than the fall-back price, $\mathrm{p_f}$, will imply that the market assesses the likelihood of deal completion is almost zero. Fidrmuc and Xia (2021) show that the price on day *d* is $\mathrm{p_d} = \mathrm{q} \times \mathrm{p_{of}} - (1 - \mathrm{q}) \times \mathrm{p_f}$. *q* denotes the probability of deal completion. The *q* can be obtained by rearranging the equation as $q = (\mathrm{p_d} - \mathrm{p_f})/(\mathrm{p_{of}} - \mathrm{p_f})$

In the study, I follow Fidrmuc and Xia (2021) to set *d* equal to 1 which is the next trading day after the announcement date. To estimate the *q*, I employ two similar but different methods. For the first method, I follow Samuelson and Rosenthal (1986) to estimate the fall-back price as the weighted average of $\mathrm{p_{-42}}$ which is the stock price 42 trading days before the announcement and $\mathrm{p_{of}}$: $\mathrm{p_f} = 0.63 \times \mathrm{p_{-42}} + 0.37 \times \mathrm{p_{of}}$. The deal completion probability is then computed as $q = (\mathrm{p_{+1}} - \mathrm{p_f})/(\mathrm{p_{of}} - \mathrm{p_f})$. I denote the estimated probability as $\mathrm{Mkt\_pro_j}$ report the result in Table 3.7 Panel C. In further robustness checks, I tried weight of (0.5, 0.5) and (0.72, 0.25), all results in Table 3.7 Panel C remain the robust.

For the second method, I follow Fidrmuc *et al.* (2018) to estimate probability *q*. Fidrmuc *et al.* (2018) assumes that the target price unaffected by the deal announcement, and the equation simplifies to $\mathrm{q} = (\mathrm{p_{+1}} - \mathrm{p_{-42}})/(\mathrm{p_{of}} - \mathrm{p_{-42}})$. I do not report the result using this version of estimated probability but all results in Table 3.7 Panel C remain robust.

Chapter 4

Trading strategies of corporate insiders at the 52-week high and low[50]

Abstract

Previous studies concluded that investors suffer from the 52-week high/low anchoring biases. I expand this evidence to corporate insiders, the conventionally viewed as informed traders. I find that insiders systematically trade at these price extremes. They do not suffer from anchoring biases. I identify the characteristics of those sophisticated enough to exploit other investors' anchoring biases by undertaking opportunistic profitable trades and dissimulation strategies to conceal their informational advantage. I find that a long-short strategy based on a portfolio built on the top decile 52-week high (low) recency of their transactions generates an annual abnormal return of approximately 31%.

Keywords: Insider Trading; 52-Week Price High/Low; Anchoring Bias; Recency Bias; Trading Strategies; Stock Market Anomalies

JEL Classification: G14; G11; G12; G40; G41

[50] This chapter is co-authored with Lasfer Meziane. I tank Ian Marsh and Richard Payne and seminar participants at Birmingham Business School and Swansea Business School for their constructive comments. All errors remain my responsibility.

"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, the shares decreased by -3.3% ($CAR_{10\text{ to }16\text{ Nov }20}$ = -6.9%), when rival Moderna reported higher success rate and its share price rose by 8%, and 90 days later, $CAR_{10\text{ Nov }20\text{ to }22\text{ Mar }21}$ = -12%.

4.1 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 reckon the 52-week high as the resistance level, referred to as the anchoring bias, adopt a contrarian trading strategy by selling at the peak.[51] George and Hwang (2004)'s 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 behavioral models that consider that short-term momentum and long-term reversals are an integrated process.[52]

In this paper, I extend George and Hwang (2004) analysis by assessing whether insiders are subject to or exploit other investors' anchoring biases around the 52-week high/low. Since they are truly privy of the firms' future cash flow realizations (Piotroski and Roulstone, 2005; Jiang and Zaman, 2010; Cosemans and Frehen, 2022), they tend to trade against investors' existing sentiment and correct stock misevaluation (Rozeff and Zaman, 1998).[53] They are expected to exploit other investors' anchoring biases associated with the 52-week high and low

[51] In the literature, contrarian trading is only proxied by momentum, which I control for to isolate anchoring bias.
[52] The behavioral 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.
[53] Seyhun (1986, 1990), Lakonishok and Lee (2001), Huddart and Ke (2007), Agrawal and Cooper (2015), Beneish and Markarian (2019) provide reviews of the relatively vast insider trading and its profitability literature.

by adopting contrarian strategies by systematically selling (buying) when prices reach their 52-week high (low). However, 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, leading them to suffer from anchoring bias, like other investors.

I use a sample of 586,742 transactions undertaken by US insiders between 1994 and 2018 to test my research question. While I cannot detect insiders' trade incentives ex-ante, I attempt to infer their motivation ex-post from the performance of their trades. I find that they adopt contrarian strategies as they are more likely to sell at 52-week high and buy at 52-week low, but my first results provide mixed evidence, as their net sell trades result in post-trade annualized 4-factor model α of 2.4%, consistent with the anchoring bias, while their net purchases α is 12.04%, in line with informed trading. It is possible that these contradictory results between the net buys and net sells reflect the arguments of Lakonishok and Lee (2001) 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. My results are also consistent with recent evidence on trading by institutional investors as Akepanidtaworn *et al* (2021) report evidence of skill in buying, while sell trades underperform. This discrepancy is related to an asymmetric allocation of cognitive resources such as attention, as investors are subject to systematic, costly heuristic process when selling but not when buying. I consider that insiders are likely to use dissimulation strategies to avoid regulators' attention. Kyle (1985) proposes that as insiders possess long-lived information. They will split their trades to minimize any price impact and camouflage their informational advantage by hiding behind random noise traders. Similarly, Kose and Ranga (1997) argue that informed insiders manipulate the market by trading against their information to preserve their information advantage and increase their trading profits. However, the short swing regulation presents trades within the 2 directions within 6 months. Huddart, Hughes and Levine (2001) suggest that insiders will also dissimulate their information by randomly making noisy transactions to disguise their informed transactions. I follow Biggerstaff, Cicero and Wintokie (2020) and identify insider sell trades based on only long-lived information, and classify dissimulation sell as Sequence Sells. I further differentiate between the unconditional Buy-and-Hold Abnormal Return (BHAR) that the literature has predominately focused on, and the Scaled Holding Return that assumes that insiders close all their positions in simultaneous Sequence Sells. I show that after accounting for dissimulation strategies, the results of my net buy trades remain unchanged, but the Sequence Sells at the 52-week high are loss averting as they generate significant BHAR of -3.00%, suggesting that sophisticated insiders who dissimulate their trades are likely to exploit other investors' anchoring biases associated with the 52-week high and low. My results are robust when I account for the nine asset pricing anomalies, including momentum to proxy for contrarian strategy in Stambaugh, Yu and Yuan (2012).

I analyze further the information content embedded in insiders' dissimulation transactions at the 52-week high by focusing on the predictability of future fundamentals and earnings surprises. I use the 3-day cumulative abnormal return (CAR) and Standardized Unexpected Earnings (SUE) to proxy for the future earnings surprises. I 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, I deepen my understanding of corporate insiders who frequently employ dissimulation strategy by identifying their heterogeneous characteristics. I 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), I find that SH insiders are more sophisticated in materializing their private information and LH insiders are more likely to trade on long-lived information. I 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). I find that male insiders are more likely to dissimulate their private information at the 52-week high. I also document that the board members, particularly CEOs, that Cohen, Malloy and Pomorskie (2012) define as opportunistic traders, are more likely to dissimulate their trades.

I subject my results to various robustness tests. I 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. I match insider trading events with the dates when stocks reach their 52-week/low. I find that, at the 52-week high, their sell trades are 8 times their buy trades but their one-year loss (BHARs) of 1.8% is significantly lower than their respective profit of 12.8% from their buy trades. In contrast, at 52-week low, their sell trades are only half their buy trades, but their one-year loss-avoidance is a significant -9.7%, compared to their respective profit from their buy trades of 9.6%. I collect data of all CRSP stocks after they reach these price extremes. I find that their unconditional on insider trading one-year BHARs at 52-week high are 4.4%, in line with George and Hwang (2004), and 4.7% after reaching the 52-week low. Since these profits are lower than in stocks where insiders buy, but lower loss-avoiding than stocks where insiders sell, I conclude that both their buy and sell trades at the 52-week high and low are informative.

I 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. I devised a trading strategy based on a portfolio built on the top decile 52-week high (low) recency. I find that such a portfolio generates a one-year net BHARs of 30.8%. A similar trading strategy that does not account for the recency to the 52-week high/low yields 19.2%. I contrast such portfolio with that of George and Hwang (2004). I show that one-year BHARs post-52-week high in the top decile among all stocks in CRSP database are 8.4%. I 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 generates only 14.2% one-year BHARs. I find similar results when I use the Fama and French (1993)-Carhart (1997) 4-factor α and when I include numerous control variables in my regressions.

To my best knowledge, only Lee and Piqueira (2019) and Li *et al.* (2019) analyze insiders' anchoring bias. I extend this literature by studying the post-transaction returns, controlling for the role of recency of insiders' trade to 52-week high/low dates and by assessing the impact of insiders' dissimulation strategies. Overall, in contrast to their findings, my results imply that opportunistic insiders are not more susceptible to the 52-week high anchoring bias. Moreover, unlike Cen, Hilary and Wei (2013) and Clarkson, Nekrasov, Simon and Irene (2020) that claim that financial analysts suffer from anchoring bias, I show that corporate insiders are not likely to be subject to such behavioral predisposition, 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.

My results provide support to Luo, Subrahmanyam and Titman (2021) theoretical argument that markets where insider trading is prevalent, exhibit more momentum. I find empirically that this momentum is common in stocks that reach their 52-week high and lows. Similarly, my findings are in line with Anginer, Hoberg, and Seyhun, (2018) wo find that insiders exploit anomalies in the market. I focus on the 52-week high/low price extreme, a normally irrelevant but salient and readily available piece of information, which, according to George and Hwang (2004), creates anchoring behavioral bias by uniformed investors, whose trading is likely to be governed by emotional investing driven by behavioral pulses rather than fundamentals. I show that the long-run excess returns generated by stocks subject to strategic insider trading at the 52-week high/low do not revert, unlike those that are neglected by insiders, suggesting that their prices converge to their fundamental values, and that such insider trades are informative. While George and Hwang (2004) also examine the profitability of the 52-week low momentum and show that it is positive but insignificant, I report profitable trading strategies at both the 52-week high and low price levels in stocks where insiders trade and use dissimulation strategies to overcome regulatory constraints and to exploit other investors' anchoring biases associated with these two extreme price levels. However, I show that insiders do not behave homogenously in their propensity to dissimulate their trades, and thus, to be sophisticated, as this depends on their gender, organizational position, and investment horizons.

The remainder of the paper proceeds as follows. In Section 4.2, I review the relevant literature on anchoring bias and informed trading. Section 4.3 describes my sample and the constructions of variables. Section 4.4 presents the summary statistics, the results from the univariate and multivariate analysis, and the impact of insider dissimulation strategy. Section 4.5 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. Section 4.6 presents the robustness test by controlling for alternative asset pricing anomalies and other sample screens. The conclusions are in Section 4.7.

4.2 Literature Review on Anchoring bias in informed trading

Tversky and Kahneman (1974) propose that humans often utilize simple heuristics under uncertain and complex situations. 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.[54]

Financial studies considered, amongst other factors, the share price 52 week/low as a reference point. George and Hwang (2004) uncover 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-momentum trading strategies. They suggest that investors systematically underreact to good news when the stock prices approach their 52-week high because they recognize 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 over-react 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) 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 is less conclusive as to whether informed traders are also vulnerable to this behavioral bias. Since informed traders have superior information than retail traders, they are not expected to suffer from behavioral 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 behavioral biases widely recognized in the economics and finance

[54] For example, Kahneman, Slovic and Tversky (1982) showed participants a randomly generated number, then asked them to estimate the number of African nations in the UN. Their estimates were systematically high (lower) for the group presented with a higher (lower) random number, suggesting that they use the randomly generated and intrinsically irrelevant number as a reference point, leading to "anchoring bias". 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.

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 behavioral 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 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 recognized as informed stock market participants, make over-optimistic forecasted earnings per share because they anchor them to the industry means. Clarkson *et al.* (2020) further confirm anchoring bias in financial analysts' information sets, and Campbell and Sharpe (2009) document experts' consensus forecasts of macroeconomic indicators systematically deviate from the previous estimates.

Other studies recognize that the recency of the reference point is important but usually omitted 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. Bhootra and Hur (2013) characterize recency as one of the alternative explanations for anecdotal evidence in empirical finance and news in media.[55] 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

[55]These include, 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.

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 recognized informed traders in the stock markets (Jaffe, 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. I follow Biggerstaff *et al.* (2020) who argue that insiders trade sequentially, rather than in single transaction, on long-lived information, and disentangle the duration of information and further investigate insider dissimulation strategy at the 52-week high. Overall, I 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.

4.3 Sample and Variable Construction

I use Smart Insider Ltd, which collects all insider transactions information from Form 4 submitted to SEC to compile my sample of all U.S. insider transactions from January 1994, when the coverage is comprehensive, to December 2018.[56] In line with previous insider trading literature, I 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). I manually review all the different classes of common shares of the same company to ensure that the transactions match the correct identifier as different common share classes of one company are generally priced

[56] This database (https://www.smartinsider.com/), formerly known as Directors Deal Ltd, gathers information from Form 5, the annual statement of change in beneficial ownership and reports any and exempt transactions not reported on Form 4. It is the same as Thomson Reuters database used in previous studies. It is used also by Hoque and Lasfer (2015) and Goergen, Renneboog and Zhao (2019) and mainstream financial Henderson (2020).

differently. I 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).

I exclude the exercise of options trades because they are often motivated by personal liquidity demand or portfolio rebalancing reasons, and hence, not considered to be informative (Ofek and Yermack, 2000). I 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 firms 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.[57] I exclude any pre-scheduled trades, known as 10b5-1 plan trades, because the information content embedded is likely to be trivial.[58] In line with previous studies (e.g., Lakonishok and Lee, 2001; Lee and Piqueira, 2019), I focus on insider trading with transactions price above $1 and trading volume greater than 100 shares to minimize noise and remove outliers.

Finally, Smart Insider 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, I only focus on the executive status classified by Smart Insider as Executive, Non-Executive and Senior Officer, which account for about 92% of the raw sample.[59] 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.[60] I aggregate these trades at the insider-day level. My final insider-trading sample consists of 586,742 insider-day observations comprised of 103,530 distinct insiders and 11,090 unique firms. I report the screening details in Table 4.1. The largest exclusion category is “not open market buy/sell trades”, which are mainly option exercises, stock dividends, subscription to new shares, and companies stock awards to their executives.

---

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

[58] The SEC adopted in 2002 Rule 10b5-1, which protects insiders against allegations of illegal insider trading by allowing them to set up planned pre-announced trades, executed by their brokers, generally at a fixed time interval, regardless of the market condition and/or private information. However, Larcker *et al* (2021) report opportunistic use of 10b5-1 plans, particularly those with a short cooling-off period, those that entail only a single trade, and plans adopted in quarters that begin trading before that quarter’s earnings announcement.

[59]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.

[60]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.

I use CUSIP code to merge the insider transactions sample with stock price and holding period return data from CRSP. I extract all accounting and financial data from the annual or quarterly financial statement from COMPUSTAT. I 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. I eliminate firms with incomplete coverage from these three databases; therefore, my sample size varies in my regressions because of data availability across these three databases. I manually checked all the 586,742 transactions-stock and corresponding financial and accounting data to ensure the maximum matching accuracy. I use the CRSP Cumulative Factor to adjust stock prices, the number of shares outstanding, and transaction volume. I 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, I replace the last trading day return with delisting return.[61] Appendix 4.1 presents the details of variable constructions and data sources.

I 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:[62]

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

where $return_i$ is the holding period return, and mkt_i is the benchmark return for the holding period t. I 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 that occur within the six months, it is known as "short-

[61] 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.
[62] My unreported results are robust if I use size, book-to-market two-way sorted 10×10 value-weighted portfolio, 10-industry value-weighted portfolio, and 49-industry value-weighted portfolio as the benchmark return.

Table 4.1: Detailed Information on Loss of Sample Size

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

	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**

swing profit rule". Therefore, the six months is the shortest realistic investment horizon for insiders to materialize their private information, making this period particularly attractive to analyze. 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, I use 30, 180 and 365 calendar day as the holding 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. We, therefore, follow Agrawal and Nasser (2012) and require a minimum 20-, 120- and 243-day valid return data for each of the respective accumulation period.

I use Kenneth French's Data Library[63] 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:

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

where 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; and $SMB,$, and 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 Kothari 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). I use Baker-Wurgler investor sentiment index to alleviate the concern that market sentiment instead of behavioral bias drives insiders to trade around the 52-week high/low. This index is the first principal component of five standardized sentiment proxies where each proxy is orthogonalized 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).[64] The first principal component of the orthogonalized five components is the Baker-Wurgler index. However, Sibley, Wang,

[63] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. I thank Prof. French for making these data publicly available.
[64] http://people.stern.nyu.edu/jwurgler/. I am grateful to Prof. Wurgler for making the index publicly available.

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, I follow Sibley *et al.* (2016) and Chue, Gul and Mian (2019) to further orthogonalize the Baker-Wurgler index by regressing it on the 3-month T-bill rate I obtain from WRDS, and Lee (2011) liquidity factor, I calculate using CRSP. I use the residual from this regression, denoted as *Sento*, as a proxy for the market investor sentiment.

