University of Alberta

Three Essays on Insider Trading

by

Zhenyang Tang

A thesis submitted to the Faculty of Graduate Studies and Research in partial fulfillment of the requirements for the degree of

Doctor of Philosophy

in

Finance

Faculty of Business

University of Alberta

Abstract

The first essay of the thesis examines the effect of legal insider trading intensity on stock price informativeness. Open market transactions by corporate insiders are considered informative because they predict future stock returns and future firm-specific cash flows. As a result, it may seem natural to assume a positive association between the intensity of reported insider trading and stock price informativeness. However, it is also possible that insider trading discourages outsiders from information collection, and the overall informational efficiency may be lowered if outsider information collection is crowded out. I find that firms with higher insider trading intensity tend to have higher firm-specific return variation. Stocks of firms with higher insider trading intensity experience less negative abnormal returns around SEO announcements, and are less affected by long-term return reversal. The findings support the view that legal insider trading makes stock prices more informative.

The second essay investigates whether insider trading affects firm value. If insider trading intensity promotes informational efficiency, it may enhance firm value by lowering cost of capital. I find that firms with larger and more frequent insider trading have higher values of Tobin's q, after accounting for other determinants of firm value. The positive associations are robust if only insider purchases or sales are analyzed, and are stronger for firms with higher information asymmetry. The incidence of firm-level insider trading restrictions is negatively associated with Tobin's q. Consistent with the view that the intensity of legal insider trading affects firm value by lowering cost of capital, I find a negative association between insider trading intensity and implied cost of capital.

The third essay investigates how insider trading affects price formation prior to mergers and acquisitions. I find that about one third of the total price run-up in M&As occurs before announcements, and the pre-announcement price run-up does not seem to be caused by market anticipation or trading reported by corporate insiders. Instead, the pre-announcement price run-up is significantly larger when media attention on insider trading is lower, when institutional ownership is lower, and when probability of informed trading is higher. The findings are consistent with the view that the target stock price run-up prior to M&A announcements is caused by unreported illegal insider trading.

Acknowledgement

I wish to express my most sincere gratitude to my supervisor, Dr. Randall Morck. I could not have finished this thesis without his invaluable guidance and support throughout the years. I have benefited greatly from his vision and expertise, his amazing knowledge in everything, and his great personality. It is truly fortunate of me to have Randall as my supervisor.

I would like to thank the other members of my supervisory committee, David McLean and Masahiro Watanabe. They have been instrumental in shaping and developing my research, not limited to the thesis, and I am much indebted to their time and help. I am grateful as well to Mark Huson and Mengxin Zhao. Mark has spent a great amount of time discussing the thesis with me, and I appreciate his incisive comments on the big picture as well as on the details of the thesis. Mengxin has given me a lot of research guidance, and I do not know how to express my gratitude for her constant support all through these years. My appreciation also goes to Ying Duan, Vikas Mehrotra, Heather Wier and Moin Yahya for their extremely helpful comments on my thesis and to Dr. Craig Dunbar for his insightful comments from the perspective of an external examiner.

Other PhD students at the University of Alberta have given me a lot of help and support. Though it is not possible to thank every one of them, I would like to express my particular gratitude to Xiaowei Xu, Claire Liang, Parianan Veeren and Rengong Zhang. I also wish to thank seminar participants at the University of Alberta and discussants at the meetings of the NFA and the FMA for their suggestions.

Table of Contents

List of Tables

List of Figures

Chapter 1. Introduction

Insider trading refers to the trading of a public company's stock by "insiders", who may have access to non-public information about the company. The term of "insider trading" can sometimes be confusing because many people associate it with illegal conduct only. In fact, insider trading can either be legal or illegal depending on the nature of the non-public information. Generally speaking, trading by corporate insiders (such as managers, directors and beneficial owners) is legal in most countries as long as it is not based on material non-public information. However, if corporate insiders or any other investors (known as de-facto insiders) trade stocks based on material inside information, their trading will be considered illegal.

Illegal insider trading has been under the spotlight ever since the scandalous Ivan Boesky insider trading case in the 1980s. With famous names such as Martha Stewart and Rajat Gupta, illegal insider trading attracts so much attention that many people fail to not realize that legal insider trading is a much more important component of the stock market. In the period 1986 - 2010, an average of 133,488 open market trades were reported to the SEC every year by corporate insiders from over 4,500 public firms, with an approximate overall value of $50 billion per year. For a median firm in that period, 1 share out of every 500 shares was traded by an insider.

These insider transactions are closely watched by newspapers, financial websites and analysts. Many investors believe that though corporate insiders are not supposed to trade on material inside information, their trades likely reflect immaterial information which could be used to predict future returns. A large body of literature, including Seyhun (1986), Seyhun (1988) and Lakonihok and Lee (2001), has documented that insider transactions (especially purchases) predict future stock returns. Subsequent studies by Piotroski and Roulstone (2005) and Jiang and

Zaman (2010) also provide evidence that legal insider trading reveals information of future firm-specific cash flows. Data of illegal insider trading is very limited, but Meulbroek (1992) finds significant abnormal returns on illegal insider trading days.

Both the legal conduct and illegal conduct of insider trading are based on information. One may therefore wonder how different legal insider trading is from illegal trading, and it is worthwhile to have some brief discussion along the line before I move on to the main body of my thesis. There are at least two distinct types of information asymmetry in the literature of information environment: the first is the information asymmetry between corporate insiders and outside investors, described in Myers and Majluf (1984), and the second is the information asymmetry between informed traders and uninformed traders, described in Kyle (1985). Illegal insider trading usually does not involve corporate insiders and is not reported to the public; therefore, it is not related to the Myers and Majluf type of information asymmetry, and is only associated with the Kyle type of information asymmetry. Legal insider trading, in contrast, involves two stages: in the first stage, corporate insiders make their trades but the information is not yet known to the SEC and the public. In this stage, legal insider trading is associated with the Kyle type of information asymmetry only. But in the second stage, insider transactions are filed with the SEC and become public information, and part of the inside information turns into public information in this process. Information asymmetry between corporate insiders and outside investors (the Myers and Majluf type of information asymmetry) is reduced as a result.

Thus, legal insider trading and illegal insider trading are different from the perspective of informational efficiency. Because legal insider trading information is available to the public, it changes the distribution between private information and public information and reduces the Myers and Majluf type of information asymmetry, while illegal insider trading may increase the

Kyle type of information asymmetry if outside investors are discouraged from collecting information (Fishman and Hagerty, 1992).

The three essays in my thesis explore different effects of insider trading on price formation and firm value. The first and second essays focus on legal insider trading that is reported to the SEC, and the third essay examines both legal insider trading and illegal insider trading in a special setting of M&A. Though my three essays are independent papers, they are related to each other because they are all motivated by the informational content of insider trading.

The first essay directly examines whether the intensity of legal insider trading leads to higher informational efficiency. Many scholars believe insider trading makes stock prices more informative by incorporating private information into stock prices (see Manne, 1966; Leland, 1992; Piotroski and Roulstone, 2004), while some scholars disagree because insider trading may discourage outside investors from information collection (see Glosten, 1989; Fishman and Hagerty, 1992). How does insider trading affect stock price informativeness in general? Does a firm have more informative stock prices if insiders trade more? These are the questions to be answered in the first essay.

