Three Essays on Insider Trading

Jason F. Moschella
Desautels Faculty of Management
McGill University, Montreal, Quebec, Canada

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Table of Contents

Abstract

Insiders exercise their informational advantage for personal gain, and there is a rich body of literature that documents this. While researchers have done an excellent job cataloguing how insiders trade in relation to major corporate events, what remains less explored is how corporate insiders trade on information about their ability to compete. Moreover, researchers have only recently begun to scratch the surface on the individual personal characteristics that drive insider trading.

In my first study, I develop new measures of insider sentiment that capture the clustering of insider trades across peers in the same industry and across the broad market. These measures serve as indications of conviction among insiders within an industry and at an aggregate market level. I find that my measures of aggregate insider sentiment are positively related to firm-level insider trading activity, and that these relationships are economically meaningful. Results of cross-sectional tests reveal that the effects of industry-level insider sentiment are moderated by product market competition, intra-industry earnings co-movement, and firm-level information asymmetry. In addition, the effects of market-wide insider sentiment are moderated by economic policy uncertainty and firm-level information asymmetry. Finally, I find a strong association between aggregate insider sentiment and future abnormal stock returns, even though aggregate insider sentiment does not map well to firms' future earnings and cash flow processes. I also document a high degree of co-movement in insider sentiment across the Industrials, Consumer Discretionary, Health Care, and Technology sectors, and that the co-movement is somewhat persistent over a 1-quarter time horizon.

Cash is one resource that firms can deploy to gain a competitive advantage or use as a cushion against downside risk. In my second study, I explore the relationship between insider trading and firms' cash holdings. I find that various measures of cash and excess cash holdings are positively related to insider net selling activity and intensity, and that these relationships are economically meaningful and robust. Results of cross-sectional tests reveal that in certain situations, holding higher cash balances are perceived by insiders as having strategic value. Results of channel analyses suggest that when insiders are buying, high-cash firms will invest in research and development with greater intensity, which leads to lower operating cash flow margins. Finally, I find that levels of cash holdings amplify the relationships between abnormal stock returns and insider trading over 3-, 6-, 9-, and 12-month investment horizons.

Upper echelons theory posits that the decisions executives take are related to executives' values, experiences, and personalities. In my third study, I explore the relationship between Chief Executive Officers' (CEOs) personalities and their propensity to engage in insider trading. I use data on CEOs' Big 5 personality characteristics – openness, conscientiousness, extraversion, agreeableness, and neuroticism – that are machine-learned by the IBM Watson Personality Insights service based on CEOs' responses to analyst questions during quarterly company earnings conference calls. I find that more conscientious CEOs are more likely to be net buyers of their firms' shares and purchase shares with more intensity. These findings are robust to

different model specifications that attempt to correct for endogeneity and the fact that insider trading is autocorrelated and personality characteristics are time-invariant. I also find that risk tolerant CEOs are more likely to be net sellers of their firms' shares, and less likely to be net buyers of their firms' shares.

Résumé

Les initiés exercent leur avantage informationnel à des fins de gain personnel, ce que documente une abondante littérature. Si les chercheurs ont fait un excellent travail en cataloguant la façon dont les initiés effectuent des transactions en relation avec les événements majeurs de l'entreprise, ce qui reste moins exploré est la façon dont les initiés des entreprises effectuent des transactions sur la base d'informations concernant leur capacité à être compétitifs. De plus, les chercheurs n'ont que récemment commencé à effleurer les caractéristiques personnelles individuelles qui motivent les délits d'initiés.

Dans ma première étude, je développe des nouvelles mesures de sentiment des initiés qui captent le regroupement des transactions d'initiés parmi les pairs dans la même industrie et au niveau du marché global. Ces mesures servent d'indicateurs de la conviction des initiés au sein d'un secteur et au niveau du marché global. Mes mesures de sentiment sont positivement liées au délit d'initié au niveau de l'entreprise, et que ces relations sont économiquement significatives. Les résultats des tests transversaux révèlent que les effets du sentiment au niveau du secteur sont modérés par la concurrence dans le marché des produits, la co-mobilité des bénéfices au sein du secteur et l'asymétrie d'information au niveau de l'entreprise. En outre, les effets du à l'échelle du marché sont modérés par l'incertitude de la politique économique et l'asymétrie d'information au niveau de l'entreprise. Enfin, je trouve une forte association entre le sentiment global des initiés et les rendements anormaux futurs des actions, même si le sentiment global des initiés ne correspond pas bien aux processus de bénéfices et de flux de trésorerie futurs des entreprises. Je constate également un degré élevé de co-mouvement du sentiment des initiés dans les secteurs de l'industrie, de la consommation discrétionnaire, de la santé et de la technologie, et que ce co-mouvement est quelque peu persistant sur un horizon d'un trimestre.

La trésorerie est une ressource importante que les entreprises peuvent déployer dans le but d'obtenir un avantage concurrentiel ou d'avoir un coussin pour mitiger le risque de pertes. Dans ma deuxième étude, j'explore la relation entre les délits d'initiés et les liquidités des entreprises. Je constate que diverses mesures des liquidités et des excédents de liquidités sont positivement liées à l'activité et à l'intensité des ventes nettes des initiés, et que ces relations sont économiquement significatives et robustes. Les résultats des tests transversaux révèlent que dans certaines situations, les initiés perçoivent la détention de liquidités comme ayant une valeur stratégique. Les résultats des analyses de médiation suggèrent que lorsque les initiés achètent, les entreprises à forte trésorerie investissent plus intensément dans la recherche et le développement, ce qui entraîne des marges de flux de trésorerie plus faibles. Enfin, je constate que les niveaux de trésorerie amplifient les relations entre les rendements anormaux des actions et les opérations d'initiés sur des horizons d'investissement de 3, 6, 9 et 12 mois.

La théorie des échelons supérieurs postule que les décisions prises par les dirigeants sont liées à leurs valeurs, leurs expériences et leurs personnalités. Dans ma troisième étude, j'explore la relation entre la personnalité des présidents-directeurs généraux (PDG) et leur propension à commettre des délits d'initiés. J'utilise des données sur les caractéristiques de la personnalité des

PDG – ouverture, conscienciosité, extraversion, agréabilité et névrose – qui sont apprises automatiquement par le service IBM Watson Personality Insights sur la base des réponses des PDG aux questions des analystes lors des conférences téléphoniques trimestrielles sur les résultats des entreprises. Je constate que les PDG plus consciencieux sont plus susceptibles d'être des acheteurs nets d'actions de leur entreprise et d'acheter des actions avec plus d'intensité. Ces résultats sont robustes aux différentes spécifications du modèle qui tentent de corriger l'endogénéité et le fait que les délits d'initiés et les caractéristiques de la personnalité sont stables dans le temps. Je constate également que les PDG ayant une tolérance au risque plus forte sont plus susceptibles d'être des vendeurs nets d'actions de leur entreprise et moins susceptibles d'en être des acheteurs nets.

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I thank our Creator for allowing me to see this project to fruition and further my life's mission to help others learn and realize their potential and share my knowledge with others. I am blessed and grateful for (among other things) staying in good health, having the opportunity and resources I need to succeed, and for being surrounded by wonderful people in my life, whose love, support, and encouragement helped me make it over the finish line. May these trends continue, Amen.

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To my brother, Michael, and my sister, Cassandra, may you be blessed to share your gifts with the world.

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Any errors of analysis and interpretation are my own.

Table of Figures and Illustrations

EQUATIONS

FIGURES

TABLES – CHAPTER 1

TABLES – CHAPTER 2

TABLES – CHAPTER 3

Introduction

On 7 September 2017, Equifax, one of the three largest firms trusted with maintaining consumer credit and identity information in North America, announced that its data repository was hacked and that approximately 143 million people's personal information had been compromised (Equifax, 2017). Even more serious is the fact that the company claims to have had knowledge of the breach since March 2017 and did not appear to take any definitive action (Riley et al., 2017). Notably, three Equifax executives sold $1.8 million worth of stock at over $140 per share in August 2017 before the breach was publicly disclosed. Once the news was made public, Equifax's shares plummeted over 35% within a few days. The company's former chief information officer was subsequently charged with insider trading and was sentenced to four months in prison after pleading guilty[1].

More recently in September 2021, Eric Rosengren and Robert Kaplan, then the respective presidents of the Federal Reserve Banks of Boston and Dallas, resigned after being outed by government watchdogs for having traded and profited extensively during the COVID pandemic. This came at a time when the Federal Reserve was actively intervening in financial markets on an unprecedented scale, to which Rosengren and Kaplan had front-row seats[2]. Although these trades technically do not fall into the category of insider trading *per se*, and the trades were technically legal, the perception of a conflict of interest was enough for Rosengren and Kaplan to resign from their positions.

Situations like these bring the matter of insider trading to the forefront of the general public's attention. As Bainbridge (1995) notes, the public's anger "over insider trading […] has nothing to do with a loss of confidence in the integrity of the market, but instead arises principally from envy of the insider's greater access to information" (p. 1242). Academic debate surrounding insider trading tends to echo public sentiment, with most scholars arguing that insider trading is morally wrong (e.g. Green, 2006) and "just another form of cheating" (Klaw and Mayer, 2019)[3].

[1] https://www.justice.gov/usao-ndga/pr/former-equifax-employee-sentenced-insider-trading
[2] https://www.npr.org/2021/09/27/1041059924/2-top-federal-reserve-officials-retire-after-trading-disclosures
[3] Anderson (2018) and Bhattacharya (2014) provide excellent summaries of the ongoing debate in this sphere. Scholars advocating in favour of allowing insider trading (e.g. Fischer, 1992) build on Manne's (1966, 1967) work,

Indeed, because of the potential to extract gains from private information, regulators scrutinize insider trading activity. As an example, the United States Securities and Exchange Commission regularly initiates actions in alleged violation of insider trading laws as part of their mandate to "protect investors, maintain fair, orderly, and efficient markets, and facilitate capital formation"[4]. The U.S. Securities and Exchange Commission's (SEC's) recent enforcement actions in the areas of dark pool trading[5], cryptocurrency[6] and trading by members of government[7] support the view that they are executing their mandate with rigour.

Firms also take insider trading seriously, as most public companies have insider trading policies that place restrictions on insider trading activities, most commonly in the form of blackout periods (restricted trading windows), required pre-approval (for example by in-house legal counsel or compliance groups), and prohibiting short sales and derivative transactions (Bettis et al., 2000; Jagolinzer et al., 2011). These restrictions, however, are not one-size-fits-all and vary according to firm-level informational asymmetry, the strength of external monitoring, and executives' liquidity needs (Guay et al., 2022).

While prior research shows that insiders have private information about their firms and use it to trade profitably, little is known about if and how information beyond the firm factors into insiders' trading decisions. For instance, are corporate insiders attentive to trades made by other insiders who work at competing firms? Although scholars have investigated the issue of investor attention and gradual diffusion of information in multiple contexts in the past 20 years, research into these issues vis-à-vis insider trading remains largely uncharted. In my first study, I develop new measures of insider sentiment that capture the clustering of insider trades across peers in the same industry and across the broad market. These measures serve as indications of conviction among insiders within an industry and at an aggregate market level. Given the positive

wherein it is argued that insider trading should be legal because it enhances market efficiency and is a victimless crime (e.g. Engelen and Van Liederkerke, 2007; McGee, 2008).

[4] Source: https://www.sec.gov/about/whatwedo.shtml

[5] https://www.wilmerhale.com/en/insights/client-alerts/20211223-sec-insider-trading-enforcement-highlights-from-2021

[6] https://www.sec.gov/litigation/complaints/2022/comp-pr2022-127.pdf

[7] https://www.sec.gov/news/press-release/2022-129

correlation in firms' performance within an industry, following others' insider trades may inform executives' views on future industry conditions and help them glean insights into how their firms may be affected (and, accordingly, trade profitably).

Using a sample of 227,267 firm-quarters, which covers 8,000 firms from 1996 through 2021, I test whether insiders are more likely to trade when insiders at industry peer firms are trading and when insider trading activity outside of a firm's industry is higher. I find that my measures of aggregate insider sentiment are positively related to firm-level insider trading activity, and that these relationships are economically meaningful. Results of cross-sectional tests reveal that the effects of industry-level insider sentiment are moderated by product market competition, intra-industry earnings co-movement, and firm-level information asymmetry. In addition, the effects of market-wide insider sentiment are moderated by economic policy uncertainty and firm-level information asymmetry. Finally, I find a very strong association between aggregate insider sentiment and future abnormal stock returns, even though aggregate insider sentiment does not map well to firms' future earnings and cash flow processes. I also document a high degree of co-movement in insider sentiment across the Industrials, Consumer Discretionary, Health Care, and Technology sectors, and that this co-movement is somewhat persistent over a 1-quarter time horizon.

With this first study, I contribute to the literature in accounting and financial economics. First, I add to the insider trading literature. While prior research shows that insiders have private information about their firms and use it to trade profitably, little is known about if and how information beyond the firm factors into insiders' trading decisions. I find evidence of clustering of trading activity at the industry and market level, which builds on prior findings of trade clustering at the firm level (Alldredge and Blank, 2019; Moschella, 2019). Second, I contribute to the literature on information spillovers and the gradual diffusion of information by providing strong evidence that insiders are much more likely to trade when peers are trading.

I explore the relationship between insider trading and firms' cash holdings. That insiders exercise their informational advantage for personal gain is well documented (Ravina and Sapienza, 2010 and Cohen, Malloy, and Pomorski, 2012), especially in relation to major corporate events. What remains less explored, however, is how corporate insiders trade in relation to information about their firms' ability to engage in competitive efforts. While on the one hand, having a cash buffer affords firms additional means to capture upside and mitigate downside risk, holding more cash than necessary can increase agency problems because managers can invest these funds suboptimally (Jensen, 1986).

I find that cash and excess cash holdings are positively related to insider net selling activity and intensity, and that these relationships are economically meaningful and robust. Results of cross-sectional tests reveal that in certain situations, holding higher cash balances are perceived by insiders as having strategic value. Specifically, insiders at high-cash firms are more likely to buy, but only when industry competition and firm-level informational asymmetry are high, and insiders at high-cash firms are less likely to sell when economic policy uncertainty and firm-level informational asymmetry are high. Results of channel analyses suggest that when insiders are buying, high-cash firms will invest in research and development with greater intensity, which leads to lower operating cash flow margins. However, this does not translate into an economically meaningful impact on accrual-based profitability. Finally, I find that levels of cash holdings amplify the relationships between abnormal stock returns and insider trading over 3-, 6-, 9-, and 12-month investment horizons: Abnormal returns on insider purchases at high-cash firms are significantly higher than at their low cash counterparts, and abnormal returns on insider sales at high-cash firms are significantly negatively larger that at their low cash counterparts.

My second study makes two main contributions to the literature. First, I contribute to the body of work on insider trading. As of now, apart from innovation, research, and development (Aboody and Lev, 2000) and major customer relationships (Alldredge and Cicero, 2015), we do not know much about which competitive advantages insiders trade on, even though there is a multitude of ways for firms to build "organizational capital" (Lev, 2001) and extract economic rents in the short run. Although cash balances are publicly disclosed and are subject to very little (if any) estimation risk relative to other accounting line items, management's specific plans for cash remain mostly opaque and private.

Second, I contribute to the burgeoning literature on cash holdings. While researchers have done an excellent job assessing the value of companies' cash holdings under various circumstances, there is scant work on how managers profit from excess cash holdings. To my knowledge, I am the first to examine the relationship between cash holdings and insider trading behaviour.

My third study addresses two research questions. First, do insiders' personality characteristics impact their propensity to trade? Second, do insiders' personality characteristics impact their ability to trade profitability? Using a sample of 17,632 firm-years at 2,953 companies, I find that more conscientious Chief Executive Officers (CEOs) are more likely to be net buyers of their firms' shares and purchase shares with more intensity. These findings are robust to different model specifications that attempt to correct for endogeneity and the fact that insider trading is autocorrelated and personality characteristics are time-invariant. I also find that risk tolerant CEOs are more likely to be net sellers of their firms' shares, and less likely to be net buyers of same.

My third study contributes to the academic literature in at least two ways. First, I add to the literature on insider trading. Hillier et al. (2015) note that "we still know little about the extent to which insiders' personal characteristics affect returns following their trades" (p. 150) and, by extension, the personal characteristics that drive insiders to trade in the first place. They conclude that "Individual trading behaviors thus seem to be deeply rooted in personalities" (p. 151), and that "trading performance is closely aligned to the abilities and character of individual insiders" (ibid.). This claim is supported by recent work which demonstrates a relationship between insider trading and individual attitudes such as overconfidence (Malmiender and Tate, 2005), materialism (Bushman et al., 2018), recklessness and rebelliousness (Davidson et al., 2019). However, while studies correlating individual attitudes or behaviour to insider trading support the notion that executive heterogeneity matters, there remains a gap in terms of our understanding of the link between insider trading and the innate personality characteristics that drive behaviour. I fill this gap with my findings that conscientiousness is positively related to insider buying propensity and intensity.

Second, I answer Plöckinger et al.'s (2016) call for research that "more closely investigate[s] the magnitudes of managerial influence and more strongly utilize[s] interdisciplinary research approaches" (p. 56). In so doing, I also contribute to a growing body of literature in business studies that explores relationships between the Big 5 personality characteristics and corporate decision-making[8]. What distinguishes insider trading from corporate decisions, however, is that: 1) there is a difference in the access to information of insiders vs. outsiders (i.e. an informational edge exists); 2) there are incentives to exploit said private information by adding or reducing personal exposure to firms without doing anything to the firms themselves; and, 3) there are harsh penalties for doing so in a haughty and brazen manner (Bainbridge, 1995).

[8] For example, Colbert et al. (2014), Gow et al. (2016), Benische et al. (2019), Harrison et al. (2019, 2020), Hrazdil et al. (2020, 2021), and Mahmoudian et al. (2021).

Chapter 1: Do Insiders Follow their Competitors' Trades?

1.1 INTRODUCTION

Are corporate insiders attentive to trades made by other insiders who work at competing firms? Although scholars have investigated the issue of investor attention and gradual diffusion of information in multiple contexts in the past 20 years, research into these issues vis-à-vis insider trading remains largely uncharted. In this study, I develop new measures of insider sentiment that capture the clustering of insider trades across peers in the same industry and across the broad market. These measures serve as indications of conviction among insiders within an industry and at an aggregate market level. Given the positive correlation in firms' performance within an industry, following others' insider trades may inform executives' views on future industry conditions and help them glean insights into how their firms may be affected (and, accordingly, trade profitably).

Using a sample of 227,267 firm-quarters, which covers 8,000 firms from 1996 through 2021, I test whether insiders are more likely to trade when insiders at industry peer firms are trading and when insider trading activity outside of a firm's industry is higher. I find that my measures of aggregate insider sentiment are positively related to firm-level insider trading activity, and that these relationships are economically meaningful. Results of cross-sectional tests reveal that the effects of industry-level insider sentiment are moderated by product market competition, intra-industry earnings co-movement, and firm-level information asymmetry. In addition, the effects of market-wide insider sentiment are moderated by economic policy uncertainty and firm-level information asymmetry. Finally, I find a very strong association between aggregate insider sentiment and future abnormal stock returns, even though aggregate insider sentiment does not map well to firms' future earnings and cash flow processes. I also document a high degree of co-movement in insider sentiment across the Industrials, Consumer Discretionary, Health Care, and Technology sectors, and that this co-movement is somewhat persistent over a 1-quarter time horizon.

With this study, I contribute to the literature in accounting and financial economics. First, I add to the insider trading literature. While prior research shows that insiders have private information about their firms and use it to trade profitably, little is known about if and how information beyond the firm factors into insiders' trading decisions. I find evidence of clustering of trading activity at the industry and market level, which builds on prior findings of trade clustering at the firm level (Alldredge and Blank, 2019; Moschella, 2019). Second, I contribute to the literature on information spillovers and the gradual diffusion of information by providing strong evidence that insiders are much more likely to trade when peers are trading.

In Section 1.2, I present a review of the literature on insiders' information sets and the information they leverage to trade profitably, information spillovers and peer firms' reactions to competitors' actions, and insider trade herding. I follow this literature review by presenting my hypotheses. In Section 1.3, I outline my empirical approach for testing my hypotheses. In Section 1.4, I present the results of my empirical analysis. I provide a brief discussion and conclude in Section 1.5.

1.2 LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

1.2.1 Insiders' Information Set

What differentiates trading by insiders from trading activity by other market participants such as retail and institutional investors is that corporate insiders, by virtue of their positions, have access to valuable private information about the firms they work for. Researchers have extensively documented that insiders use this information for personal gain by opportunistically trading in their firms' stock in their personal portfolios (Ravina and Sapienza, 2010 and Cohen, Malloy, and Pomorski, 2012)[9] and spread their trades out if the information they have represents a long-lived advantage (Biggerstaff, Cicero, and Wintoki, 2020). On average, insiders have insight into and trade ahead of the release of material firm-level information such as future earnings (Ke,

[9] Foundational work in this sphere includes, but is not limited to, Lorie and Niederhoffer (1968), Jaffe (1974), Seyhun (1986, 1988), Rozeff and Zaman (1988), Lin and Howe (1990), Bettis, Vickery, and Vickery (1997), Lakonishok and Lee (2001), and Marin and Olivier (2008), among others, provide evidence in support of this claim. Seyhun (1998) packages earlier work in this area and presents several actionable strategies for investors to realize significant abnormal returns.

Huddart, and Petroni, 2003 and Piotroski and Roulstone, 2005), news (Fidrmuc, Goergen, and Renneboog, 2006), mergers and acquisitions (Keown and Pinkerton, 1981; Agrawal and Nasser, 2012), management forecast updates (Cheng and Lo, 2006), stock buybacks (Bonaimé and Ryngaert, 2013), restatements (Agrawal and Cooper, 2015), weak internal controls (Skaife, Veenman, and Wangerin, 2013), and defaults on debt obligations (Beneish, Press, and Vargus, 2012)[10]. Despite this massive suite of information, however, researchers remain puzzled with how little firm-level characteristics explain abnormal returns following insider trades. Hillier, Korczak, and Korczak (2015) posit that individual insider characteristics help explain a large portion of the variability in post-trade returns and justify their claim by showing that models using insider fixed effects have much more explanatory power than models with firm fixed effects. Still, they do not rule out the possibility that elements larger than individual firms or executives are driving abnormal returns.

1.2.2 Intra-Industry Information Transfers and Peer Reactions

Firms do not operate in a vacuum; on the contrary, they (and the people who work with them) are interconnected via complex economic and social networks. Firms within the same industry are related because they are often subject to the same supply and demand drivers, operating risk, and regulatory environment. In securities markets, given the similarity among industry peers, information released by one firm often influences investors to update their expectations about peer firms (Foster, 1981; Baginski, 1987; Kim, Lacina, and Park, 2008). Moreover, financial market participants and information intermediaries such as financial analysts tend to be specialized by industry (Hong, Torous, and Valkanov, 2007) and thus are limited in their ability to process more than a small fraction of new information that is released (Hong and Stein, 1999). The resultant information diffusion process, in which market prices do not absorb new information instantaneously, results in predictable returns across connected companies (Cohen and Frazzini, 2008; Menzly and Ozbas, 2010).

Executives pay attention to what their peers are doing, and act accordingly even though the signals they receive contain noise. For example, firms are more inclined to increase capital

[10] Additionally, Beneish and Vargus (2002) and Sawicki and Shrestha (2014) find evidence of insiders timing their trades ahead of reversals in managed earnings.

investments after peers do so (Bustamante and Frésard, 2020). Researchers also document evidence of peer pressure on capital structure choices such as leverage (Leary and Roberts, 2014) and dividend policy (Adhikari and Agrawal, 2018) Executives are also attentive to goings on in their supply chain. Alldredge and Cicero (2015) find evidence that insiders profitable dispose of stock in their firms based on contemporaneous information released by their firms' major customers. Still, the authors note that they "cannot be certain whether insiders are ever motivated solely by public information when they trade, or if their actions reflect consideration of a mosaic of public and private signals" (p. 86).

1.2.3 Insider herding and trade clustering

Because attention and time are scarce resources (Kahneman, 1973), investors may cast aside their own signals and impressions and follow their peers instead (Hirshleifer and Teoh, 2003), a phenomenon known as herding. Scholars have documented the strong presence of herding amongst various types of investors in retail and institutional settings and across various asset classes and investment vehicles[11]. There is, however, a paucity of evidence on whether corporate insiders, who are among the most sophisticated investors, behave similarly. Alldredge and Blank (2019) find evidence of clustered trading within firms and when multiple executives at a firm trade within a few days of one another, abnormal stock returns that follow are more pronounced than in periods during which only one executive trades. Ben-David, Birru, and Rossi (2019) find that insiders tend to prefer to trade in stocks in the same industry that they work in more frequently because of their intimate industry expertise – an advantage that they leverage profitably. What remains unknown, however, is whether insider trading is clustered across firms within the same industry, the presence of which could signal potential information cascades; and, whether insiders follow the trades of certain insiders at firms that they view as bellwethers and not those of others, which could be indicative of herding. By looking into insider trading patterns across firms within an industry, we can gain greater insight into the information set that insiders use when trading in their own firms' shares.

[11] Cui, Gebka, and Kallinterakis (2019) provide an excellent summary of the empirical literature on herding and find evidence of herding in closed-end funds.

Gilstrap, Petkevich, and Wang (2019) study insider trading aggregated at the industry level. They find that trends in insider trading are marginally informative in explaining future equity outperformance at an industry level. Their measure of insider sentiment is constructed by aggregating net buying activity at the industry level, and therefore ignores what individual insiders are doing. Moreover, because both the number and dollar value of insider sales dwarfs those of insider purchases, findings industries that have net insider buying is virtually impossible. My study differs from Gilstrap, Petkevich, and Wang (2019) because I focus on individual insiders' behaviour. Studying the relationship between aggregate insider trading activity and insider trading activity at an individual level helps to further our understanding of how information cascades and diffuses within industries and the market more broadly and provides insight into the information set that insiders rely on when consummating their trades.

1.2.4 Hypothesis Development

I ground my hypotheses on the presumption that corporate insiders are among the most attentive classes of equity investors. Executives and directors have a primary mandate to increase shareholder wealth and their wealth is heavily concentrated in the firms they work at. They tend to hold undiversified equity stakes and their compensation and future job prospects depend on how well their firms do. They therefore have large incentives to stay informed with regards to market and industry developments that affect the positioning of their firms within the competitive landscape.

Insider trades are a timely[12] signal of future firm performance. Because insider trades are filed with the Securities and Exchange Commission (SEC) and form part of the available suite of publicly available filings, executives at one firm can, with relative ease, incorporate trade activity at peer firms into their decision-making process by consulting Form 4 filings filed by peer-firm executives[13]. Given that firm performance within an industry is positively correlated, following others' insider trades may inform executives' views on future industry conditions and help them

[12] Since 2002, insider trades must be filed with the Securities and Exchange Commission on Form 4 within 48 hours of the time of trade.

[13] Several online subscription-based services that screen insider transactions such as openinsider.com, secform4.com, and finviz.com also exist. Users can search, screen, and visualize insider trades and incorporate them into their trading strategies.

glean insights into how their firms may be affected. Following this line of logic leads to an expectation of clustering in insider trading. In addition, even if insiders at competing firms do not pay attention to each other's trading behaviour, it is possible that insiders will synthesize industry information and trade on it at around the same time[14], albeit independently, leading to a cascade of trading.

However, it is plausible that while executives may be attentive to what competing firms are doing and investing in, they simply do not have time to pay close attention to how individual insiders at competing firms are managing their personal portfolios. For example, Chief Executive Officers (CEOs) are heavily time constrained and spend most of their working time in meetings related to handling organizational issues (Porter and Nohria, 2018). In addition, insider trading profits have a large firm-specific component and are positively correlated with idiosyncratic (i.e. firm-specific) information asymmetry (Gider and Westheide, 2016). Studying insider trades at peer firms may, therefore, be a poor investment of an extremely scare resource (time). At an extreme, mimicking insider trades at peer firms can, in fact, be a poor investment decision because executives at peer firms may be trading on a peer's future unrealized competitive advantage that will enhance the peer firm's position. In such situations, assuming peer insider trades are credible signals, it would be rational to sell shares when others are buying, and vice versa.

On balance, therefore, whether the clustering of insider trades across firms happens with regularity is an empirical question. Industry factors do explain a material portion of the cross-sectional variation in firm profitability (McGahan, 1999; Mauri and Michaels, 1998)[15], which implies that information arrives in a lumpy manner and diffuses over time within an industry. Moreover, firms' earnings exhibit co-movement with earnings of industry peers and firms in the overall market (Brown and Ball, 1967), and the degree of earnings co-movement impacts stock price spillovers from peer firms' earnings releases (Hameed et al., 2015) and the informativeness of peer firms' earnings releases (Jackson, Li, and Morris, 2020). As noted above, insiders have

[14] To expect trades to occur at exactly the same time would be unrealistic, given heterogeneity in executives' ability to process information, thresholds for acting on information, and their financial situations.
[15] These researchers estimate that industry factors explain between 6% and 30% of cross-sectional variation in firm profitability.

insight into and trade ahead of the release of material firm-level information such as future earnings (Ke, Huddart, and Petroni, 2003 and Piotroski and Roulstone, 2005); therefore, I do expect to find evidence of some baseline level of clustering of insider trading within an industry. This leads to the following hypothesis:

> *H1.1: Insiders are more likely to buy (sell) when insiders at industry peer firms are buying (selling) more actively.*

More broadly, because industries themselves are also interdependent and macroeconomic and geopolitical developments affect all industries (albeit to differing degrees), I also expect to find evidence of insider trade clustering at an aggregate market level. This leads to the following hypothesis:

> *H1.2: Insiders are more likely to buy (sell) when insiders at firms outside of a firm's industry are buying (selling) more actively.*

1.3 RESEARCH DESIGN AND SAMPLE CONSTRUCTION

1.3.1 Data

I source insider trade data from the Thomson Reuters insider filings database and collect firm fundamental data and stock prices from the matched CRSP/Compustat database. I restrict my insider trading sample to include only those line items that are cleansed by the data vendor[16] and classified as open-market purchases or sales[17] and then aggregate line items by firm[18], by insider, by day according to the dates that trades are filed with the SEC. For each filing, I identify the person making the trade and classify them based on their position at the company. I distinguish between CEOs and equivalents (*_CEO*), Chief Financial Officers (CFOs) and equivalents (*_CFO*), other company executives (*_EXEC*), and all other filers, which include independent

[16] Cleanse codes A or S.
[17] The trade codes that I classify as open-market purchases are P and L. The trade codes that I classify as open-market sales are F, I, and S.
[18] I differentiate firms by 6-digit CUSIP because it is possible for companies to issue several classes of tradable securities.

directors and large blockholders[19]. I compute the total net dollar value and number of shares involved in each case.

Next, I classify open-market insider purchases (*BUY*) and sales (*SALE*) as either routine (*ROUT*) or opportunistic (*OPP)* based on the methods used in Cohen et al. (2012). Open-market insider trades include activity that have net cash flow implications for an investor, such as purchasing shares with their own money or selling shares to generate liquidity but exclude derivative transactions and other actions that do not change an investor's exposure to a firm's shares. If an insider consummates trades of the same sign in the same month at least three years in a row, I classify the trade as routine (*ROUT*) starting in the third consecutive year. I classify trades that do not meet the criteria for routine trades as opportunistic (*OPP)*[20]. I then aggregate insider trading activity at a quarterly level to code my dependent variables, $NETB\_FIRM_{it}$ and $NETS\_FIRM_{it}$. Firms that have net opportunistic insider buying activity by executives (i.e. when the number of shares purchased opportunistically exceeds the number of shares sold opportunistically) are coded as $NETB\_FIRM_{it} = 1$ and firms that have net opportunistic insider selling activity by executives are coded as $NETS\_FIRM_{it} = 1$. Firms that have zero net opportunistic insider trading activity receive values of zero for $NETB\_FIRM_{it}$ and $NETS\_FIRM_{it}$.

Next, I group firms into industries according to Fama and French's (1997) 30-industry classification, which provides a level of granularity similar to using three-digit SIC codes. My first pair of variables of interest, $NETB\_IND\%_{ikt}$ and $NETS\_IND\%_{ikt}$, are calculated as the percentage of industry peers excluding firm *i* where there is net opportunistic insider buying (selling) during a quarter. My second pair of variables of interest, $NETB\_MKT\%_{kt}$ and $NETS\_MKT\%_{kt}$, are calculated as the percentage of firms outside of industry *k* where there is net opportunistic insider buying (selling) during a quarter. These metrics serve as measures of

[19] I classify insiders with a role code of "CEO" as CEO, those with a role code of "CFO" or "C" (controller) as CFO, and those with role codes of "O", "CI", "CO", "CT", "EVP", "OB", "OT", "P", "SVP", "GC", "C", "F", "M", and "OE" as other executives, with the proviso that the latter do not occupy a CEO, CFO, or controller role in the company.

[20] For example, if a CFO buys shares for the first time in November 2015, I code that trade as opportunistic. The insider buying by the CFO during a firm-quarter would be coded as $OPPBUY\_CFO = 1$. If the same CFO buys shares in the same firm in November 2016, that trade is also coded as opportunistic. If, in November 2017, the CFO purchases shares anew, that trade is coded as routine because the CFO bought shares in November of each of the two preceding years.

sentiment and consensus among groups of executives within and outside of an industry. I also compute alternative industry-level insider trading aggregates based on share and dollar volume that exclude trading activity at the firm but include trading activity at industry peer firms. In addition, I generate market-level insider trading aggregates based on share and dollar volume that exclude trading activity within a firm's industry. Additional details regarding these measures can be found in Panel A of Appendix 1.A.

1.3.2 Empirical Model

To test my hypotheses (H1.1 and H1.2), I run the following panel logit regression for insider purchases:

$$\begin{aligned} P(NETB\_FIRM_{it}) = \; & \alpha_0 + \alpha_1 * NETB\%\_IND_{ikt} + \alpha_2 * NETB\%\_MKT_{kt} \\ & + \alpha_3 * NETB\_FIRM_{t-1} + \Sigma(\beta_i * CONTROLS) + \\ & \Sigma(\gamma_k * \text{Industry-Year Indicator Variables})) + \varepsilon; \qquad (1) \end{aligned}$$

I include the lagged value of the dependent variable *(*$NETB\_FIRM_{it-1}$) because insider trading inside a firm is autocorrelated (Alldredge and Blank, 2019). I also run a similar panel logit regression for opportunistic selling activity (*NETS_FIRM*). I expect α_1 and α_2 to be positive for both purchases and sales. In addition, I consider alternate model specifications that have the natural logarithm of the net number of shares traded and their associated dollar values in constant 2020 dollars as the dependent variables. I present additional detailed explanations for these variables in Panel A of Appendix 1.A.