I 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. I follow Lasfer, Melnik and Thomas (2003) to control for the effects of short-term abnormal price movements driven by shocks by defining *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. I find that the daily mean (median) number of transactions executed by the same insider in the same company is 1.086 (1.00). Previous studies aggregate insider trading monthly (Seyhun, 1988; Lakonishok and Lee, 2001; Lee and Piqueira, 2019), while Alldredge and Blank (2019) and 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. I 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. To better capture the short-term insider trading momentum and return predictability, I aggregate insider transaction data at the insider-day level to account for this intensity and provide a weighted-average measure for return profitability where the weight is the number of firm's daily insider trading. I compute the net purchasing value (NPV) as the net dollar value over the total dollar value as:

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

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

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

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

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

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

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

The relative 52-week high/low ratio measures insiders' trading decision prior to prices reaching their 52-week high/low. This ratio is 1 if insiders trade at the 52-week high/low, while if it is high, insiders are trading when the stock price is approaching the 52-week high (low). The recency ratio gauges insiders' reaction to the attainment of the previous 52-week high/low. A ratio of 1 means that insiders trade on the day prices hit a new 52-week high (52-week low). A high (low) ratio implies that the 52-week high (low) is in the recent (distance) past.[65]

4.4 Empirical Result

4.4.1 Summary Statistics

Table 4.2 Panel A reports the summary statistics of 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 for the sample as a whole and for four relevant sub-periods: 1994-2001 (pre-Sarbanes-Oxley), 2002-2007 (Sarbanes-Oxley), 2008-2009 (financial crisis) and 2010-2018 (Dodd-Frank Act). Unless stated, I aggregate all insider transactions at the insider-day level.

The last column of Table 4.2 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 (e.g., Lakonishok and Lee, 2001; Ali *et al.*2011), 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. The negative NPV of -33.87% further confirms that insiders are net sellers on average, but, since I excluded Sale-Post Exercise, it is higher than the -57.67% reported by Lee and Piqueira (2019) for the management group in

[65] I test for robustness of my results to various specifications. I replicate my regressions at the firm-month level and when I use Net Purchasing Ratio, NPR, based on the number of shares traded, as in Lakonishok and Lee (2001). I 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, as in Li *et al*. (2019), or closing price on day t-1 over the 52-week high/low price on day t-1. I use one minus the ratio of the average time distance from the 52-week high/low in (t-30, t-1) over 364, or one minus the ratio of the time distance from the 52-week high/low in t-1 over 364. My results are robust.

1990-2014. 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.[66] The median reporting lag before 2003 is 22 days, and two days after 2003 in my 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 smaller than the 39,900 ($820,000) shares sold.[67]

I investigate further the trend in insider trading intensity. I calculate the monthly and yearly average transaction size for each month and year for buy and sell trades separately. Figure 4.1 shows that the sell trades are more pronounced than the 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 its burst and the enactment of SOX, insiders' sell trades permanently dropped, but their buys remained random. Figure 4.1 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 behavior 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 4.2.

Panel C presents the number of purchases and sells at the periodic peaks and troughs. I consider that a transaction is executed at the peak (trough) when the $\_52\_W\_H$ ($\_52\_W\_L$) is greater (less) than or equal to 0.98 (1.02).[68] 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 behavior. I 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, $p < 0.00$),

[66] Sarbanes-Oxley act came into force in 30 July 2002 and shortened the reporting deadline to SEC from 10 days to 2 days after the end of the month in which insiders executed the transactions. 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.
[67] The average dollar volume in my sample is smaller than previous studies as my minimum insider transactions share price is $1, compared to $5 in e.g., Lee and Piqueira (2019).
[68]The cut-off point is arbitrary. My results are robust to cut-off points of 0.9 (1.1), 0.95 (1.05) and 0.99 (1.01).

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 sells 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.

Table 4.3 presents the summary statistics of my key variables, which are winsorized at bottom 0.5% and top 99.5% to avoid outliers. The superscripts in column (5) (column (7)) relate to t-test (Wilcoxon rank-sum test) for the differences in means (medians) between net buys and net sells sub-sample. 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 my 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.

The average firm size, not reported, is $4.36 billion dollars, in line with $3.53 billion reported by Lee and Piqueira (2019).[69] However, Table 4.3 shows that net purchasers are more likely to trade in small firms with an average (median) market capitalization 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). I use log to account for outliers.

The average momentum is 31.48% for net sellers sell, in line with the previously documented contrarian behavior (Lakonishok and Lee, 2001), while for the net buy prices

[69] The figures suggest that the database is titled towards large firms where insiders trade more.

Table 4.2: 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). I 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 4.1. 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 minorized 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.

	Panel A. Summary statistics					
	1994-2001	**2002-2007**	**2008-2009**	**2010-2018**		**All**
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***

Figure 4.1: Monthly average size of insider transactions between 1994 and 2018
The figure displays the average size of insider transactions for each month between January 1994 and December 2018. All open market buy and sell trades are treated separately, not aggregated. The dollar amounts are minorized at the top and bottom 1% and 99% to eliminate outliers.

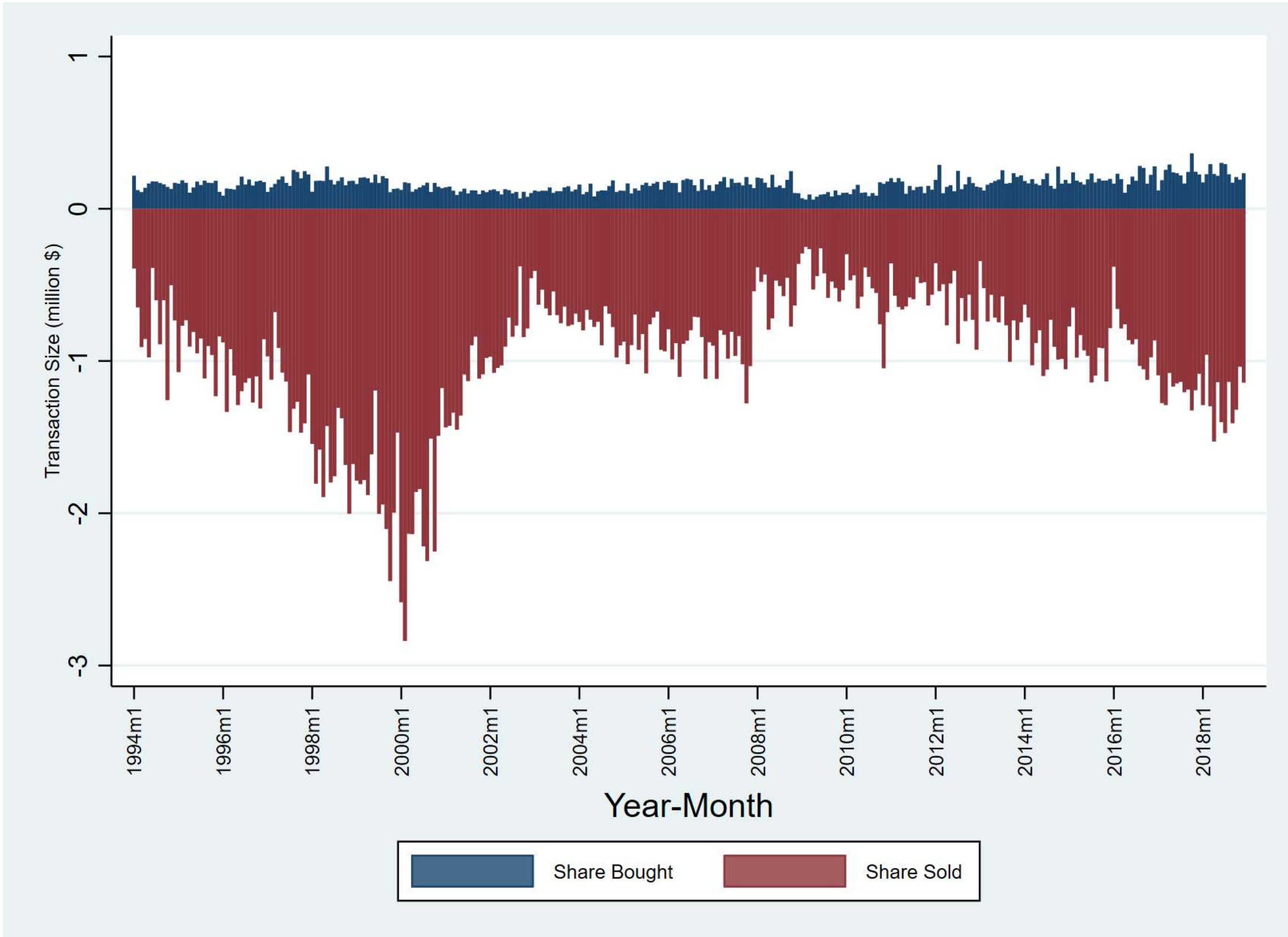
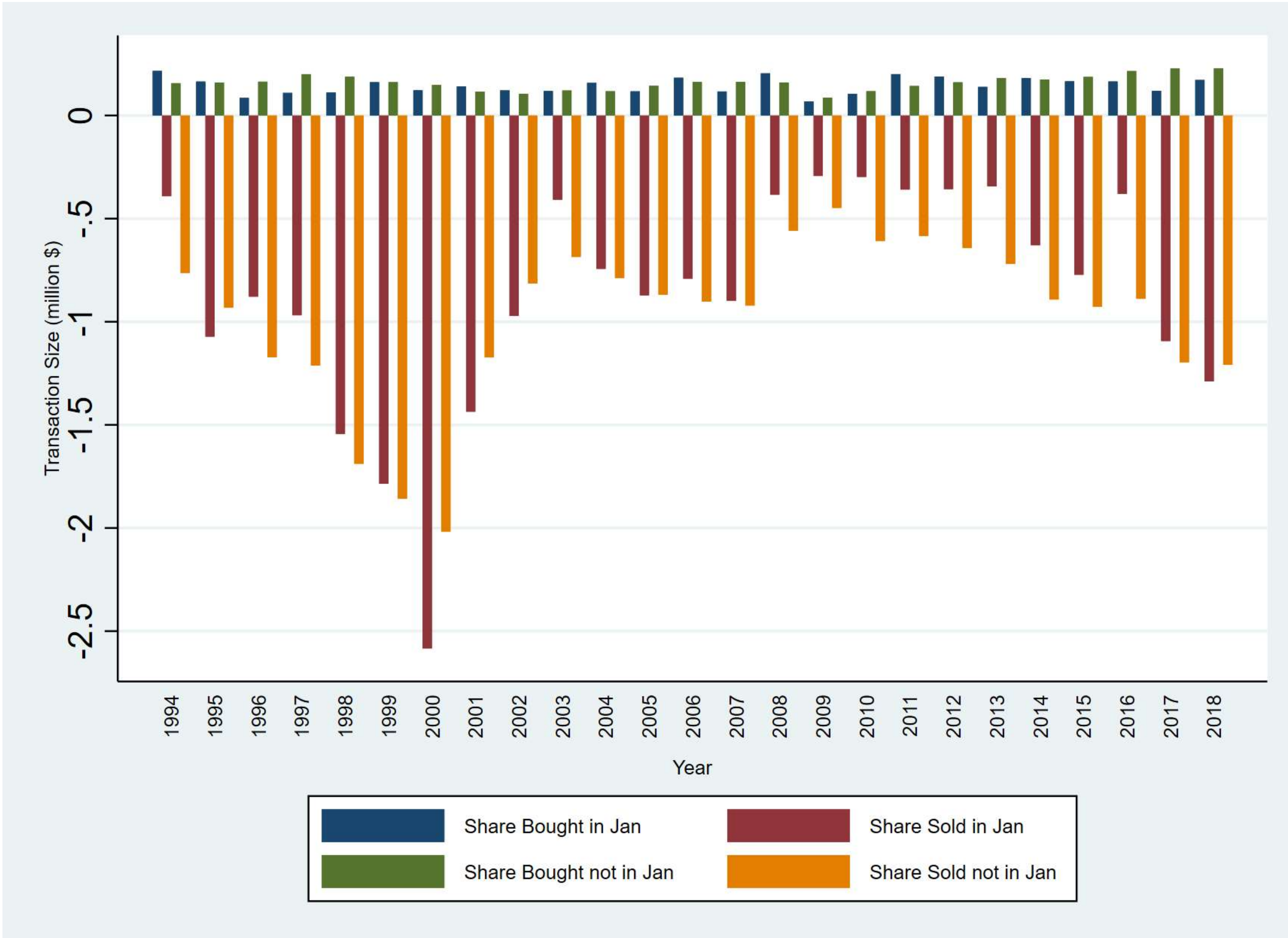


Figure 4.2: Average insider transactions size in January and non-January between 1994 and 2018
This figure compares the average size of insider transactions in January and remaining months of the year. All open market buy and open market sell are treated separately and un-aggregated. The dollar sizes of all open market transactions are minorized at the top and bottom 1% and 99% to eliminate outliers.



increase by only 7.51%, suggesting price support. The unreported overall mean (median) book-to-market (*bm)* of 0.644 (0.495) is in line with 0.591(0.592) reported by Lee and Piqueira (2019), but these levels are statistically higher for net buys than net sells, consistent with the momentum results. The mean *ROE* is negative for net purchasers, but the median is positive, suggesting that the distribution is also left-skewed, but a typical firm is profitable.

I use both CRSP value-weighted market index adjusted Buy-and-Hold abnormal return, BHAR, and Fama-French-Carhart 4-factor alpha to measure insider trading profitability. The 30-, 180- and 365-day average (median) BHARs for the buy trades are 2.714% (1.072%), 5.671% (0.709%) and 9.808% (-0.043%), respectively, with the corresponding alphas of 3.092% (1.797%), 7.503% (5.773%) and 12.043% (10.408%), based on 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). In line with my results, Jagolinzer *et al.* (2011) report a six-month average daily profit of 0.06%, annualized to 7.56%, and Beneish and Markarian (2019) find a six-month daily profit of 0.07%, equivalent to 8.82% per year.[70] The lower medians suggest that the distribution is right skewed with a long tail, consistent with Wolfgang *et al.* (2020) who postulate that corporate insiders' purchases are followed by an increase in the idiosyncratic skewness.[71] In contrast, the BHARs for the net sell trades are significant only for the 365-day holding period. These results are in line with Lakonishok and Lee (2001) who argue 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 is to seek profit.

4.4.2 Aggregated insider's profit predictability at 52-week high or low

George and Hwang (2004) show that investors tend to underreact to good news when the stock price is closer to its 52-week high, leading to a positive return momentum associated with the relative price to the 52-week high. I first validate this return predictability in my sample period by replicating their result with the additional inclusion of *Recency* variable. The results reported in Appendix 4.2 show that the 52-week high return anomaly persists, as return

[70] I also use 10×10 size, book-to-market two-way sorted value-weighted portfolio return to proxy for market return. I find that 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. I also find similar results when I use Fama-French 10-industry portfolio returns or 49-industry portfolio returns to adjust BHARs.

[71] My results remain unchanged if I winsorise the right tail of the return distribution to restrict the median is not below the mean to alleviate the concern that my results are driven by extreme returns.

Table 4.3: Summary Statistics II

This table presents the summary statistics of key variables for the period of 1994-2018. All variables are minorized at 0.5% and 99.5% level and described in Appendix 4.1. Insider transactions are aggregated at the insider-day level. I multiply the 4-factor αs for 30/180/365 holding periods by the respective median numbers of trading days of 22, 126 and 252. ***, **, * indicate statistical significance at .01, .05 and.1 levels, respectively. [a], [b], [c] in column (5) and (7) test for the mean difference between Net Buyer and Net Seller, 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
$\alpha t+1, t+30$ (%×22)	3.092***	-4.833	1.797	9.802	-0.127**[a]	-6.241	-0.084[a]	5.960
$\alpha t+1, t+180$ (%×126)	7.503***	-10.232	5.773	24.258	0.743***[a]	-13.283	1.160[a]	15.322
$\alpha t+1, t+365$ (%×252)	12.043***	-13.290	10.408	36.596	2.418***[a]	-17.127	2.794	22.282

predictabilities are 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 returns whereas the recency to the previous 52-week low is associated with a negative return momentum. These results suggest that investors without private information should buy at the 52-week high or sell immediately after the stock plummeted to its 52-week low to profit from their positions

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 materialize their private information, otherwise they are suffering from the anchoring bias. Since insiders are informed market participants, they will trade at any direction at any price level if their private information heralds trading opportunities. I cannot infer the motivation behind their trading decisions without a thorough study of their post-transaction returns. Therefore, to detect their motivation to trade ex-post, I focus on the subsequent returns of: (i) stocks that reached 52-week high/low in the last fifteen days, equivalent to restricting my sample to *Recency* greater or equal to 0.96, or (ii) stocks breaking their 52-week high or low in the next fifteen days.

We, first, identify the event date 0, the day the stock reached its 52-week high/low, defined as when the price is higher (lower) than the 52-week high (low) in the previous trading day to eliminate all cases that a stock reached its 52-week high/low due to the lapse of time. I only consider the first hit if a stock breaks its 52-week high multiple times in the next 30 days. Then, I aggregate all insiders' transactions for the stock within three distinct window periods, annotated as (-15, -1), (0, 0) and (1, 15) and 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, while $NPV_{(0,0)}$ implies that insiders traded exactly on the day that the stock reached its 52-week high/low. Finally, I calculate the adjusted BHARs using CRSP market value-weighted index from day 1 to the next 30-, 180- and 365-calender days, excluding day 0.[72] Table 4.4 reports the results, and Appendix 4.3 reports the risk-adjusted return (4-factor alpha) for robustness checks.

Table 4.4, Panel A indicates that when corporate insiders are net buyers at exactly the 52-week high, their trading decisions are informative and have consistently predicted a positive BHAR of 2.6%, 10.5% and 12.8% for the next 30-, 180- and 365-day holding periods,

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

Table 4.4: 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, I 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, I restrict there must be at least 20/120/243 trading days within the corresponding 30/180/365 estimation windows. I exclude stocks that listed less than 120 trading days and reached a 52-week high because of time elapse. In Panel D, I 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. All BHAR_m_*i* are minorized at the top 99.5% and the bottom 0.5%. ***, **, * indicate the coefficients are statistically significant at 0.01, 0.05% and 0.01levels, respectively.