To provide an empirical answer, I test the association between insider trading intensity and stock price informativeness, as measured by firm-specific return variation (see Morck, Yeung and Yu, 2000). I find that firms with greater and more frequent insider trading have higher firm-specific return variation. Besides, stocks of these firms experience less negative cumulated abnormal returns after seasoned equity offering announcements, and are less affected by long-term return reversal. The findings are consistent with the idea that insider trading promotes informational efficiency and makes stock prices more informative.

An important question follows: if insider trading promotes informational efficiency, does insider trading affect firm value? The second essay hence continues to investigate this question. Using Tobin's q ratio as a measure of firm value, I find that firms with larger and more frequent insider trading have higher Tobin's q, after accounting for other determinants of firm value. A likely channel is through insider trading reducing cost of capital, and a negative association between insider trading and cost of capital is documented. The results are not driven by only insider purchases or insider sales and are consistent in various robustness tests.

Findings of the first and second essays can be linked directly to insider trading regulations. Since the Securities Exchange Act of 1934, insider trading laws have become more and more prohibitive, and legal insider trading has become more and more restricted (see Section 2.2.2). Should insider trading laws be made more prohibitive? Should legal insider trading be allowed at all? The findings suggest that prohibiting legal insider trading may not be desirable. Since insider trading reduces information asymmetry, blocking the information channel may result in a worse information environment, lower firm value and cost shareholders.

Findings of the first and second essays also cast some doubt on the prevailing firm-level insider trading restrictions. Bettis, Coles and Lemmon (2000) find that most of US public companies have some kind of insider trading restrictions, with black-out window being the most popular restriction. If legal insider trading promotes informational efficiency and enhances firm value, firm-level insider trading restrictions may have negative effects on firm value rather than protecting shareholder wealth. Consistent with the idea, I find a negative association between insider trading restrictions and Tobin's q, suggesting that firm-level insider trading restrictions may potentially undermine shareholder value.

The third essay examines one type of the most influential corporate events: mergers and acquisitions (M&As). It has been documented that a substantial portion of price reaction in M&As occurs before announcements (Keown and Pinkerton, 1981), and the pre-announcement price run-up has caught a lot of attention. Though some researchers believe the market may be efficient enough to anticipate future takeovers (see Jarrell and Poulsen, 1989 and King, 2009), many researchers suspect the pre-merger price run-up is a result of insider trading (see Keown and Pinkerton, 1981; Bris, 2005; Beny and Seyhun, 2012). Given the findings in the first two essays, it may be natural to suspect that legal insider trading plays an important role in price formation prior to M&A announcements and causes the run-up. I do not find any evidence supporting the view. Corporate insiders seem to stay away from trading before takeovers, probably because takeovers are high-profile events and it would be too risky to trade before M&A announcements. Instead, I find some indirect evidence supporting the view of unreported illegal insider trading causing the pre-announcement price run-up. I find that in periods when media attention on illegal insider trading is higher, the pre-merger price run-up is significantly smaller. The magnitude of pre-merger price run-up is also negatively associated with institutional ownership, and positively associated with the probability of informed trading (PIN).

Overall, the thesis provides evidence supporting the view that legal insider trading incorporates information into stock prices and makes stock prices more informative. The improved informational efficiency further translates into higher firm value and benefit shareholders. Corporate insiders do not seem to make much profit by trading prior to M&As, and the big pre-announcement price run-up is likely caused by unreported illegal insider trading.

References

Beny, L. N., and H. N. Seyhun, 2012, Has Insider Trading Become More Rampant in the United States? Evidence from Takeovers. University of Michigan Law & Econ Research Paper No. 12-012

Bettis, J. C., J. L. Coles, and M. L. Lemmon, 2000, Corporate policies restricting trading by insiders, *Journal of Financial Economics* 57, 191-220.

Bris, A., 2005, Do Insider Trading Laws Work? *European Financial Management* 11, 267–312.

Fishman, M. J., and K. M. Hagerty, 1992, Insider Trading and the Efficiency of Stock Prices, *The Rand journal of economics* 23, 106-122.

Glosten, L. R., 1989, Insider Trading, Liquidity, and the Role of the Monopolist Specialist, *The Journal of Business* 62, 211-235.

Jarrell, G. A., and A. B. Poulsen, 1989, Stock Trading before the Announcement of Tender Offers: Insider Trading or Market Anticipation? *Journal of Law, Economics, & Organization* 5, 225-248.

Jiang, X., and M. A. Zaman, 2010, Aggregate insider trading: Contrarian beliefs or superior information? *Journal of Banking & Finance* 34, 1225-1236.

Keown, A. J., and J. M. Pinkerton, 1981, Merger Announcements and Insider Trading Activity: An Empirical Investigation, *The Journal of Finance* 36, 855-869.

King, M. R., 2009, Prebid Run-Ups Ahead of Canadian Takeovers: How Big Is the Problem? *Financial Management* 38, 699-726.

Kyle, A. S., 1985, Continuous Auctions and Insider Trading, *Econometrica* 53, 1315-1335.

Lakonishok, J., and I. Lee, 2001, Are Insider Trades Informative? *The Review of Financial Studies* 14, 79-111.

Leland, H. E., 1992, Insider Trading: Should It Be Prohibited? *Journal of Political Economy* 100, 859-887.

Manne, H., 1966, *Insider Trading and the Stock Market*, New York: Free Press.

Meulbroek, L. K., 1992, An Empirical Analysis of Illegal Insider Trading, *The Journal of Finance* 47, 1661-1699.

Morck, R., B. Yeung, and W. Yu, 2000, The information content of stock markets: why do emerging markets have synchronous stock price movements? *Journal of Financial Economics* 58, 215-260.

Myers, S. C., and N. S. Majluf, 1984, Corporate financing and investment decisions when firms have information that investors do not have, *Journal of Financial Economics* 13, 187-221.

Piotroski, J. D., and D. T. Roulstone, 2004, The Influence of Analysts, Institutional Investors, and Insiders on the Incorporation of Market, Industry, and Firm-Specific Information into Stock Prices, *The Accounting Review* 79, 1119-1151.

Piotroski, J. D., and D. T. Roulstone, 2005, Do insider trades reflect both contrarian beliefs and superior knowledge about future cash flow realizations? *Journal of Accounting and Economics* 39, 55-81.

Seyhun, H. N., 1986, Insiders' profits, costs of trading, and market efficiency, *Journal of Financial Economics* 16, 189-212.

Seyhun, H. N., 1988, The Information Content of Aggregate Insider Trading, *The Journal of Business* 61, 1-24.

Chapter 2. Does the Intensity of Legal Insider Trading Affect Stock Price Informativeness?