I control for factors that are known to influence insider trading activity including firm market capitalization in constant 2020 dollars (*MCAP*), the book-to-market ratio (*BOOKMKT*), raw stock returns over the preceding 12 months (*SRET*), leverage (*LEVERAGE*), research and development (R&D) intensity (*RDINT*), advertising intensity (*ADINT*), profitability (*RONA*), negative earnings (*LOSS*), probability of bankruptcy (*ALTMAN_Z*), the presence of a qualified audit opinion (*QUAL_OP*), periods that will later be restated (*RESTATE*), weak internal controls (*IC_WEAK*), and industry concentration (*IND_HHI*). I also include industry-year fixed effects to control for other factors that affect groups of firms during periods of time. I present detailed explanations for each control variable in Panel B of Appendix 1.A.

1.3.3 Sample Construction and Descriptive Statistics

In Table 1.1, I present details about my sample. I begin with 606,886 firm-quarter observations between 1996 and 2021 that have stock prices in CRSP and have associated CUSIP[21] numbers and matching GVKEYs in Compustat. I remove observations for firms domiciled outside of Canada and the United States and companies in the financial services sector (Fama-French industry code 28) because it includes entities such as hedge funds, closed-end funds, royalty flow-through companies, pensions, whose primary activity is to manage portfolios of investments in other firms. I then drop observations with stock prices below $2 as these are at risk of being delisted and observations for firms that have negative shareholders' equity. Finally, I drop observations with missing data from Compustat that prevent the calculation of one or more control variables. My final sample contains 227,267 firm-quarter observations from 8,007 unique firms.

I present a frequency table for net insider trading activity by calendar year and by industry in Table 1.2. Open-market insider purchases are relatively rare, with only 5.9% of firm-quarters net opportunistic insider buying activity. Open-market insider sales occur much more frequently compared to open-market purchases, especially in business cycles after the 2008 financial crisis, and make up approximately 83% of the firm-quarters for which there is some open-market insider trading activity. In terms of dollar volume, the amount of insider selling vastly exceeds that of insider buying ($291 billion of net insider sales versus $2 billion of net insider purchases since 1996). Insider trading activity is most concentrated in the Personal and Business Services, Business Equipment, and Healthcare, Medical Equipment, and Pharmaceutical Products industries.

[Insert Table 1.2 about here]

In Table 1.3, I present descriptive statistics. The average (median) net amount sold of $4.1 million ($772,000) for firm-quarters with net opportunistic sales by directors and officers is

[21] Committee on Uniform Securities Identification Procedures. See https://www.investor.gov/introduction-investing/investing-basics/glossary/cusip-number.

many times larger than as the average (median) firm-quarter with net purchase activity of \$152,000 (\$60,000). These data are consistent with previous studies. Close to 90% of net insider trading activity is relatively small relative to total firm value, and accounts for less than 0.25% of a firm's shares outstanding. Relative to net insider sales, net insider purchasing activity is more concentrated in firms that are smaller, have lower retained earnings (which cumulate over time), are less profitable, have lower book-to-market ratios, and have worse trailing 52-week returns. In untabulated results, I do not find any major differences in financial leverage, R&D intensity, and advertising intensity between firm-quarters that have net insider buying activity versus firm-quarters with net insider selling activity. I do, however, find a lower incidence of qualified audit opinions and future restatements, and a slightly higher incidence of internal control weaknesses for firm-quarters that have net insider buying activity.

[Insert Table 1.3 about here]

1.3.4 Insider Trading Co-movement across Industries

In panel C of Table 1.3, I show the correlations between firm-, industry-, and market-level measures of insider trading activity. Net insider buying activity at all levels is positively correlated across different levels and is negatively correlated with net insider selling activity. Net insider selling activity is positively correlated at all levels. Net insider buying (selling) activity at the industry level (*NET[B/S]_IND%*) is significantly correlated to net insider buying (selling) outside of the industry (*NET[B/S]_MKT%*), and very highly so (r = 0.668 for insider buying and 0.809 for insider selling). These findings suggest a high degree of co-movement of insider trading activity across industries, which I explore in greater detail below.

[Insert Table 1.4 about here]

For each GICS[22] sector-quarter, I generate time series of industry-aggregated net insider buying activity ($NETB\_IND\_\$_{st} = \Sigma_{ist} NETB\_FIRM\_\$$) and net insider selling activity ($NETS\_IND\_\$_{st} = \Sigma_{ist} NETS\_FIRM\_\$$). To capture industry-level insider sentiment, I compute the purchase-to-sale ratio ($NETBS\_IND_{st}$) by dividing $NETB\_IND\_\$_{st}$ by $NETS\_IND\_\$_{st}$. In Panel A of Table 1.4, I

[22] Global Industry Classification System. See https://www.msci.com/our-solutions/indexes/gics.

present results of analyses of the co-movement of net insider trading activity across the 11 GICS sectors. I find that contemporaneous correlations of $NETBS\_IND_{st}$ are most highly correlated across the Industrials, Consumer Discretionary, Health Care, and Technology sectors ($r > 0.60$), which suggests that the co-movement of insider trading sentiment is highest within this subset of sectors. Notably, there are marked spikes in $NETBS\_IND_{st}$ for these sectors in 2000, 2008, 2018, and 2020, all of which marked turning points in the economy and stock markets (see Figure 1.1).

[Insert Figure 1.1 about here]

Insider trading sentiment in the Utilities and Real Estate sectors co-moves with sentiment in other sectors less closely. Next, I examine whether there is evidence of leadership in insider trading by computing correlations of $NETBS\_IND_{st}$ with 1- and 4-quarter lagged values for each sector ($NETBS\_IND_{st-1}$ and $NETBS\_IND_{st-4}$, respectively). As shown in Panel B of Table 1.4, insider trading sentiment is somewhat persistent within industries (cells in bold), and across the Industrials, Consumer Discretionary, Health Care, and Technology sectors over a 1-quarter horizon. Relative to other sectors, I do not find that insider sentiment in the Real Estate, and Utilities sectors leads insider sentiment in other sectors. I do not find strong evidence of leadership in insider sentiment over a 4-quarter horizon (Panel C of Table 1.4; $r < 0.30$ for industry-pairs). In summary, I find a high degree of co-movement in insider sentiment across the Industrials, Consumer Discretionary, Health Care, and Technology sectors, and that this is somewhat persistent over a 1-quarter time horizon.

1.4. ANALYSIS AND RESULTS

1.4.1 Main Tests

Table 1.5 shows results of the main tests. Panel A contains the test results for the variables of interest related to insider buying, *NETB_IND%* (panel A, model 1, $\alpha_1 = 3.70$, $p < 0.01$) and *NETB_MKT%* (panel A, model 2, $\alpha_2 = 13.19$, $p < 0.01$). Both *NETB_IND%* and *NETB_MKT%* are positively related to *NETB_FIRM*. The effects are not subsumed by control variables (models 4 and 5); however, when including both *NETB_IND%* and *NETB_MKT%* in the same regression (model 3), the sign on *NETB_IND%* changes from positive to negative because of collinearity between *NETB_IND%* and *NETB_MKT%*. With respect to marginal effects, a one standard deviation increase in *NETB_IND%* from its mean results in an 18% higher predicted probability[23] for *NETB_FIRM* (see Figure 1.2). A one standard deviation increase in *NETB_MKT%* results in a 62% higher predicted probability[24] for *NETB_FIRM* (see Figure 1.3).

[Insert Figure 1.2 and Figure 1.3 about here]

Panel B of Table 1.5 contains the test results for the variables of interest related to insider selling, *NETS_IND%* (panel B, model 1, $\alpha_1 = 3.70$, $p < 0.01$) and *NETS_MKT%* (panel B, model 2, $\alpha_2 = 13.19$, $p < 0.01$). Both *NETS_IND%* and *NETS_MKT%* are positively related to *NETS_FIRM*. The effects are not subsumed by control variables (models 4 and 5); however, by including both *NETS_IND%* and *NETS_MKT%* in the same regression (model 3), the sign on *NETS_IND%* changes from positive to negative because of collinearity between *NETS_IND%* and *NETS_MKT%*. With respect to marginal effects, a one standard deviation increase in *NETS_IND%* from its mean results in a 12% higher predicted probability[25] for *NETS_FIRM* (see Figure 1.4). A one standard deviation increase in *NETS_MKT%* results in a 26% higher predicted probability[26] for *NETS_FIRM* (see Figure 1.5).

[Insert Table 1.5, Figure 1.4, and Figure 1.5 about here]

Panel A of Table 1.6 shows results of tests of the impact of *NETB_IND%* and *NETB_MKT%* on net insider buying intensity. Dependent variables are both the natural logarithm of one plus the net number of shares purchased by executives during a firm quarter (*NETB_FIRM_SH*; models 1 and 3), and the natural logarithm of one plus the net dollar value of executives' share purchases during a firm quarter (*NETB_FIRM_$*; models 2 and 4). Consistent with the main tests, results indicate that *NETB_IND%* and *NETB_MKT%* are positively related to both *NETB_FIRM_SH* and *NETB_FIRM_$*. When compared to the relatively small average size of net insider buys, the economic impacts of *NETB_IND%* and *NETB_MKT%* is meaningful. Specifically, a one

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[23] (0.070 – 0.059) / 0.059
[24] (0.096 – 0.059) / 0.059
[25] (0.327 – 0.292) / 0.292
[26] (0.368 – 0.451) / 0.292

standard deviation increase in *NETB_IND%* from its mean results in 41,800 more shares purchased (e^[27.94 * 4.60%] * 11,570), an increase of $753,000 (e^[34.77 * 4.60%] * $152,110). The impact of *NETB_MKT%* is even larger, as a one standard deviation increase in *NETB_IND%* from its mean results in 237,500 more shares purchased (e^[91.85 * 3.29%] * 11,570), or $7.1 million (e^[116.84 * 3.29%] * $152,110).

Next, Panel B of Table 1.6 presents results of tests of the impact of *NETS_IND%* and *NETS_MKT%* on net insider selling intensity. For the dependent variables, I use both the natural logarithm of one plus the net number of shares sold by executives during a firm quarter (*NETS_FIRM_SH*; models 1 and 3), and the natural logarithm of one plus the net dollar value of executives' share sales during a firm quarter (*NETS_FIRM_$*; models 2 and 4). Consistent with the main tests, *NETS_IND%* and *NETS_MKT%* are positively related to both *NETS_FIRM_SH* and *NETS_FIRM_$*. The economic impacts of *NETS_IND%* and *NETS_MKT%* are meaningful. Specifically, a one standard deviation increase in *NETS_IND%* from its mean results in 414,300 more shares sold (e^[16.82 * 12.78%] * 48,275), an increase of $80.1 million (e^[23.31 * 12.78%] * $4.1 million). The impact of *NETS_MKT%* is even larger, as a one standard deviation increase in *NETS_IND%* from its mean results in 1.1 million more shares sold (e^[29.16 * 10.61%] * 48,275), or $274.1 million (e^[39.63 * 10.61%] * $4.1 million).

[Insert Table 1.6 about here]

Table 1.7 shows the results of first-differenced (change) models. Consistent with evidence shown so far, there are significant relationships between net insider buying activity (*NETB_FIRM_SH* and *NETB_FIRM_$*) and *NETB_IND%* and *NETB_MKT%*. Similarly, there are significant relationships between *NETS_IND%* and *NETS_MKT%* and net insider selling activity (*NETB_FIRM_SH* and *NETB_FIRM_$*). While the effect sizes in the change models are slightly smaller than in the baseline regressions, they remain highly significant, which helps to alleviate concerns that my results are driven by autocorrelation.

[Insert Table 1.7 about here]

1.4.2 Cross-Sectional Tests

Firms operating in more competitive environments face higher information asymmetry and insiders in these firms trade more profitably (Rahman et al., 2021). It would therefore be plausible that product market competition amplifies the impact of industry-level insider trading activity on the firm-level opportunistic insider trading. To investigate this possibility, I partition my sample into quintiles based on industry-wide product market fluidity (*FLUIDITY*; Hoberg, Phillips, and Prabhala, 2014) and present results in Table 8. I find that as *FLUIDITY* increases, the impact of *NETB_IND%* on *NETB_FIRM* increases monotonically, and that the difference in coefficients between the highest and lowest quintiles of *FLUIDITY* is highly significant (χ^2 = 15.03, p = 0.0001). I also find that as *FLUIDITY* increases, the impact of *NETS_IND%* on *NETS_FIRM* increases, and that the difference in coefficients between the highest and lowest quintiles of *FLUIDITY* is highly significant (χ^2 = 14.93, p = 0.0001). Consistent with the notion that *FLUIDITY* measures intra-industry competition and is not a point-in-time estimate of global competition, I do not find that *FLUIDITY* moderates the effects of *NETB_MKT%* on *NETB_FIRM* or of *NETS_MKT%* on *NETS_FIRM* in a significant way.

[Insert Table 1.8 about here]

Information asymmetry can also manifest itself at a broad macroeconomic level. Uncertainty and risk "about *who* will make economic policy decisions, *what* economic policy actions will be undertaken and when, and the economic effects of policy actions (or inaction)" (Baker, Bloom, and Davis, 2016, p. 1598) is of concern to all individuals and businesses; therefore, it is plausible that economic policy uncertainty amplifies the impact of market-level insider trading activity on firm-level opportunistic insider trading. To investigate this possibility, I partition my sample into quintiles based on U.S. economic policy uncertainty (*EPU*; Baker, Bloom, and Davis, 2016) and present results in Table 1.9. I find that as *EPU* increases, the impact of *NETB_MKT%* on *NETB_FIRM* decreases, and that the difference in coefficients between the highest and lowest quintiles of *EPU* is close to a significance threshold (χ^2 = 2.56, p = 0.1094). I also find that as *EPU* increases, the impact of *NETS_MKT%* on *NETS_FIRM* increases, and that the difference in coefficients between the highest and lowest quintiles of *EPU* is highly significant (χ^2 = 8.48, p = 0.0036). Consistent with the notion that *EPU* is a market-level measure of uncertainty and risk that affects all industries (albeit to differing degrees), I do not find that *EPU* moderates the effects of *NETB_IND%* on *NETB_FIRM* or of *NETS_IND%* on *NETS_FIRM* in a significant way.

[Insert Table 1.9 about here]

Information asymmetry can also manifest itself at a local level (i.e. within a firm). Gider and Westheide (2016) find that insider trading profits have a large firm-specific component and are positively correlated with idiosyncratic (i.e. firm-specific) information asymmetry. Chung and Charoenwong (1998) find that insider trading activity is positively related to bid-ask spreads, which serve as a proxy for information asymmetry[27]. It is therefore plausible that as bid-ask spreads increase due to firm-specific information asymmetry/risk explaining a larger portion of equity returns, the effect of industry- and market-level insider trading activity on firm-level insider trading activity will be lower. To investigate this possibility, I partition my sample into quintiles based on firm bid-ask spreads (*BA_SPREAD*) relative to industry peers and present the results of these tests in Table 1.10. I find that as *BA_SPREAD* increases, the impacts of *NETB_IND%* and *NETB_MKT%* on *NETB_FIRM* decrease, and that the differences in coefficients between the highest and lowest quintiles of *BA_SPREAD* are significant (χ^2 = 3.27, p = 0.0708 for *NETB_IND%*; χ^2 = 4.07, p = 0.0436 for *NETB_MKT%*). I also find that as *BA_SPREAD* increases, the impacts of *NETS_IND%* and *NETS_MKT%* on *NETS_FIRM* decrease, and that the differences in coefficients between the highest and lowest quintiles of *BA_SPREAD* are highly significant (χ^2 = 3.27, p = 0.0708 for *NETB_IND%*; χ^2 = 4.07, p = 0.0436 for *NETB_MKT%*). In summary, higher firm-level information asymmetry appears to crowd out the effect of industry- and market-wide insider trading activity on firm-level insider trading activity.

[Insert Table 1.10 about here]

[27] As Coller and Yohn (1997) note, "Kim and Verrecchia (1994) explain that […] Because specialists sustain losses from trading with informed traders, an increase in information asymmetry causes the specialist to widen the bid-ask spread in order to recoup these losses" (p. 181).

Another question worthy of consideration is whether insiders trade on information that is firm-specific or pertinent industry-wide. At an intuitive level, the answer is most likely both. If this is, indeed, the case, it is plausible to expect that as performance is driven more by industry-wide factors as opposed to by idiosyncratic factors, the impact of industry-level opportunistic insider trading activity on the probability of firm-level opportunistic insider trading should increase. As noted above, firms' earnings exhibit co-movement with earnings of industry peers and firms in the overall market (Brown and Ball, 1967), and the degree of earnings co-movement impacts stock price spillovers from peer firms' earnings releases (Hameed et al., 2015) and the informativeness of peer firms' earnings releases (Jackson, Li, and Morris, 2020). To investigate whether earnings co-movement affects insider trading co-movement, I partition my sample into terciles based on intra-industry earnings co-movement (*ROA_CORR*) and present the results of these tests in Table 1.11. I also find that as *ROA_CORR* increases, the impacts of *NETS_IND%* and *NETS_MKT%* on *NETS_FIRM* decrease, and that the differences in coefficients between the highest and lowest terciles of *ROA_CORR* are significant (χ^2 = 5.59, p = 0.0180 for *NETS_IND%*; χ^2 = 4.48, p = 0.0342 for *NETS_MKT%*). I also find that as *ROA_CORR* increases, the impacts of *NETB_IND%* and *NETB_MKT%* on *NETB_FIRM* decrease; however, the differences in coefficients between the highest and lowest terciles of *ROA_CORR* are not significant (χ^2 = 0.93, p = 0.3359 for *NETB_IND%*; χ^2 = 0.12, p = 0.7431 for *NETB_MKT%*). In summary, higher earnings co-movement implies that firm-specific information is less relevant relative to industry- or market-wide information, which results in an amplification of the effect of industry- and market-wide insider trading activity on firm-level insider trading activity.

[Insert Table 1.11 about here]

The final set of cross-sectional tests investigates whether executives in different roles exhibit different insider trading patterns. In their development of upper echelons theory, Hambrick and Mason (1984) argue that researchers should incorporate executive heterogeneity into their empirical models because "executives' experiences, values, and personalities greatly influence their interpretations of the situations they face and, in turn, affect their choices" (Hambrick, 2007, p. 334). It is therefore possible that depending on their positions, there will be heterogeneity in how executives assimilate information and act on it. To investigate this possibility, I distinguish between insider trading activity by CEOs (*NET[B/S]_CEO*), CFOs (*NET[B/S]_CFO*), and other members of top management teams (*NET[B/S]_Exec*). I present the results of these tests in Table 1.12. The coefficients on *NET[B/S]_CEO_MKT%* are larger than *NET[B/S]_CFO_MKT%* and *NET[B/S]_Exec_MKT%* in 5 out of 6 models, which can be explained by the fact that CEOs engage in insider trading activity much more frequently than other executives (Moschella, 2019). I do not find any significant differences in the coefficients for my variables of interest within models or across models (*p*-values > 0.10). Results (untabulated) for the impact at the industry level (*NET[B/S]_CEO_IND%*, *NET[B/S]_CFO_IND%* and *NET[B/S]_Exec_IND%)* do not show a discernible pattern.

[Insert Table 1.12 about here]

1.4.3 Impact of Industry- and Market-Wide Insider Sentiment on Firm Outcomes

The focus in previous sections is on the determinants of firm-level insider trading activity, paying specific attention to how firm-level insider trading activity is associated with industry-level and market-wide insider trading activity. I now pivot my attention to analyzing the impact of industry- and market-wide insider sentiment on firm outcomes with the goal of better understanding the channels which mediate the relationships between firm-level insider trading activity and aggregate insider trading sentiment.

First, I test the relation between *NETB_MKT%* and *NETS_MKT%* and 1- and 4-quarter ahead profitability, measured by returns on assets (*ROA*), and operating cash flow margins (*CFM*). Because insider trading and firm-level earnings and operating cash flows exhibit autocorrelation, I run dynamic panel models estimated using the generalized method of moments methodology (Arellano and Bond, 1991). I present the results of these tests in Table 1.13. Both *NETB_MKT%* and *NETS_MKT%* are positively associated with 1- and 4-quarter ahead *ROA* and *CFM*; however, the economic impact of *NETB_MKT%* and *NETS_MKT%* is small (less than one percentage point of margin in all cases). Looking 4 quarters ahead, *NETB_MKT%* and *NETS_MKT%* are both positively associated with *CFM* and *ROA*. There is no discernible pattern in these results, and it is possible that one quarter's worth of insider trading does not map well to future earnings and cash flow processes.

[Insert Table 1.13 about here]

Next, I test the impact of *NETB_MKT%* and *NETS_MKT%* on future abnormal stock returns. I use the Event Study by WRDS module from Wharton Research Data Services[28] to generate 3-, 6-, 9-, and 12-month cumulative abnormal stock return estimations based on Fama and French's (1993) 3-factor model with a momentum factor (Carhart, 1997). I present the results of these tests in Table 1.14. Consistent with prior studies (e.g. Cohen et al., 2012), I find that net insider buying (selling) activity is highly significantly associated with positive (negative) future abnormal returns, to the tune of close to 1% per month for firms with net insider buying, and -0.25% per month for firms with net insider selling. I also find evidence that even among insiders, being a contrarian can be profitable. When *NETS_MKT%* is higher, meaning a higher proportion of firms have net insider selling, abnormal stock returns are positively impacted. Similarly, when more insiders globally are buying (*NETB_MKT%* is higher), abnormal stock returns are negatively impacted. Another way to interpret these findings is that insiders, even though they are among the most sophisticated investors, are fallible and can exhibit herding behaviour just like retail and institutional investors.

[Insert Table 1.14 about here]

In summary, I find that my measures of aggregate insider sentiment, *NET[B/S]_IND%* and *NET[B/S]_MKT%* are highly positively related to firm-level insider trading activity, and that these relationships are economically meaningful. Results of cross-sectional tests reveal that the effects of industry-level insider sentiment (*NET[B/S]_IND%*) are moderated by product market competition, intra-industry earnings co-movement, and firm-level information asymmetry. In addition, the effects of market-wide insider sentiment (*NET[B/S]_MKT%*) are moderated by economic policy uncertainty and firm-level information asymmetry. Finally, I find a very strong association between aggregate insider sentiment and future abnormal stock returns, even though aggregate insider sentiment does not map well to firms' future earnings and cash flow processes.

[28] https://wrds-www.wharton.upenn.edu/pages/get-data/event-study-wrds/us-daily-event-study-Upload-your-own-events/

1.5. DISCUSSION AND CONCLUSION

In this study, I develop new measures of insider sentiment that capture the clustering of insider trades across peers in the same industry and across the broad market. These measures serve as indications of conviction or consensus among insiders within an industry and at an aggregate market level. Given the positive correlation in firms' performance within an industry, following others' insider trades may inform executives' views on future industry conditions and help them glean insights into how their firms may be affected (and, accordingly, trade profitably).

Using a sample of 227,267 firm-quarters, which covers 8,000 firms from 1996 through 2021, I test whether insiders are more likely to trade when insiders at industry peer firms are trading and when insider trading activity outsider of a firm's industry is higher. I find that my measures of aggregate insider sentiment are highly positively related to firm-level insider trading activity, and that these relationships are economically meaningful.

In addition to the contributions I make to the academic literature, I offer insights relevant to practice. For analysts and portfolio managers, my findings suggest that practitioners should consider both firm-, industry-, and market-level insider trading metrics as part of their security screening and selection processes, as doing so could ultimately lead to a market-beating investment strategy. My findings are also relevant to regulators and standard setters in that I confirm the economic importance of insiders' trading signals both at the individual firm and aggregate levels.

APPENDIX 1: VARIABLE DEFINITIONS

Panel A: Main Variables

NET[B/S]_FIRM$_{it}$	Indicator variable that takes a value of 1 if during a firm-quarter, the net number of shares opportunistically traded (purchases minus sales) by executives at is [greater than/less than] zero. Source: Thomson Reuters
NET[B/S]_[SH/$]_FIRM$_{it}$	Net [number of shares/dollar value of shares] opportunistically traded (purchases minus sales) by all executives at firm *i* during quarter *t*. Source: Thomson Reuters
NET[B/S]_IND%$_{ikt}$	Percentage of peer firms in industry *k* (excluding firm i) that have net opportunistic insider [buying/selling] during quarter *t* Source: Thomson Reuters
NET[B/S]_MKT%$_{kt}$	Percentage of all firms outside of industry *k* that have net opportunistic insider [buying/selling] during quarter *t* Source: Thomson Reuters
NET[B/S]_[CEO/CFO/Exec]$_{it}$	Net [number of shares/dollar value of shares] opportunistically traded (purchases minus sales) by [the CEO/the CFO/executives other than the CEO and CFO] of firm *i* during quarter *t*. Source: Thomson Reuters
ROA	Return on assets; calculated as earnings before extraordinary items [IB] divided by total assets [AT] Source: Compustat
CFM	Operating cash flow margin; calculated as operating cash flow [OANCF] divided by sales [SALE] Source: Compustat
CAR	Cumulative abnormal stock returns; estimated using Fama and French's (1993) 3-factor model plus momentum (Carhart, 1997) Source: Wharton Research Data Services

APPENDIX 1, CONTINUED

Panel B: Control and Other Variables

CPI_Factor	US Consumer price index factor, chained and rebased to 2020 dollars Source: U.S. Bureau of Labor Statistics
PRC_adj	Adjusted stock price; calculated as (abs[PRC])/[CFACPR] Source: CRSP
SHR_adj	Adjusted number of shares outstanding; calculated as [SHROUT*CFACSHR] Source: CRSP
ICODE	Fama-French 30-industry classification (Fama and French, 1997) Source: Kenneth French Data Library at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
MCAP	Firm market capitalization; calculated as *PRC_adj*SHR_adj*, deflated by *CPI_Factor*, presented in millions of $US Source: CRSP
LN(MCAP)	Natural logarithm of *MCAP*
BOOKMKT	Ratio of book value of shareholders' equity [SEQ] to *MCAP* Sources: CRSP and Compustat
SRET	Raw trailing 12-month stock return; calculated as (PRC_adj_{it} – PRC_adj_{it-4}) divided by PRC_adj_{it-4} Source: CRSP
LEVERAGE	Ratio of long-term debt [DLTT] to total assets [AT] Source: Compustat
RDINT	R&D intensity; calculated as research and development expenses [XRD] divided by sales [SALE] Source: Compustat
RONA	Return on net operating assets; calculated income before interest and taxes [IBQ + (XINTQ*(100% – (TXTQ/PIQ)))] divided by net operating assets [CEQQ + DLCQ + DLTTQ + PSTKQ – CHEQ] Source: Compustat
LOSS	Indicator variable that takes a value of 1 if *RONA* is less than 0, and zero otherwise
ALTMAN_Z	Altman's (1968) Z-score for financial health; calculated as (1.2***A**) + (1.4***B**) + (3.3***C**) + (0.6***D**) + (1.0***E**), where: **A** = (current assets [ACT] less current liabilities [LCT]) divided by total assets [AT] **B** = retained earnings [RE] divided by total assets [AT] **C** = earnings before interest and taxes [SALE – COGS – XRD – XSGA – DP] divided by total assets [AT] **D** = *MCAP* divided by total liabilities [LT] **E** = sales [SALE] divided by total assets [AT] Source: Compustat
RESTATE	Indicator variable that takes a value of 1 if a firm's earnings for the period are subsequently restated, and zero otherwise Source: Audit Analytics

APPENDIX 1, CONTINUED

Panel B, Continued

QUAL_OP	Indicator variable that takes a value of 1 if the firm's auditor did not issue an unqualified opinion for the year [AUOP > 1], and zero otherwise Source: Compustat
IC_WEAK	Indicator variable that takes a value of 1 if a firm's auditor identified deficient internal controls for the year [AUOPIC > 1], and zero otherwise Source: Compustat
FLUIDITY	Industry-year average of a text-based measure of product market competition (Hoberg, Phillips, and Prabhala, 2014) Source: Hoberg and Phillips Data Library at http://hobergphillips.tuck.dartmouth.edu
EPU	Average monthly value of U.S. economic policy uncertainty during a firm-quarter (Baker, Bloom, and Davis, 2016) Source: https://www.policyuncertainty.com/all_country_data.html
BA_SPREAD	Time-weighted average of daily closing bid-ask spreads; calculated as ([ASK/HI] – [BID/LO])/abs[PRC] Source: CRSP
ROA_CORR	Intra-industry correlation between current-year *ROA* and 4-quarter lagged *ROA*

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FIGURE 1.1: INDUSTRY-WIDE INSIDER BUY-TO-SELL RATIO TIME SERIES

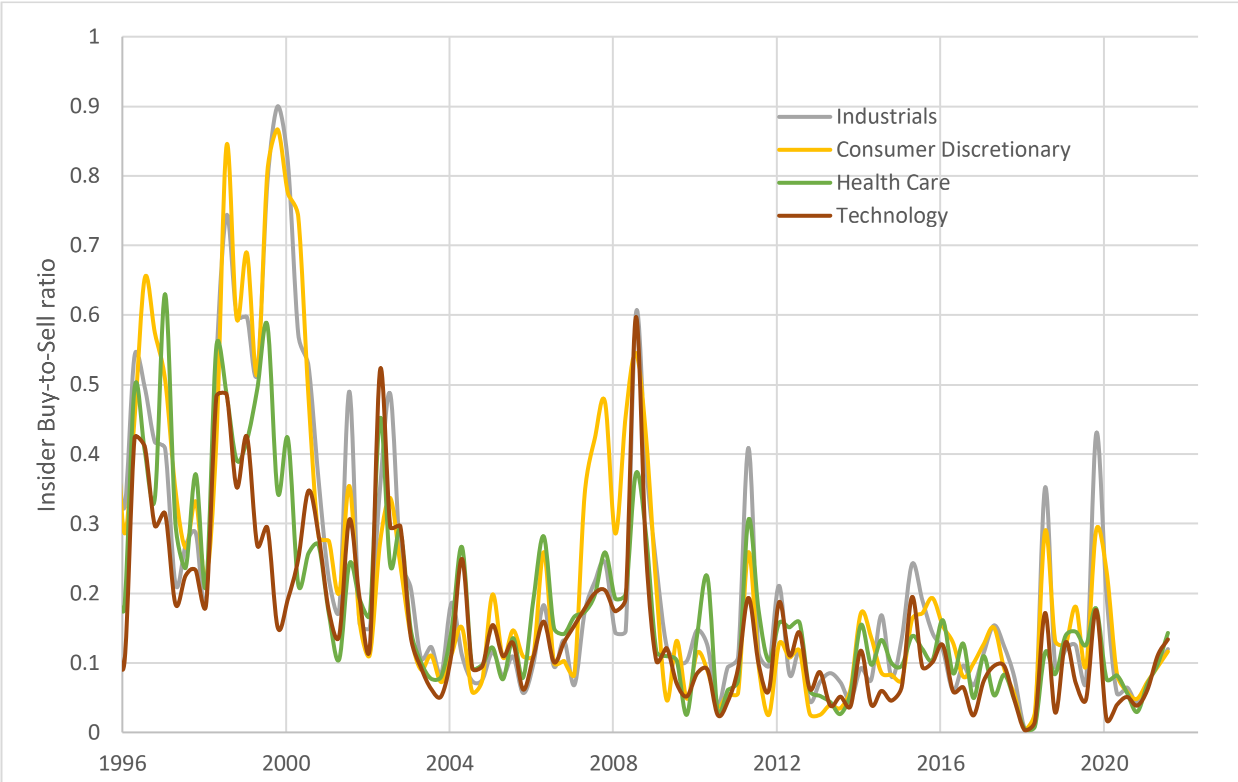
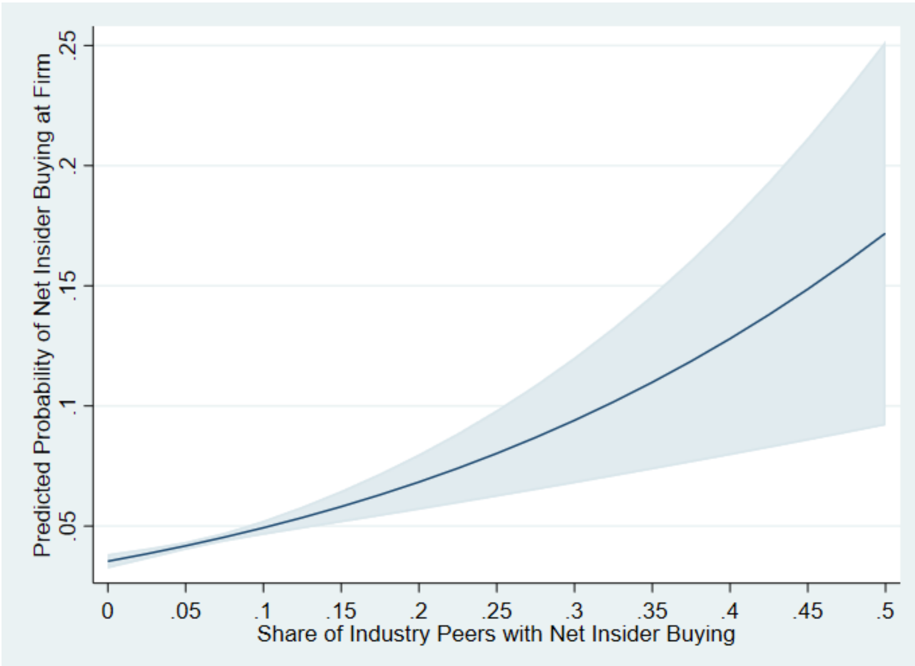
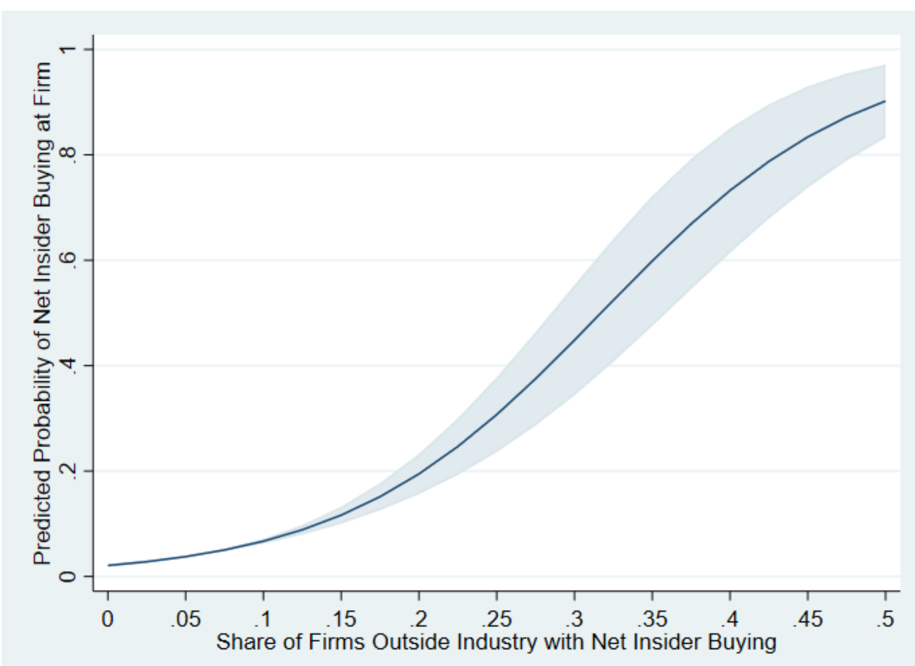