Panel A: 52-Week High Reached

	BHAR_m_30			BHAR_m_180			BHAR_m_365		
	Purchase	Sell	Diff	Purchase	Sell	Diff	Purchase	Sell	Diff
$NPV_{(0,0)}$	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	
$NPV_{(1,15)}$	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	
$NPV_{(-15,-1)}$	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	

Panel B: 52-Week Low Reached

	BHAR_m_30			BHAR_m_180			BHAR_m_365		
	Purchase	Sell	Diff	Purchase	Sell	Diff	Purchase	Sell	Diff

$NPV_{(0,0)}$	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	
$NPV_{(1,15)}$	-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	
$NPV_{(-15,-1)}$	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	

Panel C: Unconditional Return

	BHAR_m_30	BHAR_m_180	BHAR_m_365
52-Week High	0.011***	0.032***	0.044***
Reached	(0.000)	(0.001)	(0.001)
	125,860	138,589	131,848
52-Week Low	0.008***	0.009**	0.047***
Reached	(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
$NPV_{(0,0)}$	1.00	1.00	1.00	1.00
$NPV_{(1,15)}$	1.01	1.02	0.97	1.00
$NPV_{(-15,-1)}$	0.92	0.94	1.11	1.14

respectively. I can observe the same positive return predictability if I define insider net buying pressure by aggregating insider transactions fifteen days before or after the stock reached a 52-week high. However, their net sells are also followed by positive returns, albeit significantly lower than those of the net buys. These results are mixed, as, while they suggest that insiders' buy trades at 52 week high are profitable, their sells are not. At exactly the 52 week low, Panel B shows that both their buy and sell trades are profitable, but their trades 15 days pre- and post-the 52 week low event are mixed. These results suggest that not insiders do not always exploit the behavior bias of uninformed investors and 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, independently of insiders' trading activity. A comparison with Panel A suggests that stocks that reached their 52-week high with insiders' buy trades outperform the average sample return. Similarly, the positive returns generated by stocks in which they sell at 52-week high are lower than the average sample return. In unreported result, the difference between insider sell return and average sample return is statistically significant for the 180- and 365-day holding periods. These results suggest that insiders are informed traders at 52-week high. I can observe similar informativeness embedded in insider trading at the 52-week low.

Moreover, the sample size for stocks that experienced aggregated net selling pressure from insiders at the 52-week high from day -15 to +15 is more than 23,000, with only around 4,000 occurring 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 my result in summary statistics in Table 4.2 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 findings are 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 indicates that insiders do actively pre-empt their positions at the 52-week low to signal undervaluation, as shown in Panel D, a result 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 the claimed behavioral bias.

4.4.3 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. Their results on the 52-week low are not statistically significant. Bhootra and Hur (2013) show that further sorting on the 52-week high recency ratio will enhance the profitability of the zero-cost trading strategy. In the previous section, I inferred insiders' ex-ante informativeness in their trade 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 realization of their firms. If insiders also trade at the 52-week high/low, their trades will provide a signal to the uninformed investors in addition to the 52-week high ratio and the recency ratio. Furthermore, the rigorous insider trading regulation 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, I 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.

I first sort stocks that recently reached their 52-week high (low) and insiders' buy (sell) trades. At the end of each month day t, I 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. I then sort these two categories of stocks according to their 52-week high/low price ratio on day t. I 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. I skip all January returns when cumulating all the BHAR.[73] I rebalance the long and short portfolios monthly and report the BHAR for the holding periods of 6 and 12-month in Table 4.5 Panel A. Similarly, in Panel B, I sort stocks according to their 52-week high/low recency ratios on day t. I 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. I, thus, long (short) stocks bought (sold) by insiders immediately after they reached their 52-week high (low).

[73] This is to avoid any January potential effect. My results are robust to the inclusion of January.

Table 4.5: Trading strategy based on the relative price and recency

The table reports the BHARs in the top and bottom deciles defined by the level of the 52-week high/low to the current price (Panel A) and insiders' trading recency (Panel B) over the sample period 1994 to 2018. At the end of each month, I calculate the total insider trading pressure *NPV* for stock *s*. If *NPV* is higher (less) than 0, the stock *s* is net-bought (net-sold) by insiders. I 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. I long (short) the portfolio which contains stocks in the top (bottom) 52-week high (low) ratio decile and net-bought (net-sold) by insiders. I rebalance the long and short portfolios monthly. Similarly, in Panel B I sort stocks according to their 52-week high/low recency ratios on day *t*. I long (short) stocks in the top (top) 52-week high (low) recency decile and net-bought (net-sold) by insiders. The BHAR, for the next 6 or 12-month holding periods, excluding January returns, are CRSP value-weighted market index adjusted. Columns (3) and (6) are Average 52-Week High/Low Ratio in Panel A and Recency Days (Ratio) in Panel B. Standard errors are in parentheses. ***, **, * significant at .01, .05 and .1 levels, respectively. All return variables are minorized at bottom 0.5% and top 99.5%.

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

Table 4.5, Panel A shows that the difference between the BHARs of the top and bottom 52-week high/low ratio portfolios is 9.3% and 19.2% in the 6- and 12-month holding periods, respectively. In column (4) and (5), I report the BHAR without conditioning on insider trading. A long (short) strategy of the portfolio with the top (bottom) 52-week high (low) results in non-significant differences in BHARs 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 trading strategies without insider trading underperform their counterparts 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 for their sell trades at the 52-week low.

In Panel B, I sort the stocks into their 52-week high/low recency ratio deciles. The trading strategy further improves the BHAR to 15.2% and 30.8% in the 6- and 12-month holding periods, respectively. If I 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 BHAR of 2.5% and 5.7%, implying positive returns for short sellers in the two holding periods, respectively. The trading strategy without insider trading generates only 6.4% and 14.2% BHARs in the 6- and 12-month periods, respectively, significantly lower than its counterpart with insider trading in both the long- and short-leg, as reported in last columns (7) and (8).

My results in Appendix 4.4, are robust if I use Fama-French-Carhart 4 factor alpha. A trading strategy based on 52-week high/low ratio with insider trading generates a statistically significant 7% and 5% alphas for the 6-and 12-month investment horizons, respectively. The equivalent αs of a trading strategy based on 52-week high/low recency and insider trading are 5.4% and 5.5%, respectively. Similarly, both trading strategies outperform their unconditional on insider trading counterparts. These results are consistent with my 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.

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

I extend my analysis on the insider trading motivation at the 52-week high and low through multivariate analysis to control for other potential effects. I first investigate the propensity of insiders to trade conditional on the relative price and recency using the following logit specification:

$$\begin{aligned}P(y=1|\mathbf{z}) = G(&\alpha + \beta_1 \times \_52\_W\_H_{t-1} + \beta_2 \times \_52\_W\_H\_Rec_{t-1} + \beta_3 \times mom_{t-1} \\ &+ \beta_4 \times ret_t + \beta_5 \times lnmcap_{t-1} + \beta_6 \times bm_{t-1} + \beta_7 \times illiq_{t-1} + \beta_8 \times roe_{t-1} \\ &+ \beta_9 \times leverage_{t-1} + \beta_{10} \times RD_{t-1} + \beta_{11} \times numest_{t-1} + \beta_{12} \times Sento_{t-1} + \beta_{13} \\ &\times UpDummy_{t-1} + \beta_{14} \times DownDummy_{t-1} + u_t)\end{aligned}$$

where *G* represents the logistic function. The dependent variable is equal to one if an insider is a net purchaser (NPV$>$ 0) on a given day or month depending on the aggregating level, zero otherwise.[74] I describe in Appendix 4.1. the constructions of all variables. I 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. I carefully followed the procedure outlined in Sibley *et al.* (2016) and compared my 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 my sample and methodology are correct. *UpDummy* (*DownDummy*) capture the effect of both exogenously and endogenously price shocks 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). Standard Errors are clustered at the firm level because Alldredge and Blank (2019) have provided evidence for insiders' herding behavior within a firm. Clustering at the firm level also allows for controlling both

[74] All results remain robust if I use probit. I use the last fiscal year to construct the accounting variables.

arbitrary time-series correlation within a firm and arbitrary cross-section dependence between different insiders within a firm (Jagolinzer, *et al.* 2020). output.

Table 4.6 reports the results.[75] 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) reports the equivalent results for the 52-week low. The coefficient of $\_52\_W\_L$ is negative, but 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 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 my previous univariate findings, my 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 previous studies (e.g., Seyhun, 1992; Lakonishok and Lee, 2001; Cheng and Kin, 2006; Beneish and Markarian, 2019). The coefficient of *mom* and *Lnmcap* are negative, suggesting that insiders are contrarians by selling (buying) when the stock returns are high (low) and net sellers in larger firms and buyers in smaller ones, respectively. The proxies for higher information asymmetry environment, *bm* and *RD*, are positive, but *numest* is negative, suggesting that when the information asymmetry is high, the likelihood of insiders being caught for materializing their private information becomes lower, reducing their litigation risk, and increasing their buying propensity. *Sento* is positive indicating that insiders increase their holdings when market sentiment is high, in line with 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 price shock dummies are positive implying that insiders actively respond to extreme abnormal returns by increasing their holdings, incorporating private information into stock prices, in line with Ali *et al.* (2011) and Anginer

[75] Less than 0.01% of the sample has NPV that is equal to zero, suggesting that insiders rarely close their positions in the same day that they open them. Therefore, the coefficient is virtually one minus the coefficients in Table 4.6. if the dependent variable is set to be one for the net seller instead of the net buyer.

et al. (2018). The positive coefficient of *DownDummy* suggests that insiders quickly increase their holding when the stock prices decrease to the valley.

In columns (3) to (8), I use the fixed-effect estimator to regress the post transactions returns on the same set of independent variables. I 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% (-0.089 x 2) lower. For 365 days holding period, the coefficients of _52_W_L and _52_W_H_Rec are 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. 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 insiders buy strategically when the price is close to its 52-week high, and immediately after the 52-week high, while they sell when the price 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.

I further consider the possibility that some corporate insiders exploit other investors' anchoring bias by systematically buying (selling) at the 52-week high (low) because uninformed investors sell (buy) at the high (low) when they have no material information regarding firm's true valuation. I define sophisticated buyer (seller) as those who have made at least one purchase (sell) transaction at the 52-week high (low). Among all 103,530 distinct managers, 39,502 (38%) of them have made transactions at the 52-week high, but only 9,603 (9.3%) of 103,530 have increased their ownerships at the 52-week high. On the other hand, 32,270 (31%) of insiders have made transactions at the 52-week low, but only 7,446 (7.2%) of them have sold at the low. I recognize that all transactions made by these sophisticated insiders before (after) they have been classified are unsophisticated (sophisticated) trades. I define a dummy variable High_TraderD (Low_TraderD) that equals to one when the transaction is made by a sophisticated trader who have bought-at-top (sold-at-bottom), zero otherwise. I interact the dummy with 52-week high and low ratio and report the result in Table 4.6 Panel B.

Table 4.6: 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. The dependent variable in columns (1) to (2) is one if NPV>0 (net purchaser), zero otherwise, and BHARs in column (3) to (8). In Panel B, dummy variable High_TraderD (Low_TraderD) is equal to one when the transaction is made by a sophisticated trader who have made at least one purchase (sell) transaction at the 52-week high (low), zero otherwise. All independent variables are defined in Appendix 4.1. The return variables are restricted to have at least 20/120/243 observations within each estimation window. Standard errors are in parentheses. I use robust standard errors for Logit, and I cluster the standard errors at the firm level for fixed-effect regression. I control for firm, month and director fixed effects in column (3) to (8). All independent variables are minorized 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). ***, **and * indicate the coefficients are statistically significant at 0.01, 0.05% and 0.01levels, respectively.

	Panel A: Baseline Regression							
	Logit		Fixed-Effect					
	Net Purchaser	Net Purchaser	Net Purchaser			Net Seller		
			BHAR_m_30	BHAR_m_180	BHAR_m_365	BHAR_m_30	BHAR_m_180	BHAR_m_365
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
_52_W_H	-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
Insider FE			Yes	Yes	Yes	Yes	Yes	Yes
S.E	Robust	Robust	Firm	Firm	Firm	Firm	Firm	Firm
			Panel B: Sophisticated Insiders					
	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
_52_W_H	-2.132***		-0.061***	0.034	0.109**	0.008	0.079***	0.054*
	(0.279)		(0.010)	(0.030)	(0.046)	(0.008)	(0.023)	(0.031)
High_TraderD	-0.450***		-0.038***	-0.063	-0.062			
	(-0.053)		(0.013)	(0.042)	(0.061)			
High_TraderD*_52_W_H	2.882***		0.055***	0.127***	0.154**			
	(0.062)		(0.014)	(0.043)	(0.065)			
_52_W_H_Rec	-0.328***		0.015***	0.005	-0.016	0.008***	0.027***	0.027***
	(0.015)		(0.004)	(0.012)	(0.016)	(0.002)	(0.006)	(0.009)
_52_W_L		-0.029***	0.003	0.005	0.000	-0.001	-0.001	-0.002
		(0.008)	(0.002)	(0.005)	(0.005)	(0.001)	(0.003)	(0.004)
Low_TraderD		-2.727***				0.006	0.026**	0.075***
		(0.055)				(0.004)	(0.012)	(0.021)
Low_TraderD*_52_W_L		0.300***				0.001	0.004	-0.011
		(0.037)				(0.002)	(0.006)	(0.012)
_52_W_L_Rec		0.984***	-0.016***	-0.064***	-0.089***	-0.010***	-0.027***	-0.038***
		(0.014)	(0.003)	(0.010)	(0.015)	(0.003)	(0.007)	(0.009)
N	451,941	451,941	96,498	120,712	116,916	222,727	270,920	262,419
R-squared	0.28	0.26	0.03	0.10	0.16	0.02	0.10	0.16
Month FE			Yes	Yes	Yes	Yes	Yes	Yes
Firm FE			Yes	Yes	Yes	Yes	Yes	Yes
Insider FE			Yes	Yes	Yes	Yes	Yes	Yes
S.E	Robust	Robust	Firm	Firm	Firm	Firm	Firm	Firm

I observe that the interaction term is positive and significant in both column (1) and (2). These results confirm that these sophisticated traders are more likely to exploit other's anchoring bias because they are more likely to buy (sell) at the top (bottom). In column (3) to (5), I find that the return predictability embedded in the transactions made by sophisticated buyers is higher when the price is closer to its 52-week high because the interaction term is positive and statistically significant. These sophisticated buyers can better time the market and reap higher abnormal return than other insiders when the price is close to the 52-week high. In contrast, there is no significant difference in the return predictability between sophisticated sellers and other sellers when the current price is close to the 52-week low. The significance and signs of other variables are consistent with my previous results.

I 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 behavior is robust across different level of price tightness, I 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, normalized using the current stock price.[76] I 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 4.7 Panel A reports the descriptive statistics. 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 normalized 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 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, I observe the same scenario. These positive and statistically significant coefficients for $\_52\_W\_L$ and $\_52\_W\_L\_Rec$ imply that, for the same level of relative price or recency, insiders are more likely to increase their holding when the price range is broader, as when the 52-week high is

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

distant from the 52-week low, their selling pressures are attenuated because they are less concerned about the potential that stock prices may decline.

Overall, these results show that insiders unambiguously reduce their holding at the 52-week high but increase it at the 52-week low. Their sell-at-peak transactions are systematically followed by positive stock returns, implying losses to insiders, whereas their buy-at-through trades generate positive returns that represent trading profits to themselves. These results support the arguments of Lee and Piqueira (2019) that insiders are, on average, uninformed at the 52-week high, as they suffer from anchoring bias. However, these results do not account for insider dissimulation introduced by Huddart *et al.* (2001), a strategy which is overlooked in most previous studies. I attempt to disentangle this possibility in the next section.

4.4.5 Insider dissimulation strategy at these price extremes

Huddart *et al.* (2001) argue that the implementation of the U.S security law will increase the market scrutiny of insiders' transactions and reduce insider dealing profitability by strictly regulating corporate insiders to publicly disclose their transactions 2 days after execution. Despite potential lessening of their returns by as much as a half because of the improved market efficiency, trading on private information remains a profitable strategy for insiders. Consequently, profit-maximizing insiders who actively materialize their private information, have incentives to dissimulate their private information by randomly trading in a manner that is inconsistent with their informational agent role. If their private information is long-lived,[77] they will intentionally make noisy transactions to thwart outsiders who intend to follow them. Since I have not ruled out the possibility that insiders are not suffering from anchoring bias, I consider that they dissimulate 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, I expect a higher likelihood that they will blindly follow the trading decision of informed investors. In response to the severe miss-pricing at the price peak, I hypothesize that insiders will more actively make uninformative trades to disguise their private information. To the best of my knowledge, I am the first to advance insider dissimulation strategy at the 52-week high, partly because of the difficulty of differentiating long-lived from short-lived information.

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

Table 4.7: Insider trading propensity with interaction term on tightness

This table reports the Summary statistics for tightness (Panel A) and the Logit and Fixed-effect regression outputs (Panel B) where the dependent variable is one if NPV>0 (net purchaser), zero otherwise. In each month, I sort all insider transactions into quantiles in accordance with their tightness, defined as $\frac{52-we \quad high-52-week\ low}{Current\ price}$. The independent variables are defined in Appendix 4.1. The return variables are restricted to have at least 20/180/243 observations within each estimation window. Standard errors are in parentheses. I use robust standard error in Panel B column (1) and (2) and clustered standard error in column (3) and (4). I control for firm, month, and insider fixed effects in column (3) and (4). All independent variables are minorized at bottom 0.5% and top 99.5%. 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 0.01, 0.05, and 0.1 levels, respectively. ***, **, * indicate the coefficients are statistically significant at 0.01, 0.05% and 0.01levels, respectively.

Panel A. Summary statistics for tightness

	Top Quantile (Low tightness)					Bottom Quantile (High tightness)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variable	Mean	Std	Quantile 1	Median	Quantile 3	Mean	Std	Quantile 1	Median	Quantile 3
_52_W_H	0.530***	0.243	0.345	0.513	0.703	0.921***[a]	0.072	0.880	0.939	0.979
_52_W_H_Rec (days)	218***	239	336	252	104	128***[a]	243	230	92	13
_52_W_L	2.032***	2.147	1.102	1.376	2.171	1.223***[a]	0.171	1.102	1.198	1.306
_52_W_L_Rec (days)	147***	227	293	101	12	207***[a]	241	323	229	102
tightness	1.772***	1.371	0.857	1.192	2.110	0.265***[a]	0.102	0.201	0.253	0.315

Panel B. Regression result

	Logit		**Fixed-Effect**	
	Net Purchaser	Net Purchaser	NPV	NPV
	(1)	(2)	(3)	(4)
_52_W_H	-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

I follow Biggerstaff *et al.* (2020) who argue 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 this trading strategy is that a sequence of sell transactions can better minimize 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, I 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, I 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. I hypothesize that if insiders indeed dissimulate their long-lived private information and gradually incorporate them into the stock price, their transactions in sequence sells should 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 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 my study. The *Scaled Holding Return* best mimics the return that an insider would be able to realize in the entire duration of a sequence sell.[78] The hypothesis implies that if uninformed investors opt to replicate insiders' sell transactions at the 52-week high, they will incur a loss if they randomly pick and replicate such sell transactions because the average return is positive. They can only generate a negative return if they are able to identify those noisy sells or replicate

[78] As 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 Oct 2014, and 06 Nov 2014 respectively. I recognize these two sells as one *sequence sells*. 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 $\frac{-12+\ .78}{2\times252} = -0.020\%$ respectively. The *Scaled Holding Return* is the average daily return calculated from the total return cumulated from 28 Oct 2014 to 30, 180 and 365 days after 06 Nov 2014, is -0.044%, -1.134% and -6.804%, respectively. I classify the *sequence sells* as dissimulating sell for 30- and 180-day holding periods.

the entire sequence of sell trades. I make a logical assumption that uninformed investors, by definition, are not capable of differentiating between dissimulating sell from informative sell.