Abstract

Open market transactions by corporate insiders are considered informative because they predict future stock returns and future firm-specific cash flows. As a result, it may seem natural to assume a positive association between the intensity of legal insider trading and stock price informativeness. However, it is also possible that insider trading discourages outsiders from information collection, and the overall informational efficiency may be lowered if outsider information collection is crowded out. This chapter investigates how the intensity of legal insider trading affects stock price informativeness. I find that firms with higher insider trading intensity tend to have higher firm-specific return variation. Stocks of firms with higher insider trading intensity experience less negative abnormal returns around SEO announcements, and are less affected by long-term return reversal. The findings support the view that legal insider trading intensity makes stock prices more informative.

2.1 Introduction

Does insider trading affect stock price informativeness? The question is at the center of the ongoing debate on the legality of insider trading. On one hand, open market transactions by corporate insiders are believed to reveal valuable inside information and reduce information asymmetry between managers and outside investors. For example, Seyhun (1986) finds that insider trading predicts future stock price movements; Lakonishok and Lee (2001) document cross-sectional predictive power of insider trading; Piotroski and Roulstone (2005) and Jiang and Zaman (2010) show that insider trading contains information about future cash flows; and Aktas, de Bodt and Van Oppens (2007) report hastened price discovery on insider trading days. The predictive power of insider trading is more pronounced in firms with higher information asymmetry, such as smaller firms (Lakonishok and Lee, 2001) and firms followed by fewer analysts (Frankel and Li, 2004). In my working paper with Xiaowei Xu and Rengong Zhang (which is not included in my thesis), we find higher insider trading informativeness in firms with more opaque earnings and less informative stock prices. Overall, these findings suggest that by incorporating private information into stock prices, the intensity of insider trading may make stock prices more informative and promote informational efficiency (Manne, 1966).

However, on the other hand, insider trading may undermine the long-term informational efficiency even if each single insider transaction impounds information. Glosten (1989) argues that insider trading creates inefficiency because market makers reduce market liquidity in response to insider traders. Fishman and Hagerty (1992) show that under certain circumstances, insider trading leads to less informative stock prices because it discourages outsiders from acquiring information. Although the "insider trading" described in the two models mentioned above are closer to the illegal conduct of insider trading, legal trading reported by corporate insiders is suspected to have a negative impact on informational efficiency in studies like Gunny and Zhang (2012).

Both views are legitimate under certain assumptions; therefore, how insider trading affects informational efficiency becomes an empirical question. While there are many studies on short-term informativeness of insider trading at the transaction level, it is not clear how the intensity of insider trading affects long-term informational efficiency at the firm level. This chapter aims to fill the gap in the literature. Using a sample of insider transactions filed with the SEC from 1986 to 2012, I find that the intensity of legal insider trading is positively associated with stock price informativeness, measured by firm-specific return variation. I also find that stocks of firms with more intense insider trading are less affected by long-term return reversal and have less abnormal price movements in important corporate events like seasoned equity offerings (SEO). My findings support the view that insider trading promotes market efficiency by incorporating valuable information into stock prices.

Given the size of aggregate insider trading activities reported in Chapter 1, this study is economically important to both researchers and practitioners. The findings suggest that since legal insider trading promotes efficiency, trading by corporate insiders should be allowed and should not be overly restricted. The findings also lead to further questions: if legal insider trading is beneficial due to its informativeness, does it increase firm value and benefit shareholders in general? Do legal insider trading and illegal insider trading play different roles in price formation prior to important corporate events such as M&As? These questions will be discussed in Chapter 3 and Chapter 4.

The remainder of the chapter is organized as follows: Section 2.2 introduces insider trading and its regulations as well as the research background. Section 2.3 describes the data and key variables used in this study. Section 2.4 contains empirical results and discussion. Section 2.5 presents findings in further tests and Section 2.6 concludes the chapter.

2.2 Research background

2.2.1 Insider trading

The term of insider trading can be confusing as it is often associated with illegal conduct. However, the SEC has a clear definition of "legal insider trading". When corporate insiders – including officers, directors, employees, large beneficial owners (with more than 10% of a class of the company's equity securities) and other affiliates[1] – trade their own company's shares, they must file with the SEC within two business days[2] and reveal the transaction details (including trading date, number of shares traded, trading price and personal details of the insider). An insider's initial filing is on Form 3, and every time she trades shares (resulting in a change in ownership) the transaction should be reported on Form 4. Transactions that should have been reported earlier on a Form 4 or deferred reporting should be reported on Form 5.

Insider trading filings are available to the public. There are many ways an investor can track trading records of insiders. First, many newspapers and websites routinely publish recent large transactions (especially purchases) by insiders. Second, the SEC has required insiders to submit electronic forms through the SEC's EDGAR system since June 30, 2003, and investors can access the EDGAR system free of charge for insider trading details. The EDGAR system also allows investors to sign up for RSS feeds to receive timely updates on insider trading filings.

[1] Detailed definition of "corporate insiders" can be found under Section 12 of the Securities Exchange Act of 1934.
[2] The two-day deadline started on August 27, 2002 after the SEC adopted amendments to Section 16 of the Securities Exchange Act as required by the provisions of the Sarbanes-Oxley Act of 2002. Before that, the deadline could be up to 40 days after the trading day (within 10 days after the end of the month when insider transactions take place).

It is difficult to draw a clear line between legal insider trading and illegal insider trading. Though most of these reported insider transactions are legal, some of the transactions reported by insiders are later discovered illegal. Examples include trades placed by executives of Enron in 2001. If insiders are found in possession of material private information when they trade their company's shares, their trading would be considered illegal. In practice, it is extremely difficult to prove whether insiders have "material" private information or not, and that results in a gray area of insider trading (Bainbridge, 2013).

2.2.2 Insider trading regulations

The general public appears to dislike illegal insider trading and often associate the term with corporate scandals. Huge profits based on insider information evoke a sense of unfairness in people's minds; therefore, almost every big illegal insider trading scandal is followed by angry outcries and sterner regulations. In the United States, the Securities Act of 1933 and its later revised version of the Securities Exchange Act of 1934, which contains strong regulations such as the "short-swing" rule, was enacted as early as 1930s after the general public witnessed the Albert Wiggin scandal. In 1984 and 1988, the Insider Trading Sanctions Act and Securities Fraud Enforcement Act were passed to further regulate insider trading activities, about the same time as the Levine-Siegel-Boesky-Milken case. After a recent set of revisions to the Securities Exchange Act, it is now a lot more difficult for insiders to trade on profitable private information. The international development of insider trading laws is somewhat similar. As of today, most major stock exchanges have insider trading laws or regulations. In Bhattacharya and Daouk (2002) sample of 103 countries, 87 have established insider trading laws.

The criticism of insider trading also leads to strict trading regulations imposed by firms. In Bettis, Coles and Lemmon (2000) sample, over 92% firms have policies restricting insider trades, and 78% have blackout periods during which insider trading is prohibited. Such policies bring implicit costs to firms, as Roulstone (2003) find firms restricting insider trades pay a premium in executive compensation.

2.2.3 Informativeness of insider trades

Despite the stern regulations on insider trading, many people still believe insider trades are informative. R. Foster Winans, the Wall Street Journal columnist who was involved in an infamous insider trading case, once said: "The only reason to invest in the market is because you think you know something others don't." It is the same for insiders, especially those who buy their own firms' stocks. In a perfectly efficient market, one would not expect a board director or an officer to buy more shares due to diversification considerations or potential litigation costs of insider trading; however, we do observe a lot of buying activities from directors or key officers like CEOs.