FIGURE 1.2: ADJUSTED PREDICTIONS FOR OPPORTUNISTIC INSIDER PURCHASES BASED ON INDUSTRY-PEER INSIDER BUYING



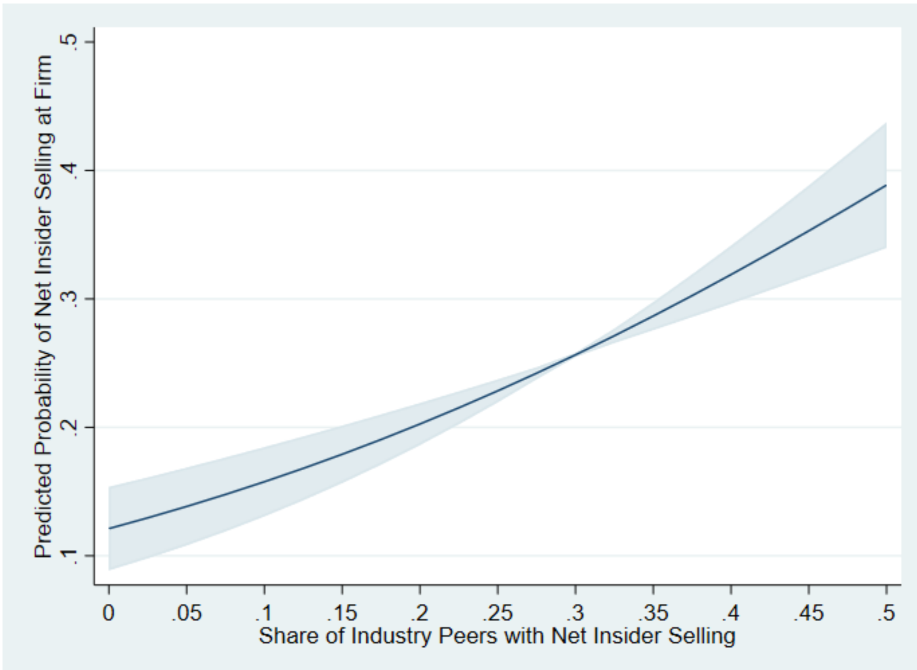
Note: Shaded areas represent 95% confidence intervals for predictions

FIGURE 1.3: ADJUSTED PREDICTIONS FOR OPPORTUNISTIC INSIDER PURCHASES BASED ON MARKET-WIDE INSIDER BUYING



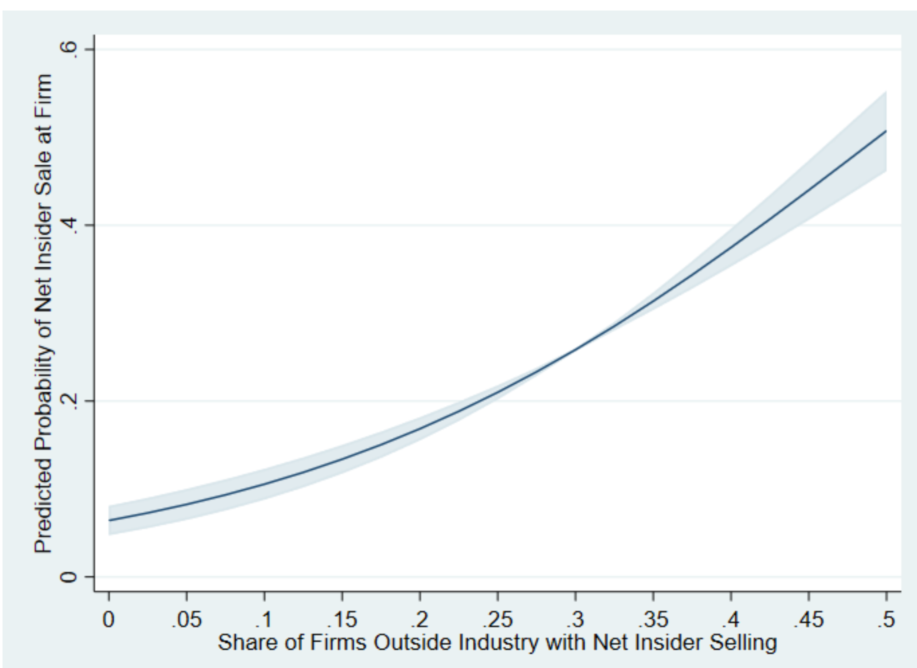
Note: Shaded areas represent 95% confidence intervals for predictions

FIGURE 1.4: ADJUSTED PREDICTIONS FOR OPPORTUNISTIC INSIDER SALES BASED ON INDUSTRY-PEER INSIDER SELLING



Note: Shaded areas represent 95% confidence intervals for predictions

FIGURE 1.5: ADJUSTED PREDICTIONS FOR OPPORTUNISTIC INSIDER SALES BASED ON MARKET-WIDE INSIDER SELLING



Note: Shaded areas represent 95% confidence intervals for predictions

TABLE 1.1: SAMPLE ATTRITION

Firm-quarters between January 1996 and December 2021 with CRSP stock prices, CUSIPs, and matching Compustat GVKEYs	606,886
Less: Firms domiciled outside of Canada or the United States	(81,872)
Less: Financial services firms (Fama-French Industry #29)	(116,067)
Less: Closing prices below $2	(60,010)
Less: Insolvent firms with negative shareholders' equity	(10,722)
Less: Firms with missing data in Compustat and/or CRSP	(52,871)
Less: Firms with missing prior-period (lagged) data	(58,077)
Final sample (firm-quarters)	**227,267**
Number of unique firms	**8,007**

TABLE 1.2: OPPORTUNISTIC INSIDER TRADING ACTIVITY BY EXECUTIVES AND OFFICERS

Panel A: Opportunistic Insider Trading Activity by Year

Year	Opportunistic Purchases (#)	Opportunistic Purchases ($)*	Opportunistic Sales (#)	Opportunistic Sales ($)*
1996	687	125.0	1,542	6,970.0
1997	703	91.7	1,981	11,100.0
1998	1,117	237.0	2,404	14,300.0
1999	1,188	232.0	2,045	14,800.0
2000	998	227.0	2,026	18,400.0
2001	627	76.5	2,120	10,600.0
2002	671	83.5	2,241	9,850.0
2003	429	24.2	2,703	14,300.0
2004	397	30.2	3,139	18,000.0
2005	385	22.8	3,035	16,000.0
2006	426	44.6	3,141	14,600.0
2007	551	80.5	3,026	13,600.0
2008	780	175.0	2,307	6,490.0
2009	431	39.7	2,424	5,380.0
2010	242	19.8	2,526	9,660.0
2011	419	56.6	2,767	8,860.0
2012	378	37.6	2,860	10,900.0
2013	206	10.5	3,263	13,100.0
2014	345	45.3	3,054	10,000.0
2015	448	69.4	2,689	7,330.0
2016	334	49.0	2,681	7,180.0
2017	356	57.7	2,860	8,350.0
2018	96	6.0	944	2,410.0
2019	433	68.5	2,950	10,700.0
2020	452	81.6	2,782	16,200.0
2021	296	46.4	2,808	12,000.0
Total	**13,395**	**2,040.0**	**66,318**	**291,000.0**

* In millions of dollars, chained and rebased to 2020 using U.S. consumer prices (CPI)

TABLE 1.2, CONTINUED

Panel B: Share of Net Opportunistic Insider Trading Activity by Industry

Industry	Net Opportunistic Purchases*	% of Total	Net Opportunistic Sales*	% of Total
Food Products	50.8	2.49%	6,880.0	2.36%
Beer and Liquor	4.2	0.21%	1,780.0	0.61%
Tobacco Products	0.7	0.03%	942.0	0.32%
Recreation	66.2	3.25%	6,850.0	2.35%
Printing and Publishing	29.6	1.45%	1,430.0	0.49%
Consumer Goods	37.8	1.85%	7,950.0	2.73%
Apparel	25.7	1.26%	7,760.0	2.67%
Healthcare, Medical Equipment, and Pharmaceutical Products	217.0	10.64%	40,200.0	13.81%
Chemicals	63.9	3.13%	5,980.0	2.05%
Textiles	21.0	1.03%	491.0	0.17%
Construction and Construction Materials	70.5	3.46%	9,200.0	3.16%
Steel and Metal Works	42.3	2.07%	2,270.0	0.78%
Fabricated Products and Machinery	88.9	4.36%	12,500.0	4.30%
Electrical Equipment	24.1	1.18%	2,390.0	0.82%
Automobiles and Trucks	38.9	1.91%	4,000.0	1.37%
Aircraft, Ships, and Railroad Equipment	31.7	1.55%	3,630.0	1.25%
Precious Metals, Non-Metallic, and Industrial Metal Mining	9.0	0.44%	805.0	0.28%
Coal	8.7	0.43%	128.0	0.04%
Petroleum and Natural Gas	102.0	5.00%	11,400.0	3.92%
Utilities	29.9	1.47%	5,970.0	2.05%
Communications	60.4	2.96%	6,430.0	2.21%
Personal and Business Services	274.0	13.43%	50,000.0	17.18%
Business Equipment	221.0	10.83%	47,600.0	16.36%
Business Supplies and Shipping Containers	37.2	1.82%	2,480.0	0.85%
Transportation	58.6	2.87%	8,170.0	2.81%
Wholesale	90.1	4.42%	9,840.0	3.38%
Retail	133.0	6.52%	22,600.0	7.77%
Restaurants, Hotels, and Motels	67.9	3.33%	6,150.0	2.11%
Other 1	21.6	1.06%	1,560.0	0.54%
Other 2	111.0	5.44%	3,820.0	1.31%
Total	**2,037.6**	**100%**	**291,206.0**	**100%**

* In millions of dollars, chained and rebased to 2020 using U.S. consumer prices (CPI). Totals may not be the same as in Panel A due to rounding.

TABLE 1.3: DESCRIPTIVE STATISTICS

Panel A: Opportunistic Insider Purchases (n = 13,395)

	Mean	St. dev.	5th pct	25th pct	Median	75th pct	95th pct
Shares purchased	11,570	18,235	142	1,500	5,000	13,500	45,100
$ value*	$152,110	$241,862	$498	$15,696	$59,940	$182,076	$616,090
% firm shares O/S	0.07%	0.23%	<0.01%	<0.01%	0.02%	0.06%	0.30%

Panel B: Opportunistic Insider Sales (n = 66,318)

	Mean	St. dev.	5th pct	25th pct	Median	75th pct	95th pct
Shares sold	48,275	86,397	374	3,959	15,000	50,000	220,110
$ value*	$4,144,594	$9,156,629	$15,695	$157,917	$772,377	$3,431,624	$21,200,000
% firm shares O/S	0.21%	0.92%	<0.01%	0.01%	0.04%	0.15%	0.84%

TABLE 1.3, CONTINUED

Panel C: Variables of Interest and Control Variables (All Firm Quarters, N = 227,267)

	Mean	St. dev.	5th pct	25th pct	Median	75th pct	95th pct
NETB_IND%	5.89%	4.60%	0.00%	2.94%	4.84%	7.85%	14.75%
NETB_MKT%	5.92%	3.29%	2.51%	3.67%	4.74%	7.55%	12.46%
NETS_IND%	29.18%	12.78%	8.57%	20.00%	28.74%	37.68%	50.00%
NETS_MKT%	29.06%	10.61%	11.44%	22.53%	29.53%	36.92%	44.71%
MCAP($mn*)	$6,422.1	$32,010.9	$40.9	$202.5	$742.4	$2,883.3	$24,282.6
LN(MCAP)	6.71	1.91	3.74	5.32	6.61	7.97	10.10
ASSETS($mn*)	$4,833.8	$13,666.3	$38.7	$199.8	$717.7	$2,859.7	$24,811.9
LN(ASSETS)	6.69	1.90	3.68	5.30	6.58	7.96	10.12
BOOK_MKT	0.62	0.54	0.10	0.28	0.48	0.78	1.62
52W_SRET	17.01%	74.58%	-55.21%	-19.27%	6.03%	35.45%	119.87%
LEVERAGE	18.35%	17.59%	0.00%	0.66%	15.23%	30.32%	51.99%
RDINT	8.72%	25.51%	0.00%	0.00%	0.89%	7.45%	19.72%
ROA	0.96%	25.20%	-20.58%	0.23%	2.14%	4.29%	15.42%
LOSS	23.20%	42.21%	0	0	0	0	1
ALTMAN_Z	3.51	6.57	-0.66	0.56	1.62	3.87	14.23
QUAL_OP	28.52%	45.15%	0	0	0	1	1
RESTATE	7.93%	27.02%	0	0	0	0	1
IC_WEAK	2.72%	16.28%	0	0	0	0	0
IND_HHI	8.71%	6.96%	3.29%	4.63%	6.89%	9.85%	22.30%

*Panel D: Spearman Correlations** for Insider Trading Measures (All Firm Quarters, N = 227,267)*

	(1)	(2)	(3)	(4)	(5)	(6)
NETB_FIRM (1)	1.000					
NETS_FIRM (2)	-0.161	1.000				
NETB_IND% (3)	0.109	-0.054	1.000			
NETS_IND% (4)	-0.044	0.230	-0.256	1.000		
NETB_MKT% (5)	0.120	-0.047	0.668	-0.213	1.000	
NETS_MKT% (6)	-0.038	0.224	-0.225	0.809	-0.303	1.000

* Chained and rebased to 2020 dollars using U.S. consumer prices (CPI)
** All correlations are significant at the 1% level

TABLE 1.4: INSIDER TRADING CO-MOVEMENT ACROSS INDUSTRIES

Panel A: Contemporaneous Correlations

	[1] t	[2] t	[3] t	[4] t	[5] t	[6] t	[7] t	[8] t	[9] t	[10] t
[1] Energy - time t	1.00									
[2] Materials	0.56	1.00								
[3] Industrials	0.65	0.82	1.00							
[4] Consumer Discretionary	0.65	0.74	0.89	1.00						
[5] Consumer Staples	0.41	0.69	0.64	0.64	1.00					
[6] Health Care	0.55	0.65	0.81	0.82	0.64	1.00				
[7] Technology	0.44	0.59	0.76	0.71	0.52	0.81	1.00			
[8] Communications	0.30	0.42	0.52	0.54	0.44	0.65	0.61	1.00		
[9] Utilities	0.40	0.31	0.43	0.40	0.35	0.44	0.49	0.35	1.00	
[10] Real Estate	0.48	0.38	0.36	0.37	0.27	0.34	0.17	0.03	0.17	1.00

Panel B: 3-month Lagged Correlations (current buy/sell ratio on vertical axis and 3-month lagged buy/sell ratio on horizontal axis)

	[1] t-1	[2] t-1	[3] t-1	[4] t-1	[5] t-1	[6] t-1	[7] t-1	[8] t-1	[9] t-1	[10] t-1
[1] Energy - time t	0.36	0.35	0.33	0.36	0.26	0.24	0.08	0.09	0.15	0.35
[2] Materials	0.23	0.47	0.47	0.47	0.28	0.33	0.25	0.19	0.23	0.19
[3] Industrials	0.34	0.58	0.60	0.59	0.46	0.50	0.41	0.36	0.24	0.22
[4] Consumer Discretionary	0.32	0.61	0.57	0.62	0.49	0.52	0.42	0.38	0.25	0.27
[5] Consumer Staples	0.19	0.31	0.36	0.42	0.29	0.29	0.21	0.28	0.16	0.16
[6] Health Care	0.27	0.48	0.51	0.52	0.33	0.49	0.45	0.40	0.28	0.12
[7] Technology	0.09	0.38	0.39	0.35	0.23	0.34	0.43	0.34	0.24	-0.02
[8] Communications	0.11	0.29	0.27	0.35	0.28	0.26	0.32	0.26	0.20	0.02
[9] Utilities	0.10	0.09	0.15	0.13	0.01	0.11	0.11	0.09	0.02	-0.04
[10] Real Estate	0.34	0.25	0.21	0.18	0.12	0.13	0.02	0.10	0.16	0.35

TABLE 1.4, CONTINUED

Panel C: 12-month Lagged Correlations (current buy/sell ratio on vertical axis and 12-month lagged buy/sell ratio on horizontal axis)

	[1] t-4	[2] t-4	[3] t-4	[4] t-4	[5] t-4	[6] t-4	[7] t-4	[8] t-4	[9] t-4	[10] t-4
[1] Energy - time t	0.10	0.11	0.06	0.09	0.03	-0.04	-0.10	-0.10	-0.05	0.16
[2] Materials	0.16	0.31	0.27	0.25	0.15	0.17	0.12	0.16	0.00	0.10
[3] Industrials	0.18	0.30	0.27	0.29	0.19	0.22	0.21	0.20	0.06	0.05
[4] Consumer Discretionary	0.15	0.28	0.29	0.31	0.20	0.24	0.23	0.18	0.08	0.10
[5] Consumer Staples	0.06	0.17	0.19	0.23	0.14	0.13	0.10	0.20	0.05	0.01
[6] Health Care	0.02	0.16	0.15	0.18	0.10	0.13	0.18	0.14	0.11	0.05
[7] Technology	-0.08	0.12	0.12	0.12	0.12	0.15	0.19	0.12	0.05	-0.12
[8] Communications	-0.03	0.13	0.13	0.19	0.16	0.18	0.20	0.18	0.06	-0.02
[9] Utilities	0.16	0.19	0.22	0.22	0.18	0.21	0.18	0.12	0.08	-0.03
[10] Real Estate	0.13	0.02	0.02	0.05	-0.04	-0.01	-0.13	-0.09	-0.08	0.28

Note: For all panels, results presented are Spearman rank correlations of insider trading buy-to-sell ratios between industry pairs. Correlations with absolute values greater than 0.25 are significant at the 1% level. N = 104 quarters for each sector.

TABLE 1.5: MAIN TESTS OF THE IMPACT OF INDUSTRY-PEER AND MARKET-WIDE INSIDER TRADING ACTIVITY ON FIRM-LEVEL INSIDER TRADING

Panel A: Opportunistic Insider Purchases; Logit Models, DV=NETB_FIRM$_{it}$

Model	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
***NETB_IND%$_t$* (H1.1 +)**	**3.7025***** **(0.7222)**		**-3.5896***** **(0.6582)**	**3.5029***** **(0.6467)**	
***NETB_MKT%$_t$* (H1.2 +)**		**13.1890***** **(0.8958)**	**16.9395***** **(1.2358)**		**12.1545***** **(0.9173)**
NETB_FIRM$_{t-1}$				1.4153*** (0.0449)	1.4057*** (0.0460)
LN(MCAP)				-0.1918*** (0.0158)	-0.1956*** (0.0159)
BOOKMKT				0.0846*** (0.0210)	0.0600*** (0.0187)
52W_SRET				-0.3806*** (0.0625)	-0.3421*** (0.0516)
LEVERAGE				0.6569*** (0.0688)	0.6615*** (0.0692)
RDINT				0.0001 (0.0001)	0.0001 (0.0001)
RONA				0.1203** (0.0609)	0.1081* (0.0652)
LOSS				0.1566*** (0.0271)	0.1525*** (0.0286)
ALTMAN_Z				-0.0238*** (0.0031)	-0.0239*** (0.0031)
QUAL_OP				0.0519 (0.0377)	0.0524 (0.0363)
RESTATE				0.0341 (0.0335)	0.0392 (0.0344)
IC_WEAK				-0.0142 (0.0717)	-0.0112 (0.0724)
IND_HHI				-0.5213 (0.8256)	-1.4134* (0.8156)
Constant	-2.5657*** (0.0739)	-3.0660*** (0.0617)	-2.9576*** (0.0656)	-1.7901*** (0.1138)	-2.1502*** (0.1281)
Fixed effects	Industry X Calendar Year	Industry X Calendar Year	Industry X Calendar Year	Industry X Calendar Year	Industry X Calendar Year
Observations	225,889	225,889	225,889	225,889	225,889
Pseudo R^2	0.0388	0.0511	0.0525	0.1012	0.1108
Correctly classified	94.07%	94.07%	94.07%	94.06%	94.08%
Naïve random classification	88.84%	88.84%	88.84%	88.84%	88.84%

TABLE 1.5, CONTINUED

Panel B: Opportunistic Insider Sales; Logit Models, DV=NETS_FIRM$_{it}$

Model	(1)	(2)	(3)	(4)	(5)
***NETS_IND%$_t$* (H1.1 +)**	**2.8158*****		**-1.3957*****	**3.0868*****	
	(0.5331)		**(0.2363)**	**(0.5176)**	
***NETS_MKT%$_t$* (H1.2 +)**		**5.3146*****	**6.7157*****		**5.4566*****
		(0.4374)	**(0.5375)**		**(0.4640)**
NETS_FIRM$_{t-1}$				1.1301***	1.1187***
				(0.0347)	(0.0343)
LN(MCAP)				0.2629***	0.2640***
				(0.0067)	(0.0067)
BOOKMKT				-0.3301***	-0.3279***
				(0.0237)	(0.0237)
52W_SRET				0.2054***	0.1926***
				(0.0365)	(0.0325)
LEVERAGE				-0.1947***	-0.1891***
				(0.0656)	(0.0660)
RDINT				-0.0003***	-0.0003***
				(0.0001)	(0.0001)
RONA				-0.0449	-0.0486
				(0.0342)	(0.0328)
LOSS				-0.1810***	-0.1929***
				(0.0311)	(0.0318)
ALTMAN_Z				0.0018	0.0025
				(0.0020)	(0.0020)
QUAL_OP				0.0488*	0.0543**
				(0.0275)	(0.0275)
RESTATE				0.0951***	0.0992***
				(0.0199)	(0.0191)
IC_WEAK				-0.1596***	-0.1602***
				(0.0318)	(0.0326)
IND_HHI				0.5185	-0.2751
				(0.6408)	(0.7172)
Constant	-2.4266***	-2.9123***	-2.9706***	-4.1579***	-4.5933***
	(0.0589)	(0.0658)	(0.0697)	(0.0727)	(0.0915)
Fixed effects	Industry X Calendar Year	Industry X Calendar Year	Industry X Calendar Year	Industry X Calendar Year	Industry X Calendar Year
Observations	227,240	227,240	227,240	227,240	227,240
Pseudo R^2	0.0497	0.0595	0.0602	0.1653	0.1731
Correctly Classified	71.08%	71.24%	71.17%	75.47%	75.75%
Naïve Random Classification	58.67%	58.67%	58.67%	58.67%	58.67%

Notes: Standard errors are clustered at the calendar-year level and shown in parentheses. The number of observations for each model may be less than the full sample size because insider trading in some industry-years can be predicted perfectly. Continuous variables are winsorized at the 1% and 99% levels for each quarter. * $p < .10$, ** $p < .05$, *** $p < .01$

TABLE 1.6: IMPACT OF INDUSTRY-PEER AND MARKET-WIDE INSIDER TRADING ACTIVITY ON FIRM-LEVEL INSIDER TRADING INTENSITY

Panel A: Opportunistic Insider Purchases; Tobit Models

Model	**(1)** **DV = *LN*** **(*NETB_FIRM_SH)***	**(2)** **DV = *LN*** **(*NETB_FIRM_$)***	**(3)** **DV = *LN*** **(*NETB_FIRM_SH)***	**(4)** **DV = *LN*** **(*NETB_FIRM_$)***
NETB_IND%$_t$ **(H1.1 +)**	**27.9438*****	**34.7700*****		
	(5.0288)	**(6.4762)**		
NETB_MKT%$_t$ **(H1.2 +)**			**91.8546*****	**116.8440*****
			(6.6932)	**(8.4926)**
NETB_FIRM_[SH/$]$_{t-1}$	1.2519***	1.2992***	1.2234***	1.2705***
	(0.0499)	(0.0518)	(0.0509)	(0.0528)
Constant	-16.9047***	-22.3084***	-19.2138***	-25.3238***
	(0.6621)	(0.9113)	(0.9436)	(1.2881)
Controls	YES	YES	YES	YES
Fixed effects	Industry X Calendar Year	Industry X Calendar Year	Industry X Calendar Year	Industry X Calendar Year
Observations	227,267	227,267	227,267	227,267
Pseudo R^2	0.0570	0.0550	0.0624	0.0599

Panel B: Opportunistic Insider Sales; Tobit Models

Model	**(1)** **DV = *LN*** **(*NETS_FIRM_SH)***	**(2)** **DV = *LN*** **(*NETS_FIRM_$)***	**(3)** **DV = *LN*** **(*NETS_FIRM_SH)***	**(4)** **DV = *LN*** **(*NETS_FIRM_$)***
NETB_IND%$_t$ **(H1.1 +)**	**16.8215*****	**23.3097*****		
	(3.0449)	**(4.1741)**		
NETB_MKT%$_t$ **(H1.2 +)**			**29.1640*****	**39.6336*****
			(2.9484)	**(4.0421)**
NETS_FIRM$_{t-1}$	0.6302***	0.6415***	0.6142***	0.6260***
	(0.0232)	(0.0258)	(0.0227)	(0.0252)
Constant	-22.7390***	-29.3223***	-24.8257***	-32.1146***
	(0.8576)	(1.2923)	(1.0077)	(1.4977)
Controls	YES	YES	YES	YES
Fixed effects	Industry X Calendar Year	Industry X Calendar Year	Industry X Calendar Year	Industry X Calendar Year
Observations	227,267	227,267	227,267	227,267
Pseudo R^2	0.0707	0.0695	0.0739	0.0725

Notes: Standard errors are clustered at the calendar-year level and shown in parentheses. Continuous variables are winsorized at the 1% and 99% levels for each quarter. * $p < .10$, ** $p < .05$, *** $p < .01$

TABLE 1.7: CHANGE MODELS

Panel A: Opportunistic Insider Purchases; OLS Models

Model	**(1)** **DV = *ΔLN*** ***(NETB_FIRM_SH)***	**(2)** **DV = *ΔLN*** ***(NETB_FIRM_$)***	**(3)** **DV = *ΔLN*** ***(NETS_FIRM_SH)***	**(4)** **DV = *ΔLN*** ***(NETS_FIRM_$)***
NETB_IND%$_t$ **(H1.1 +)**	**4.0901*****	**4.8958*****		
	(0.5086)	**(0.5602)**		
NETB_MKT%$_t$ **(H1.2 +)**			**8.5448*****	**10.3556*****
			(0.2404)	**(0.3415)**
Constant	-0.0285***	-0.0071	-0.0642***	-0.0505***
	(0.0072)	(0.0081)	(0.0061)	(0.0066)
Controls	YES	YES	YES	YES
Fixed effects	Industry X Calendar Year	Industry X Calendar Year	Industry X Calendar Year	Industry X Calendar Year
Observations	222,452	222,452	222,452	222,452
R^2	0.0124	0.0110	0.0163	0.0145
Adjusted R^2	0.0089	0.0075	0.0128	0.0110

Panel B: Opportunistic Insider Sales; OLS Models

Model	**(1)** **DV = *ΔLN*** ***(NETB_FIRM_SH)***	**(2)** **DV = *ΔLN*** ***(NETB_FIRM_$)***	**(3)** **DV = *ΔLN*** ***(NETS_FIRM_SH)***	**(4)** **DV = *ΔLN*** ***(NETS_FIRM_$)***
NETB_IND%$_t$ **(H1.1 +)**	**8.4381*****	**12.6954*****		
	(0.4228)	**(0.7240)**		
NETB_MKT%$_t$ **(H1.2 +)**			**12.4718*****	**18.8253*****
			(0.2751)	**(0.3222)**
Constant	0.0082	0.1120***	0.0783***	0.2175***
	(0.0102)	(0.0153)	(0.0106)	(0.0151)
Controls	YES	YES	YES	YES
Fixed effects	Industry X Calendar Year	Industry X Calendar Year	Industry X Calendar Year	Industry X Calendar Year
Observations	222,452	222,452	222,452	222,452
R^2	0.0298	0.0332	0.0365	0.0411
Adjusted R^2	0.0263	0.0297	0.0331	0.0377

Notes: Standard errors are clustered at the calendar-year level and shown in parentheses. The number of observations for each model may be less than the full sample size because insider trading in some industry-years can be predicted perfectly. Continuous variables are winsorized at the 1% and 99% levels for each quarter. * p < .10, ** p < .05, *** p < .01

TABLE 1.8: CROSS-SECTIONAL TESTS FOR IMPACT OF INDUSTRY COMPETITION

Model	**(1) DV = *NETB_FIRM***	**(2) DV = *NETS_FIRM***	**(3) DV = *NETB_FIRM***	**(4) DV = *NETS_FIRM***
NET[B/S]IND%$_t$ (Q1)	**1.2455 (1.1416)**	**2.5516*** (0.7781)**		
NET[B/S]IND%$_t$ (Q2)	**2.2694** (1.0455)**	**2.3435*** (0.6945)**		
NET[B/S]IND%$_t$ (Q3)	**3.5168*** (0.9078)**	**3.2726*** (1.0143)**		
NET[B/S]IND%$_t$ (Q4)	**4.5765*** (1.0708)**	**3.6231*** (0.4843)**		
NET[B/S]IND%$_t$ (Q5)	**6.4860*** (0.9521)**	**4.3868*** (0.4449)**		
NET[B/S]MKT%$_t$ (Q1)			**12.6234*** (1.3726)**	**6.0965*** (0.6502)**
NET[B/S]MKT%$_t$ (Q2)			**12.4164*** (1.5019)**	**4.8607*** (0.6090)**
NET[B/S]MKT%$_t$ (Q3)			**12.0478*** (1.2648)**	**5.8495*** (0.7542)**
NET[B/S]MKT%$_t$ (Q4)			**11.6225*** (0.9465)**	**5.3574*** (0.5804)**
NET[B/S]MKT%$_t$ (Q5)			**11.6360*** (1.3401)**	**6.0003*** (0.5464)**
Constants for each group	YES	YES	YES	YES
Controls	YES	YES	YES	YES
Fixed effects	Industry X Calendar Year	Industry X Calendar Year	Industry X Calendar Year	Industry X Calendar Year
Chi-square test for differences in coefficients (*Q5 – Q1*)	**15.03*** p = 0.0001**	**14.93*** p = 0.0001**	**0.57 p = 0.4496**	**0.04 p = 0.8870**
Observations	222,452	222,452	222,452	222,452

Notes: All models are nested logit models. Observations are sorted into quintiles based on industry competition, measured by product market fluidity (Hoberg and Phillips, 2014). Product market fluidity data are only available through 2019. Standard errors are clustered at the calendar-year level and shown in parentheses. The number of observations for each model may be less than the full sample size because insider trading in some industry-years can be predicted perfectly. Continuous variables are winsorized at the 1% and 99% levels for each quarter. * $p < .10$, ** $p < .05$, *** $p < .01$

TABLE 1.9: CROSS-SECTIONAL TESTS FOR IMPACT OF ECONOMIC POLICY UNCERTAINTY

Model	**(1)** **DV =** ***NETB_FIRM***	**(2)** **DV =** ***NETS_FIRM***	**(3)** **DV =** ***NETB_FIRM***	**(4)** **DV =** ***NETS_FIRM***
NET[B/S]IND%$_t$ (Q1)	**3.2929***** **(0.8191)**	**3.2930***** **(0.7685)**		
NET[B/S]IND%$_t$ (Q2)	**0.7217** **(1.0651)**	**2.8874***** **(0.4536)**		
NET[B/S]IND%$_t$ (Q3)	**0.1433** **(0.8977)**	**2.1371***** **(0.3558)**		
NET[B/S]IND%$_t$ (Q4)	**2.3330**** **(1.1427)**	**4.0924***** **(1.0638)**		
NET[B/S]IND%$_t$ (Q5)	**3.4328***** **(0.9768)**	**2.5772***** **(0.5362)**		
NET[B/S]MKT%$_t$ (Q1)			**15.3378***** **(0.6419)**	**6.1695***** **(0.4843)**
NET[B/S]MKT%$_t$ (Q2)			**11.9750***** **(1.3662)**	**5.6256***** **(0.5889)**
NET[B/S]MKT%$_t$ (Q3)			**11.1993***** **(1.7596)**	**4.7158***** **(0.4346)**
NET[B/S]MKT%$_t$ (Q4)			**10.9615***** **(1.0017)**	**6.5146***** **(0.7197)**
NET[B/S]MKT%$_t$ (Q5)			**12.6614***** **(1.6116)**	**4.3926***** **(0.3439)**
Constants for each partition	YES	YES	YES	YES
Controls	YES	YES	YES	YES
Fixed effects	Industry X Calendar Year	Industry X Calendar Year	Industry X Calendar Year	Industry X Calendar Year
Chi-square test for differences in coefficients (*Q5 – Q1*)	**0.01** **p = 0.9150**	**0.59** **p = 0.4406**	**2.56** **p = 0.1094**	**8.48***** **p = 0.0036**
Observations	222,452	222,452	222,452	222,452

Notes: All models are logit models. Observations are sorted into quintiles based on the average level of U.S. economic policy uncertainty (Baker, Bloom, and Davis, 2016) during a firm-quarter. Standard errors are clustered at the calendar-year level and shown in parentheses. The number of observations for each model may be less than the full sample size because insider trading in some industry-years can be predicted perfectly. Continuous variables are winsorized at the 1% and 99% levels for each quarter. * $p < .10$, ** $p < .05$, *** $p < .01$