Following Biggerstaff *et al.* (2020), I define a sequence 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. I define the rest of sell transactions as isolated sell.[79] While Biggerstaff *et al.* (2020) aggregate insider transactions at the end of month, I keep all my sample at the insider-day level to conduct a finer analysis. I classify Sell-At-Peak insider transaction when the $\_52\_W\_H \geq 0.98$.[80] I focus on sequences that contain at least one sell trade classified as Sell-At-Peak. To better capture the sequence that occurred at the 52-week high, I 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)*). I test for robustness using sequence initiated at most 60 days before and terminated at most 60 days after the Sell-At-Peak transactions (*sequence (60)*). The choice of these dates is arbitrary, a longer period will allow a larger sample size but will reduce the relevance of insiders' trading informativeness. If a sequence is initiated well before the price reaches its 52-week high, insiders are less likely to have factored the price peak into their information sets at the time they initiated the sequence. I also combine buy and sell transactions. I remove Sale-Post Exercise in the construction of sequence. In addition to the *All* and *Scaled holding return*, I also calculate the termination sell return denoted as *Following Sequence*. To maximize the comparability, I 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. I present the results in Table 4.8.

Panel A reports the summary statistics of sequence and isolated sell by dividing the sample into *Sell-At-Peak* group and *Other* group. I classify 392,692 sell transactions as either isolated or sequence sells, more than half of total sells are sequence sells.[81] At the 52-week high, the number of isolated sells is 38,868, very close to sequence sells of 34,036. Out of 34,036 sequence sells, 18,804 (55%) occurred in *Sequence (30)*. Column (4) to (6) indicate that most sells occur when the stock price is away from the peak. The recency of *Sequence (30)* for Sell-At-Peak is 18 days, statistically less than the 157 days for *Sequence (30)* that occurred

[79] To illustrate, if an insider made four sell transactions on each of 1st and 15th Jan, 2nd of Feb and 10th of Mar, the first three are defined as one sequence sell and the one occurred in March is recognized as one isolated sell.
[80] My results are robust if I use 0.9, 0.95 or 0.99 cut-off points, or the top decile classification in Section 4.3.
[81] 55.3% sell transactions are sequence sells: (34,036+176,326)/392,692 = 0.536

Table 4.8: BHAR for isolated and sequenced insider transactions at the 52-week high/low

This table reports the summary statistics and the BHAR for isolated and sequenced transactions at the 52-week high/low. 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 *et al.* (2020) as 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 sell transaction in a sequence is executed when the _52_W_H is ≥ 0.98, I define the entire sequence as Sell-At-52-Week High and I focus on these sequences in Panel C. Sale-post exercise of stock option is not considered in constructing sequence sells. *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, I 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, I 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, I denote these samples with "(30)" and "(60)", respectively. In Panel D, I combine insider purchase transactions within insider sell sequence. The definition of a sequence remains the same and I 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) reports 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. ***, **, * indicate the coefficients are statistically significant at 0.01, 0.05% and 0.01levels, respectively. All returns are minorized at bottom 0.5% and top 99.5%.

Sell trades

Panel A: Summary Statistics						
	Sell-At-Peak: _52_W_H≥0.98			Other: _52_W_H<0.98		
	Isolated	Sequence (30)	Sequence (all)	Isolated	Sequence (30)	Sequence (all)
	(1)	(2)	(3)	(4)	(5)	(6)
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 Sells		
	BHAR_m_30	BHAR_m_180	BHAR_m_365	BHAR_m_30	BHAR_m_180	BHAR_m_365
	(1)	(2)	(3)	(4)	(5)	(6)

All	-0.004***	-0.008***	-0.006***	0.002***	0.005***	0.013***
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
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 Sells		
	BHAR_m_30	BHAR_m_180	BHAR_m_365	BHAR_m_30	BHAR_m_180	BHAR_m_365
	(1)	(2)	(3)	(4)	(5)	(6)
All	0.001*	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 Sells 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	

Buy trades

Panel A: Summary Statistics						
	Sell-At-Peak: _52_W_H≥0.98			Other: _52_W_H<0.98		
	Isolated	Sequence (30)	Sequence (all)	Isolated	Sequence (30)	Sequence (all)
	(1)	(2)	(3)	(4)	(5)	(6)
Number of observations (All Buy: 194,016)	9,591 (4.93%)	2,193(1.13%)	4,513(2.32%)	106,329(54.80%)	41,389(21.33%)	73,583(37.93%)
Average 52 W H Rec (days)	15	22	21	201	217***a	215***a
Average sequence transaction number		3.19	26.58		3.51***a	29.48***a
Average sequence length (days)		12.27	127.34		12.66***a	128.97***a

Panel B: Unconditional BHAR						
	Isolated Buy			Sequence Buys		
	BHAR_m_30	BHAR_m_180	BHAR_m_365	BHAR_m_30	BHAR_m_180	BHAR_m_365
	(1)	(2)	(3)	(4)	(5)	(6)
All	0.030***	0.054***	0.091***	0.023***	0.061***	0.109***
	(0.000)	(0.001)	(0.002)	(0.000)	(0.001)	(0.002)
Observations	94,947	111,766	108,094	63,821	75,712	73,273
Scaled Holding return				0.007***	-0.019***	-0.056***
				(0.000)	(0.001)	(0.002)

Observations				77,654	76,270	73,687
Following Sequence				0.034***	0.058***	0.107***
				(0.000)	(0.002)	(0.002)
Observations				62,342	75,475	72,664
Panel C: BHAR for Buy-At-Peak: _52_W_H≥0.98						
	Isolated Buy			Sequence Buy		
	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	0.027***	0.047***	0.071***	0.028***	0.086***	0.119***
	(0.000)	(0.004)	(0.005)	(0.002)	(0.005)	(0.007)
Observations	7,929	9,338	9,117	3,759	4,385	4,273
Scaled holding return (30)				0.042***	0.076***	0.060***
				(0.002)	(0.006)	(0.009)
Observations				2,183	2,143	2,076
Scaled holding return (60)				0.041***	0.084***	0.076***
				(0.002)	(0.005)	(0.008)
Observations				3,133	3,070	2,976
Following Sequence (30)				0.026***	0.081***	0.112***
				(0.003)	(0.007)	(0.010)
Observations				1,792	2,116	2,074
Following Sequence (60)				0.027***	0.084***	0.117***
				(0.002)	(0.006)	(0.008)
Observations				2,559	3,029	2,967

not at the peak, as 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.[82] The average sequence length is 1,267 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.

I report the unconditional BHAR in Panel B. After separating sales into isolated sell and sequence sells, I find isolated sells become informative on average whereas sequence sells remain uninformative, in line with Biggerstaff, *et al.* (2020). The average daily transaction returns *All* for sequence sells of 0.2%, 0.5% and 1.3% for these three horizons, respectively, are statistically significant. However, as I stressed before, treating each sell in a sequence as independent transaction is misleading because some dissimulated sells are noisy, biasing the average daily returns upward. Furthermore, a sequence sell transactions will yield -0.1%, -3.3% and -6.6% *Scaled holding returns* in the next 30-, 180- and 365-day holding periods, respectively. All these returns are statistically significant at the 99% confidence level. If I 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, all significant at the 99% confidence level. These results are consistent with the main findings in Biggerstaff, *et al.* (2020) who 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 my return measures.

In Panel C, I 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, in line with my previous findings that insiders are less informed at the 52-week high. The same positive returns can be observed if I calculate the average transaction return of each sell in a sequence. If I assume each transaction in a sequence is closed at different point of time, then insider sell transactions will generate significant 0.5%, 1.8% and 2.0% BHAR in the next 30-. 180- and 365-day investment horizons, respectively. If I assume insiders realize 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 realize

[82] 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 my identification scheme, they are two different isolated sells.

their capital gain. *Scaled holding return (60)* generates statistically significant returns of 0.7% for the mid-term. For the 365-day holding period, *Scaled holding return (30)* predicts statistically significant negative returns 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, both are statistically significant at the 99% confidence level, respectively. However, *Following Sequence (30)* and *Following Sequence (60)* generate zero returns 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 returns predictability embedded in *All* and the negative return predictability of *Scaled holding return (30)* both are consistent with my hypothesis and further confirm that insiders do dissimulate their private information by conducting uninformative sell transactions at the 52-week high.

Nonetheless, I reckon that the change from the unconditional positive BHAR predictability of sequence sells to the negative BHAR predictability of *Scaled holding return (30)* or *Scaled holding return (60)* of sequence sells may be caused by the exclusion of sequence that is initiated long time prior to the 52-week high. Therefore, I further calculate the unconditional BHAR for the sample of sequence sells I used to calculate *Scaled holding return (30)* and *Scaled holding return (60)*. I find, but do not report, that the BHARs for three holding periods for both series are all positive and statistically significant at the 99% confidence level, implying that for the same sample of sequence sells initiated and terminated close to the 52-week high, the return predictability persists. My results reaffirm the importance to consider the sequence return rather than transaction returns; they show that the change in return predictability is robust to the removal of sequence sells that began in the remote past.

Kose and Ranga (1997) develop a theoretical model which predicts that insiders will intentionally trade at the wrong direction or trade against their own private signal to manipulate the market and then earn higher returns, as uninformed investors will miss-percept their transactions at the wrong direction. I consider this possibility for both the buy and sell trades with sequence transactions occurring only at the most 60 days apart. I 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), I report the unconditional sequence return. I 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 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 minimize the price impact of their transactions. In Column (4) and (5), I 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 returns* for mixed sequences are statistically indifferent from zero in the 30- and 180-day periods but are -8.7%, significant, in the 365-day investment horizon. However, the difference between columns (4) and (5) is not significant. The sample size of net-selling sequence mixed with buy is relatively small. For unconditional sequence, only 2.8% of the sample is mixed sequence, decreasing to 1.3% if I focus on the sequence that occurred at the 52-week high. According to the short-swing rule, insiders are not allowed to realize any capital gain from two off-setting trades within the first 6-month. The short-swing rule will inevitably apply to the buy transactions identified in a mixed net-selling sequence and weakens the market reaction to these mixed sequences (Kose and Ranga, 1997). Consequently, corporate insiders rarely mix buy and sell transactions in a sequence. Nevertheless, there is weak evidence to show that the return is lower when insiders mix buy and sell trades in a net-selling sequence at the 52-week high.

Lastly, I re-estimate results in Table 4.6 by removing sequence sells at the 52-week high and low. I 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 my previous findings remain robust. In sum, I 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.

4.5 Robustness Test

4.5.1 Anchoring bias with the presence of asset pricing anomalies

Although I provide 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) show that informed participants, such as arbitrageurs and short-sellers, actively trade on these eleven anomalies to reap abnormal profits. 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 context of thirteen asset-pricing anomalies to show 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, my previous results do not rule out the possibility that insiders exploit these market anomalies instead of trading on the 52-week high price levels when the stock price approaches the past extremes. We, therefore, investigate whether my main result is robust with the inclusion of asset pricing anomalies.

I repeat the results in Table 4.6 following Anginer *et al.* (2018) and Lee and Piqueira (2017) by replicating eight out of eleven anomalies introduced in Stambaugh *et al.* (2012), Total Accruals (TA), Net Operating Assets (NOP), Gross Profitability (GP), Asset Growth (AG), Return on Assets (ROA), Investment-to-Assets (IA), failure probability (FP), and net stock issue (NSI), as described in Appendices 5 to 7. I omit Ohlson's (1980) O-score and composite equity issues because they capture the same underlying risks as Campbell, Hilscher and Szilagyi (2008)'s FP and NSI. I already controlled for momentum anomaly, suggested by Jegadeesh and Titman (1993), one of the eleven anomalies. FP is a fitted value of regression with eight independent variables whose coefficients are computed by Campbell *et al.* (2008), as detailed in Appendix 3.6. 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 unreported results, I find that the correlation between these anomaly variables is generally low, in line with Anginer *et al.* (2018).

Among these eight anomalies, only ROA and GP are positively, while the other six are negatively associated with the stock future abnormal return, in line with Stambaugh *et al.* (2012). However, Anginer *et al.* (2018) show that insiders do not necessarily trade with the normative direction indicated by the anomaly; the discord among insiders and anomaly is not unusual. If insiders possess private information not incorporated in stock prices, they will trade against the anomaly to exploit outside investors who naively follow these normative directions. Therefore, the anomaly variable coefficient in my logit model 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 results are broadly suggesting that insiders actively react to market anomalies and trade on them.

Table 4.9 Panel A reports the regression result for 52-week high and 52-week low separately. I 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 results for 52-week low are 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.

4.5.2 Impact of identity of the insider

To alleviate the concern that these less informative transactions drive my previous findings, and to make my results more comparable to previous evidence, I account for the type of insider by focusing on only executive and non-executive board members. I 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. I lost around 34% of the entire sample. Table 4.9 Panel B displays the regression output. The results mimic those reported in Table 3.6. The $\_52\_W\_L$ is negative and significant, suggesting that when the current price is dropping to its 52-week low, insiders unambiguously increase their holding to signal their firm's undervaluation, as expected because they 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 one of the key determinants for insider trading.

I also replicate my results using an alternative measure of the relative price and recency ratio. Following Lee and Piqueira (2019), instead of using the 30-day average price and 30-day average distance, I base my measures on the price and 52-week high or low at the end of last calendar month, as follows:

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

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

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

Table 4.9: 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, I include eight anomaly variables by following Stambaugh *et al.* (2012) and discussed in detail in Appendix 4.5 and Appendix 4.6. 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 4.6. 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. I use robust standard error. All independent variables are minorized at bottom 0.5% and top 99.5%. ***, **, * indicate the coefficients are statistically significant at 0.01, 0.05% and 0.01levels, respectively.

	Net Purchaser (1)	**Net Purchaser** (2)	**Net Purchaser** (3)	**Net Purchaser** (4)	**Net Purchaser** (5)	**Net Purchaser** (6)	**Net Purchaser** (7)	**Net Purchaser** (8)
Panel A: Probability Model with Asset Pricing Anomalies-Logit – 52 Week High								
_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 Week Low								
_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 (1)				Net Purchaser (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			

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

That is, for any insider transactions that occurs on day t, the ratio is computed by using the stock price and 52-week high or low on day $m-1$, the last trading day at the end of last calendar month. Then I repeat the logit and fixed-effect regression with the same regression specification in Table 4.6. In unreported results, all the signs of coefficients of both variables with interests remain unchanged.

Next, I restrict my 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. I 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. I repeat Table 4.6 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). I find, but not report for brevity reasons, similar results to those reported in Table 4.6.

As the fourth robustness test, I 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, my result could be driven by samples that are irrelevant to the previous 52-week high or low. I repeat Table 4.6 without $\_52\_W\_H\_Rec_t$ and $\_52\_W\_L\_Rec_t$. In untabulated result, I 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 my conclusion that insiders predominately sell at the 52-week high.

As the fifth robustness test, I exclude insider trading occurred in January from my sample. George and Hwang (2004) and Bhootra and Hur (2013) show that investors' trading behavior 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. I find similar results. When I repeat my regressions using a much smaller January sample, all the results remain robust, except the coefficient of the 52-week low ratio which becomes insignificant.

4.6 Extension

4.6.1 Informational content in dissimulation sell

In the previous sections, I documented that some insiders execute profitable dissimulation sell transactions when the stock price is close to the 52-week high. They outperform the average insider sell transactions. They materialize their private information by generating more negative BHAR. The return predictability originates from either the future fundamental or the subsequent price correction process. On the other hand, some insiders often buy at the 52-week high to exploit the anchoring bias of other investors. In this section, I disentangle the source of return predictability behind their trading decisions.

I employ two commonly used proxies to measure earnings surprises. The first is the 3-day Cumulative Abnormal Return (CAR) around the q+4 quarterly earnings announcements estimated using market model.[83] I 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, I follow Bernard and Thomas (1990) to construct Standardized Unexpected Earnings, SUE, as follows:

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

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 the last 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) 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, I expect the regression coefficients and statistical significance could be different between the regressions using these two different dependent variables.

In addition, I also examine whether these transactions can predict the change in the return on asset from (t, t+1) denoted as ΔROA with year *t* being the insider transaction year and the change in investor sentiment denoted as $\Delta Sentiment$. I compute the market-to-book ratio decomposition of Rhodes–Kropf, Robinson and Viswanathan (2005) defined as the residual from the following regression

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

[83]My result remains consistent if I use 5-day event window or estimate the CAR using Market-Adjusted Model.

where subscript *j* indexes for Fama-French 12 industries, *i* for firms and *t* for year. I estimate the regression for each industry-year. $\mathrm{I}_{(<0>)}$ is a dummy variable equal to one for loss-making firms, and zero otherwise. The firm-specific residual obtained from the regression is the part of the firm's market value not explained by fundamentals or by changes in the market valuation common across firms in the same industry. Cziraki, Lyandres and Michaely (2021) argue the method can separate the firm-specific sentiment from industry-level sentiment and is appealing to insider trading studies because insiders are more likely to possess private information on the former than on the latter.