The informativeness of insider trading is confirmed by academic evidences. Seyhun (1986) finds insiders can predict future returns and profit from trading. The finding is later corroborated by Lakonishok and Lee (2001). Insider trading also occurs before major corporate events, such as earnings announcement (Huddart, Ke and Shi, 2007), dividend announcements (John and Lang, 1991), bankruptcy (Seyhun and Bradley, 1997), and to some extent, mergers and acquisitions (Arshadi and Eyssell, 1991; Harlow and Howe, 1993; Agrawal and Jaffe, 1995; Agrawal and Nasser, 2012). Aggregate insider trading measures, such as net insider buys, is found to predict future market returns (Seyhun, 1992; Jiang and Zaman, 2010).

Insider transactions vary in informativeness. Seyhun (1986) finds insider trading informativeness is greater for trades by directors than for trades by beneficial owners. Lakonishok and Lee (2001) find higher insider trading informativeness in smaller firms. Besides, insider trades better predict stock returns in firms with higher information asymmetry (Frankel and Li, 2004; Tang, Xu and Zhang, 2013).

2.2.4 Costs and benefits of insider trading

While the general public ubiquitously dislikes insider trading, a branch of researchers seem to believe insider trading is good and should be deregulated. Milton Friedman once said: "You want more insider trading, not less. You want to give the people most likely to have knowledge about deficiencies of the company an incentive to make the public aware of that." One of the earliest works about the benefits of insider trading is Manne (1966), with the main argument that insider trading promotes price efficiency. When stock prices are more accurate and reveal more information, information asymmetry between managers and outside investors is reduced and corporate resources are allocated more efficiently (Leland, 1992; Khanna, Slezak and Bradley, 1994; Subrahmanyam and Titman, 1999; Roll, Schwartz and Subrahmanyam, 2009).

One major view against insider trading is from a perspective of fairness. Early advocators of insider trading regulation claim insider trades are not "fair", and Bainbridge (2013) provides an excellent review of them. In an economic framework, "fairness" may be modeled with information asymmetry: when insiders have superior information, they have informational advantage in trading against outsiders; outsiders, knowing their information disadvantage, reduce their investments, which drives down asset prices (Ausubel, 1990). Besides, when insider trading is prevalent, outsiders may not have enough incentive to collect information; in other words, outsider information collection is "crowded out" by insider trading. As a result, insider trading may make stock prices less informative if the crowd-out effect is strong enough, as in Fishman and Hagerty (1992).

2.3 Data and variables

2.3.1 Sample

I obtain data on insider trading activity from Thomson Reuters insider filings database (TFN). Specifically, I download all open-market transactions as reported on Forms 3, 4, 5 and 144 from 1986 to 2012[3]. Section 16a of the Securities Exchange Act of 1934 defines statutory corporate insiders who are subject to filing requirements, and requires that transactions by statutory corporate insiders be promptly filed with the SEC. Our sample includes transactions by board directors, corporate officers, beneficial owners with more than 10% ownership and other affiliated persons such as financial advisors and members of various committees.

I keep open-market purchases and sales only (with a transaction code of "P" or "S" in the database) and exclude stock grants, private transactions and option exercises from my sample. As a result, "passive" trades that do not necessarily reflect insider opinions are not included in the sample[4]. I also drop observations with duplicate document control number (DCN), duplicate sequence number or missing number of shares traded. The final sample consists of 4,476,832 transactions. Summary of the insider trading sample is reported in Panel A of Table 2.1.

[Insert Table 2.1 here]

[3] The Thomson Reuters insider filings database starts in 1986.
[4] I also tried excluding all sales following option exercises and the results are not affected much.

Of the 4,476,832 trades, 1,222,194 are purchases and 3,254,638 are sales. Insider sales tend to be more frequent compared to purchases, but there are some extremely large purcahses. The median trading size is 1,500 shares, but the mean trading size is over 50,000 shares due to some extreme observations. The sample consists of 22,347 unique firms and 220,317 unique insiders, and the average number of insiders covered in the sample is about 10 per firm. The sample is similar in size and characteristics with previous studies such as Cohen, Malloy and Pomerski (2012).

The sample of insider transactions is merged with CRSP and Compustat. This step reduces the sample to 17,710 unique firms, of which 13,112 firms have valid insider trading data.

2.3.2 Insider trading measures

The purpose of this study is to find the association between stock price informativeness and insider trading intensity. Therefore, directional measures such as net purchase ratio are not appropriate in the analysis. I measure insider trading intensity in two ways. The first measure is the total number of the firm's insider trading in the year, and the second measure is the total dollar volume of the firm's insider trading in the year. These measures are non-directional measures including both insider purchases and sales, and are defined in a similar way with Peress (2010).

Kyle (1985) suggests that insiders may trade more if outside investors are more active in trading. Besides, a same-sized insider trade may be more informative for a thinly-traded stock than for a frequently-traded stock. To address the variation in total trading intensity, I scale the aforementioned two measures by the total number of trades in the year and the total dollar volume of trades in the year, respectively. The scaling is the same as in Piotroski and Roulstone

(2004). After scaling, the two measures of insider trading intensity are defined as follows: the frequency measure, *IT_NUM*, is the total number of a firm's insider trades divided by the annual number of trades by all investors (in hundreds); the volume measure, *IT_VOL*, is defined as the total absolute volume of the firm's insider trades divided by the annual trading volume by all investors (in hundreds). Intuitively, *IT_NUM* measures the percentage of trades made by insiders, and *IT_VOL* measures the percentage of volume contributed by insiders. They both measure the amount of information revealed by reported insider trading.

Since both measures are non-directional, it raises some concern on the legitimacy of adding the intensity of sales to the intensity of purchases. My argument is that if both purchases and sales make stock prices more informative (or less informative), in the long run they should both have a positive (or negative) effect on stock price informativeness. Because the measure of stock price informativeness is firm-specific return variation, which is not directional, it is not clear why the direction of trading should bias my results. The method is to some extent similar to a study by Roll, Schwartz and Subrahmanyam (2009), in which option volumes are aggregated annually regardless of their directions.

2.3.3 Stock price informativeness

The main measure of stock price informativeness used in this study is firm-specific return variation. Roll (1988) finds that firm-specific return variation is not related to public news; Morck, Yeung and Yu (2000) argue that firm-specific return variation reflects the content of information not explained by the market index and thus could be used as a measure of informational efficiency. Durnev, Morck, Yeung and Zarowin (2003) and Durnev, Morck and Yeung (2004) find further evidence that firm-specific return variation signals more informative stock pricing rather than noise. Firm-specific return variation is used as a measure of stock price informativeness in subsequent studies such as Fernandes and Ferreira (2009) and Fresard (2012).

Following the literature, for each firm in each year I estimate the following model:

$$r_{i,t} = \alpha_i + \beta^{Mkt}{}_i * r_{Mkt,t} + \beta^{Ind}{}_i * r_{Ind,t} + \varepsilon_{i,t}$$

$r_{i,t}$ is the daily return of firm i on day t, $r_{Mkt,t}$ is the daily return of a value-weighted market index on day t, and $r_{Ind,t}$ is the daily return of a value-weighted SIC 2-digit industry index on day t. $\beta^{Mkt}{}_i$ and $\beta^{Ind}{}_i$ are the market beta and the industry beta.