TABLE 1.10: CROSS-SECTIONAL TESTS FOR IMPACT OF FIRM-LEVEL INFORMATIONAL ASYMMETRY

Model	**(1) DV = *NETB_FIRM***	**(2) DV = *NETS_FIRM***	**(3) DV = *NETB_FIRM***	**(4) DV = *NETS_FIRM***
NET[B/S]IND%$_t$ (Q1)	**4.2817***** **(0.6168)**	**3.0390***** **(0.6342)**		
NET[B/S]IND%$_t$ (Q2)	**4.2013***** **(0.7595)**	**3.3976***** **(0.5257)**		
NET[B/S]IND%$_t$ (Q3)	**3.4722***** **(0.7420)**	**3.5290***** **(0.4749)**		
NET[B/S]IND%$_t$ (Q4)	**3.3471***** **(0.7047)**	**3.0878***** **(0.4609)**		
NET[B/S]IND%$_t$ (Q5)	**2.9454***** **(0.8118)**	**2.3883***** **(0.4364)**		
NET[B/S]MKT%$_t$ (Q1)			**13.7018***** **(1.2668)**	**5.8186***** **(0.5280)**
NET[B/S]MKT%$_t$ (Q2)			**13.5530***** **(1.0813)**	**5.8123***** **(0.4414)**
NET[B/S]MKT%$_t$ (Q3)			**12.4117***** **(1.0410)**	**5.8372***** **(0.4483)**
NET[B/S]MKT%$_t$ (Q4)			**11.9747***** **(1.1911)**	**5.1528***** **(0.4164)**
NET[B/S]MKT%$_t$ (Q5)			**11.0488***** **(0.8984)**	**4.2757***** **(0.4559)**
Constants for each partition	YES	YES	YES	YES
Controls	YES	YES	YES	YES
Fixed effects	Industry X Calendar Year	Industry X Calendar Year	Industry X Calendar Year	Industry X Calendar Year
Chi-square test for differences in coefficients (*Q5 – Q1*)	**3.27*** **p = 0.0708**	**4.07**** **p = 0.0436**	**5.57**** **p = 0.0182**	**15.38***** **p = 0.0001**
Observations	222,452	222,452	222,452	222,452

Notes: All models are logit models. Observations are sorted into quintiles based on firm-level informational asymmetry, measured by bid-ask spreads (*BA_SPREAD*). Standard errors are clustered at the calendar-year level and shown in parentheses. The number of observations for each model may be less than the full sample size because insider trading in some industry-years can be predicted perfectly. Continuous variables are winsorized at the 1% and 99% levels for each quarter. * $p < .10$, ** $p < .05$, *** $p < .01$

TABLE 1.11: CROSS-SECTIONAL TESTS FOR IMPACT OF INTRA-INDUSTRY PROFITABILITY CORRELATIONS

Model	**(1)** **DV =** ***NETB_FIRM***	**(2)** **DV =** ***NETS_FIRM***	**(3)** **DV =** ***NETB_FIRM***	**(4)** **DV =** ***NETS_FIRM***
NET[B/S]_IND%$_t$ (LOW)	**4.3623***** **(0.6048)**	**3.4224***** **(0.5984)**		
NET[B/S]_IND%$_t$ (MED)	**4.3200***** **(1.0448)**	**3.5601***** **(0.3955)**		
NET[B/S]_IND%$_t$ (HIGH)	**3.1908**** **(1.3216)**	**1.9003***** **(0.3754)**		
NET[B/S]_MKT%$_t$ (LOW)			**12.5084***** **(0.9448)**	**5.6090***** **(0.5493)**
NET[B/S]_MKT%$_t$ (MED)			**11.4053***** **(1.1798)**	**5.3772***** **(0.3767)**
NET[B/S]_MKT%$_t$ (HIGH)			**11.8209***** **(1.8574)**	**4.2153***** **(0.4459)**
Constants for each partition	YES	YES	YES	YES
Controls	YES	YES	YES	YES
Fixed effects	Industry X Calendar Year	Industry X Calendar Year	Industry X Calendar Year	Industry X Calendar Year
Chi-square test for differences in coefficients (*HIGH – LOW*)	**0.93** **p = 0.3359**	**5.59**** **p = 0.0180**	**0.12** **p = 0.7431**	**4.48**** **p = 0.0342**
Observations	222,452	222,452	222,452	222,452

Notes: All models are nested logit models. Observations are sorted into *LOW*, *MED*, and *HIGH* groups based on the degree to which profitability, measured by ROA, is correlated. Industry-quarters containing fewer than 15 observations are dropped from the analysis. Standard errors are clustered at the calendar-year level and shown in parentheses. The number of observations for each model may be less than the full sample size because insider trading in some industry-years can be predicted perfectly. Continuous variables are winsorized at the 1% and 99% levels for each quarter. * $p < .10$, ** $p < .05$, *** $p < .01$

TABLE 1.12: BEHAVIOURS OF DIFFERENT GROUPS OF EXECUTIVES

Panel A: Opportunistic Insider Purchases; Logit Models

Model	**(1) DV = (*NETB_CEO*)**	**(2) DV = (*NETB_CFO*)**	**(3) DV = (*NETB_EXEC*)**
NETB_CEO_MKT%$_t$	**14.3704***** **(4.8519)**	**15.8303**** **(6.4350)**	**12.5331***** **(4.7176)**
NETB_CFO_MKT%$_t$	**2.8475** **(6.8646)**	**8.3772** **(10.6688)**	**10.1451**** **(4.9236)**
NETB_EXEC_MKT%$_t$	**4.8514*** **(2.5278)**	**2.4482** **(5.0523)**	**2.5217** **(4.1161)**
NETB_FIRM$_{t-1}$	1.3455*** (0.0472)	1.1411*** (0.0615)	1.3335*** (0.0553)
Constant	-3.0418*** (0.1310)	-3.2764*** (0.1773)	-3.1843*** (0.1118)
Controls	YES	YES	YES
Fixed effects	Industry X Calendar Year	Industry X Calendar Year	Industry X Calendar Year
Observations	227,267	227,267	227,267
Pseudo R^2	0.0996	0.0843	0.1018

TABLE 1.12, CONTINUED

Panel B: Opportunistic Insider Sales; Logit Models

Model	**(1)** **DV =** **(*NETS_CEO*)**	**(2)** **DV =** **(*NETS_CFO*)**	**(3)** **DV =** **(*NETS_EXEC*)**
NETS_CEO_MKT%$_t$	**17.9847*****	**9.2686****	**6.6769****
	(6.0142)	**(3.6872)**	**(3.3705)**
NETS_CFO_MKT%$_t$	**7.5501****	**-1.9724**	**-4.9907*****
	(3.1456)	**(2.2717)**	**(1.6087)**
NETS_EXEC_MKT%$_t$	**-1.1202**	**5.6762*****	**8.0404*****
	(1.3629)	**(1.6073)**	**(1.2734)**
NETS_FIRM$_{t-1}$	0.9017***	0.8157***	1.0800***
	(0.0611)	(0.0293)	(0.0319)
Constant	-5.4152***	-5.3841***	-4.9790***
	(0.1166)	(0.1061)	(0.1003)
Controls	YES	YES	YES
Fixed effects	Industry X Calendar Year	Industry X Calendar Year	Industry X Calendar Year
Observations	189,994	226,902	227,240
Pseudo R^2	0.1460	0.1188	0.1706

Standard errors are clustered at the calendar-year level and shown in parentheses. The number of observations for each model may be less than the full sample size because insider trading in some industry-years can be predicted perfectly. Continuous variables are winsorized at the 1% and 99% levels for each quarter. * $p < .10$, ** $p < .05$, *** $p < .01$

TABLE 1.13: IMPACT OF INSIDER TRADING ACTIVITY ON FUTURE PROFITABILITY AND OPERATING CASH FLOW MARGINS

Model	**(1)** **DV = ROA_{t+1}**	**(2)** **DV = ROA_{t+4}**	**(3)** **DV = CFM_{t+1}**	**(4)** **DV = CFM_{t+4}**
$NETB\_MKT\%_t$	**-0.0004**	**-0.0149*****	**0.4320****	**0.5025*****
	(0.0027)	**(0.0028)**	**(0.1685)**	**(0.1386)**
$NETS\_MKT\%_t$	**-0.0032*****	**-0.0080*****	**0.0249**	**0.1740*****
	(0.0009)	**(0.0009)**	**(0.0560)**	**(0.0453)**
$NETB\_FIRM_t$	0.0010***	0.0004	0.0033	-0.0003
	(0.0003)	(0.0004)	(0.0210)	(0.0184)
$NETS\_FIRM_t$	-0.0002	0.0004**	0.0027	-0.0059
	(0.0002)	(0.0002)	(0.0117)	(0.0097)
LAG (DV)	0.1598***	0.1378***	-0.0108***	0.1570***
	(0.0036)	(0.0042)	(0.0033)	(0.0028)
Constant	0.2272***	0.0830***	-1.7883***	-0.3118
	(0.0039)	(0.0046)	(0.2396)	(0.2052)
Controls	YES	YES	YES	YES
Observations	188,105	144,415	188,105	144,415
Chi-square statistic	11175.2***	3643.0***	1178.1***	10547.2***

Notes: All models are dynamic panel models estimated using the generalized method of moments methodology (Arellano and Bond, 1991). The number of observations for each model may be less than the full sample size due to insufficient lagged data. Standard errors are calculated using the generalized method of moments method and shown in parentheses. Continuous variables are winsorized at the 1% and 99% levels for each quarter. * $p < .10$, ** $p < .05$, *** $p < .01$

TABLE 1.14: IMPACT OF INSIDER TRADING ACTIVITY ON ABNORMAL STOCK RETURNS

Model	**(1)** **DV = $CAR_{t, t+1}$**	**(2)** **DV = $CAR_{t, t+2}$**	**(3)** **DV = $CAR_{t, t+3}$**	**(4)** **DV = $CAR_{t, t+4}$**
$NETB\_MKT\%_t$	**-0.0536**	**-0.1618**	**-0.3674***	**-0.9544****
	(0.1400)	**(0.2514)**	**(0.2055)**	**(0.3693)**
$NETS\_MKT\%_t$	**0.1118****	**0.2552*****	**0.2400*****	**0.4558*****
	(0.0442)	**(0.0883)**	**(0.0820)**	**(0.1494)**
$NETB\_FIRM_t$	0.0324***	0.0640***	0.0589***	0.1056***
	(0.0050)	(0.0087)	(0.0082)	(0.0125)
$NETS\_FIRM_t$	-0.0137***	-0.0234***	-0.0214***	-0.0353***
	(0.0025)	(0.0046)	(0.0041)	(0.0072)
Constant	-0.0304	-0.0626	-0.0236	-0.0160
	(0.0244)	(0.0431)	(0.0374)	(0.0502)
Controls	YES	YES	YES	YES
Fixed effects	Industry X Calendar Year	Industry X Calendar Year	Industry X Calendar Year	Industry X Calendar Year
Observations	166,949	166,796	166,152	164,524
R^2	0.1193	0.1897	0.1739	0.2521
Adjusted R^2	0.1151	0.1858	0.1699	0.2484

Notes: All models are ordinary least squares models. The number of observations for each model may be less than the full sample size due to insufficient data needed to computer abnormal stock returns. Standard errors are clustered at the calendar-year level and shown in parentheses. Continuous variables are winsorized at the 1% and 99% levels for each quarter. * $p < .10$, ** $p < .05$, *** $p < .01$

<u>Chapter 2: Insider Trading and Cash Holdings</u>

"The one thing I will tell you is the worst investment you can have is cash. Everybody is talking about cash being king and all that sort of thing. Most of you don't look like you are overburdened with cash anyway. Cash is going to become worth less over time. […] But you always want to have enough so that nobody else can determine your future essentially."

Warren Buffett, speaking with Bill Gates at Columbia Business School in 2009[29]

2.1 INTRODUCTION

In free, competitive markets, firm profitability tends to mean-revert in the cross-section of firms (Freeman et al., 1982; Fairfield et al., 1996; Nissim and Penman, 2001). However, companies exert significant effort in the hope of gaining competitive advantages so that they can – at least temporarily – earn excess profits. Although an exhaustive listing of actions that firms can take does not exist, Porter's (1980) Five Forces model[30] is among the most widely known tool for assessing firms' market positioning and competitive advantages. These advantages can be sources of future economic rents, and for this reason, should form an integral part of company valuations and profitability forecasts (Dickinson and Sommers, 2012; Maury, 2018).

Cash is one resource that firms can deploy to gain a competitive advantage or use as a cushion against downside risk. As of the end of the second quarter of 2021, S&P Global reported that "cash and short-term investments on [global] corporate balance sheets in the second quarter of 2021 have reached a record high of $6.84 trillion. That level is 45% higher than the average in the five years before the [COVID-19] outbreak in early 2020 and a nearly 3% increase compared to Q1"[31]. Jamie Dimon, J.P. Morgan's long-time Chief Executive Officer (CEO), said in August 2021 that the bank has "a lot of cash and capability and [they]'re going to be very patient,

[29] Source: https://www.buffettfaq.com
[30] The Five Forces are the threat of new market players, the threat of substitute products, bargaining power of customers, bargaining power of suppliers, and industry rivalry, which determines the competitive intensity and attractiveness of a market.
[31] https://www.investingdaily.com/66217/corporate-cash-hoards-buoy-stocks/. According to the U.S. Federal Reserve (https://www.federalreserve.gov/datadownload/Choose.aspx?rel=Z1), U.S.-domiciled firms were sitting on $2.81 trillion of cash as at the end of March 2021.

because [they] think you have a very good chance inflation will be more than transitory"[32]. Although central banks globally have recently begun hiking short-term interest rates to stave off rampant inflation, nominal and real interest rates remain historically low, and what companies are doing with their record cash stockpiles continues to attract media attention. For example, Tesla and MicroStrategy announced forays into bitcoin and other cryptocurrencies[33], while Palantir Technologies bought $51 million worth of physical gold bars to hedge against a 'black swan' event[34].

In this paper, I explore the relationship between insider trading and firms' cash holdings. That insiders exercise their informational advantage for personal gain is well documented (Ravina and Sapienza, 2010 and Cohen, Malloy, and Pomorski, 2012)[35], especially in relation to major corporate events[36]. What remains less explored, however, is how corporate insiders trade in relation to information about their firms' ability to engage in competitive efforts. While on the one hand, having a cash buffer affords firms additional means to capture upside and mitigate downside risk, holding more cash than necessary can increase agency problems because managers can invest these funds suboptimally (Jensen, 1986).

I find that cash and excess cash holdings are positively related to insider net selling activity and intensity, and that these relationships are economically meaningful and robust. Results of cross-sectional tests reveal that in certain situations, holding higher cash balances are perceived by insiders as having strategic value. Specifically, insiders at high-cash firms are more likely to buy, but only when industry competition and firm-level informational asymmetry are high, and

[32] https://www.cnbc.com/2021/06/14/jamie-dimon-jpmorgan-is-hoarding-cash-because-very-good-chance-inflation-here-to-stay.html
[33] https://protos.com/how-bitcoin-impacted-tesla-microstrategy-and-squares-q2-earnings/
[34] https://finance.yahoo.com/news/palantir-buys-51-million-gold-173724022.html
[35] Foundational work in this sphere includes, but is not limited to, Lorie and Niederhoffer (1968), Jaffe (1974), Seyhun (1986, 1988), Rozeff and Zaman (1988), Lin and Howe (1990), Bettis, Vickery, and Vickery (1997), Lakonishok and Lee (2001), and Marin and Olivier (2008), among others, provide evidence in support of this claim. Seyhun (1998) packages earlier work in this area and presents several actionable strategies for investors to realize significant abnormal returns.
[36] On average, insiders have insight into and trade ahead of the release of material firm-level information such as future earnings (Ke, Huddart, and Petroni, 2003 and Piotroski and Roulstone, 2005), news (Fidrmuc, Goergen, and Renneboog, 2006), mergers and acquisitions (Keown and Pinkerton, 1981; Agrawal and Nasser, 2012), management forecast updates (Cheng and Lo, 2006), stock buybacks (Bonaimé and Ryngaert, 2013), restatements (Agrawal and Cooper, 2015), weak internal controls (Skaife, Veenman, and Wangerin, 2013), and defaults on debt obligations (Beneish, Press, and Vargus, 2012).

insiders at high-cash firms are less likely to sell when economic policy uncertainty and firm-level informational asymmetry are high. Results of channel analyses suggest that when insiders are buying, high-cash firms will invest in research and development (R&D) with greater intensity, which leads to lower operating cash flow margins. However, this does not translate into an economically meaningful impact on accrual-based profitability. Finally, I find that levels of cash holdings amplify the relationships between abnormal stock returns and insider trading over 3-, 6-, 9-, and 12-month investment horizons: Abnormal returns on insider purchases at high-cash firms are significantly higher than at their low cash counterparts, and abnormal returns on insider sales at high-cash firms are significantly negatively larger that at their low cash counterparts.

I make two main contributions to the literature. First, I contribute to the body of work on insider trading. As of now, apart from innovation, research, and development (Aboody and Lev, 2000) and major customer relationships (Alldredge and Cicero, 2015), we do not know much about which competitive advantages insiders trade on, even though there is a multitude of ways for firms to build "organizational capital" (Lev, 2001) and extract economic rents in the short run. Although cash balances are publicly disclosed and are subject to very little (if any) estimation risk relative to other accounting line items, management's specific plans for cash remain mostly opaque and private.

Second, I contribute to the burgeoning literature on cash holdings. While researchers have done an excellent job assessing the value of companies' cash holdings under various circumstances[37], there is scant work on how managers profit from excess cash holdings. To my knowledge, I am the first to examine the relationship between cash holdings and insider trading behaviour.

In addition to the contributions I make to the extant bodies of literature on insider trading and firms' cash holdings and liquidity management, I provide insights that are relevant to practice. Investors who incorporate insider trading into their investment strategies can benefit from including cash holdings in their analysis, given that cash holdings significantly amplify returns on insider trades. Financial analysts who follow firms can benefit from asking more detailed

[37] See Ferreira da Cruz, Kimura, and Amorim Sobreiro (2019) for an excellent review of recent research on company cash holdings.

questions to managers regarding plans for cash balances, especially when managers are engaging in insider trading activity, given the association between insider trading and future financial outcomes at high-cash firms. My findings are also relevant for regulators who are interested in better understanding the information dynamics that surround insider trading.

In Section 2, I present my review of the related literature on cash holdings and insider trading and develop my hypotheses. I detail my research design and empirical approach in Section 3. In Section 4, I share the results of my findings. In Section 5, I discuss implications for practitioners and conclude the paper.

2.2 LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.2.1 Related Literature

Firms create sustained value by operating well as opposed to engaging in financial transactions (Penman, 2010). Under a resource-based view of the firm, companies acquire, control, deploy and marshal resources to make products and/or services (Wernerfelt, 1984). These resources include "assets, capabilities, organizational processes, firm attributes, information, knowledge, etc." (Barney, 1991, p. 101) controlled by firms that potentially improve the efficiency and effectiveness of firms' operations (Daft, 2004). Although firm profitability tends to mean-revert in the cross-section of firms (Freeman et al., 1982; Fairfield et al., 1996; Nissim and Penman, 2001; Healy et al., 2014), companies exert significant effort in the hope of gaining competitive advantages[38] so that they can – at least temporarily[39] – earn excess profits. Sources of competitive advantage can arise from holding a protected market position (Porter, 1980) or firm-specific resources and capabilities (Barney, 1991).

Cash is a homogeneous but nevertheless valuable resource because it is fungible and convertible into strategic assets (Amit and Schoemaker, 1993). Barney (1991) explains that "these valuable

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[38] Wiggins & Ruefli (2002) define a competitive advantage as "a capability (or set of capabilities) or resource (or set of resources) that gives the firm an advantage over its rivals which ceteris paribus leads to higher relative profitability" (p. 84).

[39] Polson and Scott (2012) find that only a small fraction (2%) of firms in their long-horizon study sustain superior performance over periods of 5 years or more.

but common resources can help ensure a firm's survival when they are exploited to create competitive parity in an industry" (p. 106). Baskin (1987) underscores the view that cash is a strategic asset and argues that "the empirical evidence is entirely consistent with the model wherein liquid assets are employed both to signal commitment to retaliate against encroachment and to enable firms to rapidly pre-empt new opportunities" (Baskin, 1987, p. 319). Fresard (2010) echoes this view, noting that "a firm can rely on a strong balance sheet to challenge rivals' bottom lines and future prospects through aggressive pricing" (p. 1098) and "may also use its cash reserves to fund competitive choices, such as the location of stores or plants, the construction of efficient distribution networks, the use of advertising targeted against rivals, or even the employment of more productive workers" (p. 1098).

Empirical research confirms that cash holdings, indeed, are associated with capturing upside, as reflected in future firm operating performance. For example, Lev, Li, and Sougiannis (2010) find that changes in working capital (an accounting metric that includes cash) are among a small handful of accounting estimates that are associated with future cash flows. Dickinson and Sommers (2012) find that having excess cash is associated with significantly higher year-ahead operating profitability. Fresard (2010) finds that firms with higher cash reserves than peers are on average able to gain higher product market shares. Higher cash holdings also enable firms to have greater visibility and plan investment programmes in advance instead of being at the mercy of capital markets for financing research and development expenditures and other growth opportunities (Opler et al, 1999; Brown and Petersen, 2011). This is particularly relevant for riskier firms with lumpier cash flows that have correspondingly higher external financing costs (Palazzo, 2011), and for firms that have opportunities to expand during difficult economic times (Ahrends, Drobetz, and Puhan, 2018).

Holding more cash also provides firms with a buffer that helps protect them against downside risk. Moreover, according to pecking order theory (Myers and Majluf, 1984), cash provides a valuable buffer because external financing is costly. Almeida et al. (2014) posit that firms must hold some cash because the liquidity required to continue funding investment projects may not always be available on demand from outside sources. Borrowers that have higher cash holdings enjoy lower interest rate spreads on debt (Acharya, Davydenko, and Strebulaev, 2012), which according to the authors reflects creditors' perceptions of lower default risk at firms that have excess liquidity. When companies face higher uncertainty with tax outcomes (Hanlon, Maydew, and Saavedra, 2017) or are financially constrained (Denis and Sibilkov, 2010), they respond by holding more cash. Subramaniam et al. (2011) provide evidence in support of the contrapositive to the above with their finding that diversified firms that have several business segments and more predictable cash flows hold less cash on their balance sheets.

However, because of its fungibility and convertibility, cash is an asset that carries a high risk of moral hazard because it can easily be misused by managers whose personal interests may not necessarily be aligned with those of shareholders (hereinafter, *free cash flow theory*, Jensen, 1986). It would therefore be in shareholders' interest for firms to hold less cash in order to mitigate potential agency problems (Stulz, 1990). There is some evidence in support of free cash flow theory. Harford, Mansi, and Maxwell (2008) find that poorly governed firms with excess cash are more likely to make wasteful investments[40]. Firms with lower-quality earnings and poor accruals quality tend to hold more cash (Sun, Yung, and Rahman, 2012; Garcia-Teruel, Martinez-Solano, Sanchez-Ballesta, 2009). Harford (1999) finds that cash-rich firms are more likely to pursue acquisitions, and tend to overbid when they do so, destroying shareholder value in the process. Cunha (2014) builds on earlier work and finds that value-destroying acquisitions by high-cash firms are less likely when those firms raise funds by issuing debt.

Investors tend to recognize the risk of the agency costs of excess cash. While the market value of a marginal dollar of cash on a firm's balance is close to face value on average (Pinkowitz and Williamson, 2004), investors do place a material haircut on the value of cash held by firms that are poorly governed (Dittmar and Mahrt-Smith, 2007), and have internal control weaknesses (Gao and Jia, 2016). Investors also penalize high-cash firms that are domiciled in regimes that have strong protections for minority shareholders (Kalcheva and Lins, 2007), have CEOs who are not sufficiently incentivized to take risk (Tong, 2010), and have more predictable cash flows on account of them being more diversified (Tong, 2011).

[40] "Good" governance in the form of monitoring can come from various sources such as debt covenants (Chava and Roberts, 2008; Roberts and Sufi, 2009; Nini, Smith, and Sufi, 2009), the presence of large shareholders (Gao, Harford, and Li, 2013), and pressure from the corporate takeover market (Harford, Mansi, and Maxwell, 2008).

There are also situations that can exacerbate the information asymmetry associated with cash holdings. For example, U.S. multinational firms that hold cash abroad are subject to even greater informational uncertainty because of the increased difficulty in ascertaining where the cash is, what it may be used for, and how it might be taxed (Fabrizi et al., 2021). In addition, investors punish firms with excess cash and overconfident CEOs because these firms tend to systematically overinvest (Aktas, Louca, and Petmezas, 2019). To attenuate the risk of moral hazard, firms can simply choose to hold less cash, which is what Chung et al. (2015) observe for firms that operate in higher information asymmetry environments. They can also be more conservative with their financial reporting (Louis, Sun, and Urcan, 2012) or signal that they are responsible by enhancing their corporate social responsibility disclosures (Lu, Shailer, and Yu, 2016).

In summary, having a cash buffer affords firms flexibility to capture upside and mitigate downside risk. However, holding more cash increases the risk of agency problems because managers can invest these funds suboptimally.

2.2.2 Hypothesis Development

The notion that insiders exercise their informational advantage for personal gain is well established in academic literature (Ravina and Sapienza, 2010 and Cohen, Malloy, and Pomorski, 2012)[41]. If cash holdings affect firm value, will insiders trade on the fact that they have more timely and precise access to this information? Kyle's (1985, 1989) models of informed trading offer some clues.

Kyle (1985) predicts that in equilibrium, "The informed trader trades in such a way that his private information is incorporated into prices gradually (p. 1316)", and "not all information is incorporated into prices by the end of trading" (p. 1326). He therefore concludes that an "insider makes positive profits by exploiting his monopoly power optimally in a dynamic context" (p. 1315). However, trading and information production do not happen in a vacuum, and Kyle's second (1989) model allows for the acquisition of private information by outside investors. He

[41] See footnote 2 for a listing of foundational work in this area.

concludes that "while uninformed speculators break even on average, informed speculators make money 'at the expense' of noise traders" (p. 337), and that "with imperfect competition, prices never reveal more than one-half the private precision of informed speculators" (p. 344). Therefore, even if outsiders can obtain valuable information on firms' cash holdings, insiders are still expected to profit from insider trading. Notably, in Kyle's (1985) model, insider trading profitability increases with the variance of the liquidation value of the specific investment.

Given that insiders are more likely to trade when their firms face more information asymmetry (Wu, 2019) and firms with high cash holdings have higher information asymmetry (Drobetz, Grüninger, and Hirschvogl, 2010) and a greater risk of agency problems (Jensen, 1986), it is plausible that insiders, at the margin, will be more likely to sell if their employers hold more cash. Moreover, although firms that hold excess cash do tend to outperform in the short run on an operating basis, their stocks tend to underperform over the same horizon (Dickinson and Sommers, 2012). This is consistent with the higher likelihood that managers will engage in wasteful investments (Harford, Mansi, and Maxwell, 2008) and acquisitions that destroy value (Harford, 1999). I therefore expect insiders of companies that hold more cash to be more active sellers in their firms' shares, which leads to the following hypothesis that I present in alternative form:

H2.1: All else equal, insiders at firms that hold more cash are more likely to sell shares.

Making a prediction regarding the association between cash holdings and insider buying activity is more difficult. On the one hand, because cash holdings are a source of information asymmetry (Drobetz, Grüninger, and Hirschvogl, 2010) and insiders are more likely to buy when information asymmetry is higher (Wu, 2019), it is plausible to expect a positive relationship between cash holdings and insider buying. On the other hand, insiders are savvy investors[42] and the negative relationship between cash holdings and future stock outperformance would play against insiders buying. The relationship between cash holdings and insider buying activity, therefore, is an empirical question. I therefore posit the following competing hypotheses:

[42] See footnote 2 for a listing of foundational work in this area.

H2.2a: All else equal, insiders at firms that hold more cash are more likely to buy shares.

H2.2b: All else equal, insiders at firms that hold more cash are less likely to buy shares.

2.3 SAMPLE CONSTRUCTION AND RESEARCH DESIGN

2.3.1 Data and Sample Construction

In Table 2.1, I present details about my sample. I begin with 676,760 firm-quarter observations between 1996 and 2021 that have stock prices in CRSP and have associated CUSIP[43] numbers and matching GVKEYs in Compustat. I remove observations for firms domiciled outside of Canada and the United States and companies in the financial services sector (Fama-French industry code 28) because it includes entities such as hedge funds, closed-end funds, royalty flow-through companies, pensions, whose primary activity is to manage portfolios of investments in other firms. I then drop observations with stock prices below $2 as these are at risk of being delisted and observations for firms that have negative shareholders' equity. Finally, I drop observations with missing data from Compustat that prevent the calculation of one or more control variables. My final sample contains 223,096 firm-quarter observations from 7,839 unique firms.

[Insert Table 2.1 about here]

I source insider trade data from the Thomson Reuters insider filings database and collect firm fundamental data and stock prices from the matched CRSP/Compustat database. I restrict my insider trading sample to include only those line items that are cleansed by the data vendor[44] and classified as open-market purchases or sales[45] and then aggregate line items by firm[46], by insider, by day according to the dates that trades are filed with the SEC. For each filing, I identify the person making the trade and classify them based on their position at the company. I distinguish

[43] Committee on Uniform Securities Identification Procedures. See https://www.investor.gov/introduction-investing/investing-basics/glossary/cusip-number.

[44] Cleanse codes A or S.

[45] The trade codes that I classify as open-market purchases are P and L. The trade codes that I classify as open-market sales are F, I, and S.

[46] I differentiate firms by 6-digit CUSIP because it is possible for companies to issue several classes of tradable securities.

between CEOs and equivalents (*_CEO*), Chief Financial Officers (CFOs) and equivalents (*_CFO*), other company executives (*_EXEC*), and all other filers, which include independent directors and large blockholders[47]. I compute the total net dollar value and number of shares involved in each case.

Next, I classify open-market insider purchases (*BUY*) and sales (*SALE*) as either routine (*ROUT*) or opportunistic (*OPP)* based on the methods used in Cohen et al. (2012). Open-market insider trades include activity that have net cash flow implications for an investor, such as purchasing shares with their own money or selling shares to generate liquidity but exclude derivative transactions and other actions that do not change an investor's exposure to a firm's shares. If an insider consummates trades of the same sign in the same month at least three years in a row, I classify the trade as routine (*ROUT*) starting in the third consecutive year. I classify trades that do not meet the criteria for routine trades as opportunistic (*OPP)*[48]. I then aggregate insider trading activity at a quarterly level to code my dependent variables, $NETB\_FIRM_{it}$ and $NETS\_FIRM_{it}$. Firms that have net opportunistic insider buying activity by executives (i.e. when the number of shares purchased opportunistically exceeds the number of shares sold opportunistically) are coded as $NETB\_FIRM_{it} = 1$ and firms that have net opportunistic insider selling activity by executives are coded as $NETS\_FIRM_{it} = 1$. Firms that have zero net opportunistic insider trading activity receive values of zero for $NETB\_FIRM_{it}$ and $NETS\_FIRM_{it}$. I also compute measures of insider trading intensity based on net number of shares traded ($NETB\_SH\_FIRM_{it}$ and $NETS\_SH\_FIRM_{it}$) and their associated dollar values in constant 2020 dollars ($NETB\_\$\_FIRM_{it}$ and $NETS\_\$\_FIRM_{it}$). I present additional detailed explanations for these variables in Panel A of Appendix 2.

[47] I classify insiders with a role code of "CEO" as CEO, those with a role code of "CFO" or "C" (controller) as CFO, and those with role codes of "O", "CI", "CO", "CT", "EVP", "OB", "OT", "P", "SVP", "GC", "C", "F", "M", and "OE" as other executives, with the proviso that the latter do not occupy a CEO, CFO, or controller role in the company.

[48] For example, if a CFO buys shares for the first time in November 2015, I code that trade as opportunistic. The insider buying by the CFO during a firm-quarter would be coded as *OPPBUY_CFO = 1*. If the same CFO buys shares in the same firm in November 2016, that trade is also coded as opportunistic. If, in November 2017, the CFO purchases shares anew, that trade is coded as routine because the CFO bought shares in November of each of the two preceding years.

2.3.2 Empirical Model

To test my main hypotheses, I run the following panel logit regressions for insider sales:

$$P(NETS\_FIRM_{it}) = \alpha_0 + \alpha_1 * (Ln[CASH_t]) + \Sigma(\beta_i * CONTROLS) + \Sigma(\gamma_k * \text{Industry-year Indicator Variables}) + \varepsilon; \quad (2)$$

My main variable of interest is $Ln(CASH_t)$, which is the level of a company's cash holdings, calculated as the ratio of a firm's cash and cash equivalents to total assets at time *t*. I expect α_1 to be positive for insider sales (hypothesis 2.1). I also run a similar panel logit regression for opportunistic selling activity (*NETB_FIRM*) but do not have a directional prediction for insider purchases (hypothesis 2.2). I control for factors that are known to influence insider trading activity including firm market capitalization in constant 2020 dollars (*MCAP*), the book-to-market ratio (*BOOKMKT*), raw stock returns over the preceding 12 months (*SRET*), leverage (*LEVERAGE*), R&D intensity (*RDINT*), advertising intensity (*ADINT*), profitability (*RONA*), negative earnings (*LOSS*), probability of bankruptcy (*ALTMAN_Z*), the presence of a qualified audit opinion (*QUAL_OP*), periods that will later be restated (*RESTATE*), weak internal controls (*IC_WEAK*), and industry concentration (*IND_HHI*). I include the lagged value of the dependent variable ($NETB\_FIRM_{it-1}$) because insider trading inside a firm is autocorrelated (Alldredge and Blank, 2019). I also include industry-year fixed effects to control for other factors that affect groups of firms at various moments in time. I present detailed explanations for each control variable in Panel B of Appendix 2.

In addition to using $Ln(CASH_t)$ as the main variable of interest, I run alternate sets of models that have excess cash holdings (*Ln*[*EXC_CASH*]) as the variable of interest. I follow Opler et al. (1999) and Simutin (2013) and estimate Ln[*EXC_CASH*] as the residual of a regression designed to predict cash holdings. The results of the regression are comparable to those obtained by Opler et al. (1999) and Simutin (2013) and are presented in Table 2.2.

[Insert Table 2.2 about here]

2.3.3 Descriptive Statistics

I present a frequency table for net insider trading activity by calendar year and by industry in Table 2.3. Open-market insider purchases are relatively rare, with only 5.9% of firm-quarters having net opportunistic insider buying activity. Open-market insider sales occur much more frequently compared to open-market purchases, especially in business cycles after the 2008 financial crisis, and make up approximately 83% of the firm-quarters for which there is some open-market insider trading activity. In terms of dollar volume, the amount of insider selling vastly exceeds that of insider buying ($286 billion of net insider sales versus $2 billion of net insider purchases since 1996). Insider trading activity is most concentrated in the Personal and Business Services, Business Equipment, and Healthcare, Medical Equipment, and Pharmaceutical Products industries.

[Insert Table 2.3 about here]

In Table 2.4, I present descriptive statistics. The average (median) net amount sold of $4.1 million ($770,000) for firm-quarters with net opportunistic sales by executives is many times larger than as the average (median) firm-quarter with net purchase activity of $152,000 ($60,000). These data are consistent with previous studies. Close to 90% of net insider trading activity is relatively small relative to total firm value, and accounts for less than 0.25% of a firm's shares outstanding. Relative to net insider sales, net insider purchasing activity is more concentrated in firms that are smaller, have lower retained earnings (which cumulate over time), are less profitable, have lower book-to-market ratios, and have worse trailing 52-week returns. In untabulated results, I do not find any significant differences in financial leverage, R&D intensity, or capital expenditure intensity between firm-quarters that have net insider buying activity versus firm-quarters with net insider selling activity. I do, however, find a lower incidence of qualified audit opinions and future restatements, and a slightly higher incidence of internal control weaknesses for firm-quarters that have net insider buying activity.