I take these four measures for the t+4 quarterly earnings announcements as dependent variables and regress them on dummy variables for insider sell-at-peak transactions and insider dissimulation variables. I define *SellpeakD* as one when $\_52\_W\_H \geq 0.98$ and $NPV < 0$. *Dissimulation365D* is dummy variable that equal to one if *Scaled Holding Return* is negative while unconditional *BHAR* is positive for 365-day holding periods. Control variables are the same as Table 4.6 with the additional inclusion of lagged dependent variable. The variables of interest is the interaction variable between *SellpeakD* and *DissimulationD*. If insiders are trading on their private information regarding the firm's future fundamental, I expect the coefficient to be negative and statistically significant. I control for the firm, month, insider fixed effects and cluster standard error at firm-month level. I run the regression by using insider sell sample only and present the regression result in Table 4.10. For brevity, I do not report all control variables whose signs and significance are consistent with the existing literature.

Table 4.10 Panel A shows that *SellpeakD* is mostly insignificant except when the dependent variable is $\Delta ROA_{(\mathbf{t},t+1)}$. *SellpeakD* is insignificant, consistent with my previous findings that insiders' sell at the peak is on average non-information driven motives. These results are as expected because the sample only consists of insider sell. I 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 their holdings. 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.

Table 4.10: Informational content embedded in insider transactions

This table reports the regressions of earning surprise, change in return on asset, change in investor sentiment on the set of group dummies. In column (1), the earning surprise is proxied the 3-day earnings announcement CARs for the next q+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. I use 250 days for estimation period, and there are minimum 100 days. Estimation period end 50 days before Event Date. In column (2) , 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. In column (3), the dependent variable is the change in return on asset between fiscal year (t,t+1). In column (4), the dependent variable is the change in investor sentiment computed by following Rhodes–Kropf, *et al.* (2005). In Panel A, SellpeakD is dummy variable that takes value of one for the stocks with _52_W_H ≥ 0.98 and NPV< 0, and zero otherwise. I restrict my sample must have non-missing value of both *Scaled Holding Return*_t and BHAR_m_i. The *Dissimulation_365D* is dummy variable equal to one if the BHAR_365_i >0 but the *Scaled Holding Return*_t ≤0, and zero otherwise. The construction of *Scaled Holding Return*_t is described in Table 4.8. The constructions of control variables are reported in Appendix 4.1. The regression is only using insider sell sample. In Panel B, buypeakD is dummy variable that takes value of one for the stocks with _52_W_H ≥0.98 and NPV>0, and zero otherwise. I 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 minorized at bottom 0.5% and top 99.5%. ***, **, * indicate the coefficients are statistically significant at 0.01, 0.05% and 0.01levels, respectively.

Panel A: Informational content embedded in dissimulation sell

	$CAR_{(q+4)}$	$SUE_{j,q+4}$	$\Delta ROA_{(t,t+1)}$	$\Delta Sentiment_{(t,t+1)}$
	(1)	(2)	(3)	(4)
SellpeakD	0.001	0.042	0.003**	0.019
	(0.002)	(0.024)	(0.001)	(0.020)
Dissimulation365D	-0.008**	0.020**	-0.007**	-0.150***
	(0.004)	(0.041)	(0.003)	(0.026)
SellpeakD*Dissimulation365D	-0.016**	0.084	-0.008**	-0.081*
	(0.007)	(0.060)	(0.004)	(0.045)
Lag(CAR)	-0.018			
	(0.018)			
Lag(SUE)		-0.315***		
		(0.013)		
Control	Yes	Yes	Yes	Yes
Fixed Effect	Firm,Month, Directors	Firm,Month, Directors	Firm,Month, Directors	Firm,Month, Directors
Clustered S.E	Firm-Month	Firm-Month	Firm-Month	Firm-Month

N	53,143	51,668	66,105	49,720
Adjusted R-squared	0.34	0.47	0.64	0.52
Panel B: Informational content embedded in buy-at-top				
	$CAR_{(q+4)}$	$SUE_{j,q+4}$	$\Delta ROA_{(t,t+1)}$	$\Delta Sentiment_{(t,t+1)}$
	(1)	(2)	(3)	(4)
BuypeakD	-0.001	0.071***	0.009***	0.066***
	(0.002)	(0.024)	(0.002)	(0.012)
Lag(CAR)	-0.060			
	(0.011)			
Lag(SUE)		-0.398***		
		(0.008)		
Control	Yes	Yes	Yes	Yes
Fixed Effect	Firm,Month, Directors	Firm,Month, Directors	Firm,Month, Directors	Firm,Month, Directors
Clustered S.E	Firm-Month	Firm-Month	Firm-Month	Firm-Month
N	86,347	81,444	116,746	77,189
Adjusted R-squared	0.27	0.30	0.60	0.40

In contrast, *Dissimulation365D* is negative and statistically significant when the dependent variable is CAR, $\Delta ROA_{(\mathbf{t},t+1)}$ and $\Delta Sentiment_{(\mathbf{t},t+1)}$, but positive when the dependent variable is $SUE_{j,q+4}$. My results suggest that dissimulation sell transactions can systematically predict future decreases in $CAR_{(q+4)}$, $\Delta ROA_{(\mathbf{t},t+1)}$ and $\Delta Sentiment_{(\mathbf{t},t+1)}$, the predictability is not only witnessed at the 52-week high. More importantly, the interaction terms between *SellpeakD* and *Dissimulation365D* are statistically negative for $CAR_{(q+4)}$ but not $SUE_{j,q+4}$, suggesting that the profitability of insider dissimulation sell at the 52-week high originates not from accounting-based information but announcement-based information. Insiders affect the stock price through other channels such as private communication, conference calls etc. Undoubtedly, this information is endogenously released, and insiders can profit from this information. The interaction term is also negative and statistically significant for $\Delta ROA_{(\mathbf{t},t+1)}$ and $\Delta Sentiment_{(\mathbf{t},t+1)}$ at the 95% and 90% confidence level, respectively. These results suggest that when insiders dissimulate their private negative information at the 52-week high, they trade on the material information regarding the worsening in firm's future ROA and change in the investor sentiment.

In Panel B, I focus on the purchase transactions that insiders made when they stock price is close to its 52-week high. I define *BuypeakD* as one when $\_52\_W\_H \geq 0.98$ and $NPV > 0$. I examine the informational content embedded in these transactions to investigate how sophisticated buyers exploit the anchoring bias of other investors. *BuypeakD* is positive and statistically significant at the 99% confidence level in all columns (2) to (4). These results highlight that buy-at-top transactions will systematically predict increases in $SUE_{j,q+4}$ $\Delta ROA_{(t,t+1)}$ and $\Delta Sentiment_{(t,t+1)}$. In contrast to the dissimulation sell, these transactions do not have predictive power for the $CAR_{(q+4).}$ Overall, my results shed light on the information content embedded in the insider dissimulation sell and purchase at the peak transactions.

4.6.2 Characteristics of insiders who employ dissimulation strategy.

In this section, I attempt to identify four heterogeneous characteristics of insiders who employ dissimulation sell at the 52-week high. I recognize that insider dissimulation strategy is only feasible with their sell transactions because their purchases are informed on average. Consequently, I 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 realize profit or loss. They discover that SH insiders are systematically more informed than LH, and thus, there is more information content embedded in their trading decisions. Motivated by their results, I further expand my 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. I 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, I define Horizon, HOR, as:

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

That is, for each year, I compute the annual NPV, calculated in the same way as I outlined in the methodology section but in yearly frequency, for each insider *i* in firm *j* in year *t* in the last ten calendar years. Then, I 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. I 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 I 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. We, then, sort each insider in each year HOR into quantiles. Insider in the top (bottom) quantile is defined as SH (LH) insider. I reclassify each insider at the beginning of each year.[84] My 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 I use the first 10-year data to identify the investment horizon of insiders, the regression only uses net selling sample after 2003[85].

The results reported in Table 4.11 Panel A show that both SH and LH insiders adopt more actively dissimulation strategies at the 30- and 365-day holding horizons when selling, but 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 access 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 boards must have at least 40% female representation following the enactment of board gender-balancing law in 2005. They show 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. I investigate whether male investors are more likely to dissimulate their trades. As gender information is not provided by my database, I first use Lax-Martinez and Saito (2016)'s worldwide gender-name dictionary to match insiders' first name with their gender. I obtain three groups: insiders with a male first name such as Robert, those with a female first name such as Christina,

[84] Akbas *et al*. (2020) have many LH insiders with HOR=-1, as they define SH insiders as those with HOR above the median of the rest of the sample. My method to define SH and LH insiders is different as my screening process and database used are not the same. I find, but not report, same results if I follow their methodology.
[85] I find, but do not report, same result if I use an identification period of 7 or 13 years.

Table 4.11: 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 4.8. In column (1), (2), (3), the *Dissimulation_Dummy_i* 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). I define $HOR_{i,j,t} = \left|\frac{\sum_{Year-}^{Year-1} NPV_t}{N}\right| \times (-1)$ That is, for each month, I compute the annual NPV for each insider *i* in firm j in year t in the last 10 calendar years, then I 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 I take the absolute value of the average annual NPV and times -1. For each month, I 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 I create a dummy variable 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 recognized 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. I use robust standard error. All independent variables are minorized at bottom 0.5% and top 99.5%. The control variables are identical to Table 4.6. ***, **, * indicate the coefficients are statistically significant at 0.01, 0.05% and 0.01levels, respectively.

	Dissimulation_Dummy_30	***Dissimulation_Dummy_180***	***Dissimulation_Dummy_365***
	(1)	(2)	(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	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

and those with a unisex first name such as Joey. Then, I 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)[86]. I 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. I create a dummy variable that equals to one for male and zero otherwise. Table 4.11 Panel B displays the regression outputs. In summary, I find evidence to support that male insiders are more likely to employ dissimulation trading strategy. The results provide 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, I focus on the propensity of board member to employ dissimulation strategy. I use Smart Insider to extract Board members' information. Table 4.11 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. I 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 at the 30-day holding horizon, but mixed for the remaining periods.

For the fourth characteristics, I focus on the propensity of opportunistic insiders to employ dissimulation strategy. I follow Cohen *et al.* (2012) and define routine traders as insiders who have previously traded in either direction in the same calendar month for at least three consecutive calendar years, and all other insiders are opportunistic traders. I 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. I hypothesize 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 materialize their informational advantages over uninformed investors. Table 4.11 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 dummies are significant.

[86]Inci *et al.* (2017) sample is from 1975 to 2012, when the female board representation is relatively rare.

The results can explain Lee and Piqueira (2019) and Li *et al.* (2019) puzzling finding that opportunistic traders who have higher profitability empirically, are more susceptible to the anchoring bias. My results suggest the opposite. Since opportunistic traders are more likely to employ dissimulation strategy, they display a higher propensity to sell at the 52-week high.

4.6.3 Insider trading propensity and post transaction returns during the COVID period.

I extend my sample period to include insider transactions occurred during COVID-19 period in this section. I follow Erin, Plesko and Rawson (2022) to define the beginning of COVID period as January 19 2020. I create dummy variable $\mathtt{COVID}_t$ for all insider transactions occurred between January 19 2020 and December 31 2020, and re-estimate the Table 4.6 by including all insider transactions during the COVID period. Table 4.12 reports the result. I expect that insiders are more likely to sell at the 52-week high and buy when their firms update a new 52-week low because these informed agents should understand the market was crushing temporarily and would rebound soon. I control for the same set of variables as in Table 4.6 apart from $Sento$ because of data unavailability. I omit the coefficients of control variables for brevity.

In column (1) and (2), I observe that the coefficient of COVID*_52_W_H is negative and statistically significant, meaning insiders are more likely to sell their shares when the stock price is closer to the 52-week high during the COVID period. More interestingly, the coefficients of both COVID*_52_W_L and COVID*_52_W_L_Rec are positive and significant, indicating insiders are less likely to purchase shares when their stock prices are dropping to the previous 52-week low, but they are more likely to purchase shares when their firms just broke the previous 52-week low. There are four stock trading curbs occurred during the 2020 stock market crash, many firms consecutively updated their 52-week low in a short period of time during these four trading curbs. The result highlights insiders' ability to time the market and only increase their holdings when their stocks have updated the 52-week low rather than buying when the share price is dropping to the previous 52-week low.

In column (3) to (8) I observe that insider's purchase transactions will generate higher abnormal return if the transaction is executed at a stock price far from the 52-week high or the 52-week high was in a distant past. On the other hand, their sell transactions are systematically more informative if it is executed at the 52-week high, or the 52-week high was in the recent past. Overall, insiders trading decision at these two price extremes further highlight their roles in the financial market at informed agent, and the 52-week high and low remain as two significant determinants in their trading decisions.

Table 4.12: Insider Trading Propensity and Post Transactions Returns at the 52-week High and Low during the COVID period

This table reports the Logit and Fixed-effect regression outputs. The dependent variable in columns (1) to (2) is one if NPV>0 (net purchaser), zero otherwise, and BHARs in column (3) to (8). In Panel B, dummy variable High_TraderD (Low_TraderD) is equal to one when the transaction is made by a sophisticated trader who have made at least one purchase (sell) transaction at the 52-week high (low), zero otherwise. All independent variables are defined in Appendix 1. The return variables are restricted to have at least 20/120/243 observations within each estimation window. Standard errors are in parentheses. I use robust standard errors for Logit, and I cluster the standard errors at the firm level for fixed-effect regression. I control for firm, month and director fixed effects in column (3) to (8). All independent variables are minorized 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). COVID is a dummy variable for the transaction equals to one for transaction after 19 January 2020, and zero otherwise. I control for the same set of variables as in Table 4.6 apart from $Sento$ because of data unavailability. The sample additionally includes all insider transactions occurred in 2020. ***, **and * indicate the coefficients are statistically significant at 0.01, 0.05% and 0.01 levels, respectively.

			Panel A: Baseline Regression					
	Logit		Fixed-Effect					
	Net Purchaser	Net Purchaser	Net Purchaser			Net Seller		
			BHAR_m_30	BHAR_m_180	BHAR_m_365	BHAR_m_30	BHAR_m_180	BHAR_m_365
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
_52_W_H	-1.540***		-0.042***	0.105***	0.215***	0.010	0.081***	0.053*
	(0.026)		(0.010)	(0.033)	(0.047)	(0.007)	(0.021)	(0.029)
_52_W_H_Rec	-0.126***		0.018***	0.015	0.001	0.008***	0.025***	0.025***
	(0.014)		(0.004)	(0.012)	(0.016)	(0.002)	(0.006)	(0.009)
_52_W_L		-0.016***	0.002	0.002	-0.001	-0.000	-0.000	-0.003
		(0.006)	(0.002)	(0.004)	(0.005)	(0.001)	(0.003)	(0.004)
_52_W_L_Rec		0.789***	-0.017***	-0.063***	-0.091***	-0.008***	-0.023***	-0.031***
		(0.013)	(0.003)	(0.010)	(0.016)	(0.002)	(0.006)	(0.009)
COVID*_52_W_H	-1.613***		-0.097	-0.891**	-1.419**	-0.216***	-0.574***	-0.999***
	(0.426)		(0.077)	(0.403)	(0.625)	(0.062)	(0.161)	(0.224)
COVID*_52_W_H_Rec	0.080		-0.077	-0.312	-0.190	-0.013	-0.100*	-0.176**
	(0.155)		(0.076)	(0.263)	(0.287)	(0.019)	(0.052)	(0.070)
COVID*_52_W_L		0.129***	0.004	0.013	0.011	0.011**	-0.004	-0.062**
		(0.033)	(0.005)	(0.012)	(0.015)	(0.004)	(0.014)	(0.025)
COVID*_52_W_L_Rec		0.697***	-0.149**	-0.286	0.654**	-0.050*	0.082	0.051
		(0.154)	(0.076)	(0.311)	(0.316)	(0.028)	(0.067)	(0.072)
COVID	1.446***	-0.311***	1.286***	1.277***	0.218***	0.609***	1.125***	1.286***
	(0.026)	(0.126)	(0.413)	(0.481)	(0.059)	(0.142)	(0.200)	(0.413)
Fixed Effect			Firm,Month, Directors	Firm,Month, Directors	Firm,Month, Directors	Firm,Month, Directors	Firm,Month, Directors	Firm,Month, Directors
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	460,391	460,391	98,363	123,107	119,269	226,239	275,261	266,716
R-square	0.223	0.220	0.026	0.098	0.167	0.016	0.097	0.161

4.7 Conclusion

I provide 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. I first examine theirs transaction profitability 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 both their buy and, after dissimulation strategies, their sell trades are informative. Second, I find that zero-cost trading strategies condition on insiders' trading pressure and the 52-week high/low ratio or the recency of the 52-week high/low generate significant excess returns. I subject my results to a battery of robustness checks. Third, I show that their dissimulated sell trades predict future market reaction proxied by 3-day CAR around the next four quarterly earnings announcements. I argue that insiders may endogenously release news to depress the stock price and therefore to profit from it. Finally, I show that insiders with short-term and long-term investment horizons are both more likely to employ dissimulation strategy, compared to those with mid-term investment horizon. Male insiders, board members and opportunistic insiders are more likely to execute dissimulated sell trades.

I addressed the endogeneity concern by including in my regressions *UpDummy* and *DownDummy* to control for the short-term abnormal price shocks, and by using firm and month fixed effects. However, insiders' trading decision at the 52-week high/low may still be endogenous as they may intentionally decrease (increase) the price prior to their purchase (sell) transactions by releasing price-sensitive information (Korczak *et al.* 2010). Future research could investigate detailed news announcements and insider trading at 52-week high/low. If the 52-week high/low is truly in insiders' information sets, then I 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, I only focus on corporate insiders, while other market participants, such as politicians, are also likely to be informed, may trade at the 52-week high/low. The extent to which these factors will support or alter my results is a subject of further research.