The coefficient of determination (R^2) in each firm-year regression is saved. It measures the proportion of return variation that could be explained by the market index and the industry index. Since a higher R^2 suggests less informative stock prices, I then define firm-specific return variation, *FSRV*, as $\log((1 - R^2)/R^2)$. The measure is similar to firm-specific return variation defined in Morck, Yeung and Yu (2000) and Fernandes and Ferreira (2009).

2.3.4 Control variables

Kelly (2005) argues that firm-specific return variation is affected by firm size and other information asymmetry measures such as number of analysts. This imposes an endogeneity problem because insider trading intensity could be affected by firm size and information asymmetry measures as well. Thus, I include three main control variables in the main analysis: firm size, number of analysts, and accounting opacity. The first variable, firm size, is a common control variable used in a large number of papers and has been shown to affect stock returns and insider trading (Fama and French, 1992; Piotroski and Roulstone, 2004). I define firm size as the log of market capitalization at the beginning of the fiscal year, denoted *LOGMV*.

Besides firm size, I also use two measures of the Myers and Majluf type of information asymmetry as control variables. The first information asymmetry measure is number of analysts following. Analyst forecast is an important channel of information. Frankel and Li (2004) find that insider trading is more informative when the firm has poorer analyst coverage, and number of analysts has been constantly used as a measure of information asymmetry in a large number of studies including Huddart and Ke (2007) and Peress (2010). Number of analysts is defined as the number of unique analysts following a firm in the previous year, recorded in I/B/E/S. It is then log-transformed and denoted *ANALYSTS*.

The second measure of information asymmetry is accounting opacity defined in Hutton, Marcus and Tehranian (2009). The measure is defined as the absolute magnitude of discretionary accruals in the past three fiscal years and captures information asymmetry arising from earnings management. Earnings management, and particularly accruals management, is well documented in the accounting literature and is found to obscure information about firm fundamentals and may even result in mispricing (e.g. Sloan, 1996; Bhattacharya, Daouk and Welker, 2003). In a closely-related paper, Aboody, Hughes and Liu (2005) find accruals management is associated with high cost of capital and insider trading profitability.

I use the modified Jones model (Dechow, Sloan and Sweeny, 1995) to estimate discretionary accruals. The modified Jones model is estimated for each two-digit SIC year grouping as follows:

$$\frac{TA_{i,t}}{Assets_{i,t-1}} = k_{1t} * \frac{1}{Assets_{i,t-1}} + k_2 * \frac{\Delta REV_{i,t}}{Assets_{i,t-1}} + k_3 * \frac{PPE_{i,t}}{Assets_{i,t-1}} + \varepsilon_{i,t}$$

For fiscal year t and firm i, $\mathrm{TA}_{\mathrm{i,t}}$ represents total accruals calculated as the difference between earnings before extraordinary items and operating cash flows, and is scaled by last fiscal year ends' total assets. $\Delta\mathrm{REV}_{\mathrm{i,t}}$ is the change in firms' sales from year t-1 to year t. $\mathrm{PPE}_{\mathrm{i,t}}$

represents the gross value of property, plant and equipment. To enhance the validity of estimates, I drop SIC years with less than 10 observations. I also drop financial industries (SIC 6000-6999) and utilities industries (SIC 4400-5000) because their accounting and financial reporting practices are different. The coefficients from the equation above are applied to the following equation to obtain estimates of firm-year specific normal accruals ($\mathrm{NA}_{\mathrm{i,t}}$), where $\Delta\mathrm{AR}_{\mathrm{i,t}}$ is change in accounts receivable from the previous year:

$$NA_{i,t} = \hat{k}_{i,t} \frac{1}{Assets_{i,t-1}} + \hat{k}_2 \frac{\Delta REV_{i,t} - \Delta AR_{i,t}}{Assets_{i,t-1}} + \hat{k}_3 \frac{PPE_{i,t}}{Assets_{i,t-1}}$$

Finally, discretional accruals ($\mathrm{DACC}_{\mathrm{i,t}}$) is calculated as the difference between total accrual and fitted value from equation 2, which is ($\mathrm{TA}_{\mathrm{i,t}}/\mathrm{Assets}_{\mathrm{i,t-1}}$) – $\mathrm{NA}_{\mathrm{i,t}}$. Accounting opacity (denoted *OPACITY* hereafter) in year *t* is defined as:

$$Opacity_{i,t} = |DACC_{i,t-1}| + |DACC_{i,t-2}| + |DACC_{i,t-3}|$$

Hutton, Marcus and Tehranian (2009) find that higher *OPACITY* corresponds to lower firm-specific return variation and argue that it is a measure of opacity in financial statements.

Panel B of Table 2.1 describes the market capitalization, return volatility, number of analysts and accounting opacity of sample firms as well as insider trading characteristics. In Panel C, I report the same statistics for sub-samples sorted by the insider trading frequency measure (*IT_NUM*). The distribution of insider trading years is reported in Panel D of Table 2.1.

2.4 Empirical results

2.4.1 Univariate tests

As a first step in investigating how insider trading intensity affects stock price informativeness, I study whether firms with recent insider trading records have higher firm-specific return variation compared to firms without recent insider trading records. Because the decision to have insider trading or not is highly endogenous, the sample of firms with insider trading may be affected by the sample selection bias. It is important to find a proper match for each observation with insider trading history. To find the appropriate match, I first define a dummy variable, *IT_DUMMY*, to indicate whether a firm has recent insider trading history in year *t*. A firm is considered to have recent insider trading records (*IT_DUMMY*=1) in year *t* if at least one insider transaction is recorded in the one-year period ending three months before the fiscal year end[5] (e.g., prior -15 month to -4 month), and is considered to have no recent trading records (*IT_DUMMY*=0) if no insider transaction is recorded in the three-year period ending three months before the fiscal year end (e.g., prior -39 month to prior -4 month). In other words, if a firm does not have any insider trading in the past three years, the firm is considered a potential match for firms with recent insider trading records in the past year.

I first match firms by size. Specifically, in each fiscal year, each firm with recent insider trading is matched with firms without recent insider trading if they are in the same SIC 2-digit industry and have a market capitalization difference of less than 10% of the sample firm's market capitalization. I also use 5% and 1% as alternative thresholds. Matching firms using the 10% size difference gives 167,349 matches, which is larger than the original sample size of 53,821. Summary statistics of the matches are reported in Panel A of Table 2.2. Firms with insider trading history seem to have slightly greater return volatility, more analysts following and higher accounting opacity. They also appear to have higher R^2 compared to firms without recent insider trading.

[Insert Table 2.2 here]

[5] By making the assumption I assume the information from insider trading will be fully reflected in market prices after three months. The assumption is conservative enough to me given the reporting deadline is 2 days after 2002 and no more than 40 days before 2002. The results are virtually not affected if other timing assumptions are used.