Panel C of Table 2.4 contains a correlation matrix of the variables of interest. Insider net buying and net selling are autocorrelated, consistent with Alldredge and Blank's (2019) findings.

Ln(CASH) and *Ln(EXC_CASH)* are highly correlated with each other (r = 0.72) and are highly autocorrelated ($r_{t-1,\,t}$ = 0.95 for *Ln(CASH)* and 0.89 for *Ln*[*EXC_CASH*]).

[Insert Table 2.4 about here]

2.4 ANALYSIS AND RESULTS

2.4.1 Main Tests

Table 2.5 shows baseline results of the main tests. Panel A contains the test results for the variables of interest related to insider selling, *Ln(CASH)* (panel A, model 1, α_1 = 0.0409, p < 0.01) and *Ln(EXC_CASH)* (panel A, model 3, α_2 = 0.1384, p < 0.01), both of which are significantly related to *NETS_FIRM*. This evidence supports hypothesis 2.1. The effects are attenuated but not subsumed by control variables (models 2 and 4). With respect to marginal effects, a one standard deviation increase in *Ln(CASH)* or *Ln(EXC_CASH)* from their means results in a 5% higher predicted probability[49] for *NETS_FIRM* (see Figures 2.1 and 2.2).

[Insert Table 2.5, Figure 2.1, and Figure 2.2 about here]

Panel B of Table 2.5 contains the test results for the variables of interest related to insider buying, *Ln(CASH)* (panel A, model 1, α_1 = -0.1522, p < 0.01) and *Ln(EXC_CASH)* (panel A, model 3, α_2 = -0.1418, p < 0.01). Both *Ln(CASH)* and *Ln(EXC_CASH)* are significantly associated with *NETB_FIRM*. The effects are attenuated but not subsumed by control variables (models 2 and 4). With respect to marginal effects, a one standard deviation increase in *Ln(CASH)* or *Ln(EXC_CASH)* from their means results in an 11% lower predicted probability[50] for *NETB_FIRM* (see Figures 2.3 and 2.4).

[Insert Figure 2.3 and Figure 2.4 about here]

[49] (0.308 – 0.293) / 0.293
[50] (0.052 – 0.059) / 0.059

Panel A of Table 2.6 presents results of tests of the impact of *Ln(CASH)* and *Ln(EXC_CASH)* on net insider selling intensity. For the dependent variables, I use both the natural logarithm of one plus the net number of shares sold by executives during a firm quarter (*NETS_FIRM_SH*; models 1 and 3), and the natural logarithm of one plus the net dollar value of executives' share sales during a firm quarter (*NETS_FIRM_$*; models 2 and 4). Consistent with the main tests, *Ln(CASH)* and *Ln(EXC_CASH)* are positively related to both *NETS_FIRM_SH* and *NETS_FIRM_$*. The economic impacts of *Ln(CASH)* and *Ln(EXC_CASH)* are meaningful, which further supports H2.1. Specifically, a one standard deviation increase in *Ln(CASH)* from its mean results in 51,100 more shares sold (e^[0.1907 * 0.32] * 48,074), an increase of $4.4 million (e^[0.2251 * 0.32] * $4.1 million). The economic impact of *Ln(EXC_CASH)* is of a similar magnitude to that of *Ln(CASH)*.

Next, Panel B of Table 2.6 presents results of tests of the impact of *Ln(CASH)* and *Ln(EXC_CASH)* on net insider buying intensity. For the dependent variables, I use both the natural logarithm of one plus the net number of shares purchased by executives during a firm quarter (*NETB_FIRM_SH*; models 1 and 3), and the natural logarithm of one plus the net dollar value of executives' share sales during a firm quarter (*NETB_FIRM_$*; models 2 and 4). Consistent with the main tests, *Ln(CASH)* and *Ln(EXC_CASH)* are positively related to both *NETB_FIRM_SH* and *NETB_FIRM_$*. When compared to the relatively small average size of net insider buys, the economic impacts of *Ln(CASH)* and *Ln(EXC_CASH)* are meaningful. Specifically, a one standard deviation increase in *Ln(CASH)* from its mean results in 1,546 fewer shares purchased (e^[-0.5576 * 0.32] * 11,581), a decrease of $33,000 (e^[-0.7635 * 0.32] * $152,500). The economic impact of *Ln(EXC_CASH)* is of a similar magnitude to that of *Ln(CASH)*.

[Insert Table 2.6 about here]

Although baseline results suggest that cash holdings are positively related to net insider selling and negatively related to net insider buying, the logit and Tobit regression results may be misleading because of potential endogeneity in the sample. Because insider trading and cash holdings are both autocorrelated, modelling the relation between insider trading and cash holdings could be challenging if there is a feedback loop between insider trading and cash holdings. To address this concern, I run dynamic panel data regressions (Arellano and Bond, 1991) to test whether changes in cash holdings are associated with changed in insider trading activity[51]. Table 2.7 shows the results of these regressions. Consistent with evidence shown so far, there are significant relationships between net insider selling activity (*NETS_FIRM_SH* and *NETS_FIRM_$*) and cash holdings (*Ln*[*CASH*] and *Ln*[*EXC_CASH*]). While the effect sizes in the dynamic panel models are slightly smaller than in the baseline regressions, they remain highly significant, which helps to alleviate concerns that my results are driven by autocorrelation or endogeneity. However, the relationships between net insider buying activity and cash holdings are not robust, as only one of four models of insider buying intensity (model 2 in Panel B) has cash holdings as a significant covariate.

[Insert Table 2.7 about here]

2.4.2 Cross-Sectional Tests

Firms operating in more competitive environments face higher information asymmetry and insiders in these firms trade more profitably (Rahman et al., 2021). It would therefore be plausible that product market competition amplifies the impact of industry-level insider trading activity on the firm-level opportunistic insider trading. To investigate this possibility, I partition my sample into quintiles based on industry-wide product market fluidity (*FLUIDITY*; Hoberg, Phillips, and Prabhala, 2014) and present results in Table 8. I find that the coefficients for *Ln(CASH)* and *Ln(EXC_CASH)* are positively associated with *NETB_FIRM* for firms in the highest quintile of *FLUIDITY* (Q5, models 1 and 3). This evidence supports the view that in highly competitive environments, cash can be a source of competitive advantage (Fresard, 2010; Opler et al, 1999; Brown and Petersen, 2011), and that insiders recognize this and are thus more likely to buy shares opportunistically. I do not find that *FLUIDITY* moderates the effects of *Ln(CASH)* and *Ln(EXC_CASH)* on *NETS_FIRM* in a significant way.

[51] A more common approach to control for endogeneity is two-stage least squares (2SLS). However, the validity of a 2SLS model depends heavily on finding exogenous instruments for the first stage that are unrelated to the second-stage dependent variable. Unfortunately, prior empirical and theoretical work on insider trading and cash holdings use control variables that overlap, which limits the feasibility of finding a suitable instrument.

[Insert Table 2.8 about here]

Information asymmetry can also manifest itself at a broad macroeconomic level. Uncertainty and risk "about *who* will make economic policy decisions, *what* economic policy actions will be undertaken and when, and the economic effects of policy actions (or inaction)" (Baker, Bloom, and Davis, 2016, p. 1598) is of concern to all individuals and businesses; therefore, it is plausible that economic policy uncertainty amplifies the impact of market-level insider trading activity on firm-level opportunistic insider trading. To investigate this possibility, I partition my sample into quintiles based on U.S. economic policy uncertainty (*EPU*; Baker, Bloom, and Davis, 2016) and present results in Table 2.9. I find that for net insider sales (*NETS_FIRM*, models 2 and 4), the coefficients for *Ln(CASH)* and *Ln(EXC_CASH)* decrease significantly ($\chi^2 = 8.12$, $p = 0.0042$ for *Ln*[*CASH*] and $\chi^2 = 29.92$, $p = 0.0001$ for *Ln*[EXC_*CASH*]). This evidence suggests that during times when forward visibility related to economic activity is limited, insiders recognize the strategic value of cash and thus are less likely to sell opportunistically. I do not find that *EPU* moderates the effects of *Ln(CASH)* and *Ln(EXC_CASH)* in a significant way.

[Insert Table 2.9 about here]

Information asymmetry can also manifest itself at a local level (i.e. within a firm). Gider and Westheide (2016) find that insider trading profits have a large firm-specific component and are positively correlated with idiosyncratic (i.e. firm-specific) information asymmetry. Chung and Charoenwong (1998) find that insider trading activity is positively related to bid-ask spreads, which serve as a proxy for information asymmetry[52]. It is therefore plausible that as bid-ask spreads increase due to firm-specific information asymmetry/risk explaining a larger portion of equity returns, the effect of industry- and market-level insider trading activity on firm-level insider trading activity will be lower. The final set of cross-sectional tests investigates whether executives in different roles exhibit different insider trading patterns. I partition my sample into quintiles based on firm bid-ask spreads (*BA_SPREAD*) relative to industry peers and present the

[52] As Coller and Yohn (1997) note, "Kim and Verrecchia (1994) explain that […] Because specialists sustain losses from trading with informed traders, an increase in information asymmetry causes the specialist to widen the bid-ask spread in order to recoup these losses" (p. 181).

results of these tests in Table 2.10. I find that *BA_SPREAD* positively moderates the impacts of *Ln(CASH)* and *Ln(EXC_CASH)* on *NETB_FIRM* (models 1 and 3), and that the differences in coefficients between the highest and lowest quintiles of *BA_SPREAD* are significant ($\chi^2 = 5.21$, $p = 0.0225$ for *Ln*[*CASH*] and $\chi^2 = 7.23$, $p = 0.0072$ for *Ln*[*EXC_CASH*]). This evidence suggests that for firms with higher idiosyncratic uncertainty, insiders recognize the strategic value of cash and thus are more likely to buy and less likely to sell opportunistically.

[Insert Table 2.10 about here]

2.4.3 Impact of Cash Holdings and Insider Trading on Firm Outcomes

The focus in previous sections is on the determinants of firm-level insider trading activity, paying specific attention to how various factors moderate the relationship between firm-level insider trading activity and cash holdings. I now pivot my attention to analyzing the impact of these variables on firm outcomes with the goal of better understanding the channels which mediate the relationships between firm-level insider trading activity and cash holdings.

I test whether *Ln(CASH)* moderates the impact of insider trading on future R&D intensity. I partition my sample into quintiles based on *Ln(CASH)* and present the results in Table 2.11[53]. Because R&D is autocorrelated, I continue to use dynamic panel data regressions (Arellano and Bond, 1991) to address this endogeneity issue. I find that when insider are buying, firm with the highest ratios of *Ln(CASH)* invest in R&D with significantly greater intensity. The differences in coefficients are significant over 3- and 9-month time horizons ($\chi^2 = 7.67$, $p = 0.0056$ and $\chi^2 = 2.86$, $p = 0.0909$, respectively). Overall, net insider selling (*NETS_FIRM*) is not associated with future R&D intensity, and there is no evidence that *Ln(CASH)* moderates this lack of a relationship.

[Insert Table 2.11 about here]

Next, I test whether relation between *Ln(CASH)* moderates the impact of insider trading on future profitability (*ROA*) and operating cash flow margins (*CFM*). and I again partition my

[53] Results (untabulated) using *Ln(EXC_CASH)* are qualitatively similar.

sample into quintiles based on *Ln(CASH)* and present the results in Table 12[54]. Because *ROA* and *CFM* are autocorrelated, I continue to use dynamic panel data regressions (Arellano and Bond, 1991) to address this endogeneity issue. I find that while *Ln(CASH)*, is not associated with economically meaningful changes in *ROA*, there is a negative association between *Ln(CASH)* and 3- and 12-month ahead *CFM*. The differences in coefficients are significant over 3- and 9-month time horizons ($\chi^2 = 7.67$, $p = 0.0056$ and $\chi^2 = 2.86$, $p = 0.0909$, respectively). Overall, neither insider buying (*NETB_FIRM*) nor insider selling (*NETS_FIRM*) is associated with future profitability (*ROA*) or operating cash flow margins (*CFM*), and there is no evidence that *Ln(CASH)* moderates these lacks of relationships.

[Insert Table 2.12 about here]

Finally, I test the impact of *Ln(CASH)* on future abnormal stock returns. I use the Event Study by WRDS module from Wharton Research Data Services[55] to generate 3-, 6-, 9-, and 12-month cumulative abnormal stock return estimations based on Fama and French's (1993) 3-factor model with a momentum factor (Carhart, 1997). As with the previous two sets of tests, I partition my sample into quintiles based on *Ln(CASH)* and present the results in Table 13[56]. Consistent with prior studies (e.g. Cohen et al., 2012), I find that net insider buying (selling) activity is significantly associated with positive (negative) future abnormal returns. I also find that *Ln(CASH)* amplifies the relationships between abnormal stock returns and insider trading over 3-, 6-, 9-, and 12-month investment horizons: Abnormal returns on insider purchases at high-cash firms are significantly higher that at their low cash counterparts, and abnormal returns on insider sales at high-cash firms are significantly negatively larger that at their low cash counterparts. My interpretation of these findings is that when insiders are buying, they are signalling to market participants that the high cash balances will be invested responsibly into value-adding projects. Conversely, when insiders at high-cash firms are selling, market participants perceive a higher risk that the cash will either be wasted or not deployed productively.

[54] Results (untabulated) using *Ln(EXC_CASH)* are qualitatively similar.
[55] https://wrds-www.wharton.upenn.edu/pages/get-data/event-study-wrds/us-daily-event-study-Upload-your-own-events/
[56] Results (untabulated) using *Ln(EXC_CASH)* are qualitatively similar.

[Insert Table 2.13 about here]

In summary, I find that various measures of cash (*Ln*[*CASH*]) and excess cash (*Ln*[*EXC_CASH*]) holdings are positively related to insider net selling activity and intensity, and that these relationships are economically meaningful and robust. Results of cross-sectional tests reveal that in certain situations, holding higher cash balances are perceived by insiders as having strategic value. Specifically, insiders at high-cash firms are more likely to buy, but only when industry competition and firm-level informational asymmetry are high, and insiders at high-cash firms are less likely to sell when economic policy uncertainty and firm-level informational asymmetry are high. Results of channel analyses suggest that when insiders are buying, high-cash firms will invest in R&D with greater intensity, which leads to lower operating cash flow margins. However, this does not translate into an economically meaningful impact on accrual-based profitability. Finally, I find that levels of cash holdings amplify the relationships between abnormal stock returns and insider trading over 3-, 6-, 9-, and 12-month investment horizons: Abnormal returns on insider purchases at high-cash firms are significantly higher that at their low cash counterparts, and abnormal returns on insider sales at high-cash firms are significantly negatively larger that at their low cash counterparts.

2.5 DISCUSSION AND CONCLUSION

In this chapter, I explore the relationship between insider trading and firms' cash holdings. That insiders exercise their informational advantage for personal gain is well documented (Ravina and Sapienza, 2010 and Cohen, Malloy, and Pomorski, 2012), especially in relation to major corporate events. While on the one hand, having a cash buffer affords firms additional means to capture upside and mitigate downside risk (Myers and Majluf, 1984), holding more cash than necessary can increase agency problems because managers can invest these funds suboptimally (Jensen, 1986). I find that in aggregate, higher cash balances are associated with increased insider selling activity and intensity. However, in certain situations, such as when industry competition, economic policy uncertainty, and firm-level informational asymmetry are high, insiders are less likely to sell and/or more likely to buy, which may reflect insiders' perception that excess cash balances in these instances have strategic value.

In addition to the contributions I make to the extant bodies of literature on insider trading and firms' cash holdings and liquidity management, I provide insights that are relevant to practice. Investors who incorporate insider trading into their investment strategies can benefit from including cash holdings in their analysis, given that cash holdings significantly amplify returns on insider trades. Financial analysts who follow firms can benefit asking more detailed questions to managers regarding plans for cash balances, especially when managers are engaging in insider trading activity, given the association between insider trading and future financial outcomes at high-cash firms. My findings are also relevant for regulators who are interested in better understanding the information dynamics that surround insider trading.

This study is not without limitations. Notably, cash holdings and insider trading activity are highly autocorrelated. Although I use dynamic panel regressions (Arellano and Bond, 1991) to address endogeneity issues that arise from the autocorrelation in my main variables and incorporate industry-year fixed effects to control for other factors that affect groups of firms at various moments in time, it remains possible that my findings are driven by other omitted variable(s). Moreover, my use of firm-quarters as a unit of analysis may not fully capture the longer-term relationships between cash holdings, insider trading, and firm outcomes such as future R&D investments or cash flow generation.

Future research could address the limitations of my current study by taking a longer-term view and studying how the relationships between insider trading, cash holdings, and firm outcomes evolve over time. Another potential avenue for future research would be to investigate the role of corporate governance and whether it is related to the relationships between insider trading, cash holdings, and firm outcomes.

APPENDIX 2: VARIABLE DEFINITIONS

Panel A: Main Variables of Interest

NET[B/S]_FIRM$_{it}$	Indicator variable that takes a value of 1 if during a firm-quarter, the net number of shares opportunistically traded (purchases minus sales) by executives at is [greater than/less than] zero. Source: Thomson Reuters
NET[B/S]_[SH/$]_FIRM$_{it}$	Net [number of shares/dollar value of shares] opportunistically traded (purchases minus sales) by all executives at firm *i* during quarter *t*. Source: Thomson Reuters
CASH	Ratio of cash and cash equivalents [CHEQ] to total assets [ATQ] Source: Compustat
Ln(CASH)	The natural logarithm of *CASH*
Ln(EXC_CASH)	Ratio of excess cash and cash equivalents [CHEQ] to total assets [ATQ]; estimated following Opler et al. (1999) and Simutin (2013). Sources: CRSP, Compustat
RDINT	R&D intensity; calculated as research and development expenses [XRDQ] divided by sales [SALEQ] Source: Compustat
ROA	Return on assets; calculated as earnings before extraordinary items [IB] divided by total assets [AT] Source: Compustat
CFM	Operating cash flow margin; calculated as operating cash flow [OANCF] divided by sales [SALE] Source: Compustat
CAR	Cumulative abnormal stock returns; estimated using Fama and French's (1993) 3-factor model plus momentum (Carhart, 1997) Source: Wharton Research Data Services

APPENDIX 2, CONTINUED

Panel B: Control and Other Variables

CPI_Factor	US Consumer price index factor, chained and rebased to 2020 dollars Source: U.S. Bureau of Labor Statistics
PRC_adj	Adjusted stock price; calculated as (abs[PRC])/[CFACPR] Source: CRSP
SHR_adj	Adjusted number of shares outstanding; calculated as [SHROUT*CFACSHR] Source: CRSP
BA_SPREAD	Time-weighted average of daily closing bid-ask spreads; calculated as ([ASK/HI] – [BID/LO])/abs[PRC] Source: CRSP
ASSETS	Firm total assets [ATQ], presented in millions of 2020 $US Source: Compustat
Ln(ASSETS)	Natural logarithm of *ASSETS* Source: Compustat
MCAP	Firm market capitalization; calculated as *PRC_adj***SHR_adj*, deflated by *CPI_Factor*, presented in millions of 2020 $US Source: CRSP
Ln(MCAP)	Natural logarithm of *MCAP*
BOOKMKT	Ratio of book value of shareholders' equity [SEQQ] to *MCAP* Sources: CRSP and Compustat
SRET	Raw trailing 12-month stock return; calculated as (PRC_adj_{it} – PRC_adj_{it-4}) divided by PRC_adj_{it-4} Source: CRSP
DIVPAY	Indicator variable that takes a value of 1 if [DIVAMT] is greater than 0, and zero otherwise Source: CRSP
LEVERAGE	Ratio of long-term debt [DLTTQ] to total assets [ATQ] Source: Compustat
CAPEX	Capital expenditure intensity; calculated as capital expenditures [CAPXY] divided by total assets [ATQ] Source: Compustat
NETWC	Non-cash net working capital; calculated as non-cash current assets [ACTQ – CHEQ] minus current liabilities [LCTQ], all divided by non-cash assets [ATQ – CHEQ] Source: Compustat
RONA	Return on net operating assets; calculated as income before interest and taxes [IBQ + (XINTQ*(100% – (TXTQ/PIQ)))] divided by net operating assets [CEQQ + DLCQ + DLTTQ + PSTKQ – CHEQ] Source: Compustat
LOSS	Indicator variable that takes a value of 1 if *RONA* is less than 0, and zero otherwise

APPENDIX 2, CONTINUED

Panel B, Continued

OCFVOL	Operating cash flow volatility; calculated as the rolling 12-quarter standard deviation of *CFM*, minimum 10 observations required, trimmed at [-500%,+500%] Source: Compustat
ALTMAN_Z	Altman's (1968) Z-score for financial health; calculated as (1.2***A**) + (1.4***B**) + (3.3***C**) + (0.6***D**) + (1.0***E**), where: **A** = (current assets [ACTQ] less current liabilities [LCTQ]) divided by total assets [ATQ] **B** = retained earnings [RE] divided by total assets [ATQ] **C** = earnings before interest and taxes [SALEQ – COGSQ – XRDQ – XSGA – DP] divided by total assets [ATQ] **D** = *MCAP* divided by total liabilities [LTQ] **E** = sales [SALEQ] divided by total assets [ATQ] Source: Compustat
RESTATE	Indicator variable that takes a value of 1 if a firm's earnings for the period are subsequently restated, and zero otherwise Source: Audit Analytics
QUAL_OP	Indicator variable that takes a value of 1 if the firm's auditor did not issue an unqualified opinion for the year [AUOP > 1], and zero otherwise Source: Compustat
IC_WEAK	Indicator variable that takes a value of 1 if a firm's auditor identified deficient internal controls for the year [AUOPIC > 1], and zero otherwise Source: Compustat
FLUIDITY	Text-based measure of product market competition (Hoberg, Phillips, and Prabhala, 2014) Source: Hoberg and Phillips Data Library at http://hobergphillips.tuck.dartmouth.edu
ICODE	Fama-French 30-industry classification (Fama and French, 1997) Source: Kenneth French Data Library at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
EPU	Average monthly value of U.S. economic policy uncertainty during a firm-quarter (Baker, Bloom, and Davis, 2016) Source: https://www.policyuncertainty.com/all_country_data.html

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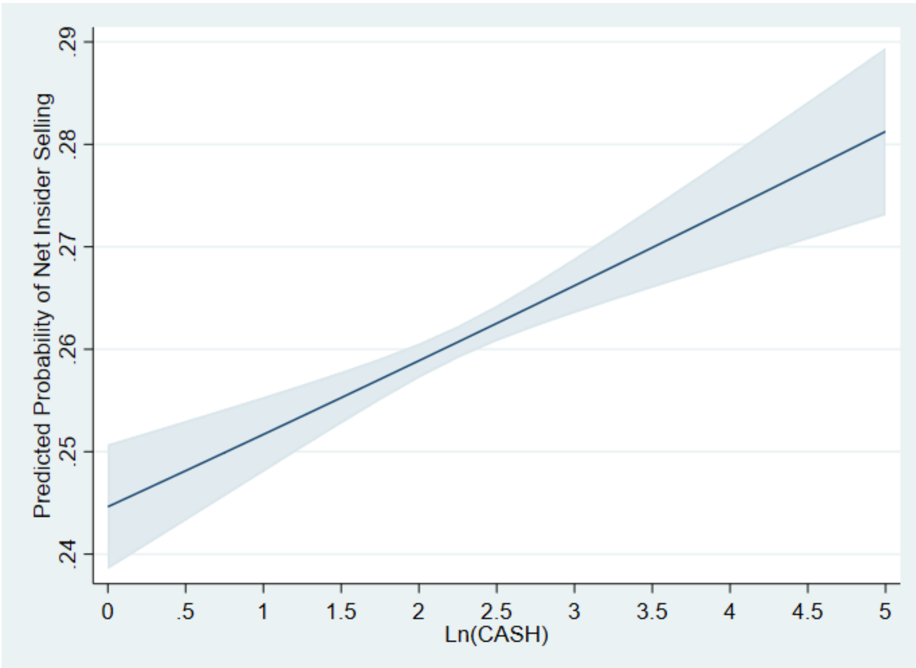
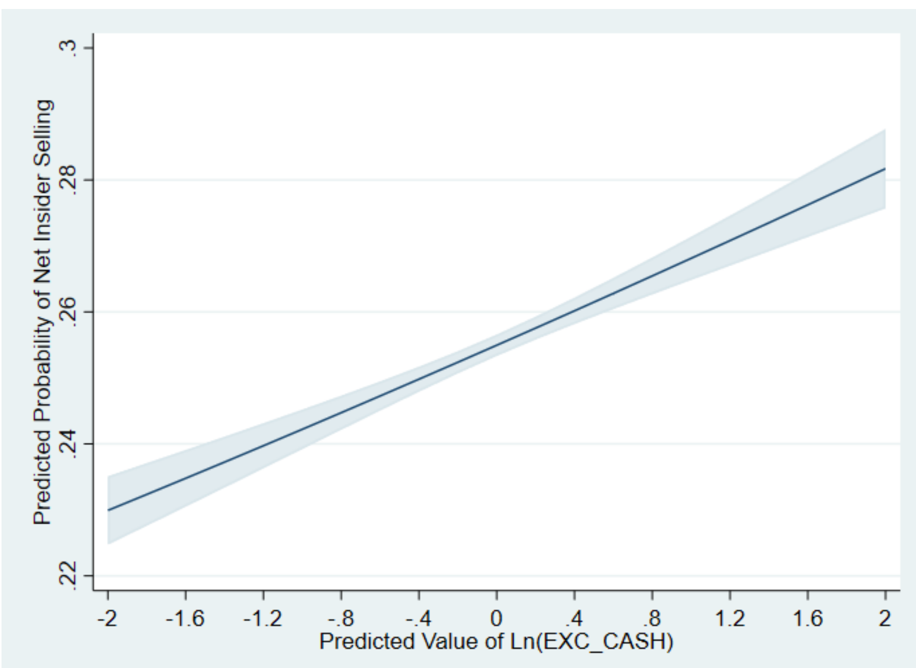
FIGURE 2.1: ADJUSTED PREDICTIONS FOR NET INSIDER SELLING BASED ON CASH HOLDINGS (Ln[*CASH]*)



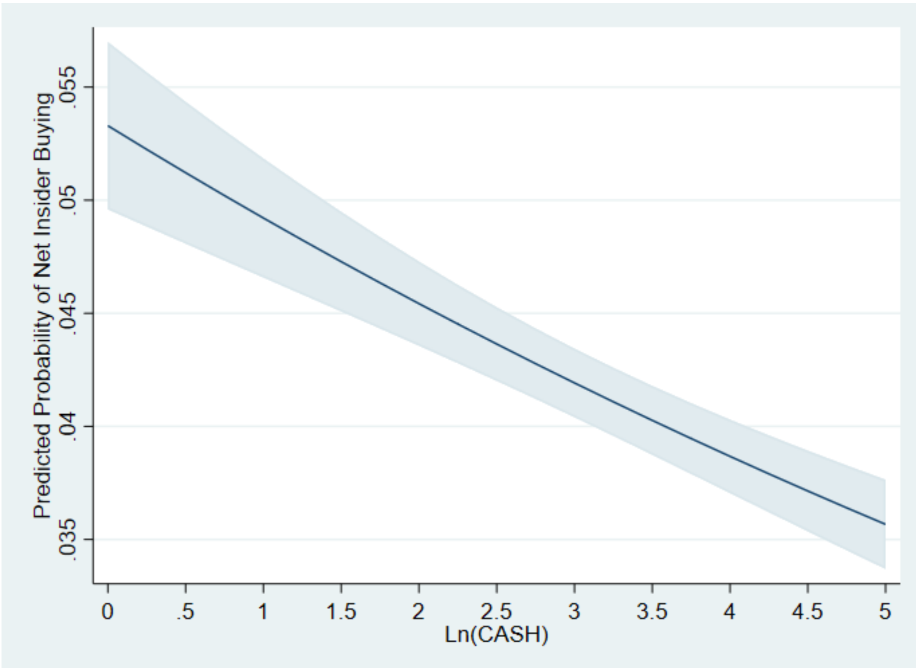
Note: Shaded areas represent 95% confidence intervals for predictions

FIGURE 2.2: ADJUSTED PREDICTIONS FOR NET INSIDER SELLING BASED ON EXCESS CASH HOLDINGS (Ln[*EXC_CASH]*)



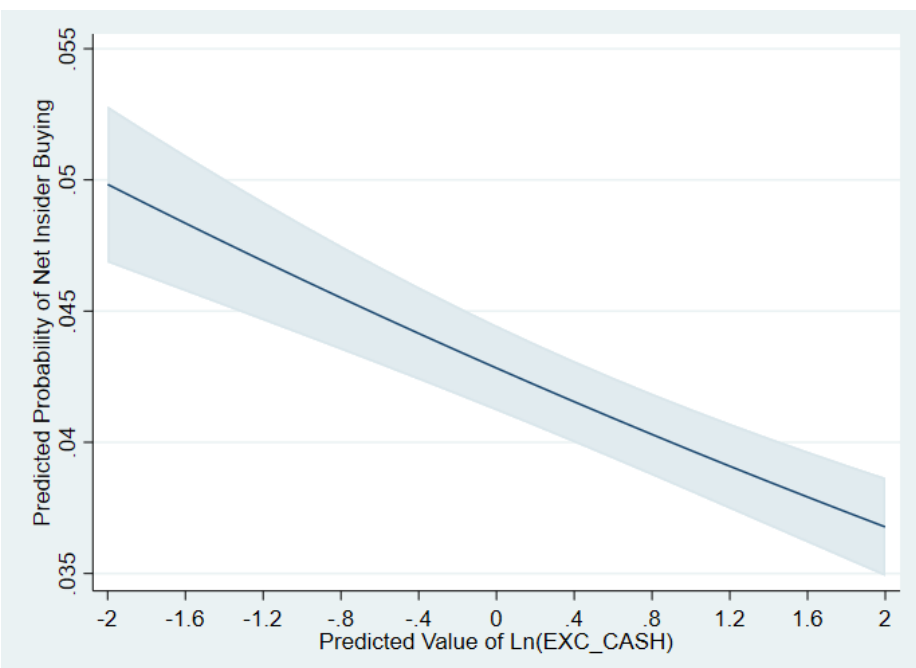
Note: Shaded areas represent 95% confidence intervals for predictions

FIGURE 2.3: ADJUSTED PREDICTIONS FOR NET INSIDER BUYING BASED ON CASH HOLDINGS (Ln[*CASH]*)



Note: Shaded areas represent 95% confidence intervals for predictions

FIGURE 2.4: ADJUSTED PREDICTIONS FOR NET INSIDER BUYING BASED ON EXCESS CASH HOLDINGS (Ln[*EXC_CASH]*)



Note: Shaded areas represent 95% confidence intervals for predictions

TABLE 2.1: SAMPLE ATTRITION

Firm-quarters between January 1996 and December 2021 with CRSP stock prices, CUSIPs, and matching Compustat GVKEYs	676,760
Less: Firms domiciled outside of Canada or the United States	(86,488)
Less: Financial services firms (Fama-French Industry #29)	(174,776)
Less: Closing prices below $2	(61,977)
Less: Insolvent firms with negative shareholders' equity	(10,800)
Less: Observations with missing data in Compustat and/or CRSP	(55,155)
Less: Observations with missing prior-period (lagged) data	(58,043)
Less: Observations with insufficient data to model excess cash holdings	(6,025)
Final sample (firm-quarters)	**223,096**
Number of unique firms	**7,839**

TABLE 2.2: ESTIMATION OF EXCESS CASH HOLDINGS

Model	DV = Ln(CASH)
BOOKMKT	-0.2572***
	(0.0115)
Ln(ASSETS)	-0.0740***
	(0.0031)
LEVERAGE	-2.1760***
	(0.0550)
RDINT	0.0004***
	(0.0001)
CAPEX	-2.1577***
	(0.1122)
NETWC	-1.7207***
	(0.0504)
CFM	-0.0563***
	(0.0082)
ALTMAN_Z	0.0194***
	(0.0018)
DIVPAY	-0.1271***
	(0.0114)
Indicator variables for quantiles of *CFVOL*	YES
Constant	3.2726***
	(0.0360)
Fixed effects	Industry X Calendar Year
Observations	223,096
R^2	0.5131
Adjusted R^2	0.5113

Notes: Cross-sectional ordinary least squares model estimated following Opler et al. (1999) and Simutin (2013). Standard errors shown in parentheses are clustered at the calendar-year level and adjusted for heteroskedasticity (White, 1980). Continuous variables are winsorized at the 1% and 99% levels for each quarter.
* $p < .10$, ** $p < .05$, *** $p < .01$

TABLE 2.3: OPPORTUNISTIC INSIDER TRADING ACTIVITY BY EXECUTIVES AND OFFICERS

Panel A: Opportunistic Net Insider Trading Activity by Year

Year	Opp. Net Purchases (#)	Opp. Net Purchases ($)*	Opp. Net Sales (#)	Opp. Net Sales ($)*
1996	509	125.0	1,106	6,970.0
1997	691	91.7	1,932	11,100.0
1998	1,087	237.0	2,338	14,300.0
1999	1,165	232.0	2,013	14,800.0
2000	992	227.0	1,997	18,400.0
2001	618	76.5	2,092	10,600.0
2002	661	83.5	2,215	9,850.0
2003	425	24.2	2,705	14,300.0
2004	397	30.2	3,133	18,000.0
2005	389	22.8	3,046	16,000.0
2006	423	44.6	3,121	14,600.0
2007	543	80.5	3,014	13,600.0
2008	779	175.0	2,282	6,490.0
2009	432	39.7	2,405	5,380.0
2010	241	19.8	2,529	9,660.0
2011	419	56.6	2,772	8,860.0
2012	373	37.6	2,858	10,900.0
2013	206	10.5	3,239	13,100.0
2014	346	45.3	3,033	10,000.0
2015	447	69.4	2,655	7,330.0
2016	332	49.0	2,651	7,180.0
2017	348	57.7	2,843	8,350.0
2018	94	6.0	939	2,410.0
2019	428	68.5	2,933	10,700.0
2020	449	81.6	2,765	16,200.0
2021	292	46.4	2,783	12,000.0
Total	**13,086**	**2,000.0**	**65,399**	**286,000.0**

* In millions of dollars, chained and rebased to 2020 using U.S. consumer prices (CPI)

TABLE 2.3, CONTINUED

Panel B: Share of Opportunistic Net Insider Trading Activity by Industry

Industry	Opp. Net Purchases*	% of Total	Opp. Net Sales*	% of Total
Food Products	49.6	2.48%	6,820.0	2.38%
Beer and Liquor	4.1	0.21%	1,790.0	0.63%
Tobacco Products	0.7	0.03%	934.0	0.33%
Recreation	64.9	3.25%	6,640.0	2.32%
Printing and Publishing	26.6	1.33%	1,410.0	0.49%
Consumer Goods	36.8	1.84%	7,860.0	2.75%
Apparel	24.7	1.24%	7,690.0	2.69%
Healthcare, Medical Equipment, and Pharmaceutical Products	212.0	10.60%	39,400.0	13.78%
Chemicals	63.0	3.15%	5,930.0	2.07%
Textiles	20.3	1.02%	485.0	0.17%
Construction and Construction Materials	69.3	3.47%	9,110.0	3.19%
Steel and Metal Works	41.5	2.08%	2,250.0	0.79%
Fabricated Products and Machinery	83.7	4.19%	12,300.0	4.30%
Electrical Equipment	24.8	1.24%	2,330.0	0.81%
Automobiles and Trucks	37.9	1.90%	3,960.0	1.38%
Aircraft, Ships, and Railroad Equipment	31.2	1.56%	3,590.0	1.26%
Precious Metals, Non-Metallic, and Industrial Metal Mining	8.7	0.44%	803.0	0.28%
Coal	8.7	0.44%	126.0	0.04%
Petroleum and Natural Gas	101.0	5.05%	11,200.0	3.92%
Utilities	31.8	1.59%	6,290.0	2.20%
Communications	57.2	2.86%	6,330.0	2.21%
Personal and Business Services	264.0	13.20%	48,200.0	16.85%
Business Equipment	214.0	10.70%	46,700.0	16.33%
Business Supplies and Shipping Containers	38.2	1.91%	2,480.0	0.87%
Transportation	57.6	2.88%	8,030.0	2.81%
Wholesale	89.2	4.46%	9,630.0	3.37%
Retail	130.0	6.50%	22,300.0	7.80%
Restaurants, Hotels, and Motels	67.0	3.35%	6,060.0	2.12%
Other 1	19.7	0.99%	1,550.0	0.54%
Other 2	117.0	5.85%	4,100.0	1.43%
Total	**2,000.0**	**100%**	**286,000.0**	**100%**

* In millions of dollars, chained and rebased to 2020 using U.S. consumer prices (CPI). Totals may not be the same as in Panel A due to rounding.