Appendix 4.1: 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: $BHAR\_m\_i = \prod_{t=1}^{i}[1 + R_{it}] - \prod_{t=1}^{i}[1 + R_{mt}]$
$\alpha_{t+1,t+i}$	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).
$\_52\_W\_H_t$	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.
$\_52\_W\_L_t$	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.
$\_52\_W\_H\_Rec_t$	CRSP	Calculated as 1 minus the distance between 52-week high and day *t* over 364. *t* is the insider transaction date.
$\_52\_W\_L\_Rec_t$	CRSP	Calculated as 1 minus the distance between 52-week high and day *t* over 364. t is the insider transaction date.
illiq	CRSP	Amihud'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 capitalization
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.
$UpDummy_{i,t}$	CRSP	I follow Lasfer *et al.* (2003) to define UpDummy for controlling short-term abnormal price movement. UpDummy equals to one for stock *i* on day *t* when the any of the stock daily return in the event of $(t - 7, t)$ is higher 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
$DownDummy_{i,t}$	CRSP	I follow Lasfer *et al.* (2003) to define UpDummy for controlling short-term abnormal price movement. UpDummy equals to one for stock *i* on day *t* when 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 yearbook value over the market capitalization in the last trading day in December. Book value is computed as the following. Book value is equal to stockholder equity $+$ deferred taxes and investment tax credit (Compustat: txditc, zero if missing) $-$preferred stock value. Stockholder equity is parent stockholder equity (Compustat: seq), or total common equity (Compustat: ceq) plus total preferred stock capital (Compustat: pstk) or the difference between the total asset (Compustat: at) and total liability (Compustat: lt), in that order, as available. Preferred stock value is, preferred stock redemption value (Compustat: pstkrv), or preferred stock liquidation value (Compustat: pstkl), or total preferred stock capital (Compustat: pstk), or zero, in that order as available. Negative bm ratio is restricted to zero.
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 transactions in day *t*, calculate as the ratio of the net dollar amount of insider transactions over the total dollar amount of insider transactions.
$SUE_{j,q}$	COMPUSTAT	Proxy for earnings surprise. I follow Bernard *et al.* (1990). Specifically, EPS is the split-adjusted earnings per share calculated using Earning Per

		Share-Excluding Extraordinary Items (Compustat: epspxq) over adjustment factor (Compustat: ajexq). $SUE_{j,q} = \frac{(EPS_{j,q} - EPS_{j,q-4} - \mu_{q-7,q})}{\sigma_{q-7,q}}$ where as$\mu_{q-7,q}$ and $\sigma_{q-7,q}$ are the mean and standard deviation of $(EPS_{j,q} - EPS_{j,q-4})$ for the past eight quarters, respectively.
$CAR_{j,q}$	CRSP	Three-day cumulative abnormal return centered around the quarterly earnings announcement (-1,1) for firm j in quarter q. CAR is calculated using market model where the benchmark return is the CRSP value-weighted index return and I restrict the estimation window is (-250, -50), and there are at least 100 days in the estimation window.
$Following\ Sequence_s$	CRSP	The BHAR accumulated between 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.
$Average\ Holding\ Return_s$	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 4.2: 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 4.1. Standard errors are Newey-West Standard Error up to lag 5, and p-values are reported in parentheses. Sample is aggregated at firm-month level. ***, **, * indicate the coefficients are statistically significant at 0.01, 0.05% and 0.01levels, 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	0.001	-0.001	-0.000	-0.003	-0.004**
	(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

Appendix 4.3: BHARs after 52-week high/low has been reached

The table reports the BHARs after a 52-week high/low is reached for first time within a 30-day period, 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, I report the BHAR_m_i returns unconditional on insider trades for these holding periods accumulated from one day after the stock hits the 52-week high or low. I restrict there must be at least 20/120/243 trading days within the corresponding 30/180/365 estimation windows. I exclude stocks that listed less than 120 trading days and reached a 52-week high because of time elapse. Panel D reports 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. ***, **, * indicate the coefficients are statistically significant at 0.01, 0.05% and 0.01levels, respectively. All BHAR_m_i are minorized 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)
N	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)
N	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 4.4: 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, I 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*, I 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. I 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. I 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. I rebalance the long and short portfolios monthly. Panel B is similar to Panel A except I sort stocks according to their 52-week high/low recency ratios on day *t*. 52-week high/low recency ratio is $(1-\frac{distance\ to\ the\ 52-week\ high/low_t}{364})$. I 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. I multiply Alpha by 6 or 12 for 6- and 12-month holding period, respectively. ***, **, * indicate the coefficients are statistically significant at 0.01, 0.05% and 0.01levels, 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 4.5: Construction of Anomalies

Anomaly	Reference	Construction
Failure Probability (FP)	Chen, *et al.* (2011)	See Chen, Novy-Marx, and Zhang (2010) for a detailed description. The construction of the variable is discussed in Appendix 4.6.
Net Stock Issuance (NSI)	Stambaugh *et al.* (2012)	The growth rate of the split adjusted number of shares outstanding for stock i in fiscal year t, computed as follows: $\log[(csho_{i,t-1} \times ajex_{i,t-1})/(csho_{i,t-2} \times ajex_{i,t-2})]$
Total Accruals (TA)	Sloan (1996)	Changes in non-cash working capital minus depreciation expense scaled by average total assets for the previous two fiscal years, computed as follows: $\frac{\Delta act_{i,t-2,t-1} - \Delta che_{i,t-2,t-1} - \Delta lct_{i,t-2,t-1} + \Delta dlc_{i,t-2,t-1} + \Delta txp_{i,t-2,t-}}{(at_{i,t-1} + at_{i,t-2})/2}$
Net Operating Assets (NOA)	Hirshleifer, Hou, Teoh and Zhang (2004)	The difference between all operating assets and all operating liabilities divided by total assets in the previous fiscal quarter, computed as follows: $\frac{(at_{i,t-1} - che_{i,t-1}) - (at_{i,t-1} - dlc_{i.t-1} - dltt_{i,t-1} - mib_{i,t-1} - pstk_{i,t}}{at_{i,t-2}}$
Gross Profitability (GP)	Novy-Marx (2013)	The gross profits scaled by assets, computed as follows: $\frac{(sale_{i,t-1} - cogs_{i,t-1})}{at_{i,t-1}}$
Asset Growth (AG)	Cooper, Gulen and Schill (2008)	The growth rate in total assets, computed as follows: $\frac{(at_{i,t-1} - at_{i,t-2})}{at_{i,t-2}}$
Return on Asset (ROA)	Fama and French (2006)	The ratio of quarterly earnings to total assets, computed as follows: $\frac{ibq_{i,t-1}}{atq_{i,t-2}}$
Investment-to-Assets (IA)	Titman, Wei and Xie (2004)	Changes in gross property, plant, and equipment plus changes in inventories divided by total assets, computed as follows: $\frac{(\Delta ppget_{i,t-2,t-1} + \Delta invt_{i,t-2,t-1})}{at_{i,t-2}}$

Appendix 4.6: 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 $\phi = 2^{-1/3}$. $NIMTA = \frac{niq}{(ltq+prcc \ \times csh \quad)}$ 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	$EXRETAVG_{t-1,t-12} = \frac{1-\phi}{1-\phi^{12}}(EXRET_{T-1} + \cdots + \phi^{11} NITMTA_{t-12})$ Where $\phi = 2^{-1/3}$. $EXRET = \log(1 + R_{i,t}) - \log(1 + R_{S\&P50 \ \ ,t})$ 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	The ratio of cash and short-term investment over the sum of market equity and total liabilities $= cheq/(ltq + prccq \times cshoq)$.
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 deferred 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), I 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 equity value, I replace those negative values to be $1 to ensure that all firms are in the right tail of the distribution.
PRICE	Each firm's log closing price (log(prccq)), 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.

Chapter 5

Conclusion

This thesis addresses the motivation and the informational content behind insider transactions in the US. I analyse their trading pattern and profitability around three main events that are not addressed in previous literature: their career promotion outcomes following CEO tournament contests, M&A announcement of their economically supply chain linked firms, and when their firms' share prices reach their 52-week high/low levels. I test various models, hypotheses from the corporate insider trading, labour economics, M&A, and behavioural finance literatures. I combine these theories with individual corporate insider transactions and monthly aggregated insider trading because their personal characteristics will shed further lights on these issues.

Chapter 2 finds that corporate insiders predominantly make informed sell transactions to generate abnormal return to compensate themselves for the forgone CEO promotion opportunity. Corporate insiders avoid making opportunistic sell transactions *ex-ante* because these transactions will lower their likelihood of becoming the next CEO. However, they will sell their shares once the CEO tournament outcome has been revealed and they have lost the promotion. These sell transactions generate abnormally lower return which is a gain to these sellers compared with their sells outside the CEO tournament. They sell their stocks against the newly appointed CEOs who make noisy purchase transactions, a finding consistent with Armstrong *et al.* (2019). In contrast, I do not find that corporate insiders systematically make more informed purchase transactions to compensate themselves. This study further investigates the informational content behind these informed trades. Insider sell transactions will predict a decrease in the return on asset, investor sentiment and an increase in the cost of capital, which implies these tournament rejectees will exert lower level of effort because their CEO promotion opportunity has been lost. Overall, the presence of insider trading opportunity will weaken the positive causal relationship document by Kale *et al.* (2019) because corporate insiders have the outside option to trade on their private information to compensate themselves for the forgone tournament incentives.

Chapter 3 finds that corporate insiders do not only have informational advantage in accessing the private information of their firms but can understand the public announcement of their economically linked firms better than the outside investors, a finding that is consistent with Alldredge and Cicero (2015). I find that the monthly aggregated insider net purchasing value, systematically becomes higher following the M&A announcement of their competitors and customers, but not suppliers. The increased purchasing pressure will predict a higher abnormal return. I further investigate the informational content behind these more informed transactions. I show that these more informed insider transactions lend support to both the productive efficiency and purchasing efficiency hypotheses. This study further relates these informed transactions to the probability of their firms to be taken over, and documents that when insiders are purchasing more after the M&A announcement, their firms are likely to become the target in a deal in the next one year. I find that insider trading measures can predict the probability of deal completion, and the predictability embedded in insider trading is in addition to the aggregate market predictability, indicating that corporate insiders have different informational channel than the market.

Chapter 4 documents that corporate insiders systematically sell (buy) at the 52-week high (low) price extreme. Although they trade in the same pattern as uninformed investors who suffer from 52-week high bias at the price extreme, they do not suffer from the anchoring bias. In contrast, both their purchase and sell transactions are profitable after adjusting the dissimulation strategy they employed. A trading strategy by longing the portfolio that the stock price is closer to the 52-week high and shorting the portfolio that the stock price is closer to the 52-week low, will yield an 19.2% abnormal return in one-year period. The trading strategy will generate an annual abnormal return of approximately 31% if I form portfolio built on the top decile 52-week high (low) recency of their transactions.

More work is needed in future to fully understand the motivation behind sell transactions. Insider trading literature has long argued that sell trades may be executed for diversification or liquidity considerations (Lakonishok and Lee, 2001), and therefore most recent insider trading studies have concluded that insider sells are not information driven. As a result, many studies tend to ignore the role played by insider sell transactions and only focus on purchase transactions. However, my results show that insiders will sell for their personal gains as well. Since sell transactions are significantly larger than purchase transactions, they will generate a large amount of dollar profit for corporate insiders. Moreover, the study shows that insiders' informational advantage also exists in understanding public information because the supply chain facilitates the flow of information. As a topic subject to further research, the role of supply chain structure should be analyzed.

Reference

Adamson, T., Canavan, J. and Ziemba, T. (2020), *The BDO 600*. Available at: https://insights.bdo.com/rs/116-EDP-270/images/2020_BDO-600-CEO-CFO_survey.pdf.

Agrawal, A. and Jaffe, J. F. (1995), Does Section 16b deter insider trading by target managers?, *Journal of Financial Economics*, 39(2–3), pp. 295–319. doi: 10.1016/0304-405X(95)00833-Z.

Agrawal, A. and Nasser, T. (2012), Insider trading in takeover targets, *Journal of Corporate Finance*, 18(3), pp. 598–625. doi: 10.1016/j.jcorpfin.2012.02.006.

Agrawal, A., and Cooper, T. (2015), Insider trading before accounting scandals. *Journal of Corporate Finance, 34*, 169–190. https://doi.org/10.1016/j.jcorpfin.2015.07.005

Akbas, F., Jiang, C. and Koch, P. D. (2020), Insider Investment Horizon, *The Journal of Finance*, 75(3), pp. 1579–1627. doi: 10.1111/jofi.12878.

Akbulut, M. E. (2013), Do Overvaluation-Driven Stock Acquisitions Really Benefit Acquirer Shareholders?, *Journal of Financial and Quantitative Analysis*, 48(4), pp. 1025–1055. doi: 10.1017/S0022109013000379.

Akepanidtaworn, Klakow, Di Mascio, Rick, Imas, Alex, and Schmidt Lawrence (2021), Selling fast and buying slow: heuristics and trading performance of institutional investors, NBER Working Paper 29076. http://www.nber.org/papers/w29076

Akhigbe, A., Borde, S. F. and Whyte, A. M. (2000), The Source of Gains to Targets and Their Industry Rivals: Evidence Based on Terminated Merger Proposals, *Financial Management*, 29(4), p. 101. doi: 10.2307/3666370.

Aktas, N., Boone, A., Croci, E., and Signori, A. (2021), Reductions in CEO career horizons and corporate policies. *Journal of Corporate Finance*, *66*, 101862. https://doi.org/10.1016/j.jcorpfin.2020.101862

Ali, Ashiq, Kelsey D. Wei, and Yibin Zhou, (2011), Insider Trading and Option Grant Timing in Response to Fire Sales (and Purchases) of Stocks by Mutual Funds, *Journal of Accounting Research, 49*, 595–632. https://doi.org/10.1111/j.1475-679X.2011.00406.x

Ali, U. and Hirshleifer, D. (2017), Opportunism as a firm and managerial trait: Predicting insider trading profits and misconduct, *Journal of Financial Economics*, 126(3), pp. 490–515. doi: 10.1016/j.jfineco.2017.09.002.

Ali, U. and Hirshleifer, D. (2020), Shared analyst coverage: Unifying momentum spillover effects, *Journal of Financial Economics*, 136(3), pp. 649–675. doi: 10.1016/j.jfineco.2019.10.007.

Alldredge, D. M. and Blank, B. (2019), Do Insiders Cluster Trades with Colleagues? Evidence From Daily Insider Trading, *Journal of Financial Research*, 42(2), pp. 331–360. doi: 10.1111/jfir.12172.

Alldredge, D. M. and Cicero, D. C. (2015), Attentive insider trading, *Journal of Financial Economics*, 115(1), pp. 84–101. doi: 10.1016/j.jfineco.2014.09.005.

Amihud, Y. (2002), Illiquidity and stock returns: cross-section and time-series effects, *Journal* *of Financial Markets*, 5(1), pp. 31–56. doi: 10.1016/S1386-4181(01)00024-6.

Anderson, John, Jeremy Kidd, and George A. Mocsary, (2020), Public Perceptions of Insider Trading, Available at SSRN: http://dx.doi.org/10.2139/ssrn.3645579

Andrews, I., Stock, J. H. and Sun, L. (2019), Weak Instruments in Instrumental Variables Regression: Theory and Practice, *Annual Review of Economics*. doi: 10.1146/annurev-economics-080218-025643.

Anginer, Deniz, Gerard Hoberg, and H. Nejat Seyhun, (2018), Do Insiders Exploit Anomalies?, Marshall School of Business Working Paper No. 17-1, Available at SSRN: http://dx.doi.org/10.2139/ssrn.2625614

Angrist, J. D. and Pischke, J. S. (2009), *Mostly harmless econometrics: An empiricist's companion*, *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton,NJ: Princeton University Press. doi: 10.1111/j.1475-4932.2011.00742.x.

Armstrong, C., Blackburne, T. and Quinn, P. (2021), Are CEOs' purchases more profitable than they appear?, *Journal of Accounting and Economics*, 71, 101378 p. 101378. doi: 10.1016/j.jacceco.2020.101378.

Baker, A., Larcker, D. F. and Wang, C. C. Y. (2021), How Much Should I Trust Staggered Difference-In-Differences Estimates?, *SSRN Electronic Journal*. doi: 10.2139/ssrn.3794018.

Baker, M., and Wurgler, J. (2013), Behavioral Corporate Finance: An Updated Survey. In *Handbook of the Economics of Finance* (pp. 357–424), https://doi.org/10.1016/B978-0-44-453594-8.00005-7

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

Barber, B. M., and Lyon, J. D. (1997), Detecting long-run abnormal stock returns: The empirical power and specification of test statistics. *Journal of Financial Economics*, *43*, 341–372. https://doi.org/10.1016/S0304-405X(96)00890-2

Barber, B. M., and Odean, T. (2001), Boys will be boys: Gender, overconfidence, and common stock investment. *Quarterly Journal of Economics*, *116*, 261–292. https://doi.org/10.1162/003355301556400

Basu, S. (1997), The conservatism principle and the asymmetric timeliness of earnings, *Journal of Accounting and Economics*, 24(1). doi: 10.1016/S0165-4101(97)00014-1.

Becher, D. A., Mulherin, J. H. and Walkling, R. A. (2012), Sources of Gains in Corporate Mergers: Refined Tests from a Neglected Industry, *Journal of Financial and Quantitative Analysis*, 47(1), pp. 57–89. doi: 10.1017/S0022109012000026.

Beneish, M. D. and Markarian, G. (2019), A Theory of Insider Purchases. Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3478344.

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

Bhagat, S. and Bolton, B. (2013), Manager Ownership, Governance, and Performance, *Journal* *of Financial and Quantitative Analysis*, 48(1), pp. 105–135. doi: 10.1017/S0022109013000045.

Bhattacharya, U. and Daouk, H. (2002), The World Price of Insider Trading, *The Journal of finance*, vol. 57, no. 1, pp. 75-108.

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

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

Boehm, J. and Sonntag, J. (2018), Vertical Integration and Foreclosure: Evidence from Production Network Data, *Sciences Po publications*.

Bourveau, T., Brochet, F., Ferri, F. and Sun, C. (2021), Say on Pay Laws and Insider Trading. Available at SSRN: https://ssrn.com/abstract=3938891 or http://dx.doi.org/10.2139/ssrn.3938891

Bradley, M., Desai, A. and Kim, E. H. (1988), Synergistic gains from corporate acquisitions and their division between the stockholders of target and acquiring firms, *Journal of Financial Economics*, 21(1), pp. 3–40. doi: 10.1016/0304-405X(88)90030-X.

Bris, A. (2005), Do Insider Trading Laws Work?, European financial management. *European Financial Management* vol. 11, no. 3, pp. 267-312.