Matching firms by size only may not give ideal matches. Firms with similar market capitalization may have very different characteristics even within the same industry. Thus, I use propensity score matching and include more firm characteristics in the matching process. A key factor in propensity score matching is a correct model predicting what firms should have insider trading. As mentioned before, *ANALYSTS* and *OPACITY* are important information asymmetry measures and should be included in propensity score calculation. The size variable, *LOGMV*, is also included because insiders are likely to trade more actively in smaller firms. To minimize endogeneity, I also include average insider trading intensity measures of firms in the same SIC 2-digit industry (excluding the sample firm) in year t-1 to remove any possible industry effect. Lakonishok and Lee (2001) find insiders are in general contrarian investors, so I also include the absolute value of momentum (defined as the cumulated return in the 11-month period ending two months before the fiscal year end[6]) in the model[7]. The propensity score estimation model is described in Appendix 2A. The propensity score model works well and can successfully predict about 73% of insider trading incidents. After obtaining propensity scores for each observation, for each fiscal year I match each firm with recent insider trading (*IT_DUMMY*=1) to another firm without recent insider trading (*IT_DUMMY*=0) if (a) they are in the same SIC 2-digit industry, (b) their difference in propensity scores is no greater than 0.1 and (c) the matched firm should be one of the two closest neighbours in propensity score (one above and one below). Summary statistics of propensity score matched firms are reported in Panel B of Table 2.2.

I continue to test the statistical significance of differences in firm-specific return variation for size-matched pairs and for propensity score matched pairs. Univariate results are reported in Table 2.3. Unconditionally, firms with recent insider trading have significantly lower firm-

[6] Using earlier momentum windows does not affect the results much in Appendix 2A.
[7] The window of [t-12, t-2] is consistent with the definition of momentum on Kenneth French's website.

specific return variation compared to firms without recent insider trading for both size-matched pairs and propensity score matched pairs. At first glance, the results seem inconsistent with the hypothesis. However, when I sort the sample of firms with recent insider trading by *IT_NUM* and report the differences in *FSRV* conditional on the intensity of insider trading, I find that the inconsistent results are driven by the two lowest quintiles. When insider trading intensity increases, firms with insider trading do seem to benefit from it and have significantly higher firm-specific return variation. I further examine the two lowest *IT_NUM* quintiles and find most of firms in these two quintiles have only 1 or 2 insider transactions in the one-year period. It is difficult to argue how the 1 or 2 insider transactions dramatically change stock price informativeness; besides, these firms are likely to have higher information asymmetry compared to their matches without insider trading record because the propensity score model could not completely eliminate the sample selection problem. Both the magnitude and statistical significance of differences in firm-specific return variation increase in insider trading intensity, suggesting that insider trading intensity is positively associated with stock price informativeness.

[Insert Table 2.3 here]

2.4.2 Regression analysis

To examine the continuity of results, I continue to investigate the association using regressions. The dependent variable is firm-specific return variation (*FSRV*). Variables of interest include the two continuous insider trading intensity measures defined earlier, *IT_NUM* and *IT_VOL*, as well as a dummy variable *IT_DUMMY* defined earlier. I include only firms with recent insider trading (IT_DUMMY=1) and firms without recent insider trading but are propensity matched to firms with insider trading in the regression. *LOGMV*, *ANALYSTS* and

OPACITY are included as control variables. Industry and year fixed effects are included in regressions. Standard errors are clustered by firm.

Regression results are reported in Table 2.4. The results are largely consistent with univariate results in Table 2.3: both insider trading measures, *IT_NUM* and *IT_VOL*, have significantly positive coefficients. Besides, the coefficient of the insider trading dummy variable (*IT_DUMMY*) is significantly positive in most of the regressions except in (1) and (3) of Panel B, possibly due to the sample selection problem discussed before. In general, the results suggest that insider trading is positively associated with stock price informativeness.

[Insert Table 2.4 here]

Can we infer causality from the results? The positive coefficients reported in Table 2.4 could also suggest a reverse causality that insiders trade more when stock prices are more informative; alternatively, some latent variable could affect both insider trading intensity and stock price informativeness. Thus, it is essential to further examine the results.

The first issue, reversed causality, does not sound very intuitive and contradicts the literature. Previous studies such as Aboody, Hughes and Liu (2005) and Frankel and Li (2004) find that insiders tend to trade less when information asymmetry is lower. In my other study (Tang, Xu and Zhang, 2013), we find insider transactions are significantly less profitable when firm-specific return variation is higher. It is difficult to imagine why insiders want to trade more when their trading is less profitable.

The second issue, endogeneity, is more difficult to address. The propensity score matching and the control variables of *LOGMV*, *ANALYSTS* and *OPACITY* may alleviate the concern to some extent, but there could be other variables that affect both firm-specific return variation and insider trading intensity. As a first attempt, I consider other possible endogeneity channels and add additional control variables to the regression. (a) ROA and ROA volatility. A firm with high and stable ROA is likely to be in a mature stage and have less firm-specific information. Since not much is going on in the firm, the firm may have very little firm-specific return variation as well as limited insider trading opportunities. (b) Financial leverage. A firm with higher financial leverage may be riskier and have higher return variation. Also, higher leverage makes insider trading potentially more attractive and could cause more intense insider trading. (c) Market power. Peress (2010) shows that market power is positively associated with insider trading intensity; if there is an association between firm-specific return variation and profit margin, market power could potentially be a source of endogeneity. (d) Illiquidity. Illiquidity could theoretically cause endogeneity if illiquid stocks have lower firm-specific return variation, though it is unlikely because Kelly (2005) finds that stocks with greater firm-specific return variation tend to have higher illiquidity, and insiders should stay away from illiquid stocks according to Kyle (1985). I include all these variables as additional control variables, but the positive association between insider trading intensity and firm-specific return variation is not affected. It is not clear to me which endogeneity story can seriously drive the results in Table 2.3 and Table 2.4.

Although the majority of studies support using firm-specific return variation as a measure of stock price informativeness, some studies argue that firm-specific return variation contains too much noise and may not truly reflect informational content in stock prices (see Kelly, 2005). Therefore, it is important to include other tests before a conclusion is reached. In the next section, I use two indirect ways to explore the association between insider trading and stock price informativeness.

2.5 Further tests

2.5.1 Abnormal returns around SEOs

If insider trading makes stock prices more informative, then stocks with higher insider trading intensity should exhibit less abnormal movements in important corporate events. I consider three common and important corporate events: mergers and acquisitions (M&As), earnings announcements, and seasoned equity offerings (SEO). Of the three events, M&As are the most high-profile events and I study it separately in Chapter 4 of the thesis. Earnings announcements are common and occur every quarter, but may not be appropriate in this study because the majority of public firms in the US have insider trading black-out windows before earnings announcements. Since the firm-level insider trading restriction data is not available, insider trading prior to earnings announcements would be very endogenous. Thus, I focus on SEOs in this section.

SEOs are important corporate events. It has been documented that stocks tend to experience negative abnormal returns around SEOs (see Loughran and Ritter, 1995). If insider trading promotes price efficiency, stocks with more intense insider trading should have less negative abnormal returns around SEO announcements.