TABLE 2.4: DESCRIPTIVE STATISTICS

Panel A: Opportunistic Net Insider Purchases (n = 13,086)

	Mean	St. dev.	5th pct	25th pct	Median	75th pct	95th pct
Shares purchased	11,581	18,331	140	1,450	5,000	13,665	44,892
$ value*	$152,552	$243,955	$517	$15,696	$60,064	$182,237	$616,090
% firm shares O/S	0.07%	0.23%	<0.01%	<0.01%	0.02%	0.06%	0.30%

Panel B: Opportunistic Net Insider Sales (n = 65,399)

	Mean	St. dev.	5th pct	25th pct	Median	75th pct	95th pct
Shares sold	48,074	86,070	378	3,943	15,000	50,000	220,000
$ value*	$4,131,360	$9,138,968	$15,628	$157,409	$769,844	$3,423,487	$21,000,000
% firm shares O/S	0.21%	0.94%	<0.01%	0.01%	0.04%	0.15%	0.83%

*Panel C: Spearman Correlations** for Variables of Interest (All Firm Quarters, N = 223,096)*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$NETB\_FIRM_t$ (1)	1.00							
$NETB\_FIRM_{t-1}$ (2)	0.17	1.00						
$NETS\_FIRM_t$ (3)	-0.16	-0.06	1.00					
$NETS\_FIRM_{t-1}$ (4)	-0.06	-0.15	0.33	1.00				
$Ln(CASH_t)$ (5)	-0.05	-0.05	0.05	0.04	1.00			
$Ln(CASH_{t-1})$ (6)	-0.05	-0.05	0.05	0.04	0.95	1.00		
$Ln(EXC\_CASH_t)$ (7)	-0.03	-0.03	0.05	0.04	0.72	0.65	1.00	
$Ln(EXC\_CASH_{t-1})$ (8)	-0.03	-0.03	0.05	0.04	0.66	0.72	0.89	1.00

Panel D: Variables of Interest and Control Variables (All Firm Quarters, N = 223,096)

	Mean	**St. dev.**	**5th pct**	**25th pct**	**Median**	**75th pct**	**95th pct**
CASH	17.67%	20.54%	0.34%	2.57%	9.17%	25.60%	64.27%
Ln(CASH)	2.28	1.22	0.29	1.27	2.32	3.28	4.18
EXC_CASH	38.13%	112.23%	-78.26%	-43.27%	9.41%	83.77%	261.87%
Ln(EXC_CASH)	0.32	0.75	-1.53	-0.57	0.09	0.61	1.29
MCAP($mn*)	$6,583.6	$32,898.2	$41.1	$205.6	$759.6	$2,951.4	$24,616.7
Ln(MCAP)	6.73	1.91	3.74	5.33	6.63	7.99	10.11
BOOK_MKT	0.62	0.54	0.10	0.28	0.48	0.78	1.63
SRET	16.81%	73.93%	-54.93%	-19.14%	6.00%	35.13%	118.60%
DIVPAY	13.98%	34.68%	0	0	0	0	1
ASSETS($mn*)	$4,926.2	$13,794.6	$39.0	$205.1	$738.5	$2,951.6	$25,458.6
Ln(ASSETS)	6.71	1.91	3.69	5.33	6.61	7.99	10.14
NETWC	28.90%	20.12%	2.37%	12.62%	26.56%	42.03%	66.95%
LEVERAGE	18.42%	17.57%	0.00%	0.69%	15.41%	30.41%	51.94%
CAPEX	3.33%	4.26%	0.15%	0.81%	1.89%	4.11%	11.62%
RDINT	19.15%	118.86%	0.00%	0.00%	0.00%	6.93%	39.13%
CFM	8.45%	104.46%	-108.14%	0.65%	16.18%	39.78%	106.54%
RONA	1.00%	25.01%	-19.86%	0.26%	2.15%	4.29%	15.28%
LOSS	5.21%	15.57%	0.00%	0.26%	2.15%	4.29%	15.28%
ALTMAN_Z	3.49	6.55	-0.66	0.55	1.61	3.83	14.10
QUAL_OP	28.68%	45.23%	0	0	0	1	1
RESTATE	2.75%	16.34%	0	0	0	0	0
IC_WEAK	8.02%	27.17%	0	0	0	0	1
IND_HHI	8.76%	7.07%	3.26%	4.61%	6.89%	9.85%	23.14%

* Chained and rebased to 2020 dollars using U.S. consumer prices (CPI)
** All correlations are significant at the 1% level

TABLE 2.5: MAIN TESTS OF THE IMPACT OF CASH HOLDINGS ON INSIDER TRADING ACTIVITY

Panel A: Opportunistic Net Insider Sales; DV=NETS_FIRM$_{it}$

Model	**(1)**	**(2)**	**(3)**	**(4)**
Ln(CASH$_t$) **[H2.1, +]**	**0.0409***** **(0.0084)**	**0.0365***** **(0.0062)**		
Ln(EXC_CASH$_t$) **[H2.1, +]**			**0.1384***** **(0.0101)**	**0.0699***** **(0.0070)**
NETS_FIRM$_{t-1}$		1.1279*** (0.0351)		1.1262*** (0.0352)
Ln(MCAP)		0.2590*** (0.0070)		0.2573*** (0.0071)
BOOKMKT		-0.3154*** (0.0248)		-0.3123*** (0.0243)
SRET		0.2442*** (0.0436)		0.2436*** (0.0436)
LEVERAGE		-0.1223* (0.0640)		-0.1912*** (0.0632)
RDINT		-0.0003*** (0.0001)		-0.0002*** (0.0001)
RONA		-0.1056*** (0.0399)		-0.1253*** (0.0405)
LOSS		-0.1922*** (0.0315)		-0.1948*** (0.0312)
ALTMAN_Z		-0.0010 (0.0021)		-0.0005 (0.0021)
QUAL_OP		0.0428 (0.0269)		0.0428 (0.0267)
RESTATE		0.0901*** (0.0186)		0.0905*** (0.0187)
IC_WEAK		-0.1568*** (0.0337)		-0.1584*** (0.0340)
IND_HHI		0.5362 (1.2947)		0.5647 (1.3002)
Constant	-2.1846*** (0.0138)	-3.9089*** (0.0848)	-2.1226*** (0.0007)	-3.8283*** (0.0889)
Fixed effects	Industry X Calendar Year	Industry X Calendar Year	Industry X Calendar Year	Industry X Calendar Year
Observations	223,069	223,069	223,069	223,069
Pseudo R^2	0.0416	0.1586	0.0435	0.1589
Correctly Classified	70.75%	75.13%	70.84%	75.15%
Naïve Random Classification	58.67%	58.67%	58.67%	58.67%

TABLE 2.5, CONTINUED

Panel B: Opportunistic Net Insider Purchases; DV=NETB_FIRM$_{it}$

Model	**(1)**	**(2)**	**(3)**	**(4)**
***Ln(CASH$_t$)* [H2.2, ?]**	**-0.1522*****	**-0.0745*****		
	(0.0141)	**(0.0104)**		
***Ln(EXC_CASH$_t$)* [H2.2, ?]**			**-0.1418*****	**-0.0770*****
			(0.0119)	**(0.0109)**
NETB_FIRM$_{t-1}$		1.3972***		1.3969***
		(0.0486)		(0.0485)
Ln(MCAP)		-0.1885***		-0.1861***
		(0.0153)		(0.0153)
BOOKMKT		0.0818***		0.0897***
		(0.0242)		(0.0245)
SRET		-0.4207***		-0.4187***
		(0.0717)		(0.0718)
LEVERAGE		0.5285***		0.6645***
		(0.0772)		(0.0738)
RDINT		0.0001		0.0000
		(0.0001)		(0.0001)
RONA		0.2098***		0.1841***
		(0.0537)		(0.0546)
LOSS		0.1961***		0.1830***
		(0.0272)		(0.0264)
ALTMAN_Z		-0.0206***		-0.0227***
		(0.0029)		(0.0028)
QUAL_OP		0.0482		0.0480
		(0.0372)		(0.0373)
RESTATE		0.0341		0.0350
		(0.0337)		(0.0338)
IC_WEAK		-0.0101		-0.0059
		(0.0722)		(0.0719)
IND_HHI		-2.1475		-2.1696
		(2.0827)		(2.0875)
Constant	-1.9808***	-1.3059***	-2.2207***	-1.4651***
	(0.0203)	(0.1500)	(0.0013)	(0.1501)
Fixed effects	Industry X Calendar Year	Industry X Calendar Year	Industry X Calendar Year	Industry X Calendar Year
Observations	221,617	221,617	221,617	221,617
Pseudo R^2	0.0395	0.1011	0.0382	0.1010
Correctly classified	94.10%	94.09%	94.10%	94.09%
Naïve random classification	88.84%	88.84%	88.84%	88.84%

Notes: All models are logit models. Standard errors are clustered at the calendar-year level and shown in parentheses. The number of observations for each model may be less than the full sample size because insider trading in some industry-years can be predicted perfectly. Continuous variables are winsorized at the 1% and 99% levels for each quarter. * $p < .10$, ** $p < .05$, *** $p < .01$

TABLE 2.6: IMPACT OF CASH HOLDINGS ON INSIDER TRADING INTENSITY

Panel A: Opportunistic Insider Sales

Model	**(1)** **DV = *LN*** **(*NETS_FIRM_SH)***	**(2)** **DV = *LN*** **(*NETS_FIRM_$)***	**(3)** **DV = *LN*** **(*NETS_FIRM_SH)***	**(4)** **DV = *LN*** **(*NETS_FIRM_$)***
***Ln(CASH$_t$)* [H2.1, +]**	**0.1907***** **(0.0334)**	**0.2251***** **(0.0411)**		
***Ln*(*EXC_CASH$_t$*) [H2.1, +]**			**0.3830***** **(0.0362)**	**0.4916***** **(0.0435)**
NETS_FIRM$_{t-1}$	0.6417*** (0.0247)	0.6535*** (0.0274)	0.6402*** (0.0248)	0.6522*** (0.0275)
Constant	-21.4760*** (0.7692)	-27.3470*** (1.1529)	-21.0354*** (0.7821)	-26.8209*** (1.1778)
Controls	YES	YES	YES	YES
Fixed effects	Industry X Calendar Year	Industry X Calendar Year	Industry X Calendar Year	Industry X Calendar Year
Observations	223,096	223,096	223,096	223,096
Pseudo R^2	0.0678	0.0668	0.0680	0.0669

Panel B: Opportunistic Net Insider Purchases

Model	**(1)** **DV = *LN*** **(*NETB_FIRM_SH)***	**(2)** **DV = *LN*** **(*NETB_FIRM_$)***	**(3)** **DV = *LN*** **(*NETB_FIRM_SH)***	**(4)** **DV = *LN*** **(*NETB_FIRM_$)***
***Ln(CASH$_t$)* [H2.2, ?]**	**-0.5576***** **(0.0746)**	**-0.7635***** **(0.0927)**		
***Ln*(*EXC_CASH$_t$*) [H2.2, ?]**			**-0.5687***** **(0.0818)**	**-0.7853***** **(0.1052)**
NETB_FIRM_[SH/$]$_{t-1}$	1.2395*** (0.0518)	1.2862*** (0.0535)	1.2395*** (0.0517)	1.2862*** (0.0534)
Constant	-13.0475*** (1.0171)	-17.4935*** (1.2545)	-14.2320*** (1.0045)	-19.1153*** (1.2361)
Controls	YES	YES	YES	YES
Fixed effects	Industry X Calendar Year	Industry X Calendar Year	Industry X Calendar Year	Industry X Calendar Year
Observations	223,096	223,096	223,096	223,096
Pseudo R^2	0.0569	0.0552	0.0569	0.0552

Notes: All models are Tobit models with left censoring at zero. Standard errors are clustered at the calendar-year level and shown in parentheses. Continuous variables are winsorized at the 1% and 99% levels for each quarter. * $p < .10$, ** $p < .05$, *** $p < .01$

TABLE 2.7: DYNAMIC PANEL DATA REGRESSIONS (CHANGE MODELS)

Panel A: Opportunistic Net Insider Sales

Model	**(1)** DV = *ΔLN (NETS_FIRM_SH)*	**(2)** DV = *ΔLN (NETS_FIRM_$)*	**(3)** DV = *ΔLN (NETS_FIRM_SH)*	**(4)** DV = *ΔLN (NETS_FIRM_$)*
Ln(CASH$_{t-1, t}$)	**0.1396*****	**0.2328*****		
[H2.1, +]	**(0.0324)**	**(0.0458)**		
Ln(EXC_CASH$_{t-1, t}$)			**0.0871*****	**0.1460*****
[H2.1, +]			**(0.0227)**	**(0.0322)**
Lag(DV)	0.0894***	0.1022***	0.0893***	0.1022***
	(0.0027)	(0.0028)	(0.0027)	(0.0028)
Constant	-7.2710***	-11.7839***	-7.1068***	-11.5094***
	(0.4705)	(0.6659)	(0.4663)	(0.6599)
Controls	YES	YES	YES	YES
Observations	194,215	194,215	194,215	194,215
Chi-square statistic	3,474.6***	4,003.4***	3,470.7***	3,998.9***

Panel B: Opportunistic Net Insider Purchases

Model	**(1)** DV = *ΔLN (NETB_FIRM_SH)*	**(2)** DV = *ΔLN (NETB_FIRM_$)*	**(3)** DV = *ΔLN (NETB_FIRM_SH)*	**(4)** DV = *ΔLN (NETB_FIRM_$)*
Ln(CASH$_{t-1, t}$)	**-0.0238**	**-0.0433****		
[H2.2, ?]	**(0.0159)**	**(0.0205)**		
Ln(EXC_CASH$_{t-1, t}$)			**0.0160**	**0.0130**
[H2.2, ?]			**(0.0166)**	**(0.0214)**
Lag(DV)	0.0616***	0.0615***	0.0617***	0.0615***
	(0.0027)	(0.0027)	(0.0027)	(0.0027)
Constant	4.4880***	5.6576***	4.4419***	5.5667***
	(0.2487)	(0.3206)	(0.2463)	(0.3175)
Controls	YES	YES	YES	YES
Observations	194,215	194,215	194,215	194,215
Chi-square statistic	2,191.0***	1,959.4***	2,189.0***	1,954.3***

Notes: All models are dynamic panel models estimated using the generalized method of moments methodology (Arellano and Bond, 1991). Standard errors are calculated using the generalized method of moments method and shown in parentheses. The number of observations for each model may be less than the full sample size due to insufficient lagged data. Continuous variables are winsorized at the 1% and 99% levels for each quarter. * $p < .10$, ** $p < .05$, *** $p < .01$

TABLE 2.8: CROSS-SECTIONAL TESTS FOR IMPACT OF INDUSTRY COMPETITION

Model	**(1)** **DV =** ***NETB_FIRM***	**(2)** **DV =** ***NETS_FIRM***	**(3)** **DV =** ***NETB_FIRM***	**(4)** **DV =** ***NETS_FIRM***
Ln(CASH) Q1	**-0.0083** **(0.0073)**	**0.0142** **(0.0144)**		
Ln(CASH) Q2	**-0.0118*** **(0.0060)**	**-0.0155** **(0.0119)**		
Ln(CASH) Q3	**-0.0135**** **(0.0057)**	**-0.0130** **(0.0112)**		
Ln(CASH) Q4	**-0.0083** **(0.0056)**	**0.0179** **(0.0110)**		
Ln(CASH) Q5	**0.0123**** **(0.0056)**	**0.0023** **(0.0109)**		
Ln(EXC_CASH) Q1			**0.0015** **(0.0078)**	**0.0058** **(0.0156)**
Ln(EXC_CASH) Q2			**0.0015** **(0.0078)**	**-0.0199** **(0.0131)**
Ln(EXC_CASH) Q3			**-0.0036** **(0.0062)**	**-0.0087** **(0.0123)**
Ln(EXC_CASH) Q4			**0.0029** **(0.0061)**	**0.0093** **(0.0121)**
Ln(EXC_CASH) Q5			**0.0135**** **(0.0057)**	**-0.0040** **(0.0113)**
Constants for each partition	YES	YES	YES	YES
Controls and lagged DV	YES	YES	YES	YES
Chi-square test for differences in coefficients (*Q5 – Q1*)	**5.13**** **p = 0.0235**	**0.44** **p = 0.5095**	**1.57** **p = 0.2097**	**0.26** **p = 0.6090**
Observations	173,563	173,563	173,563	173,563
Chi-square statistic	12,519.1***	13,389.6***	12,678.2***	13,311.7***

Notes: All models are dynamic panel models estimated using the generalized method of moments methodology (Arellano and Bond, 1991). Observations are sorted into quintiles based on industry competition, measured by product market fluidity (Hoberg and Phillips, 2014). Product market fluidity data are only available through 2019. Standard errors are calculated using the generalized method of moments method and shown in parentheses. The number of observations for each model may be less than the full sample size due to insufficient lagged data. Continuous variables are winsorized at the 1% and 99% levels for each quarter. * $p < .10$, ** $p < .05$, *** $p < .01$

TABLE 2.9: CROSS-SECTIONAL TESTS FOR IMPACT OF ECONOMIC POLICY UNCERTAINTY

Model	**(1)** **DV =** ***NETB_FIRM***	**(2)** **DV =** ***NETS_FIRM***	**(3)** **DV =** ***NETB_FIRM***	**(4)** **DV =** ***NETS_FIRM***
Ln(CASH) Q1	**0.0002** **(0.0023)**	**0.0178***** **(0.0039)**		
Ln(CASH) Q2	**0.0023** **(0.0022)**	**0.0256***** **(0.0037)**		
Ln(CASH) Q3	**0.0002** **(0.0022)**	**0.0015** **(0.0037)**		
Ln(CASH) Q4	**0.0087***** **(0.0024)**	**-0.0044** **(0.0040)**		
Ln(CASH) Q5	**0.0047*** **(0.0024)**	**0.0050** **(0.0041)**		
Ln(EXC_CASH) Q1			**0.0002** **(0.0023)**	**0.0176***** **(0.0043)**
Ln(EXC_CASH) Q2			**0.0023** **(0.0022)**	**0.0194***** **(0.0041)**
Ln(EXC_CASH) Q3			**0.0002** **(0.0022)**	**0.0021** **(0.0040)**
Ln(EXC_CASH) Q4			**0.0087***** **(0.0024)**	**-0.0067** **(0.0043)**
Ln(EXC_CASH) Q5			**0.0047*** **(0.0024)**	**-0.0108**** **(0.0045)**
Constants for each partition	YES	YES	YES	YES
Controls and lagged DV	YES	YES	YES	YES
Chi-square test for differences in coefficients (*Q5 – Q1*)	**1.63** **p = 0.2013**	**8.12***** **p = 0.0042**	**2.48** **p = 0.1151**	**29.92***** **p = 0.0001**
Observations	194,215	194,215	194,215	194,215
Chi-square statistic	15,451.7***	19,918.1***	15,451.7***	19,889.1***

Notes: All models are dynamic panel models estimated using the generalized method of moments methodology (Arellano and Bond, 1991). Observations are sorted into quintiles based on the average level of U.S. economic policy uncertainty (Baker, Bloom, and Davis, 2016) during a firm-quarter. Standard errors are calculated using the generalized method of moments method and shown in parentheses. The number of observations for each model may be less than the full sample size due to insufficient lagged data. Continuous variables are winsorized at the 1% and 99% levels for each quarter. * $p < .10$, ** $p < .05$, *** $p < .01$

TABLE 2.10: CROSS-SECTIONAL TESTS FOR IMPACT OF FIRM-LEVEL INFORMATIONAL ASYMMETRY

Model	**(1)** **DV =** ***NETB_FIRM***	**(2)** **DV =** ***NETS_FIRM***	**(3)** **DV =** ***NETB_FIRM***	**(4)** **DV =** ***NETS_FIRM***
Ln(CASH) Q1	**-0.0057**** **(0.0025)**	**0.0200***** **(0.0046)**		
Ln(CASH) Q2	**-0.0061***** **(0.0022)**	**0.0102**** **(0.0041)**		
Ln(CASH) Q3	**-0.0035** **(0.0021)**	**0.0108***** **(0.0039)**		
Ln(CASH) Q4	**-0.0034** **(0.0022)**	**0.0083**** **(0.0041)**		
Ln(CASH) Q5	**0.0018** **(0.0026)**	**0.0071** **(0.0049)**		
Ln(EXC_CASH) Q1			**-0.0032** **(0.0028)**	**0.0144***** **(0.0050)**
Ln(EXC_CASH) Q2			**-0.0012** **(0.0024)**	**-0.0002** **(0.0045)**
Ln(EXC_CASH) Q3			**0.0029** **(0.0023)**	**0.0026** **(0.0043)**
Ln(EXC_CASH) Q4			**0.0032** **(0.0024)**	**-0.0018** **(0.0045)**
Ln(EXC_CASH) Q5			**0.0070**** **(0.0029)**	**-0.0018** **(0.0054)**
Constants for each partition	YES	YES	YES	YES
Controls and lagged DV	YES	YES	YES	YES
Chi-square test for differences in coefficients (*Q5 – Q1*)	**5.21***** **p = 0.0225**	**4.48**** **p = 0.0342**	**7.23***** **p = 0.0072**	**5.41**** **p = 0.0201**
Observations	193,071	193,071	193,071	193,071
Chi-square statistic	15,982.6***	18,880.6***	15,979.8***	18,870.4***

Notes: All models are dynamic panel models estimated using the generalized method of moments methodology (Arellano and Bond, 1991). Observations are sorted into quintiles based on firm-level informational asymmetry, measured by bid-ask spreads (*BA_SPREAD*). Standard errors are calculated using the generalized method of moments method and shown in parentheses. The number of observations for each model may be less than the full sample size because insider trading in some industry-years can be predicted perfectly. Continuous variables are winsorized at the 1% and 99% levels for each quarter. * $p < .10$, ** $p < .05$, *** $p < .01$

TABLE 2.11: IMPACT OF INSIDER TRADING ACTIVITY AND CASH HOLDINGS ON FUTURE RESEARCH AND DEVELOPMENT INTENSITY

Model	**(1)** **DV = $RDINT_{t+1}$**	**(2)** **DV = $RDINT_{t+2}$**	**(3)** **DV = $RDINT_{t+3}$**	**(4)** **DV = $RDINT_{t+4}$**
NETB_FIRM x Q1	**-0.3468** **(1.1255)**	**-0.2988** **(1.1752)**	**-0.1187** **(1.1442)**	**0.2481** **(1.1547)**
NETB_FIRM x Q2	**-0.4779** **(1.1753)**	**0.3944** **(1.2182)**	**0.2665** **(1.1831)**	**-0.3029** **(1.1938)**
NETB_FIRM x Q3	**0.1519** **(1.2337)**	**-0.8007** **(1.2795)**	**0.5126** **(1.2449)**	**-0.8488** **(1.2532)**
NETB_FIRM x Q4	**-0.7356** **(1.2881)**	**-2.1943** **(1.3397)**	**-1.0462** **(1.3062)**	**-0.0004** **(1.3124)**
NETB_FIRM x Q5	**4.5822***** **(1.3805)**	**-2.8397**** **(1.4428)**	**2.9529**** **(1.4127)**	**2.3895*** **(1.4290)**
NETS_FIRM x Q1	**0.1259** **(0.6729)**	**-0.0749** **(0.6937)**	**0.0686** **(0.6725)**	**0.1865** **(0.6740)**
NETS_FIRM x Q2	**-0.0160** **(0.6466)**	**-0.2201** **(0.6662)**	**0.2133** **(0.6444)**	**0.0286** **(0.6455)**
NETS_FIRM x Q3	**-0.3641** **(0.6426)**	**-0.1083** **(0.6632)**	**-0.3044** **(0.6411)**	**-0.3878** **(0.6421)**
NETS_FIRM x Q4	**0.6284** **(0.6499)**	**-1.0812** **(0.6707)**	**0.4899** **(0.6484)**	**0.3250** **(0.6502)**
NETS_FIRM x Q5	**0.0301** **(0.6973)**	**1.5596**** **(0.7197)**	**0.1106** **(0.6967)**	**-1.0601** **(0.6992)**
Constants for each partition	YES	YES	YES	YES
Controls and lagged DV	YES	YES	YES	YES
Chi-square test for differences in coefficients (*NETB_FIRM Q5 – Q1*)	**7.67***** **p = 0.0056**	**1.87** **p = 0.1718**	**2.86*** **p = 0.0909**	**1.36** **p = 0.2434**
Chi-square test for differences in coefficients (*NETS_FIRM Q5 – Q1*)	**0.01** **p = 0.9212**	**2.68** **p = 0.1018**	**0.01** **p = 0.9212**	**1.65** **p = 0.1990**
Observations	185,051	185,051	185,051	185,051
Chi-square statistic	6,441.9***	21,558.3***	18,838.3***	22,540.4***

Notes: All models are dynamic panel models estimated using the generalized method of moments methodology (Arellano and Bond, 1991). Observations are sorted into quintiles based on cash holdings (Ln[*CASH*]). The number of observations for each model may be less than the full sample size due to insufficient lagged data. Standard errors are calculated using the generalized method of moments method and shown in parentheses. Continuous variables are winsorized at the 1% and 99% levels for each quarter. * $p < .10$, ** $p < .05$, *** $p < .01$

TABLE 2.12: IMPACT OF INSIDER TRADING ACTIVITY AND CASH HOLDINGS ON FUTURE PROFITABILITY AND OPERATING CASH FLOW MARGINS

Model	**(1)** **DV = ROA_{t+1}**	**(2)** **DV = ROA_{t+4}**	**(3)** **DV = CFM_{t+1}**	**(4)** **DV = CFM_{t+4}**
Ln(CASH)	**-0.0015*****	**0.0015*****	**-0.0751*****	**-0.0270****
	(0.0002)	**(0.0002)**	**(0.0142)**	**(0.0123)**
NETB_FIRM	**0.0009*****	**0.0001**	**0.0091**	**0.0091**
	(0.0003)	**(0.0004)**	**(0.0213)**	**(0.0188)**
NETS_FIRM	**-0.0003***	**-0.0000**	**0.0036**	**-0.0019**
	(0.0002)	**(0.0002)**	**(0.0116)**	**(0.0097)**
LAG (DV)	0.1629***	0.1403***	0.0280***	0.1945***
	(0.0036)	(0.0042)	(0.0034)	(0.0029)
Constant	0.2433***	0.0822***	-2.0636***	-0.1313
	(0.0040)	(0.0047)	(0.2446)	(0.2135)
Controls	YES	YES	YES	YES
Observations	185,051	142,520	185,051	142,520
Chi-square statistic	11,356.1***	3,588.8***	1,812.7***	13,670.9***

Notes: All models are dynamic panel models estimated using the generalized method of moments methodology (Arellano and Bond, 1991). Standard errors are calculated using the generalized method of moments method and shown in parentheses. The number of observations for each model may be less than the full sample size due to insufficient lagged data. Continuous variables are winsorized at the 1% and 99% levels for each quarter. * $p < .10$, ** $p < .05$, *** $p < .01$

TABLE 2.13: IMPACT OF INSIDER TRADING ACTIVITY AND CASH HOLDINGS ON ABNORMAL STOCK RETURNS

Model	**(1)** **DV = *CAR_{t+1}***	**(2)** **DV = *CAR_{t+2}***	**(3)** **DV = *CAR_{t+3}***	**(4)** **DV = *CAR_{t+4}***
NETB_FIRM x Q1	**0.0213***** **(0.0061)**	**0.0462***** **(0.0097)**	**0.0358***** **(0.0098)**	**0.0774***** **(0.0150)**
NETB_FIRM x Q2	**0.0289***** **(0.0072)**	**0.0599***** **(0.0114)**	**0.0501***** **(0.0123)**	**0.0847***** **(0.0162)**
NETB_FIRM x Q3	**0.0300***** **(0.0064)**	**0.0539***** **(0.0108)**	**0.0536***** **(0.0117)**	**0.0858***** **(0.0164)**
NETB_FIRM x Q4	**0.0318***** **(0.0078)**	**0.0569***** **(0.0116)**	**0.0555***** **(0.0129)**	**0.0803***** **(0.0162)**
NETB_FIRM x Q5	**0.0407***** **(0.0080)**	**0.0788***** **(0.0142)**	**0.0688***** **(0.0159)**	**0.1251***** **(0.0230)**
NETS_FIRM x Q1	**-0.0051*** **(0.0029)**	**-0.0077** **(0.0051)**	**-0.0083** **(0.0052)**	**-0.0116** **(0.0073)**
NETS_FIRM x Q2	**-0.0069**** **(0.0029)**	**-0.0076*** **(0.0045)**	**-0.0073** **(0.0050)**	**-0.0130*** **(0.0068)**
NETS_FIRM x Q3	**-0.0072***** **(0.0028)**	**-0.0116**** **(0.0045)**	**-0.0128**** **(0.0051)**	**-0.0124** **(0.0076)**
NETS_FIRM x Q4	**-0.0121***** **(0.0031)**	**-0.0223***** **(0.0047)**	**-0.0152***** **(0.0050)**	**-0.0312***** **(0.0073)**
NETS_FIRM x Q5	**-0.0169***** **(0.0046)**	**-0.0267***** **(0.0083)**	**-0.0308***** **(0.0082)**	**-0.0455***** **(0.0145)**
Constants for each partition	YES	YES	YES	YES
Controls and lagged DV	YES	YES	YES	YES
Fixed Effects	Industry X Calendar Year	Industry X Calendar Year	Industry X Calendar Year	Industry X Calendar Year
Chi-square test for differences in coefficients (*NETB_FIRM Q5 – Q1*)	**4.18**** **p = 0.0413**	**4.18**** **p = 0.0414**	**3.20*** **p = 0.0739**	**3.25*** **p = 0.0717**
Chi-square test for differences in coefficients (*NETS_FIRM Q5 – Q1*)	**4.69**** **p = 0.0307**	**4.06**** **p = 0.0442**	**5.20**** **p = 0.0228**	**4.60**** **p = 0.0323**
Observations	163,990	163,837	163,200	161,582
R^2	0.1050	0.1628	0.1471	0.2135
Adjusted R^2	0.1046	0.1624	0.1467	0.2131

Notes: All models are ordinary least squares models. The number of observations for each model may be less than the full sample size due to insufficient data needed to computer abnormal stock returns. Standard errors are clustered at the calendar-year level and shown in parentheses. Continuous variables are winsorized at the 1% and 99% levels for each quarter. * $p < .10$, ** $p < .05$, *** $p < .01$

Chapter 3: The Big 5 Personality Characteristics and Insider Trading

3.1 INTRODUCTION

This study addresses two research questions. First, do insiders' personality characteristics impact their propensity to trade? Second, do insiders' personality characteristics impact their ability to trade profitability? In their development of upper echelons theory, Hambrick and Mason (1984) argue that researchers should incorporate executive heterogeneity into their empirical models because "executives' experiences, values, and personalities greatly influence their interpretations of the situations they face and, in turn, affect their choices" (Hambrick, 2007, p. 334). According to Hanlon et al., (2022), individual differences do matter, and that "Under this framework, the supply of accounting information can be influenced by the traits of managers, and the demand for accounting information can be shaped by investor sentiment" (p. 1152). Personality characteristics are one set of features that are unique to individuals, and the "Big 5" traits (Costa and McCrae, 1985, 1992) form the dominant theoretical framework for research on personality characteristics (Goldberg and Rosolack, 1994; Jadlow and Mowen, 2010; Harrison et al., 2019). These traits consist of openness, conscientiousness, extraversion, agreeableness, and neurotisicm[57]. Of these traits, I focus on conscientiousness because it is the most closely associated with behaviour (Pytlik Zillig et al., 2002)[58]. I follow Hrazdil et al. (2020, 2021) and Mahmoudian et al. (2021) and use Chief Executive Officer (CEO) Big 5 personality data that are machine-learned by the IBM Watson Personality Insights service ("Watson") from the transcripts of earnings conference calls.

Using a sample of 17,632 firm-years at 2,953 companies, I find that more conscientious CEOs are more likely to be net buyers of their firms' shares and purchase shares with more intensity. These findings are robust to different model specifications that attempt to correct for endogeneity and the fact that insider trading is autocorrelated and personality characteristics are largely

[57] McCrae and Costa (1987, p.85) and John and Srivastava (1999, p. 113) provide taxonomies of adjectives associated with each Big 5 trait. Costa and McCrae (1992, p. 654) provide an inventory of facets or factors that are most closely linked to each Big 5 trait.
[58] High-conscientious individuals have a strong sense of duty (Costa and McCrae, 1992), act deliberately and thoughtfully (John and Srivastava, 1999), are careful and scrupulous (McCrae and Costa, 1987), and strive for orderliness and social conformity (Gough, 1987).

invariant over time. I also find that risk tolerant CEOs are more likely to be net sellers of their firms' shares, and less likely to be net buyers of their firms' shares.