Brochet, F. (2019), Aggregate insider trading and market returns: The role of transparency. *Journal of Business Finance and Accounting*, *46*, 336–369. https://doi.org/10.1111/jbfa.12357

Brockman, P., Lee, H. S. G. and Salas, J. M. (2016), Determinants of CEO compensation: Generalist–specialist versus insider–outsider attributes, *Journal of Corporate Finance*, 39, pp. 53–77. doi: 10.1016/j.jcorpfin.2016.04.007.

Bushman, R. M., Dai, Z. and Zhang, W. (2016), Management Team Incentive: Dispersion and Firm Performance, *The Accounting Review*, 91(1), pp. 21–45. doi: 10.2308/accr-51112.

Cai, J., Song, M. H. and Walkling, R. A. (2011), Anticipation, Acquisitions, and Bidder Returns: Industry Shocks and the Transfer of Information across Rivals, *Review of Financial Studies*, 24(7), pp. 2242–2285. doi: 10.1093/rfs/hhr035.

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

Campbell, S. D., and Sharpe, S. A. (2009), Anchoring bias in consensus forecasts and its effect on market prices. *Journal of Financial and Quantitative Analysis*, *44*, 369–390. https://doi.org/10.1017/S0022109009090127

Carhart, M. M. (1997), On persistence in mutual fund performance. *Journal of Finance*, *52*, 57–82. https://doi.org/10.1111/j.1540-6261.1997.tb03808.x

Cen, L., Hilary, G., and Wei, K. C. J. (2013), The role of anchoring bias in the equity market: Evidence from analysts' earnings forecasts and stock returns. *Journal of Financial and Quantitative Analysis*, *48*, 47–76. https://doi.org/10.1017/S0022109012000609

Cen, W. and Doukas, J. A. (2017), CEO personal investment decisions and firm risk, *European Financial Management*, 23(5), pp. 920–950. doi: 10.1111/eufm.12117.

Cengiz, D. Dube, A., Lindner, A., and Zipperer, B. (2019), The Effect of Minimum Wages on Low-Wage Jobs, *The Quarterly Journal of Economics*, 134(3), pp. 1405–1454. doi: 10.1093/qje/qjz014.

Cespa, G. (2008), Information Sales and Insider Trading with Long-Lived Information, *The Journal of Finance*, 63(2), pp. 639–672. doi: 10.1111/j.1540-6261.2008.01327.x.

Chan, E. W., Evans, J. H. and Hong, D. (2022), Losers of CEO Tournaments: Incentives, Turnover, and Career Outcomes, *The Accounting Review*. doi: 10.2308/TAR-2019-0486.

Chen, L., Novy-Marx, R., and Zhang, L. (2011), An Alternative Three-Factor Model. https://doi.org/10.2139/ssrn.1418117

Cheng, Q. and Lo, K. (2006), Insider Trading and Voluntary Disclosures, *Journal of Accounting Research*, *44*, pp. 815–848. http://doi.wiley.com/10.1111/j.1475-679X.2006.00222.x

Chiang, C. H., Chung, S. G., and Louis, H. (2017), Insider trading, stock return volatility, and the option market's pricing of the information content of insider trading. *Journal of Banking and Finance*, *76*, 65–73. https://doi.org/10.1016/j.jbankfin.2016.11.027

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

Chung, B. H., Collins, D. W. and Song, J. Z. (2022), Managerial Myopia and the Unintended Real Consequences of Conditional Conservatism, *SSRN*. Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4105703.

Cline, B.N., Williamson, C.R. and Xiong, H. (2021), Culture and the regulation of insider trading across countries, *Journal of corporate finance*, vol. 67, pp. 101917.

Cohen, L. and Frazzini, A. (2008), Economic links and predictable returns, *Journal of Finance*. doi: 10.1111/j.1540-6261.2008.01379.x.

Cohen, L., Malloy, C. and Pomorski, L. (2012), Decoding Inside Information, *The Journal of Finance*, 67(3), pp. 1009–1043. doi: 10.1111/j.1540-6261.2012.01740.x.

Coles, J. L., Daniel, N. D. and Naveen, L. (2006), Managerial incentives and risk-taking, *Journal of Financial Economics*, 79(2), pp. 431–468. doi: 10.1016/j.jfineco.2004.09.004.

Coles, J. L., Daniel, N. D. and Naveen, L. (2014), Co-opted Boards, *Review of Financial Studies*, 27(6), pp. 1751–1796. doi: 10.1093/rfs/hhu011.

Contreras, H. and Marcet, F. (2021), Sell-side analyst heterogeneity and insider trading, *Journal of Corporate Finance*, 66, p. 101778. doi: 10.1016/j.jcorpfin.2020.101778.

Contreras, H., Fidrmuc, J. P., and Kozhan, R. (2017), Insiders versus short sellers: informed traders' competition around earnings announcements. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2934133

Cooper, M. J., Gulen, H., and Schill, M. J. (2008), Asset growth and the cross-section of stock returns. *Journal of Finance*, *63*, 1609–1651. https://doi.org/10.1111/j.1540-6261.2008.01370.x

Core, J. and Guay, W. (2002), Estimating the Value of Employee Stock Option Portfolios and Their Sensitivities to Price and Volatility, *Journal of Accounting Research*, 40(3), pp. 613–630. doi: 10.1111/1475-679X.00064.

Core, J. E., Guay, W. R. and Larcker, D. F. (2003), Executive Equity Compensation and Incentives: A Survey, *Economic Policy Review*, 9, pp. 27–50.

Cornett, M. M., McNutt, J. J., Strahan, P. E., and Tehranian, H. (2011), Liquidity risk management and credit supply in the financial crisis. *Journal of Financial Economics*, 101(2), 297–312. https://doi.org/10.1016/j.jfineco.2011.03.001

Cosemans, M. and Frehen, R. (2022), How Harmful Is Insider Trading for Outsiders? Evidence from the Eighteenth Century. AFA 2022 Meetings Paper. Retrieved from http://dx.doi.org/10.2139/ssrn.4008601

Custódio, C., and Metzger, D. (2014), Financial expert CEOs: CEO's work experience and firm's financial policies. *Journal of Financial Economics*, *114*, 125-154. https://doi.org/10.1016/j.jfineco.2014.06.002

Cvijanovic, D., Gantchev, N. and Li, R. (2021), CEO Succession Roulette, *SSRN Electronic Journal*. doi: 10.2139/ssrn.2862653.

Cziraki, P. and Jenter, D. (2020), The Market for CEOs, *SSRN Electronic Journal*. doi: 10.2139/ssrn.3644496.

Cziraki, P., and Gider, J. (2021), The Dollar Profits to Insider Trading. *Review of Finance*, *25*(5). https://doi.org/10.1093/rof/rfab010

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

Dang, C., Foerster, S., Li, Z., and Tang, Z. (2021). Analyst talent, information, and insider trading. *Journal of Corporate Finance*, *67*, 101803. https://doi.org/10.1016/j.jcorpfin.2020.101803

Dargenidou, C., Tonks, I., and Tsoligkas, F. (2018), Insider trading and the post-earnings announcement drift. *Journal of Business Finance and Accounting*, *45*, 482–508. https://doi.org/10.1111/jbfa.12305

Darren T. Roulstone. (2003), The Relation Between Insider-Trading Restrictions and Executive Compensation. *Journal of Accounting Research*, *41*, 525–551. https://doi.org/10.2307/3542285

Davidson, R., Dey, A., and Smith, A. (2015), Executives' "off-the-job" behavior, corporate culture, and financial reporting risk. *Journal of Financial Economics*, *117*, 5–28. https://doi.org/10.1016/j.jfineco.2013.07.004

Davis, F., Davis, S., Sha, X., and Walker, T. (2021), The impact of takeover anticipation on rival firms. *Journal of Business Finance and Accounting*. https://doi.org/10.1111/jbfa.12577.

Davis, F., Khadivar, H., Pukthuanthong, K., and Walker, T. J. (2021), Insider trading in rumored takeover targets. *European Financial Management*. https://doi.org/10.1111/eufm.12283

Davis, J. L., Fama, E. F., and French, K. R. (2000), Characteristics, covariances, and average returns: 1929 to 1997. *Journal of Finance*, *55*, 389–406. https://doi.org/10.1111/0022-1082.00209

Dellavigna, S. and Pollet, J. M. (2009), Investor Inattention and Friday Earnings Announcements, *The Journal of Finance*, 64(2), pp. 709–749. doi: 10.1111/j.1540-6261.2009.01447.x.

Derrien, F., Frésard, L., Slabik, V., and Valta, P. (2021), Industry asset revaluations around public and private acquisitions. *Journal of Financial Economics*. https://doi.org/10.1016/j.jfineco.2021.10.003

Dessaint, O., Eckbo, B. Espen , Golubov, Andrey (2022), Bidder-Specific Synergies and the Evolution of Acquirer Returns. Available at SSRN https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3437865

Dessaint, O., Foucault, T., Frésard, L., and Matray, A. (2019), Noisy Stock Prices and Corporate Investment. *The Review of Financial Studies*, 32(7), 2625–2672. https://doi.org/10.1093/rfs/hhy115

DeVaro, J. (2006), Internal promotion competitions in firms, *The RAND Journal of Economics*, 37(3), pp. 521–542. doi: 10.1111/j.1756-2171.2006.tb00029.x.

Di Giuli, A. (2013) 'The effect of stock misvaluation and investment opportunities on the method of payment in mergers', *Journal of Corporate Finance*, 21(1), pp. 196–215. doi: 10.1016/j.jcorpfin.2013.02.002.

Ding, W., Levine, R., Lin, C., and Xie, W. (2021), Corporate immunity to the COVID-19 pandemic. *Journal of Financial Economics*, *141*(2), 802–830. https://doi.org/10.1016/j.jfineco.2021.03.005

Eckbo, B. E. (1983), Horizontal mergers, collusion, and stockholder wealth, *Journal of Financial Economics*. doi: 10.1016/0304-405X(83)90013-2.

Eckbo, B. E., Makaew, T. and Thorburn, K. S. (2018), Are stock-financed takeovers opportunistic?, *Journal of Financial Economics*, 128(3). doi: 10.1016/j.jfineco.2018.03.006.

Ecobo, B. E., and Odegarrd, B. A. (2019), Insider trading and gender. Available at SSRN https://ssrn.com/abstract=3475061

Ederhof, M. (2011), Incentive Compensation and Promotion-Based Incentives of Mid-Level Managers: Evidence from a Multinational Corporation, *The Accounting Review*, 86(1), pp. 131–153. doi: 10.2308/accr.00000007.

Edmans, A., Goldstein, I. and Jiang, W. (2012), The Real Effects of Financial Markets: The Impact of Prices on Takeovers, *The Journal of Finance*, 67(3), pp. 933–971. doi: 10.1111/j.1540-6261.2012.01738.x.

Egeth, H. and Kahneman, D. (1975), Attention and Effort, *The American Journal of Psychology*, 88(2). doi: 10.2307/1421603.

Erin, H., Plesko, G., and Rawson, C. (2022). Geographic Connections to China and Insider Trading at the Start of the COVID-19 Pandemic. *Review of Accounting Studies,* Forthcoming.

Evans, J. H., Nagarajan, N. J. and Schloetzer, J. D. (2010), CEO Turnover and Retention Light: Retaining Former CEOs on the Board, *Journal of Accounting Research*, 48(5), pp. 1015–1047. doi: 10.1111/j.1475-679X.2010.00383.x.

Fama, E. F. and French, K. R. (1993), Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics*, 33(1), pp. 3–56. doi: 10.1016/0304-405X(93)90023-5.

Fama, E. F., and French, K. R. (2006), Profitability, investment and average returns. *Journal of Financial Economics*, *82*, 491–518. https://doi.org/10.1016/j.jfineco.2005.09.009

Fee, C. E. and Thomas, S. (2004), Sources of gains in horizontal mergers: Evidence from customer, supplier, and rival firms, *Journal of Financial Economics*. doi: 10.1016/j.jfineco.2003.10.002.

Feenberg, D. and Coutts, E. (1993), An Introduction to the TAXSIM Model, *Journal of Policy Analysis and Management*, 12(1), p. 189. doi: 10.2307/3325474.

Feng, H. and Rao, R. P. (2018), Cash holdings and CEO risk incentive compensation: Effect of CEO risk aversion, *International Review of Financial Analysis*, 60, pp. 162–176. doi: 10.1016/j.irfa.2018.09.009.

Fidrmuc, J. P. and Xia, C. (2022), Target insiders' preferences when trading before takeover announcements: Deal completion probability, premium and deal characteristics, *European Financial Management*, 28(1), pp. 162–207. doi: 10.1111/eufm.12308.

Fidrmuc, J. P., Korczak, A. and Korczak, P. (2013), Why does shareholder protection matter for abnormal returns after reported insider purchases and sales?, *Journal of Banking and Finance*, 37(6), pp. 1915–1935. doi: 10.1016/j.jbankfin.2012.06.019.

Fidrmuc, J. P., Roosenboom, P. and Zhang, E. Q. (2018), Antitrust merger review costs and acquirer lobbying, *Journal of Corporate Finance*, 51. doi: 10.1016/j.jcorpfin.2018.05.001.

Fishman, M. J. and Hagerty, K. M. (1992), Insider Trading and the Efficiency of Stock Prices, *The RAND Journal of Economics*, 23(1), pp. 106–122. doi: 10.2307/2555435.

Fiske, S. T. and Taylor, S. E. (1991), *Social cognition (2nd ed.)*, *McGrawHill series in social psychology*.

Franco, F. and Urcan, O. (2021), Executive Deferral Plans and Insider Trading. *Contemporary Accounting Research*, Forthcoming, Available at SSRN: https://ssrn.com/abstract=3987909

Gao, M. (2019), Get the Money Somehow: The Effect of Missing Performance Goals on Insider Trading, *SSRN Electronic Journal*. doi: 10.2139/ssrn.3495199.

Gaur, A. S., Malhotra, S. and Zhu, P. (2013), Acquisition announcements and stock market valuations of acquiring firms' rivals: A test of the growth probability hypothesis in China, *Strategic Management Journal*, 34(2). doi: 10.1002/smj.2009.

Gayle, G., Li, C., and Miller, R. (2022), Was Sarbanes–Oxley Costly? Evidence from Optimal Contracting on CEO Compensation. *Journal of Accounting Research*, *60*(4), 1189–1234. https://doi.org/10.1111/1475-679X.12436

Genesove, D., and Mayer, C. (2001), Loss aversion and seller behavior: Evidence from the housing market. *Quarterly Journal of Economics*, *116*, 1233–1260. https://doi.org/10.1162/003355301753265561

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

Gibbons, R. and Murphy, K. J. (1992), Optimal Incentive Contracts in the Presence of Career Concerns: Theory and Evidence, *Journal of Political Economy*, 100(3), pp. 468–505. doi: 10.1086/261826.

Gibbs, M. (1995), Incentive compensation in a corporate hierarchy, *Journal of Accounting and Economics*, 19(2–3), pp. 247–277. doi: 10.1016/0165-4101(94)00384-H.

Ginsburgh, V. A., and Van Ours, J. C. (2003), Expert opinion and compensation: Evidence from a musical competition. *American Economic Review*, *93*, 289–296. https://doi.org/10.1257/000282803321455296

Goergen, M., Renneboog, L. and Zhao, Y. (2019), Insider trading and networked directors, *Journal of Corporate Finance*. doi: 10.1016/j.jcorpfin.2019.02.001.

Gofman, M. and Wu, Y. (2022), Trade credit and profitability in production networks, *Journal of Financial Economics*, 143(1). doi: 10.1016/j.jfineco.2021.05.054.

Goodman, A. (2010), Why do so few CFOs become CEOs?, Financial Times. Available at: https://www.ft.com/content/9f9e7758-6d5d-11df-bde2-00144feabdc0 (Accessed: 25 October 2021).

Gort, M. (1969), An Economic Disturbance Theory of Mergers, *The Quarterly Journal of Economics*, 83(4), p. 624. doi: 10.2307/1885453.

Gregory, A., Tharyan, R., and Tonks, I. (2013), More than just contrarians: Insider trading in glamour and value firms. *European Financial Management*, *19*(4). https://doi.org/10.1111/j.1468-036X.2011.00608.x

Gregory-Smith, I. and Wright, P. W. (2019), Winners and losers of corporate tournaments, *Oxford Economic Papers*, 71(1), pp. 250–268. doi: 10.1093/oep/gpy033.

Grinblatt, M., and Keloharju, M. (2001), What makes investors trade? *Journal of Finance*, *56*, 589–616. https://doi.org/10.1111/0022-1082.00338

Gruber, M. J. (1996), Another puzzle: The growth in actively managed mutual funds. *Journal of Finance*, *51*, 783–810. https://doi.org/10.1111/j.1540-6261.1996.tb02707.x

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

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

Hauck, P. (2015), Europe's commitment to countering insider dealing and market manipulation on the basis of Art. 83 para. 2 TFEU A critical evaluation.

Henderson, R. (2020), US executives rush in record numbers to "buy the dip", Financial Times. Retrieved April 11, 2020, from Financial Times website: https://www.ft.com/content/8c76c07f-0ee1-40d6-ad32-652c85646167?shareType=nongift

Hillier, D., Korczak, A., and Korczak, P. (2015), The impact of personal attributes on corporate insider trading. *Journal of Corporate Finance*, *30*. https://doi.org/10.1016/j.jcorpfin.2014.12.003

Hirshleifer, D., Hou, K., Teoh, S. H., and Zhang, Y. (2004), Do investors overvalue firms with bloated balance sheets? *Journal of Accounting and Economics*, *38*, 297–331. https://doi.org/10.1016/j.jacceco.2004.10.002

Holmstrom, B. and Milgrom, P. (1994), The firm as an incentive system, *The American Economic Review*, 84(4), pp. 972–991. doi: 10.2307/2118041.

Hong, H. and Stein, J. C. (1999), A Unified Theory of Underreaction, Momentum Trading, and Overreaction in Asset Markets. The Journal of Finance, 54, 2143-2184 https://www.jstor.org/stable/797990

Hong, H., Torous, W. and Valkanov, R. (2007), Do industries lead stock markets?, *Journal of Financial Economics*, 83(2), pp. 367–396. doi: 10.1016/j.jfineco.2005.09.010.