I use SEO events over the period 1986 - 2012 from SDC Platinum. Then I use standard event study methodology to measure the abnormal announcement returns over the period [-1, +5][8] relative to the announcement date. The market return is the equal-weighted return in CRSP and the estimation window is [-365, -45]. Cumulated abnormal return over the window, CAR[-1, 5], is winsorized at 1%. Summary of abnormal stock returns around SEO announcements is tabulated in Table 2.5. Daily abnormal return starts to become negative on the day before SEO

[8] I consider several alternative event windows for robustness such as CAR[-1, 1], CAR[0, 1] and CAR[-1, 10]. Our results are virtually the same when alternative windows are used.

announcements, and remains negative until about 4 days after SEO announcements. I regress the cumulated abnormal return CAR[-1,5] over insider trading intensity measures (*IT_NUM*, *IT_VOL* and *IT_DUMMY*), using control variables of *LOGMV*, *ANALYSTS* and *OPACITY*. Since the SEO announcements do not always occur at the end of each fiscal year, I measure *IT_NUM* and *IT_VOL* over the one-year period ending three months before the announcements. Only observations with insider trading from month t-15 to month t-4 and observations without insider trading but with a propensity score greater than 0.5 are included. Standard errors are clustered by firm. Regression estimates are reported in Table 2.6.

[Insert Table 2.6 here]

Results in Table 2.6 are not as strong as results reported in Table 2.4, but are in general consistent with the story. Firms with recent insider trading records exhibit significantly less negative cumulated abnormal returns. The results further support the view that insider trading intensity makes stock prices more informative.

2.5.2 Long-term return reversal

Another way to test whether insider trading affects stock price informativeness is to test whether stocks of firms with higher insider trading intensity are less affected by market anomalies such as long-term reversal. Long-term reversal is an important market anomaly caused by mispricing (De Bondt and Thaler, 1985; Barberis, Shleifer and Vishny, 1998; McLean, 2010). If insiders trade against mispricing and make stock prices more informative, the reversal portfolio that buys the low past return quintile (losers) and sells the high past return quintile (winners) should earn lower profit in the high insider trading quintile than in the low insider trading quintile.

I download CRSP monthly returns for all stocks in the sample period when insider trading data is available. For each month I sort firms into long-term reversal quintiles by prior 13 month – 60 month return[9]. Firms are then independently sorted into quintiles by *IT_NUM* and *IT_VOL* measured in year t-1. Average monthly returns[10] of the 5 by 5 portfolios and the long-term reversal portfolio are reported in Table 2.7. Consistent with the view that insider trading reduces mispricing, the reversal portfolio returns (L – W) are higher for low insider trading quintiles, and lower for high insider trading quintiles. In Panel A, the reversal portfolio does not earn significant positive returns in the quintile of highest insider trading frequency. The results suggest that insider trading may reduce mispricing; firms with more frequent and larger insider trades are less affected by long-term reversal.

[Insert Table 2.7 here]

I also examined whether firms with more reported insider trades are less affected by momentum (prior 2 to 12 months) and short-term reversal (prior 1 month), but I did not find robust results. Insider trading seems to affect long-term reversal only. The findings are similar to McLean (2010) in which long-term reversal is only prevalent in high idiosyncratic risk stocks and momentum is not related to idiosyncratic risk. A possible reason is that momentum profits are within transaction costs (Lesmond, Schill and Zhou, 2004).

2.6 Concluding remarks

Whether insider trading intensity affects stock price informativeness is an important question which is missing from the literature. Though numerous studies show that transactions by insiders contain information, it is not clear if insider trading really crowds out information

[9] The window follows the long-term reversal window on Kenneth French's website.
[10] Alternatively, I use the average monthly return of the following 6 months and the results are very similar.

collection by outside investors and reduce price efficiency in the long run. This study shows that firm-level insider trading intensity is positively associated with firm-specific return variation in the long run. Stocks of firms with larger and more frequent insider trading have less negative abnormal returns around SEO announcements, and are less affected by long-term return reversal. The findings are consistent with the view that insider trading increases informational efficiency.

I would like to emphasize at the end of the chapter that the study investigates legal insider trading only. Results in this chapter may not hold for illegal insider trading. One potential difference between legal insider trading and illegal insider trading is that legal insider trading is always done by corporate insiders and always reported to the public. Since it is strictly regulated and closely monitored, legal insider trading is not likely based on important inside information. Therefore, it is likely to alleviate the Myers and Majluf type of information asymmetry without creating a lot of Kyle type of information asymmetry, as discussed in Chapter 1. In contrast, illegal insider trading is typically done by de-facto insiders who do not work for the firms, and they do not report their transactions to the public. They can base their trades on very important and material inside information, and their trades are likely to create severe information asymmetry between informed investors and uninformed investors (the Kyle type of information asymmetry).

The study serves as an important first step towards a more important question: if insider trading promotes informational efficiency, does it further affect firm value and cost of capital? The question will be investigated in Chapter 3.

References

Aboody, D., J. Hughes, and J. Liu, 2005, Earnings Quality, Insider Trading, and Cost of Capital, *Journal of Accounting Research* 43, 651-673.

Agrawal, A., and J. F. Jaffe, 1995, Does Section 16b deter insider trading by target managers? *Journal of Financial Economics* 39, 295-319.

Agrawal, A., and T. Nasser, 2012, Insider trading in takeover targets, *Journal of Corporate Finance* 18, 598-625.

Aktas, N., E. de Bodt, and H. Van Oppens, 2008, Legal insider trading and market efficiency, *Journal of Banking & Finance* 32, 1379-1392.

Arshadi, N., and T. H. Eyssell, 1991, Regulatory Deterrence and Registered Insider Trading: The Case of Tender Offers, *Financial Management* 20, pp. 30-39.

Ausubel, L. M., 1990, Insider Trading in a Rational Expectations Economy, *The American Economic Review* 80, pp. 1022-1041.

Bainbridge, S. M., 2013, *Research Handbook on Insider Trading*, Edward Elgar Publishing Ltd.

Barberis, N., A. Shleifer, and R. Vishny, 1998, A model of investor sentiment, *Journal of Financial Economics* 49, 307-343.

Bettis, J. C., J. L. Coles, and M. L. Lemmon, 2000, Corporate policies restricting trading by insiders, *Journal of Financial Economics* 57, 191-220.

Bhattacharya, U., H. Daouk, and M. Welker, 2003, The World Price of Earnings Opacity, *The Accounting Review* 78, 641-678.

Bhattacharya, U., and H. Daouk, 2002, The World Price of Insider Trading, *The Journal of Finance* 57, pp. 75-108.

Cohen, L., C. Malloy, and L. Pomorski, 2012, Decoding Inside Information, *The Journal of Finance* 67, 1009-1043.

De Bondt, W., and R. Thaler, 1985, Does the Stock Market Overreact? *The Journal of Finance* 40, 793-805.

Dechow, P. M., R. G. Sloan, and Amy P. Sweeney, 1995, Detecting Earnings Management, *The Accounting Review* 70, 193-225.

Durnev, A., R. Morck, and B. Yeung, 2004, Value-Enhancing Capital Budgeting and Firm-Specific Stock Return Variation, *The Journal of Finance* 59, 65-105.