This study contributes to the academic literature in at least two ways. First, I add to the literature on insider trading. Hillier et al. (2015) note that "we still know little about the extent to which insiders' personal characteristics affect returns following their trades" (p. 150) and, by extension, the personal characteristics that drive insiders to trade in the first place. They conclude that "Individual trading behaviors thus seem to be deeply rooted in personalities" (p. 151), and that "trading performance is closely aligned to the abilities and character of individual insiders" (ibid.). This claim is supported by recent work which demonstrates a relationship between insider trading and individual attitudes such as overconfidence (Malmiender and Tate, 2005), materialism (Bushman et al., 2018), recklessness and rebelliousness (Davidson et al., 2019). However, while studies correlating individual attitudes or behaviour to insider trading support the notion that executive heterogeneity matters, there remains a gap in terms of our understanding of the link between insider trading and the innate personality characteristics that drive behaviour. I fill this gap with my findings that conscientiousness is positively related to insider buying propensity and intensity.

Second, I answer Plöckinger et al.'s (2016) call for research that "more closely investigate[s] the magnitudes of managerial influence and more strongly utilize[s] interdisciplinary research approaches" (p. 56). In so doing, I also contribute to a growing body of literature in business studies that explores relationships between the Big 5 personality characteristics and corporate decision-making[59]. What distinguishes insider trading from corporate decisions, however, is that: 1) there is a difference in the access to information of insiders vs. outsiders (i.e. an informational edge exists); 2) there are incentives to exploit said private information by adding or reducing personal exposure to firms without doing anything to the firms themselves; and, 3) there are harsh penalties for doing so in a haughty and brazen manner (Bainbridge, 1995).

[59] For example, Colbert et al. (2014), Gow et al. (2016), Benische et al. (2019), Harrison et al. (2019, 2020), Hrazdil et al. (2020, 2021), and Mahmoudian et al. (2021).

In addition to the contributions I make to the extant bodies of literature on insider trading and firms' cash holdings and liquidity management, I provide insights that are relevant to practice. Guay et al. (2022) remark that insider trading restrictions are not one-size-fits-all and vary according to firm-level informational asymmetry, the strength of external monitoring, and executives' liquidity needs. Given my findings that CEOs' personalities impact insider trading activity, it would not be unreasonable to expect that the effectiveness of firms' insider trading policies would depend on how well they are tailored to match individual executives' personalities. In a similar vein, regulators such as the U.S. Securities and Exchange Commission (SEC) could use executive personality as a marker for insider trading risk to help better focus their efforts to catch malevolent actors, as well as more generally to better understanding the information dynamics that surround insider trading.

In Section 2, I present my review of the related literature on upper echelons theory and insider trading and develop my hypotheses. I detail my research design and empirical approach in Section 3. In Section 4, I share the results of my findings. In Section 5, I discuss implications for practitioners and conclude the paper.

3.2 LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

3.2.1 Upper Echelons Theory and Insider Trading

In their development of upper echelons theory, Hambrick and Mason (1984) argue that researchers should incorporate executive heterogeneity into their empirical models because "executives' experiences, values, and personalities greatly influence their interpretations of the situations they face and, in turn, affect their choices" (Hambrick, 2007, p. 334). This view runs counter to the neoclassical and agency views of the firm and its managers, the latter of whom are viewed as personal wealth maximizers who differ only in the degrees to which they are risk averse[60]. In addition, if managers are, indeed, rational and relatively homogeneous in their preferences and strategic decisions, then evidence of managers' personal influence and styles on

[60] See, for example, Bronfenbrenner, Sichel, and Gardner (1990), Lieberson and O'Connor (1972), and Mas-Colell, Whinston, and Green (1995).

financial reporting – a highly regulated activity – should for all intents and purposes not exist. However, a large and still growing body of empirical work points to the likelihood that individual differences do matter, and that "Under this framework, the supply of accounting information can be influenced by the traits of managers, and the demand for accounting information can be shaped by investor sentiment" (Hanlon et al., 2022, p. 1152). Indeed, in their survey of the literature on corporate financial reporting, Plöckinger et al. (2016) find that executives' personality characteristics are related to various facets of financial reporting. They note that:

> It seems more probable at first blush that managerial style and influence are more prominent in the less regulated field of corporate strategic decisions than in the highly regulated field of financial reporting. That is, accounting standards set limits on the impact of managerial idiosyncrasies. Still, influence can be exerted even in the presence of regulations, either (1) systematically by pursuing a conservative or aggressive accounting style […] or (2) opportunistically by managing earnings upward or downward whenever this seems beneficial. (p. 57)

The notion that insiders exercise their informational advantage for personal gain is well established in academic literature (Ravina and Sapienza, 2010; Cohen, Malloy, and Pomorski, 2012)[61]; however, researchers have only recently begun to investigate the impacts of executive heterogeneity on the propensity to engage in insider trading and subsequent trading performance. For example, Jia et al. (2014) examine the relationship between male CEOs' facial masculinity and find a positive connection with opportunistic insider trading. Bushman et al. (2018) use the ownership of luxury goods as a proxy for materialism and find a positive association with insider trading activity among bank CEOs. Davidson et al. (2019) find that executives who have a penchant for flouting rules, as evidenced by legal records, are more likely to engage in opportunistic insider trading than their peers and earn larger profits on these trades. Clacher et al.

[61] Foundational work in this sphere includes, but is not limited to, Lorie and Niederhoffer (1968), Jaffe (1974), Seyhun (1986, 1988), Rozeff and Zaman (1988), Lin and Howe (1990), Bettis, Vickery, and Vickery (1997), Lakonishok and Lee (2001), and Marin and Olivier (2008), among others, provide evidence in support of this claim. Seyhun (1998) packages earlier work in this area and presents several actionable strategies for investors to realize significant abnormal returns.

(2021) find that common gender insiders cluster their trades more frequently and earn higher abnormal returns. Hillier et al. (2015) find that the individual managerial styles captured using insider fixed effects dominate firm-level features in models that link insider trade performance to executives, and that gender and age are associated with post-trade performance. They surmise that "Individual trading behaviors thus seem to be deeply rooted in personalities […] and consistent with a signaling hypothesis, it may also be the case that corporate insiders with certain characteristics choose to personally signal that their firm's stock price is abnormally high or low" (Hillier et al., 2015, p. 151).

3.2.2 Hypothesis Development

The "Big 5" traits (Costa and McCrae, 1985, 1992) form the dominant theoretical framework for research on personality characteristics (Goldberg and Rosolack, 1994; Jadlow and Mowen, 2010; Harrison et al., 2019). These traits consist of openness, conscientiousness, extraversion, agreeableness, and neurotisicm[62]. Of these traits, conscientiousness, is the most closely associated with behaviour, while other traits are more closely related to affect or cognition (Pytlik Zillig et al., 2002). High-conscientious individuals have a strong sense of duty (Costa and McCrae, 1992), act deliberately and thoughtfully (John and Srivastava, 1999), are careful and scrupulous (McCrae and Costa, 1987), and strive for orderliness and social conformity (Gough, 1987).

In the ordinary course of business, insider buying is generally viewed positively in the public sphere, cast as a "positive omen" (Mladjenovic, 2016) and "a signal for outside investors to follow suit" (McClure, 2022). Legendary investor Peter Lynch wrote that "Insiders might sell their shares for any number of reasons, but they buy them for only one: they think the price will rise" (Lynch, 1989, p. 136). Indeed, when insiders buy shares and hold onto them, they further concentrate their personal portfolios and thus send a costly signal regarding their positive outlook for their employers (Bagnoli and Khanna, 1992). Contrary to popular belief, while insiders do earn abnormal returns on purchases, the dollar amount of these profits is small,

[62] McCrae and Costa (1987, p.85) and John and Srivastava (1999, p. 113) provide taxonomies of adjectives associated with each Big 5 trait. Costa and McCrae (1992, p. 654) provide an inventory of facets or factors that are most closely linked to each Big 5 trait.

averaging $12,000 per year, which amounts to under 4% of their salaries (Cziraki and Gider, 2021). Average abnormal profits are even smaller, at only $464 (Cziraki and Gider, 2021). Moreover, the SEC's enforcement actions related to insider purchases are primarily related to stock tips where insiders release material non-public information to outsiders and trading around merger announcements, indicating a tacit acceptance of (or inability to prosecute) insiders who signal their general optimism about their firms' prospects[63]. In summary, if insider buying is generally viewed as "good", then more conscientious executives, who strive for orderliness and social conformity (Gough, 1987) should be more favourable to insider buying, which leads to the following hypothesis:

H3.1: More conscientious CEOs are more likely to engage in insider buying activity.

As noted in the Introduction, stakeholders within the financial ecosystem of publicly traded firms generally view insider selling unfavourably: News media outlets paint large-block insider selling as scandalous and the SEC and other regulators vigorously pursue enforcement actions to punish those who engage in insider selling prior to the release of bad news[64]. Given the potential reputational and legal fallout, it comes as no surprise that firms actively and voluntarily implement policies with the goal of curbing insider trading. Empirical research across various settings supports the idea that people who are less conscientious are more likely to engage in deviant or behaviour (Salgado, 2002; Berry et al., 2007). For example, Egan and Taylor (2010) find that individuals who score lower on conscientiousness are more likely to shoplift and engage in other unethical consumer behaviour. The results of Hastings and O'Neill's (2009) survey suggest that lower conscientiousness is associated with more frequent instances of workplace deviance. Giluk and Postlethwaite (2015) survey the literature on academic dishonesty and conclude that "unethical academic behaviors such as cheating, plagiarism, or unauthorized help" (p. 59) are negatively related to conscientiousness. With respect to white collar crime, Collins and Schmidt (1993) find that individuals who are more tolerant, responsible, and have greater self-control (all facets of conscientiousness), are less likely to be incarcerated. If, indeed, insider selling is morally wrong (Green, 2006) and unethical (Klaw and Mayer, 2019), then more

[63] See https://www.sec.gov/litigation/litreleases.htm
[64] Ibid.

conscientious executives should be more averse to insider selling, which leads to the following hypothesis:

H3.2: More conscientious CEOs are less likely to engage in insider selling activity.

3.3 RESEARCH DESIGN AND SAMPLE CONSTRUCTION

3.3.1 Measuring the Big 5 Personality Characteristics

I follow Hrazdil et al. (2020, 2021) and Mahmoudian et al. (2021) and use CEO Big 5 personality data that are machine-learned by the IBM Watson Personality Insights service ("Watson"). Watson "infers" personality characteristics from text[65]. As in the above studies, CEOs' Big 5 personality characteristics (Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism) are measured using remarks during the question-and-answer (Q&A) sessions of quarterly earnings conference call transcripts as inputs[66]. Watson can measure Big 5 personality characteristics for blocks of text that are 100 words or longer. I focus on CEOs because they are the lead decision-makers (Graham et al., 2013) and because they tend to speak the most on conference calls. I use the Q&A sections of earnings conference calls because they contain information that is voluntarily disclosed (Davis et al., 2015) and valuable to capital market participants (Price et al., 2012). In addition, executives' remarks in the Q&A section are less likely to be scripted and are thus more suitable for personality analysis due to their relative spontaneity (Malhotra et al., 2018; Matsumoto et al., 2011).

3.3.2 Data and Sample Construction

In Table 3.1, I present details about my sample. I begin with 78,200 firm-year observations between 2005 and 2017 that have stock prices in CRSP and have associated CUSIP[67] numbers and matching GVKEYs in Compustat. I remove observations for firms domiciled outside of Canada and the United States and companies in the financial services sector (Fama-French

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[65] For further details on how the software works, please refer to Hrazdil et al. (2019) and https://cloud.ibm.com/docs/personality-insights? topic=personality-insights-science

[66] I am grateful to Ming Liu and Desmond Tsang for sharing these data. Conference call transcripts are obtained from seekingalpha.com.

[67] Committee on Uniform Securities Identification Procedures. See https://www.investor.gov/introduction-investing/investing-basics/glossary/cusip-number.

industry code 28) because it includes entities such as hedge funds, closed-end funds, royalty flow-through companies, pensions, whose primary activity is to manage portfolios of investments in other firms. I then drop observations with stock prices below $2 as these are at risk of being delisted and observations for firms that have negative shareholders' equity. Finally, I drop observations with missing data from Compustat that prevent the calculation of one or more control variables and/or their lagged values, and observations with missing or insufficient data to estimate the Big 5 personality characteristics. My final sample contains 17,632 firm-quarter observations from 2,953 unique firms.

[Insert Table 3.1 about here]

I source insider trade data from the Thomson Reuters insider filings database and collect firm fundamental data and stock prices from the matched CRSP/Compustat database. I restrict my insider trading sample to include only those line items that are cleansed by the data vendor[68] and classified as open-market purchases or sales[69] and then aggregate line items by firm[70], by insider, by day according to the dates that trades are filed with the SEC. For each filing, I identify the person making the trade and classify them based on their position at the company. I distinguish between CEOs and equivalents (*_CEO*), other company executives (*_CXO*), and all other filers, which include independent directors and large blockholders[71]. I compute the total net dollar value and number of shares involved in each case.

I then aggregate insider trading activity by fiscal year to code my dependent variables, $NETB\_CEO_{it}$ and $NETS\_CEO_{it}$. Firms that have net insider buying activity by executives other than the CEO (i.e. when the total number of shares purchased exceeds the total number of shares sold) are coded as $NETB\_CXO_{it} = 1$ and firms that have net insider selling activity by non-CEO

[68] Cleanse codes A or S.

[69] The trade codes that I classify as open-market purchases are P and L. The trade codes that I classify as open-market sales are F, I, and S.

[70] I differentiate firms by 6-digit CUSIP because it is possible for companies to issue several classes of tradable securities.

[71] I classify insiders with a role code of "CEO" as CEO, those with a role code of "CFO" or "C" (controller) as CFO, and those with role codes of "O", "CI", "CO", "CT", "EVP", "OB", "OT", "P", "SVP", "GC", "C", "F", "M", and "OE" as other executives, with the proviso that the latter do not occupy a CEO, CFO, or controller role in the company.

executives are coded as $NETS\_CXO_{it} = 1$. Firms that have zero net insider trading activity by CEOs receive values of zero for $NETB\_CEO_{it}$ and $NETS\_CEO_{it}$. Similarly, firms that have zero net insider trading activity by non-CEOs executives receive values of zero for $NETB\_CXO_{it}$ and $NETS\_CXO_{it}$.

3.3.3 Empirical Model

To test my main hypotheses, I run the following panel logit regression for insider purchases:

$$\begin{aligned} P(NETB\_CEO_{it}) = \; & \alpha_0 + \Sigma(\alpha_i\text{*Big 5 Personality Characteristics}) + \Sigma(\beta_i\text{*}CONTROLS) + \\ & \Sigma(\gamma_k\text{*Industry Indicator Variables}) + \\ & \Sigma(\tau_t\text{*Year Indicator Variables}) + \varepsilon; \qquad (3) \end{aligned}$$

My main variables of interest are *CEO_OPEN*, *CEO_CONS*, *CEO_EXTRA*, *CEO_AGREE*, and *CEO_NEUR*. Raw scores for each personality characteristic output from Watson range from zero to one; however, to facilitate discussion, I standardize personality scores to have a mean of zero and a standard deviation of one. I also run a similar panel logit regression for opportunistic selling activity (*NETS_CEO*). I expect the coefficient for *CEO_CONS* to be positive for insider purchases and negative for insider sales. I also consider alternate model specifications using insider trading intensity based on net number of shares traded ($NETB\_[CEO/CXO\_SH]_{it}$ and $NETS\_[CEO/CXO]\_SH_{it}$) and their associated dollar values in constant 2020 dollars ($NETB\_[CEO/CXO\_\$]_{it}$ and $NETS\_[CEO/CXO]\_\$_{it}$). I present additional detailed explanations for each main variable in Panel A of Appendix 3.

I control for factors that are known to influence insider trading activity including the natural logarithm of firm assets in constant 2020 dollars (*Ln*(*ASSETS)*), the book-to-market ratio (*BOOKMKT*), raw stock returns over the preceding 12 months (*SRET*), leverage (*LEVERAGE*), research and development (R&D) intensity (*RDINT*), profitability (*RONA* and *LOSS*), probability of bankruptcy (*ALTMAN_Z*), the presence of a qualified audit opinion (*QUAL_OP*), and weak internal controls (*IC_WEAK*). I include industry and calendar year fixed effects to mitigate the impact of unobserved factors on my results. I present detailed explanations for each control variable in Panel B of Appendix 3.

3.3.4 Descriptive Statistics

I present a frequency table for insider trades by category and by calendar year in Table 2. Open-market insider purchases are relatively rare, with under 10% of firm-years counting net insider buying activity by CEOs. Open-market net insider sales occur much more frequently compared to open-market net purchases and make up approximately 25% of the firm-years in my sample and 72% of firm-years during which CEOs trade.

[Insert Table 3.2 about here]

In Table 3.3, I present descriptive statistics. The average (median) net amount sold of $7.75 million ($2.14 million) for firm-years with net selling by CEOs is approximately 28 times as large as the average (median) firm-year with net purchase activity, consistent with the findings of prior researchers. In addition, close to 90% of net insider trading activity by CEOs is relatively small relative to total firm value, and accounts for less than 0.25% of a firm's shares outstanding. Relative to sales, purchases are more concentrated in firms that are smaller, have lower retained earnings (which cumulate over time), are less profitable, have lower book-to-market ratios, and have worse trailing 52-week returns. I do not find significant differences in leverage and R&D intensity in firm-quarters that have opportunistic buying activity versus firm-quarters that have opportunistic selling activity, but do find a slightly higher incidence of qualified audit opinions and internal control weaknesses. With respect to personality characteristics, I find that three of the five measures – *CEO_CONS*, *CEO_AGREE* and *CEO_NEUR* – are strongly correlated with each other.

[Insert Table 3.3 about here]

3.4 ANALYSIS AND RESULTS

3.4.1 Main Tests

Table 3.4 shows baseline results of the main tests. Panel A contains the test results for the variable of interest related to insider buying, *CEO_CONS* (panel A, model 1, $\alpha_1 = 0.1574$, $p < 0.01$) which is significant and supports H1. The effects are attenuated but not subsumed by control variables (model 5). With respect to marginal effects, a one standard deviation increase in *CEO_CONS* from its mean results in an 11% higher predicted probability[72] for *NETB_CEO* (see Figure 1). Panel B of Table 3.4 contains the test results for the association between *CEO_CONS* and insider selling. While in the reduced models, *CEO_CONS* is significant (panel B, model 1, $\alpha_1 = -0.1767$, $p < 0.01$), the effect of *CEO_CONS* on *NETS_CEO* is subsumed by control variables (Panel B, model 5) and is no longer significant.

[Insert Table 3.4, Figure 3.1, and Figure 3.2 about here]

Next, Table 3.5 presents results of tests of the impact of *CEO_CONS* on net insider buying intensity. For the dependent variables, I use both the natural logarithm of one plus the net number of shares purchased by CEOs during the year (*NETB_CEO_SH*; model 1), and the natural logarithm of one plus the net dollar value of executives' share purchases during a firm quarter (*NETB_CEO_$*; model 2). Consistent with the main tests, *CEO_CONS* is positively related to both *NETB_CEO_SH* and *NETB_CEO_$*. When compared to the relatively small average size of net insider buys, the economic impact of *CEO_CONS* is meaningful, which further supports H1. Specifically, a one standard deviation increase in *CEO_CONS* from its mean results in 20,400 more shares purchased ([e^1.0157 – 1] * 11,581), an increase of $851,000 ([e^1.0157 – 1] * $271,909). Also consistent with the main tests, I do not find a significant relationship between *CEO_CONS* and insider selling intensity.

[Insert Table 3.5 about here]

Although baseline results suggest that *CEO_CONS* is positively related to net insider buying, the logit and Tobit regression results may be misleading because of potential endogeneity in the sample. Because insider trading is autocorrelated and personality characteristics are largely time invariant, modelling the relation between insider trading and *CEO_CONS* could be challenging if there is a feedback loop between insider trading and *CEO_CONS*. To address this concern, I run dynamic panel data regressions (Arellano and Bond, 1991) to test whether changes in

[72] (0.101 – 0.091) / (0.091)

CEO_CONS are associated with changed in insider trading activity[73]. Table 3.6 shows the results of these regressions. Consistent with evidence shown so far, there are significant relationships between *CEO_CONS* and net insider buying activity (*NETB_CEO*) and intensity (*NETB_CEO_SH* and *NETB_CEO_$*). While the effect sizes in the dynamic panel models are slightly smaller than in the baseline regressions, they remain highly significant, which helps to alleviate concerns that my results are driven by autocorrelation or endogeneity. However, the relationships between *CEO_CONS* and net insider selling activity and intensity remain non-significant.

[Insert Table 3.6 about here]

3.4.2 Additional Tests

I create personality constructs using combinations of the Big 5 personality characteristics and analyze their relationships with opportunistic insider trading activity. Insider trading, especially insider selling, is risky behaviour because of the legal risk involved. It is therefore plausible to expect that CEOs with higher risk tolerance will be more likely to engage in insider trading activity. As Mahmoudian et al. (2021) note, prior research suggests that individual risk appetites are associated with high openness, low conscientiousness, high extraversion, low agreeableness, and low neuroticism[74]. Following Mahmoudian et al. (2021), I construct an index of CEO risk tolerance (*CEO_RISKT*) using standardized values of the Big 5 personality characteristics that is calculated as follows:

$$CEO\_RISKT = CEO\_OPEN - CEO\_CONS + CEO\_EXTRA - CEO\_AGREE - CEO\_NEUR \tag{4}$$

[73] A more common approach to control for endogeneity is two-stage least squares (2SLS). In a prior version of this paper, I used a two-stage instrumental variable framework. In the first stage, I instrumented CEOs' Big 5 personality characteristics using indicator variables for firms' state and provincial headquarters because researchers have found relationships between people's personalities and their location. For example, Oishi, Talhelm, and Lee (2015) find that people residing in more mountainous regions are more introverted. Götz et al. (2020) find an association between the Big 5 personality traits and local topography, and Jonason (2018) finds that people with stronger "dark triad" personality traits of narcissism, Machievellianism, and psychopathy tend to be more attracted to more densely populated urban areas. The results of specification and validity tests (untabulated) suggested that the state/provincial dummy variables were valid but weak instruments for CEOs Big 5 personality characteristics.

[74] See Clarke and Robertson (2005), Judge and Cable (1997), Nadkarni and Herrmann (2010), and Nicholson et al. (2005).

Moreover, insider trading by executives also carries reputational risk, given the widespread consensus in the media and in political circles that it is unethical even though it may be legal. Individual morality, therefore, should play a role in this setting and be associated with a lower probability of insider trading. Following Colquitt et al., (2006) and McFerran, Aquino, and Duffy (2010), I construct an index of CEO moral personality (*CEO_MORAL*) using standardized values of the Big 5 personality characteristics that is calculated as follows:

$$CEO\_MORAL = CEO\_OPEN + CEO\_CONS + CEO\_AGREE \quad (5)$$

Panel A of Table 3.7 contains the results of the tests of the impact of CEO risk tolerance constructs on the propensity to engage in insider trading activity. I find that *CEO_RISKT* is positively associated with net insider selling activity (*NETS_CEO*) and intensity (*NETS_CEO_SH* and *NETS_CEO_$*), which I interpret as evidence in favour of risk tolerant CEOs being more comfortable taking the legal risks associated with insider selling. I also find that *CEO_RISKT* is negatively associated with net insider buying activity (*NETB_CEO*) and intensity (*NETB_CEO_SH* and *NETB_CEO_$*). Panel B of Table 3.7 contains the results of tests of relationships between CEO risk tolerance and the propensity to engage in insider trading activity. While the signs of *CEO_RISKT* in each regression are negative and consistent with the notion that individual moral constitution serves as a deterrent against insider trading, which is generally perceived to be unethical, the results are not statistically significant.

[Insert Table 3.7 about here]

Next, I investigate whether conscientiousness moderates the propensity to engage in insider trading activity when firms are in more challenging situations. Specifically, I explore whether *CEO_CONS* is related to insider trading activity during periods that will receive qualified audit opinions, will be restated, or have internal control weaknesses. Table 3.8 contains the results of these tests, and the only significant finding is that more conscientious CEOs are more likely to be net buyers of their firms' shares during periods that will later be restated.

[Insert Table 3.8 about here]

Cline, Gokkaya, and Liu (2017) find that insiders vary in their ability to consistently trade profitably and identify a large subset of persistently profitable insiders. To investigate the possibility that innate personality characteristics are among the drivers of this heterogeneity in trading performance, I test whether the Big 5 personality characteristics are related to future abnormal stock returns. I use the Event Study by WRDS module from Wharton Research Data Services[75] to generate 3-, 6-, 9-, and 12-month cumulative abnormal stock return estimations based on Fama and French's (1993) 3-factor model with a momentum factor (Carhart, 1997). As shown in Table 3.9, consistent with prior studies (e.g. Cohen et al., 2012), I find that net insider buying (selling) activity is associated with positive (negative) future abnormal returns. I do not, however, find evidence of robust and economically meaningful relationships between abnormal stock returns and any of the measures of the Big 5 personality characteristics.

[Insert Table 3.9 about here]

3.5 DISCUSSION AND CONCLUSION

In summary, I find that more conscientious CEOs are more likely to be net buyers of their firms' shares and purchase shares with more intensity. These findings are robust to different model specifications that attempt to correct for endogeneity and the fact that insider trading is autocorrelated and personality characteristics are largely time invariant. While I also find that more conscientious CEOs are less likely to sell shares and do so with less intensity, these results are not statistically significant, which I attribute to a lack of power related to the use of personality measures inferred from spoken text, which are noisy. Next, I find that risk tolerant CEOs are more likely to be net sellers of their firms' shares, and less likely to be net buyers of same. Moreover, CEOs with stronger moral personalities are less likely to engage in insider trading (both purchases and sales); however, these results are not statistically significant for the reason mentioned previously. Lastly, I do not find evidence of economically meaningful

[75] https://wrds-www.wharton.upenn.edu/pages/get-data/event-study-wrds/us-daily-event-study-Upload-your-own-events/

relationships between abnormal stock returns and any of the measures of the Big 5 personality characteristics.

In addition to the contributions I make to the extant bodies of literature on insider trading and firms' cash holdings and liquidity management, I provide insights that are relevant to practice. Guay et al. (2022) remark that insider trading restrictions are not one-size-fits-all and vary according to firm-level informational asymmetry, the strength of external monitoring, and executives' liquidity needs. Given my findings that CEOs' personalities impact insider trading activity, it would not be unreasonable to expect that the effectiveness of firms' insider trading policies would depend on how well they are tailored to match individual executives' personalities. In a similar vein, regulators such as the SEC could use executive personality as a marker for insider trading risk to help better focus their efforts to catch malevolent actors, as well as more generally to better understanding the information dynamics that surround insider trading.

This study is not without limitations. Notably, executives' personalities are largely time invariant and insider trading activity is autocorrlated. Although I use dynamic panel regressions (Arellano and Bond, 1991) to address endogeneity issues that arise from the autocorrelation in my main variables and incorporate industry-year fixed effects to control for other factors that affect groups of firms at various moments in time, it remains possible that my findings are driven by other omitted variable(s). Moreover, many of my results lack statistical significance, which I attribute to a lack of power related to the use of personality measures inferred from spoken text, which are noisy.

Future research could address the limitations of my current study by taking a longer-term view and studying how the relationships between insider trading and personality characteristics evolve over time by using hazard models, as Jia et al. (2014) do. Another potential avenue for future research would be to investigate the role of corporate governance and whether it is related to the relationships between insider trading and personality characteristics, which is plausible given prior research findings that external monitoring mediates the association between conscientiousness and behaviour in non-business settings (Frink and Ferris, 1999).

APPENDIX 3: VARIABLE DEFINITIONS

Panel A: Main Variables

$NETB\_CEO_{it}$	Indicator variable that takes a value of 1 if the total number of shares purchased by the CEO of firm *i* during year *t* exceeds the total net number of shares sold, and zero otherwise Source: Thomson Reuters
$NETS\_CEO_{it}$	Indicator variable that takes a value of 1 if the total number of shares sold by the CEO of firm *i* during year *t* exceeds the total net number of shares purchased, and zero otherwise Source: Thomson Reuters
$NET[B/S]\_CEO\_[SH/\$]_{it}$	Net [number of shares/dollar value of shares] traded (purchases minus sales) by the CEO of firm *i* during year *t*. Source: Thomson Reuters
CEO_CONS_{it}	Measure of CEO Conscientiousness inferred from the CEO's spoken words in the question-and-answer section of quarterly earnings conference calls Sources: Seeking Alpha, Watson Personality Insights
CEO_AGREE_{it}	Measure of CEO Agreeableness inferred from the CEO's spoken words in the question-and-answer section of quarterly earnings conference calls Sources: Seeking Alpha, Watson Personality Insights
CEO_EXTRA_{it}	Measure of CEO Extraversion inferred from the CEO's spoken words in the question-and-answer section of quarterly earnings conference calls Sources: Seeking Alpha, Watson Personality Insights
CEO_NEUR_{it}	Measure of CEO Neuroticism inferred from the CEO's spoken words in the question-and-answer section of quarterly earnings conference calls Sources: Seeking Alpha, Watson Personality Insights
CEO_OPEN_{it}	Measure of CEO Openness inferred from the CEO's spoken words in the question-and-answer section of quarterly earnings conference calls Sources: Seeking Alpha, Watson Personality Insights
$CEO\_MORAL\_PERS_{it}$	Index of CEO's moral personality; calculated as 1/3*(*CEO_CONS* + *CEO_AGREE* + *CEO_OPEN*)
$CEO\_RISK\_TOL_{it}$	Index of CEO's risk tolerance; calculated as 1/5*(*CEO_OPEN* – *CEO_CONS* + *CEO_EXTRA* – *CEO_AGREE* – *CEO_NEUR*)
CAR	Cumulative abnormal stock returns; estimated using Fama and French's (1993) 3-factor model plus momentum (Carhart, 1997) Source: Wharton Research Data Services

APPENDIX 3, CONTINUED

Panel B: Control and Other Variables

NET[B/S]_CXO	Indicator variable that takes a value of 1 if the total number of shares [purchased/sold] by executives other than the CEO at firm *i* during year *t* exceeds the total net number of shares [sold/purchased], and zero otherwise Source: Thomson Reuters
CPI_Factor	US Consumer price index factor, chained and rebased to 2020 dollars Source: US Bureau of Labor Statistics
PRC_adj	Adjusted stock price; calculated as (abs[PRC])/[CFACPR] Source: CRSP
SHR_adj	Adjusted number of shares outstanding; calculated as [SHROUT*CFACSHR] Source: CRSP
ASSETS	Firm assets [ATQ] Source: Compustat
LN(ASSETS)	Natural logarithm of *ASSETS*
MCAP	Firm market capitalization; calculated as *PRC_adj***SHR_adj*, deflated by *CPI_Factor*, presented in millions of $US Source: CRSP
LN(MCAP)	Natural logarithm of *MCAP*
BOOKMKT	Ratio of book value of shareholders' equity [SEQ] to *MCAP* Sources: CRSP and Compustat
SRET	Raw trailing 12M stock return; calculated as (PRC_adj_{it} – PRC_adj_{it-4}) divided by PRC_adj_{it-4} Source: CRSP
LEVERAGE	Ratio of long-term debt [DLTT] to total assets [AT] Source: Compustat
RDINT	R&D intensity; calculated as research and development expenses [XRD] divided by sales [SALE] Source: Compustat
RONA	Return on net operating assets; calculated income before interest and taxes [IB + (XINT*(100% – (TXT/PI)))] divided by net operating assets [CEQ + DLC + DLTT + PSTK – CHE] Source: Compustat
LOSS	Indicator variable that takes a value of 1 if *RONA* is less than 0, and zero otherwise

APPENDIX 3, CONTINUED

Panel B, Continued

ALTMAN_Z	Altman's (1968) Z-score for financial health; calculated as (1.2***A**) + (1.4***B**) + (3.3***C**) + (0.6***D**) + (1.0***E**), where: **A** = (current assets [ACT] less current liabilities [LCT]) divided by total assets [AT] **B** = retained earnings [RE] divided by total assets [AT] **C** = earnings before interest and taxes [SALE – COGS – XRD – XSGA – DP] divided by total assets [AT] **D** = *MCAP* divided by total liabilities [LT] **E** = sales [SALE] divided by total assets [AT] Source: Compustat
QUAL_OP	Indicator variable that takes a value of 1 if the firm's auditor did not issue an unqualified opinion for the year [AUOP > 1], and zero otherwise Source: Compustat
IC_WEAK	Indicator variable that takes a value of 1 if a firm's auditor identified deficient internal controls for the year [AUOPIC > 1], and zero otherwise Source: Compustat
RESTATE	Indicator variable that takes a value of 1 if a firm's earnings for the period are subsequently restated, and zero otherwise Source: Audit Analytics
ICODE	Fama-French 30-industry classification (Fama and French, 1997) Source: Kenneth French Data Library at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