Hong, Xin, Bradford D. Jordan, and Mark H. Liu, 2015, Industry information and the 52-week high effect, *Pacific Basin Finance Journal* 32, 111–130. https://doi.org/10.1016/j.pacfin.2015.02.011

Hoque, H., and Lasfer, M. (2015), Directors' dealing and post-IPO performance. *European Financial Management*, *21*, 178–204. https://doi.org/10.1111/j.1468-036X.2013.12013.x

Hsieh, J., Ng, L. and Wang, Q. (2019) *Informativeness of Insider Traders and Analyst Recommendations*. Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=687584.

Huang, D., Jiang, F., Tu, J., and Zhou, G. (2015), Investor sentiment aligned: A powerful predictor of stock returns. *Review of Financial Studies*, *28*, 791–837. https://doi.org/10.1093/rfs/hhu080

Huang, L. and Kale, J. R. (2013), Product Market Linkages, Manager Quality, and Mutual Fund Performance, *Review of Finance*, 17(6), pp. 1895–1946. doi: 10.1093/rof/rfs038.

Huang, L. and Liu, H. (2007), Rational Inattention and Portfolio Selection, *The Journal of Finance*, 62(4), pp. 1999–2040. doi: 10.1111/j.1540-6261.2007.01263.x.

Huddart, S. J. and Ke, B. (2007), Information asymmetry and cross-sectional variation in insider trading, *Contemporary Accounting Research*, 24(1), pp. 195–232. doi: 10.1506/0277-1110-4434-M627.

Huddart, S., Hughes, J. S. and Levine, C. B. (2001), Public disclosure and dissimulation of insider trades, *Econometrica*, 69(3), pp. 665–681. doi: 10.1111/1468-0262.00209.

Hwang, B.-H., and Liu, B. (2012), Which Anomalies are More Popular? And Why? Purdue University Working Paper https://finance.business.uconn.edu/wp-content/uploads/sites/723/2014/08/Which-Anomalies-are-more-Popular.pdf

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

Jaffe, J. F. (1974), Special Information and Insider Trading. *The Journal of Business*, *47*, 410–428. https://doi.org/10.1086/295655

Jagolinzer, A. D., Larcker, D. F., and Taylor, D. J. (2011), Corporate governance and the information content of insider trades. *Journal of Accounting Research*, *49*, 1249–1279. https://doi.org/10.1111/j.1475-679X.2011.00424.x

Jagolinzer, A. D., Larcker, D. F., Ormazabal, G., and Taylor, D. J. (2020), Political Connections and the Informativeness of Insider Trades. *Journal of Finance*, *75, 1833-1876*. https://doi.org/https://doi.org/10.1111/jofi.12899

Jegadeeshm, N., and Titman, S. (1993), Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *The Journal of Finance*, *48*, 65–92. https://doi.org/10.1111/j.1540-6261.1993.tb04702.x

Jenter, D. and Lewellen, K. (2021), Performance-Induced CEO Turnover, *The Review of Financial Studies*. 34(2), pp. 569–617. doi: 10.1093/rfs/hhaa069.

Jiang, X. and Zaman, M. A. (2010), Aggregate insider trading: Contrarian beliefs or superior information?, *Journal of Banking and Finance*, 34(6), pp. 1225–1236. doi: 10.1016/j.jbankfin.2009.11.016.

Kacperczyk, M. T. and Pagnotta, E. (2021), Becker Meets Kyle: Legal Risk and Insider Trading, *SSRN Electronic Journal*. doi: 10.2139/ssrn.3142006.

Kahle, K. M. (2000), Insider trading and the long-run performance of new security issues. *Journal of Corporate Finance*, *6*, 25–53. https://doi.org/10.2469/dig.v30.n4.760

Kahneman, D., Slovic, P., and Tversky, A. (1982), *Judgment under Uncertainty: Heuristics and Biases*. Cambridge: Cambridge University Press.

Kale, J. R., Reis, E. and Venkateswaran, A. (2009), Rank-Order Tournaments and Incentive Alignment: The Effect on Firm Performance, *The Journal of Finance*, 64(3), pp. 1479–1512. doi: 10.1111/j.1540-6261.2009.01470.x.

Kaustia, M., Alho, E., and Puttonen, V. (2008), How much does expertise reduce behavioral biases? The case of anchoring effects in stock return estimates. *Financial Management*, *37*, 391–411. https://doi.org/10.1111/j.1755-053X.2008.00018.x

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

Kelley, E. K., and Tetlock, P. C. (2017), Retail short selling and stock prices. *Review of Financial Studies*, *30*, 801–834. https://doi.org/10.1093/rfs/hhw089

Khan, M. and Watts, R. L. (2009), Estimation and empirical properties of a firm-year measure of accounting conservatism, *Journal of Accounting and Economics*, 48(2–3). doi: 10.1016/j.jacceco.2009.08.002.

Kim, E. H. and Lu, Y. (2011), CEO ownership, external governance, and risk-taking, *Journal of Financial Economics*, 102(2), pp. 272–292. doi: 10.1016/j.jfineco.2011.07.002.

Kini, O. and Williams, R. (2012), Tournament incentives, firm risk, and corporate policies, *Journal of Financial Economics*, 103(2), pp. 350–376. doi: 10.1016/j.jfineco.2011.09.005.

Kishore, R., Brandt, M. W., Santa-Clara, P., and Venkatachalam, M. (2011), Earnings Announcements are Full of Surprises. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.909563

Korczak, A., Korczak, P., and Lasfer, M. (2010), To trade or not to trade: The strategic trading of insiders around news announcements. *Journal of Business Finance and Accounting*, *37*, 369–407. https://doi.org/10.1111/j.1468-5957.2010.02185.x

Kose, J., and Ranga, N. (1997), Market Manipulation and the Role of Insider Trading Regulations. *Journal of Business*, *70*, 217–247. https://doi.org/10.1086/209716

Kothari, S. P., and Warner, J. B. (1997), Measuring long-horizon security price performance. *Journal of Financial Economics*, *43*, 301–339. https://doi.org/10.1016/S0304-405X(96)00899-9

Kyle, Albert S., (1985), Continuous Auctions and Insider Trading, *Econometrica,* 53, 1315– 1335. https://doi.org/10.2307/1913210

Lakonishok, J. and Lee, I. (2001), Are insider trades informative?, *Review of Financial Studies*, 14(1), pp. 79–111. doi: 10.1093/rfs/14.1.79.

Larcker, D., Lynch, B., Quinn, P., Tayan, B., and Taylor, D.J. (2021), Gaming the system: Three "Red Flags" of Potential 10b5-1 Abuse. Retrieved from https://www.gsb.stanford.edu/sites/default/files/publication-pdf/cgri-closer-look-88-gaming-the-system.pdf

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

Lax-Martinez, G., Raffo, J., and Saito, K. (2016), Identifying the Gender of PCT inventors. Retrieved from https://ideas.repec.org/c/wip/eccode/10.html

Lazear, E. P. and Rosen, S. (1981), Rank-Order Tournaments as Optimum Labor Contracts, *Journal of Political Economy*, 89(5), pp. 841–864. doi: 10.1086/261010.

Lee, C. M. C., Sun, S. T., Wang, R., and Zhang, R. (2019). Technological links and predictable returns. *Journal of Financial Economics*, *132*(3), 76–96. https://doi.org/10.1016/j.jfineco.2018.11.008

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

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

Lee, K. H. (2011), The world price of liquidity risk. *Journal of Financial Economics*, *99*, 136–161. https://doi.org/10.1016/j.jfineco.2010.08.003

Lesmond, D. A., Ogden, J. P., and Trzcinka, C. A. (1999), A new estimate of transaction costs. *Review of Financial Studies*, *12*, 1113–1141. https://doi.org/10.1093/rfs/12.5.1113

Li, J., and Yu, J. (2012), Investor attention, psychological anchors, and stock return predictability. *Journal of Financial Economics*, *104*, 401–419.

Li, R., Wang, X., and Yan, Z. (2019), Trading against the Grain: When Insiders Buy High and Sell Low. *The Journal of Portfolio Management*, *46*, 139–151. https://doi.org/10.3905/jpm.2019.46.1.139

Lin, J.-C.-C., and Howe, J. S. (1990), Insider Trading in the OTC Market. *The Journal of Finance*, *45*, 1273–1284. https://doi.org/10.1111/j.1540-6261.1990.tb02436.x

Liu, M., Liu, Q. and Ma, T. (2011), The 52-week high momentum strategy in international stock markets, *Journal of International Money and Finance*, 30(1), pp. 180–204. doi: 10.1016/j.jimonfin.2010.08.004.

Luo, J., A Subrahmanyam, and S. Titman, (2021), Momentum and Reversals When Overconfident Investors Underestimate Their Competition. *The Review of Financial Studies*, 34, 351–393. https://doi.org/10.1093/rfs/hhaa016

Ma, Q., Whidbee, D., and Zhang, W. (2014), Recency Bias and Post-Earnings Announcement Drift. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2469308

Main, B. G. M., O'Reilly, C. A. and Wade, J. (1993), Top executive pay: tournament or teamwork?, *Journal of Labor Economics*, 11, pp. 606–28.

Malmendier, U. and Tate, G. (2008), Who makes acquisitions? CEO overconfidence and the market's reaction, *Journal of Financial Economics*, 89(1), pp. 20–43. doi: 10.1016/j.jfineco.2007.07.002.

Malmendier, U., Tate, G., and Yan, J. (2011), Overconfidence and Early-Life Experiences: The Effect of Managerial Traits on Corporate Financial Policies. *Journal of Finance*, *66*, 1687–1733. https://doi.org/10.1111/j.1540-6261.2011.01685.x

Menzly, L. and Ozbas, O. (2010), Market Segmentation and Cross-predictability of Returns, *The Journal of Finance*, 65(4), pp. 1555–1580. doi: 10.1111/j.1540-6261.2010.01578.x.

Meulbroek, L. K., 1992, An Empirical Analysis of Illegal Insider Trading, *Journal*

Mitchell, M. L., and Stafford, E. (2000), Managerial decisions and long-term stock price performance. *Journal of Business*, *73*, 287–329. https://doi.org/10.1086/209645

Morck, R., Shleifer, A. and Vishny, R. W. (1988), Management ownership and market valuation, *Journal of Financial Economics*, 20, pp. 293–315. doi: 10.1016/0304-405X(88)90048-7.

Moskowitz, T. J., and Grinblatt, M. (1999), Do industries explain momentum? *Journal of Finance*, *54*, 1249–1290. https://doi.org/10.1111/0022-1082.00146

Murdock, B. B. (1962), The serial position effect of free recall. *Journal of Experimental Psychology*, *64*, 482–488. https://doi.org/10.1037/h0045106

Nelson, J. (2005), Corporate governance practices, CEO characteristics and firm performance, *Journal of Corporate Finance*, 11(1–2), pp. 197–228. doi: 10.1016/j.jcorpfin.2003.07.001.

Novy-Marx, R. (2013), The other side of value: The gross profitability premium. *Journal of Financial Economics*, *108*, 1–28. https://doi.org/10.1016/j.jfineco.2013.01.003

of Finance, 47, 1661-1699.

Ofek, E., and Yermack, D. (2000), Taking stock: Equity-based compensation and the evolution of managerial ownership. *Journal of Finance*, *55*, 1367–1384. https://doi.org/10.1111/0022-1082.00250

Ohlson, J. A. (1980), Financial Ratios and the Probabilistic Prediction of Bankruptcy. *Journal of Accounting Research*, *18*, 109–131. https://doi.org/10.2307/2490395

Palia, D. (2001), The Endogeneity of Managerial Compensation in Firm Valuation: A Solution, *Review of Financial Studies*, 14(3), pp. 735–764. doi: 10.1093/rfs/14.3.735.

Peters, F. S. and Wagner, A. F. (2014), The Executive Turnover Risk Premium, *The Journal of Finance*, 69(4), pp. 1529–1563. doi: 10.1111/jofi.12166.

Piotroski, J. D. and Roulstone, D. T. (2004), The Influence of Analysts, Institutional Investors, and Insiders on the Incorporation of Market, Industry, and Firm-Specific Information into Stock Prices, *The Accounting Review*, 79(4), pp. 1119–1151. doi: 10.2308/accr.2004.79.4.1119.

Piotroski, J. D. and Roulstone, D. T. (2005), Do insider trades reflect both contrarian beliefs and superior knowledge about future cash flow realizations?, *Journal of Accounting and Economics*, 39(1), pp. 55–81. doi: 10.1016/j.jacceco.2004.01.003.

Rauch, J. E. (1999), Networks versus markets in international trade, *Journal of International Economics*, 48(1), pp. 7–35. doi: 10.1016/S0022-1996(98)00009-9.

Ravina, E., and Sapienza, P. (2010), What do independent directors know evidence from their trading. *Review of Financial Studies*, *23*, 962–1003. https://doi.org/10.1093/rfs/hhp027

Rhodes–Kropf, M., Robinson, D. T. and Viswanathan, S. (2005), Valuation waves and merger activity: The empirical evidence, *Journal of Financial Economics*, 77(3), pp. 561–603. doi: 10.1016/j.jfineco.2004.06.015.

Roulstone, D. T. (2003), The Relation Between Insider-Trading Restrictions and Executive Compensation, *Journal of Accounting Research*, 41(3), pp. 525–551. doi: 10.1111/1475-679X.00115.

Rozeff, M. S. and Zaman, M. A. (1998), Overreaction and Insider Trading: Evidence from Growth and Value Portfolios, *The Journal of Finance*, 53, 701–716. https://doi.org/10.1111/0022-1082.275500.

Sabherwal, S. and Uddin, M. R. (2019), Does stardom affect the informativeness of a CEO's insider trades?, *Journal of Business Finance and Accounting*, 46(9–10), pp. 1171–1200. doi: 10.1111/jbfa.12412.

Samuelson, W. and Rosenthal, L. (1986), Price Movements as Indicators of Tender Offer Success, *The Journal of Finance*, 41(2). doi: 10.1111/j.1540-6261.1986.tb05050.x.

Seyhun, H. N. (1986), Insiders' profits, costs of trading, and market efficiency, *Journal of Financial Economics*, 16(2), pp. 189–212. doi: 10.1016/0304-405X(86)90060-7.

Seyhun, H. N. (1988), The Information Content of Aggregate Insider Trading. *The Journal of Business*, *61*, 1–24. https://doi.org/10.1086/296417

Seyhun, H. N. (1990), Do Bidder Managers Knowingly Pay Too Much for Target Firms? *The Journal of Business*, *63*, 439–464. https://doi.org/10.1086/296516

Seyhun, H. N. (1992), Why Does Aggregate Insider Trading Predict Future Stock Returns?, *The Quarterly Journal of Economics*, 107(4), pp. 1303–1331. doi: 10.2307/2118390.

Shenoy, J. (2012), An Examination of the Efficiency, Foreclosure, and Collusion Rationales for Vertical Takeovers, *Management Science*, 58(8), pp. 1482–1501. doi: 10.1287/mnsc.1110.1498.

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

Skinner, D. J. (1994), Why Firms Voluntarily Disclose Bad News. *Journal of Accounting Research*,*32*, 38-60. https://doi.org/10.2307/2491386

Sloan, R. G. (1996), Do stock prices fully reflect information in accruals and cash flows about future earnings? *Accounting Review*, *71*, 289–315. https://doi.org/10.2469/dig.v27.n1.5

Slovic, P., and Lichtenstein, S. (1971), Comparison of Bayesian and regression approaches to the study of information processing in judgment. *Organizational Behavior and Human Performance*, *6*, 649–744. https://doi.org/10.1016/0030-5073(71)90033-X

Son, B. G., Chae, S. and Kocabasoglu-Hillmer, C. (2020), Catastrophic supply chain disruptions and supply network changes: a study of the 2011 Japanese earthquake, *International Journal of Operations and Production Management*, 41(6). doi: 10.1108/IJOPM-09-2020-0614.

Song, M. H. and Walkling, R. A. (2000), Abnormal returns to rivals of acquisition targets: A test of the "acquisition probability hypothesis", *Journal of Financial Economics*, 55(2). doi: 10.1016/S0304-405X(99)00048-3.

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

Stock, J. H. and Yogo, M. (2005), Testing for Weak Instruments in Linear IV Regression, in *Identification and Inference for Econometric Models*. Cambridge University Press, pp. 80–108. doi: 10.1017/CBO9780511614491.006.

Sturc, J.R., Sagayam, S., Barabas, J. and Tran E. (2012) 'Differences between US and UK market abuse regimes', Harvard Law School Forum on Corporate Governance. Available at https://corpgov.law.harvard.edu/2012/04/07/differences-between-us-and-uk-market-abuse-regimes/

Suk, I. and Wang, M. (2021), Does Target Firm Insider Trading Signal Synergies in Mergers and Acquisitions ?, *Journal of Financial Econometrics*, 142, 1115-1185. https://doi.org/10.1016/j.jfineco.2021.05.038

Titman, S., Wei, K. C. J., and Xie, F. (2004), Capital Investments and Stock Returns. *Journal of Financial and Quantitative Analysis*, *39*, 677–700. https://doi.org/10.1017/s0022109000003173

Tucker, J. W. and Zarowin, P. A. (2006), Does Income Smoothing Improve Earnings Informativeness?, *The Accounting Review*, 81(1), pp. 251–270. doi: 10.2308/accr.2006.81.1.251.

Tversky, A., and Kahneman, D. (1974), Judgment under uncertainty: Heuristics and biases. *Science*, *185*, 1124–1130. https://doi.org/10.1126/science.185.4157.1124

Walker, D. I. (2009), Evolving Executive Equity Compensation and the Limits of Optimal Contracting, *SSRN Electronic Journal*. doi: 10.2139/ssrn.1443170.

Wang, S. (2019), Informational environments and the relative information content of analyst recommendations and insider trades, *Accounting, Organizations and Society*, 72, pp. 61–73. doi: 10.1016/j.aos.2018.05.007.

Wolfgang, D., Emil, M., and Christian, W. (2020), Corporate insider trading and return skewness. *Journal of Corporate Finance*, *60*, 101485. https://doi.org/10.1016/j.jcorpfin.2019.07.008

Wu, W. (2019), Insider Purchases after Short Interest Spikes: A False Signaling Device?, *SSRN Electronic Journal*. doi: 10.2139/ssrn.2391333.

Yim, S. (2013), The acquisitiveness of youth: CEO age and acquisition behavior. Journal of Financial Economics, 108, 250–273. https://doi.org/10.1016/j.jfineco.2012.11.