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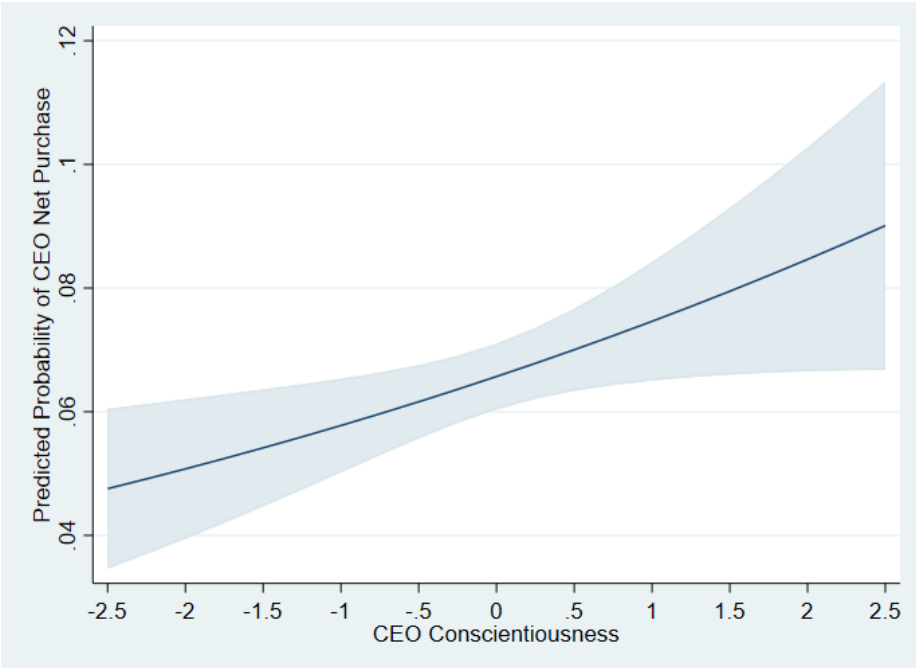
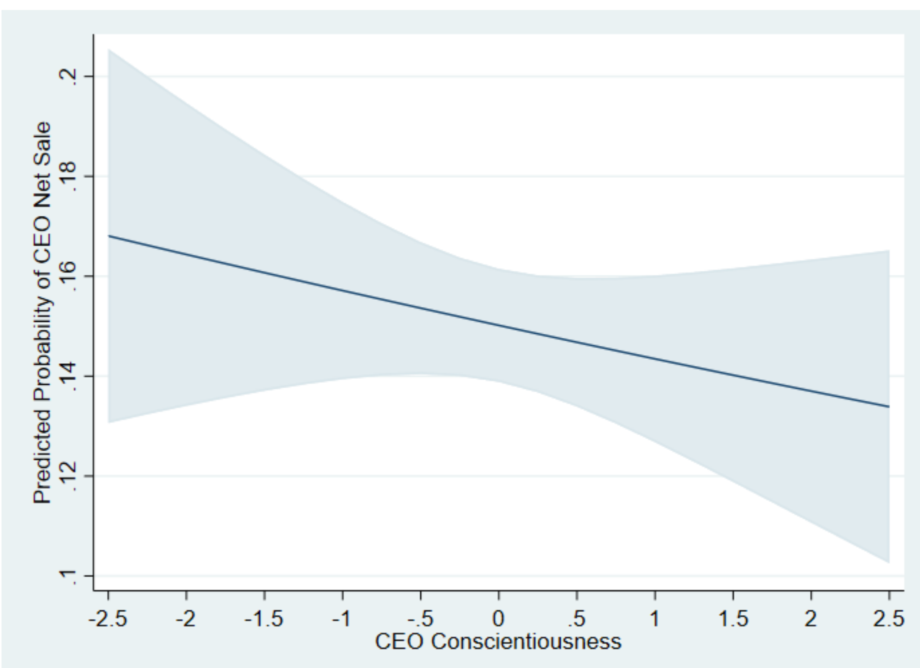
FIGURE 3.1: ADJUSTED PREDICTIONS FOR CEO NET INSIDER BUYING BASED ON CEO CONSCIENTIOUSNESS



Note: Shaded areas represent 95% confidence intervals for predictions

FIGURE 3.2: ADJUSTED PREDICTIONS FOR CEO NET INSIDER SELLING BASED ON CEO CONSCIENTIOUSNESS



Note: Shaded areas represent 95% confidence intervals for predictions

TABLE 3.1: SAMPLE ATTRITION

Firm-years from 2005 through 2017 with CRSP stock prices, CUSIPs, and matching Compustat GVKEYs	78,200
Less: Firms domiciled outside of Canada or the United States	(8,514)
Less: Financial services firms (Fama-French Industry #29)	(22,439)
Less: Closing prices below $2	(6,371)
Less: Insolvent firms with negative shareholders' equity	(1,445)
Less: Observations with missing data in Compustat and/or CRSP	(4,607)
Less: Observations with missing prior-period (lagged) data	(6,249)
Less: Observations with insufficient data to model personality characteristics	(10,943)
Final sample (firm-years)	**17,632**
Number of unique firms	**2,953**

TABLE 3.2: INSIDER TRADING ACTIVITY BY CEOS

Panel A: CEO Net Insider Trading Activity by Year

Year	CEO Net Purchases (#)	CEO Net Purchases ($)*	CEO Net Sales (#)	CEO Net Sales ($)*
2005	7	1.8	35	1,980.0
2006	79	22.6	94	4,700.0
2007	150	50.9	204	5,810.0
2008	211	102.0	224	4,340.0
2009	151	28.9	213	2,400.0
2010	70	13.2	222	3,390.0
2011	121	22.9	292	4,480.0
2012	148	31.0	403	6,050.0
2013	96	11.9	491	7,350.0
2014	143	40.7	527	6,310.0
2015	173	40.3	528	5,410.0
2016	138	31.6	489	5,170.0
2017	119	39.3	462	4,740.0
Total	**1,606**	**437.1**	**4,184**	**62,130.0**

* In millions of dollars, chained and rebased to 2020 using U.S. consumer prices (CPI)

TABLE 3.2, CONTINUED

Panel B: Share of CEO Net Insider Trading Activity by Industry

Industry	CEO Net Purchases*	% of Total	CEO Net Sales*	% of Total
Food Products	6.5	1.49%	1,320.0	2.13%
Beer and Liquor	0.2	0.04%	441.0	0.71%
Tobacco Products	0.0	0.00%	93.8	0.15%
Recreation	14.2	3.25%	1,520.0	2.45%
Printing and Publishing	3.7	0.85%	447.0	0.72%
Consumer Goods	5.4	1.23%	986.0	1.59%
Apparel	5.0	1.15%	2,530.0	4.07%
Healthcare, Medical Equipment, and Pharmaceutical Products	59.4	13.59%	8,690.0	13.99%
Chemicals	12.3	2.81%	1,700.0	2.74%
Textiles	0.7	0.16%	93.0	0.15%
Construction and Construction Materials	16.2	3.71%	1,810.0	2.91%
Steel and Metal Works	9.9	2.26%	305.0	0.49%
Fabricated Products and Machinery	10.7	2.45%	2,590.0	4.17%
Electrical Equipment	5.8	1.33%	645.0	1.04%
Automobiles and Trucks	7.8	1.78%	948.0	1.53%
Aircraft, Ships, and Railroad Equipment	8.4	1.93%	938.0	1.51%
Precious Metals, Non-Metallic, and Industrial Metal Mining	1.8	0.40%	206.0	0.33%
Coal	0.4	0.09%	13.8	0.02%
Petroleum and Natural Gas	33.9	7.76%	2,270.0	3.66%
Utilities	7.4	1.70%	1,900.0	3.06%
Communications	4.9	1.12%	1,610.0	2.59%
Personal and Business Services	60.7	13.89%	11,300.0	18.20%
Business Equipment	63.4	14.51%	8,760.0	14.11%
Business Supplies and Shipping Containers	4.4	1.00%	573.0	0.92%
Transportation	6.5	1.49%	1,540.0	2.48%
Wholesale	17.9	4.10%	2,170.0	3.49%
Retail	25.8	5.90%	4,220.0	6.80%
Restaurants, Hotels, and Motels	14.0	3.20%	1,250.0	2.01%
Other 1	4.4	1.02%	361.0	0.58%
Other 2	25.1	5.74%	894.0	1.44%
Total	**436.7**	**100%**	**62,124.6**	**100%**

* In millions of dollars, chained and rebased to 2020 using U.S. consumer prices (CPI). Totals may not be the same as in Panel A due to rounding.

TABLE 3.3: DESCRIPTIVE STATISTICS

Panel A: Opportunistic Net Insider Purchases (n = 1,606)

	Mean	St. dev.	5th pct	25th pct	Median	75th pct	95th pct
Shares purchased	24,781	31,197	1,000	5,000	11,646	33,334	85,000
$ value*	$271,909	$413,598	$0**	$14,862	$101,927	$341,047	$1,108,543
% firm shares O/S	0.06%	0.16%	<0.01%	<0.01%	0.02%	0.06%	0.27%

Panel B: Opportunistic Net Insider Sales (n = 4,184)

	Mean	St. dev.	5th pct	25th pct	Median	75th pct	95th pct
Shares sold	67,403	98,869	1,445	8,112	25,743	77,438	285,000
$ value*	$7,753,477	$13,900,000	$65,620	$493,933	$2,135,413	$7,838,806	$40,200,000
% firm shares O/S	0.20%	0.42%	<0.01%	0.02%	0.07%	0.21%	0.80%

*Panel C: Spearman Correlations*** for Variables of Interest (All Firm Quarters, N = 17,632)*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
***NETB_CEO* (1)**	1.000								
***NETS_CEO* (2)**	-0.177	1.000							
***CEO_CONS* (3)**	0.047	-0.073	1.000						
***CEO_AGREE* (4)**	0.010	-0.028	0.501	1.000					
***CEO_EXTRA* (5)**	-0.012	0.046	0.187	0.156	1.000				
***CEO_NEUR* (6)**	0.021	-0.049	0.543	0.001	0.366	1.000			
***CEO_OPEN* (7)**	-0.021	0.023	-0.161	-0.157	0.066	-0.136	1.000		
***CEO_MORAL* (8)**	0.023	-0.041	0.718	0.712	0.230	0.223	0.345	1.000	
***CEO_RISKT* (9)**	-0.040	0.087	-0.774	-0.559	0.126	-0.489	0.568	-0.404	1.000

TABLE 3.3, CONTINUED

Panel D: Variables of Interest and Control Variables (All Firm Quarters, N = 17,632)

	Mean	St. dev.	5th pct	25th pct	Median	75th pct	95th pct
CEO_CONS	0.000	1.000	-1.578	-0.659	-0.035	0.623	1.654
CEO_AGREE	0.000	1.000	-1.508	-0.649	-0.060	0.580	1.659
CEO_EXTRA	0.000	1.000	-1.635	-0.646	-0.001	0.660	1.621
CEO_NEUR	0.000	1.000	-1.629	-0.616	0.002	0.619	1.623
CEO_OPEN	0.000	1.000	-1.665	-0.598	0.041	0.634	1.523
CEO_MORAL	0.000	0.612	-0.946	-0.404	-0.022	0.369	1.004
CEO_RISKT	0.000	0.524	-0.878	-0.318	0.027	0.346	0.788
NETB_EXEC	5.29%	22.39%	0	0	0	0	1
NETS_EXEC	74.51%	43.58%	0	0	1	1	1
MCAP($mn*)	$8,144.6	$28,029.1	$106.6	$477.3	$1,493.1	$4,906.2	$32,600.1
Ln(MCAP)	7.38	1.71	4.68	6.17	7.31	8.50	10.39
BOOK_MKT	0.56	0.47	0.10	0.26	0.44	0.71	1.41
SRET	11.84%	48.07%	-53.55%	-16.09%	6.68%	31.32%	93.15%
ASSETS($mn*)	$6,740.7	$15,399.5	$97.9	$429.7	$1,439.9	$5,117.1	$35,779.4
Ln(ASSETS)	7.34	1.75	4.59	6.07	7.27	8.54	10.49
LEVERAGE	18.84%	17.14%	0.00%	0.68%	16.78%	30.53%	50.73%
RDINT	18.40%	167.80%	0.00%	0.00%	0.38%	7.89%	29.67%
RONA	10.15%	96.15%	-53.46%	2.83%	9.13%	17.58%	59.52%
LOSS	20.43%	40.32%	0	0	0	0	1
ALTMAN_Z	2.15	5.09	-3.25	-0.20	1.05	3.18	11.32
QUAL_OP	30.38%	45.99%	0	0	0	1	1
RESTATE	8.81%	28.35%	0	0	0	0	1
IC_WEAK	3.68%	18.82%	0	0	0	0	0
IND_HHI	8.66%	7.07%	3.27%	4.57%	7.01%	10.07%	22.05%

* Chained and rebased to 2020 dollars using U.S. consumer prices (CPI)
** Transaction prices not always included in insider trading Form 4 filings
*** All correlations are significant at the 1% level

TABLE 3.4: MAIN TESTS OF THE IMPACT OF PERSONALITY CHARACTERISTICS ON INSIDER TRADING ACTIVITY

Panel A: CEO Net Buying Activity; DV=NETB_FIRM$_{it}$

Model	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
***CEO_CONS* [H1, +]**	**0.1574*****	**0.2385*****	**0.1703*****	**0.2173*****	**0.1370****
	(0.0325)	**(0.0524)**	**(0.0338)**	**(0.0553)**	**(0.0554)**
CEO_AGREE		-0.0898**		-0.0697	-0.0909**
		(0.0448)		(0.0467)	(0.0459)
CEO_EXTRA		-0.0510		-0.0193	0.0419
		(0.0370)		(0.0390)	(0.0395)
CEO_NEUR		-0.0526		-0.0280	-0.1106**
		(0.0467)		(0.0506)	(0.0511)
CEO_OPEN		-0.0450		-0.0526	-0.1077***
		(0.0315)		(0.0324)	(0.0327)
NETB_CXO					2.0618***
					(0.0800)
Ln(MCAP)					-0.2890***
					(0.0316)
BOOKMKT					-0.1081*
					(0.0654)
SRET					-0.3029***
					(0.0818)
LEVERAGE					0.8302***
					(0.2172)
RDINT					0.0000
					(0.0002)
RONA					-0.0169
					(0.0440)
LOSS					0.3393***
					(0.0783)
ALTMAN_Z					-0.0048
					(0.0083)
QUAL_OP					0.2152**
					(0.0846)
RESTATE					0.0568
					(0.1148)
IC_WEAK					0.0944
					(0.1385)
IND_HHI					-0.1137
					(1.4732)
Constant	-2.3107***	-2.3154***	-4.0176***	-4.0171***	-1.7495***
	(0.0378)	(0.0378)	(0.4468)	(0.4475)	(0.5560)

TABLE 3.4, CONTINUED

Panel A, Continued

Fixed effects	No	No	Industry, Calendar Year	Industry, Calendar Year	Industry, Calendar Year
Observations	17,632	17,632	17,632	17,632	17,632
Pseudo R^2	0.0034	0.0050	0.0268	0.0276	0.1507
Correctly Classified	90.89%	90.89%	90.89%	90.89%	91.23%
Naïve Random Classification	83.47%	83.47%	83.47%	83.47%	83.47%

Panel B: CEO Net Selling Activity; DV=$NETS\_FIRM_{it}$

Model	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
***CEO_CONS* [H1, -]**	**-0.1767***** **(0.0289)**	**-0.1473***** **(0.0444)**	**-0.1647***** **(0.0304)**	**-0.1282***** **(0.0486)**	**-0.0536** **(0.0518)**
CEO_AGREE		-0.0190 (0.0395)		-0.0364 (0.0411)	0.0155 (0.0428)
CEO_EXTRA		0.1910*** (0.0325)		0.1149*** (0.0351)	0.0287 (0.0371)
CEO_NEUR		-0.1081*** (0.0404)		-0.0779* (0.0447)	-0.0010 (0.0473)
CEO_OPEN		-0.0052 (0.0281)		-0.0132 (0.0297)	0.0340 (0.0308)
NETB_CXO					3.0225*** (0.1387)
Ln(MCAP)					0.2275*** (0.0238)
BOOKMKT					-0.0397 (0.0900)
SRET					-0.1340*** (0.0500)
LEVERAGE					-0.4373** (0.2118)
RDINT					-0.0004* (0.0002)
RONA					0.0187 (0.0349)
LOSS					0.0290 (0.0716)
ALTMAN_Z					-0.0015 (0.0074)

TABLE 3.4, CONTINUED

Panel B, Continued

QUAL_OP					-0.0553 (0.0634)
RESTATE					0.0010 (0.0874)
IC_WEAK					-0.2909^{**} (0.1284)
IND_HHI					1.5339 (1.3555)
Constant	-1.1757^{***} (0.0334)	-1.1837^{***} (0.0336)	-2.2402^{***} (0.2911)	-2.2601^{***} (0.2897)	-7.2467^{***} (0.4251)
Fixed effects	No	No	Industry, Calendar Year	Industry, Calendar Year	Industry, Calendar Year
Observations	17,632	17,632	17,632	17,632	17,632
Pseudo R^2	0.0050	0.0099	0.0465	0.0479	0.1714
Correctly Classified	76.27%	76.26%	76.29%	76.30%	76.89%
Naïve Random Classification	63.85%	63.85%	63.85%	63.85%	63.85%

Notes: All models are logit models. Standard errors are clustered at the firm level and shown in parentheses. The number of observations for each model may be less than the full sample size because insider trading in some industry-years can be predicted perfectly. Continuous variables are winsorized at the 1% and 99% levels for each year. * $p < .10$, ** $p < .05$, *** $p < .01$

TABLE 3.5: IMPACT OF PERSONALITY CHARACTERISTICS ON INSIDER TRADING INTENSITY

Model	**(1)** **DV = *LN*** **(*NETB_CEO_SH)***	**(2)** **DV = *LN*** **(*NETB_CEO_$)***	**(3)** **DV = *LN*** **(*NETS_CEO_SH)***	**(4)** **DV = *LN*** **(*NETS_CEO_$)***
***CEO_CONS* [H1]**	**1.0157****	**1.4186****	**-0.3214**	**-0.2676**
	(0.3981)	**(0.5733)**	**(0.3256)**	**(0.1953)**
CEO_AGREE	-0.6449*	-0.9174**	0.0125	-0.0128
	(0.3304)	(0.4549)	(0.2712)	(0.1615)
CEO_EXTRA	0.2730	0.2188	0.2536	0.1744
	(0.2863)	(0.3907)	(0.2372)	(0.1413)
CEO_NEUR	-0.8206**	-1.2183**	-0.0748	-0.1016
	(0.3780)	(0.5368)	(0.2983)	(0.1746)
CEO_OPEN	-0.8193***	-1.0710***	0.2005	0.0882
	(0.2368)	(0.3298)	(0.1937)	(0.1102)
Constant	-15.0230***	-20.1147***	-45.1460***	-20.4782***
	(3.8518)	(5.1103)	(2.5480)	(1.6003)
Controls	YES	YES	YES	YES
Fixed effects	Industry, Calendar Year	Industry, Calendar Year	Industry, Calendar Year	Industry, Calendar Year
Observations	17,632	17,632	17,632	17,632
Pseudo R^2	0.0754	0.0807	0.0773	0.0822

Notes: All models are Tobit models with left censoring at zero. Standard errors are clustered at the firm level and shown in parentheses. Continuous variables are winsorized at the 1% and 99% levels for each year.
* $p < .10$, ** $p < .05$, *** $p < .01$

TABLE 3.6: DYNAMIC PANEL REGRESSIONS (CHANGE MODELS)

Panel A: CEO Net Buying Activity

Model	**(1)** **DV =** ***NETB_CEO***	**(2)** **DV =** ***LN*** **(*NETB_CEO_SH*)**	**(3)** **DV =** ***LN*** **(*NETB_CEO_$*)**
CEO_CONS **[H1, +]**	**0.0210*****	**0.1773*****	**0.1341***
	(0.0068)	**(0.0644)**	**(0.0751)**
CEO_AGREE	-0.0078	-0.0553	-0.0220
	(0.0059)	(0.0561)	(0.0654)
CEO_EXTRA	0.0049	0.0386	0.0295
	(0.0053)	(0.0498)	(0.0581)
CEO_NEUR	-0.0206***	-0.1750***	-0.1407**
	(0.0064)	(0.0605)	(0.0706)
CEO_OPEN	-0.0085**	-0.0794*	-0.1047**
	(0.0043)	(0.0410)	(0.0478)
Lagged DV	0.0772***	0.0774***	0.0698***
	(0.0134)	(0.0135)	(0.0132)
Constant	-0.7985**	-11.6104**	-17.1408**
	(0.3509)	(4.9364)	(6.8842)
Controls	YES	YES	YES
Observations	10,675	10,675	10,675
Model chi-square	563.3***	569.9***	467.3***

TABLE 3.6, CONTINUED

Panel B: CEO Net Selling Activity

Model	**(1) DV = *NETS_CEO***	**(2) DV = *LN* (*NETS_CEO_SH)***	**(3) DV = *LN* (*NETS_CEO_$)***
***CEO_CONS* [H2, -]**	**-0.0114**	**-0.1127**	**-0.1961**
	(0.0093)	**(0.0954)**	**(0.1512)**
CEO_AGREE	0.0121	0.1344	0.0127
	(0.0082)	(0.0833)	(0.1321)
CEO_EXTRA	-0.0043	-0.0296	0.0113
	(0.0072)	(0.0737)	(0.1165)
CEO_NEUR	0.0068	0.0731	0.0483
	(0.0088)	(0.0900)	(0.1429)
CEO_OPEN	0.0005	0.0182	-0.0313
	(0.0060)	(0.0610)	(0.0970)
Lagged DV	0.0772^{***}	0.3747^{***}	0.1360^{***}
	(0.0134)	(0.0204)	(0.0175)
Constant	-0.4595^{***}	-5.2528^{***}	-9.6205^{***}
	(0.1243)	(1.2659)	(1.9527)
Controls	YES	YES	YES
Observations	10,675	10,675	10,675
Model chi-square	357.5^{***}	391.5^{***}	516.1^{***}

Notes: All models are dynamic panel models estimated using the generalized method of moments methodology (Arellano and Bond, 1991). Standard errors are calculated using the generalized method of moments method and shown in parentheses. The number of observations for each model may be less than the full sample size due to insufficient lagged data. Continuous variables are winsorized at the 1% and 99% levels for each year. * $p < .10$, ** $p < .05$, *** $p < .01$

TABLE 3.7: IMPACT OF PERSONALITY CONSTRUCTS ON INSIDER TRADING ACTIVITY

Panel A: CEO Risk Tolerance

Model	**(1)** **DV =** ***NETB_CEO***	**(2)** **DV =** ***LN*** **(*NETB_CEO_SH*)**	**(3)** **DV =** ***LN*** **(*NETB_CEO_$*)**	**(4)** **DV =** ***NETS_CEO***	**(5)** **DV =** ***LN*** **(*NETS_CEO_SH*)**	**(6)** **DV =** ***LN*** **(*NETS_CEO_$*)**
CEO_RISKTOL	**-0.1137*** **(0.0638)**	**-0.9179*** **(0.4689)**	**-1.1462*** **(0.6495)**	**0.1124*** **(0.0603)**	**0.8420**** **(0.3776)**	**0.6562***** **(0.2309)**
Constant	-1.7971*** (0.5531)	-15.5422*** (3.8482)	-20.8628*** (5.0900)	-7.2522*** (0.4249)	-45.2040*** (2.5409)	-20.6110*** (1.5849)
Controls	YES	YES	YES	YES	YES	YES
Fixed effects	Industry, Calendar Year	Industry, Calendar Year	Industry, Calendar Year	Industry, Calendar Year	Industry, Calendar Year	Industry, Calendar Year
Observations	17,632	17,632	17,632	17,632	17,632	17,632
Pseudo R^2	0.1491	0.0745	0.0798	0.1713	0.0772	0.0821

TABLE 3.7, CONTINUED

Panel B: CEO Moral Personality

Model	**(1)** **DV =** ***NETB_CEO***	**(2)** **DV =** ***LN*** **(*NETB_CEO_SH)***	**(3)** **DV =** ***LN*** **(*NETB_CEO_$)***	**(4)** **DV =** ***NETS_CEO***	**(5)** **DV =** ***LN*** **(*NETS_CEO_SH)***	**(6)** **DV =** ***LN*** **(*NETS_CEO_$)***
CEO_MORALPERS	**-0.0443**	**-0.3186**	**-0.5383**	**-0.0093**	**-0.1436**	**-0.2351**
	(0.0562)	**(0.4065)**	**(0.5663)**	**(0.0506)**	**(0.3193)**	**(0.1890)**
Constant	-1.6804^{***}	-14.6952^{***}	-19.6746^{***}	-7.3085^{***}	-45.5569^{***}	-20.8142^{***}
	(0.5491)	(3.8262)	(5.0651)	(0.4246)	(2.5425)	(1.5906)
Controls	YES	YES	YES	YES	YES	YES
Fixed effects	Industry, Calendar Year	Industry, Calendar Year	Industry, Calendar Year	Industry, Calendar Year	Industry, Calendar Year	Industry, Calendar Year
Observations	17,632	17,632	17,632	17,632	17,632	17,632
Pseudo R^2	0.1488	0.0743	0.0796	0.1709	0.0770	0.0820

Notes: Models 1 and 4 of each panel are logit models. Models 2, 3, 5, and 6 of each panel are Tobit models with left censoring at zero. Standard errors are clustered at the firm level and shown in parentheses. Continuous variables are winsorized at the 1% and 99% levels for each year. * $p < .10$, ** $p < .05$, *** $p < .01$

TABLE 3.8: INSIDER TRADING DURING PERIODS THAT WILL RECEIVE QUALIFIED AUDIT OPINIONS, WILL BE RESTATED, OR HAVE INTERNAL CONTROL WEAKNESSES

Panel A: CEO Net Buying Activity

Model	**(1)** **DV =** **(*NETB_CEO*) |** ***QUAL_OP = 1***	**(2)** **DV = *LN*** **(*NETB_CEO*) |** ***RESTATE = 1***	**(3)** **DV = *LN*** **(*NETB_CEO*) |** ***IC_WEAK = 1***
***CEO_CONS* [H1, +]**	**0.1208** **(0.0881)**	**0.4057**** **(0.1975)**	**-0.0026** **(0.2753)**
CEO_AGREE	-0.0983 (0.0733)	-0.4528*** (0.1507)	-0.2363 (0.2084)
CEO_EXTRA	0.1527** (0.0634)	0.2591** (0.1308)	0.0170 (0.1778)
CEO_NEUR	-0.0510 (0.0755)	-0.2911 (0.1815)	0.0644 (0.2245)
CEO_OPEN	-0.2003*** (0.0538)	-0.4170*** (0.1120)	-0.3037** (0.1421)
Constant	-2.4548** (1.2454)	-0.0539 (1.1727)	-2.6277 (1.7138)
Controls	YES	YES	YES
Observations	5,356	1,452	616
Model chi-square	0.1407	0.2015	0.2476

TABLE 3.8, CONTINUED

Panel B: CEO Net Selling Activity

Model	**(1)** **DV = (*NETS_CEO*) | *QUAL_OP = 1***	**(2)** **DV = *LN* (*NETS_CEO*) | *RESTATE = 1***	**(3)** **DV = *LN* (*NETS_CEO*) | *IC_WEAK = 1***
***CEO_CONS* [H2, -]**	**-0.0246**	**0.2032**	**0.0818**
	(0.0833)	**(0.1495)**	**(0.2683)**
CEO_AGREE	0.0247	-0.1483	-0.1687
	(0.0671)	(0.1313)	(0.2211)
CEO_EXTRA	0.0043	0.1162	0.2353
	(0.0631)	(0.0964)	(0.1693)
CEO_NEUR	-0.0591	-0.1968	-0.3481
	(0.0724)	(0.1405)	(0.2358)
CEO_OPEN	0.0444	0.1402	-0.2105
	(0.0480)	(0.0970)	(0.1395)
Lagged DV	-7.2295^{***}	-7.8583^{***}	-6.3085^{**}
	(0.7257)	(1.1886)	(2.4594)
Controls	YES	YES	YES
Observations	5,356	1,541	592
Pseudo R^2	0.1591	0.2248	0.2697

Notes: All models are logit models. Standard errors are clustered at the firm level and shown in parentheses. The number of observations for each model may be less than the full sample size because insider trading in some industry-years can be predicted perfectly. Continuous variables are winsorized at the 1% and 99% levels for each year. * $p < .10$, ** $p < .05$, *** $p < .01$

TABLE 3.9: IMPACT OF PERSONALITY CHARACTERISTICS AND INSIDER TRADING ACTIVITY ON FUTURE ABNORMAL STOCK RETURNS

Model	(1) DV = CAR_{t+1}	(2) DV = CAR_{t+2}	(3) DV = CAR_{t+3}	(4) DV = CAR_{t+4}
CEO_CONS	**-0.0032**	**-0.0045**	**-0.0076***	**-0.0081**
	(0.0030)	**(0.0046)**	**(0.0046)**	**(0.0065)**
CEO_AGREE	-0.0001	-0.0026	0.0014	0.0003
	(0.0024)	(0.0036)	(0.0037)	(0.0053)
CEO_EXTRA	0.0023	0.0035	0.0033	0.0102**
	(0.0022)	(0.0032)	(0.0033)	(0.0047)
CEO_NEUR	-0.0002	0.0006	0.0025	-0.0015
	(0.0028)	(0.0043)	(0.0045)	(0.0063)
CEO_OPEN	-0.0020	-0.0022	0.0008	-0.0046
	(0.0019)	(0.0028)	(0.0029)	(0.0041)
CEO_NETB	0.0124*	0.0266**	0.0341***	0.0308*
	(0.0074)	(0.0117)	(0.0127)	(0.0165)
CEO_NETS	0.0015	0.0038	0.0084	0.0058
	(0.0037)	(0.0057)	(0.0058)	(0.0078)
Controls	YES	YES	YES	YES
Fixed Effects	Industry, Calendar Year	Industry, Calendar Year	Industry, Calendar Year	Industry, Calendar Year
Observations	13,136	13,136	13,136	13,136
R^2	0.1595	0.2341	0.2103	0.2811
Adjusted R^2	0.1556	0.2306	0.2066	0.2778

Notes: All models are ordinary least squares models. The number of observations for each model may be less than the full sample size due to insufficient data needed to computer abnormal stock returns. Robust standard errors are clustered at the firm level and shown in parentheses. Continuous variables are winsorized at the 1% and 99% levels for each year. * $p < .10$, ** $p < .05$, *** $p < .01$

Discussion and Conclusion

In my first study, I develop new measures of insider sentiment that capture the clustering of insider trades across peers in the same industry and across the broad market. These measures serve as indications of conviction or consensus among insiders within an industry and at an aggregate market level. Given the positive correlation in firms' performance within an industry, following others' insider trades may inform executives' views on future industry conditions and help them glean insights into how their firms may be affected (and, accordingly, trade profitably). Using a sample of 227,267 firm-quarters, which covers 8,000 firms from 1996 through 2021, I test whether insiders are more likely to trade when insiders at industry peer firms are trading and when insider trading activity outsider of a firm's industry is higher. I find that my measures of aggregate insider sentiment are highly positively related to firm-level insider trading activity, and that these relationships are economically meaningful.

In my second study, I explore the relationship between insider trading and firms' cash holdings. That insiders exercise their informational advantage for personal gain is well documented (Ravina and Sapienza, 2010; Cohen, Malloy, and Pomorski, 2012), especially in relation to major corporate events. While on the one hand, having a cash buffer affords firms additional means to capture upside and mitigate downside risk (Myers and Majluf, 1984), holding more cash than necessary can increase agency problems because managers can invest these funds suboptimally (Jensen, 1986). I find that in aggregate, higher cash balances are associated with increased insider selling activity and intensity. However, in certain situations, such as when industry competition, economic policy uncertainty, and firm-level informational asymmetry are high, insiders are less likely to sell and/or more likely to buy, which may reflect insiders' perception that excess cash balances in these instances have strategic value.

In my third study, I find that more conscientious Chief Executive Officers (CEOs) are more likely to be net buyers of their firms' shares and purchase shares with more intensity. These findings are robust to different model specifications that attempt to correct for endogeneity and the fact that insider trading is autocorrelated and personality characteristics are largely time invariant. While I also find that more conscientious CEOs are less likely to sell shares and do so with less intensity, these results are not statistically significant, which I attribute to a lack of power related to the use of personality measures inferred from spoken text, which are noisy. Next, I find that risk tolerant CEOs are more likely to be net sellers of their firms' shares, and less likely to be net buyers of same. Moreover, CEOs with stronger moral personalities are less likely to engage in insider trading (both purchases and sales); however, these results are not statistically significant for the reason mentioned previously. Lastly, I do not find evidence of economically meaningful relationships between abnormal stock returns and any of the measures of the Big 5 personality characteristics.

In addition to the contributions I make to the academic literature, I offer insights relevant to practice. For analysts and portfolio managers, the findings in my first study suggest that practitioners should consider both firm-, industry-, and market-level insider trading metrics as part of their security screening and selection processes, as doing so could ultimately lead to a market-beating investment strategy. These findings are also relevant to regulators and standard setters in that I confirm the economic importance of insiders' trading signals both at the individual firm and aggregate levels.

Related to my second study, investors who incorporate insider trading into their investment strategies can benefit from including cash holdings in their analysis, given that cash holdings significantly amplify returns on insider trades. Financial analysts who follow firms can benefit asking more detailed questions to managers regarding plans for cash balances, especially when managers are engaging in insider trading activity, given the association between insider trading and future financial outcomes at high-cash firms. My findings are also relevant for regulators who are interested in better understanding the information dynamics that surround insider trading.

Lastly, Guay et al. (2022) remark that insider trading restrictions are not one-size-fits-all and vary according to firm-level informational asymmetry, the strength of external monitoring, and executives' liquidity needs. Given my findings that CEOs' personalities impact insider trading activity, it would not be unreasonable to expect that the effectiveness of firms' insider trading policies would depend on how well they are tailored to match individual executives' personalities. In a similar vein, regulators such as the U.S. Securities and Exchange Commission (SEC) could use executive personality as a marker for insider trading risk to help better focus their efforts to catch malevolent actors, as well as more generally to better understanding the information dynamics that surround insider trading.

No study is without limitations, and mine are no exception. Notably, cash holdings and insider trading activity are both autocorrelated. Although I use dynamic panel regressions (Arellano and Bond, 1991) to address endogeneity issues that arise from the autocorrelation in my main variables and incorporate industry-year fixed effects to control for other factors that affect groups of firms at various moments in time, it remains possible that my findings are driven by other omitted variable(s). Moreover, my use of firm-quarters as a unit of analysis may not fully capture the longer-term relationships between cash holdings, insider trading, and firm outcomes such as future research and development (R&D) investments or cash flow generation.

Similarly, executives' personalities are largely time invariant and insider trading activity is autocorrelated. Although I use dynamic panel regressions (Arellano and Bond, 1991) to address endogeneity issues that arise from the autocorrelation in my main variables and incorporate industry-year fixed effects to control for other factors that affect groups of firms at various moments in time, it remains possible that my findings are driven by other omitted variable(s). Moreover, many of my results lack statistical significance, which I attribute to a lack of power related to the use of personality measures inferred from spoken text, which are noisy.

As regards directions for future research, several avenues emerge from my studies. Future research could address the limitations of my second study by taking a longer-term view and studying how the relationships between insider trading, cash holdings, and firm outcomes evolve over time. Another potential avenue for future research would be to investigate the role of corporate governance and whether it is related to the relationships between insider trading, cash holdings, and firm outcomes.

Future research could address the limitations of my third study by taking a longer-term view and studying how the relationships between insider trading and personality characteristics evolve over time by using hazard models, as Jia et al. (2014) do. Another potential avenue for future research would be to investigate the role of corporate governance and whether it is related to the relationships between insider trading and personality characteristics, which is plausible given prior research findings that external monitoring mediates the association between conscientiousness and behaviour in non-business settings (Frink and Ferris, 1999).

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