Durnev, A., R. Morck, B. Yeung, and P. Zarowin, 2003, Does Greater Firm-Specific Return Variation Mean More or Less Informed Stock Pricing? *Journal of Accounting Research* 41, 797-836.

Fama, E. F., and K. R. French, 1992, The Cross-Section of Expected Stock Returns, *The Journal of Finance* 47, pp. 427-465.

Fernandes, N., and M. A Ferreira, 2009, Insider Trading Laws and Stock Price Informativeness, *The Review of Financial Studies* 22, 1845-1887.

Fishman, M. J., and K. M. Hagerty, 1992, Insider Trading and the Efficiency of Stock Prices, *The Rand journal of economics* 23, 106-122.

Frankel, R., and X. Li, 2004, Characteristics of a Firm's Information Environment and the Information Asymmetry between Insiders and Outsiders, *Journal of Accounting and Economics* 37, 229-259.

Fresard, L., 2012, Cash Savings and Stock Price Informativeness, *The Review of Finance* 16, 985-1012.

Glosten, L. R., 1989, Insider Trading, Liquidity, and the Role of the Monopolist Specialist, *The Journal of Business* 62, 211-235.

Gunny, K. and T. C. Zhang, 2012, Strategic Informed Trading by Corporate Executives and Firm Value, *Working Paper*, Singapore Management University School of Accountancy Research Paper No. 1.

Harlow, W. V., and J. S. Howe, 1993, Leveraged Buyouts and Insider Nontrading, *Financial Management* 22, pp. 109-118.

Huddart, S., and B. Ke, 2007, Information Asymmetry and Cross-Sectional Determinants of Insider Trading, *Contemporary Accounting Research* 24, 195-232.

Huddart, S., B. Ke, and C. Shi, 2007, Jeopardy, Non-Public Information, and Insider Trading Around SEC 10-K and 10-Q Filings, *Journal of Accounting and Economics* 43, 3-36.

Hutton, A. P., A. J. Marcus, and H. Tehranian, 2009, Opaque financial reports, R2, and crash risk, *Journal of Financial Economics* 94, 67-86.

Jiang, X., and M. A. Zaman, 2010, Aggregate insider trading: Contrarian beliefs or superior information? *Journal of Banking & Finance* 34, 1225-1236.

John, K., and L. H. P. Lang, 1991, Insider Trading around Dividend Announcements: Theory and Evidence, *The Journal of Finance* 46, pp. 1361-1389.

Kelly, P. J., 2005, Information Efficiency and Firm-Specific Return Variation, *Working Paper*, New Economic School.

Khanna, N., S. L. Slezak, and M. Bradley, 1994, Insider Trading, Outside Search, and Resource Allocation: Why Firms and Society May Disagree on Insider Trading Restrictions, *The Review of Financial Studies* 7, 575-608.

Kyle, A. S., 1985, Continuous Auctions and Insider Trading, *Econometrica* 53, pp. 1315-1335.

Lakonishok, J., and I. Lee, 2001, Are Insider Trades Informative? *The Review of Financial Studies* 14, pp. 79-111.

Lesmond, D. A., M. J. Schill, and C. Zhou, 2004, The illusory nature of momentum profits, *Journal of Financial Economics* 71, 349-380.

Loughran, T., and J. R. Ritter, 1995, The New Issues Puzzle, *The Journal of Finance* 50, 23-51.

Manne, H., 1966, *Insider Trading and the Stock Market*, New York: Free Press.

McLean, R. D., 2010, Idiosyncratic Risk, Long-Term Reversal, and Momentum, *Journal of Financial and Quantitative Analysis* 45, 883.

Morck, R., B. Yeung, and W. Yu, 2000, The information content of stock markets: why do emerging markets have synchronous stock price movements? *Journal of Financial Economics* 58, 215-260.

Peress, J., 2010, Product Market Competition, Insider Trading, and Stock Market Efficiency, *The Journal of Finance* 65, 1-43.

Piotroski, J. D., and D. T. Roulstone, 2004, The Influence of Analysts, Institutional Investors, and Insiders on the Incorporation of Market, Industry, and Firm-Specific Information into Stock Prices, *The Accounting Review* 79, 1119-1151.

Piotroski, J. D., and D. T. Roulstone, 2005, Do insider trades reflect both contrarian beliefs and superior knowledge about future cash flow realizations? *Journal of Accounting and Economics* 39, 55-81.

Roll, R., E. Schwartz, and A. Subrahmanyam, 2009, Options trading activity and firm valuation, *Journal of Financial Economics* 94, 345-360.

Roulstone, D. T., 2003, The Relation between Insider-Trading Restrictions and Executive Compensation, *Journal of Accounting Research* 41, 525-551.

Seyhun, H. N., 1986, Insiders' profits, costs of trading, and market efficiency, *Journal of Financial Economics* 16, 189-212.

Seyhun, H. N., 1992, Why Does Aggregate Insider Trading Predict Future Stock Returns, *The Quarterly Journal of Economics* 107, 1303-1331.

Seyhun, H. N., and M. Bradley, 1997, Corporate Bankruptcy and Insider Trading, *The Journal of Business* 70, 189-216.

Sloan, R. G., 1996, Do Stock Prices Fully Reflect Information in Accruals and Cash Flows about Future Earnings? *The Accounting Review* 71, 289-315.

Subrahmanyam, A., and S. Titman, 1999, The Going-Public Decision and the Development of Financial Markets, *The Journal of Finance* 54, 1045-1082.

Tang, Z., X. Xu, and R. Zhang, 2013, Insider Trading Informativeness and Firm Opacity, *Working Paper*, University of Alberta.

Table 2.1 Summary Statistics of Insider Trading Sample

This table reports summary statistics of the entire sample as well as sub-samples by insider trading frequency quintile (*IT_NUM*, which is defined as number of insider trades divided by total number of trades in the one-year window). Panel A reports an overview of insider transactions in the sample. Panel B contains firm characteristics and summary of firm-level insider trading. Mkt Cap is the market capitalization in billions. Volatility is the stock return volatility in the year. #Analysts is the number of analysts covering the firm in the year, recorded in I/B/E/S. Opacity is the 3-year absolute value of discretionary accruals estimated using a modified Jones Model, as described in Hutton et al (2009). $ Insider Trades/Buys is the annual dollar volume of insider trades/buys in millions. % Trades/Volume by Insiders is the number/volume of insider trades as a percentage of total trading number/volume in the year. Panel C reports firm characteristics and summary of firm-level insider trading in *IT_NUM* quintiles. Panel D reports the distribution of number of years with insider trading. Continuous numbers in Panel B and Panel C are winsorized by 1%.

Panel A. Overview of insider transactions in the sample

	All	Purchases	Sales
No. of Trades	4,476,832	1,222,194	3,254,638
Mean Size (shares)	51,317.31	83,796.22	39,120.70
Median Size (shares)	1,500.00	1,200.00	1,500.00
No. of Unique Firms	22,347	20,435	19,237
No. of Unique Insiders	220,317	135,065	152,352
Average Insiders per Firm	9.86	6.61	7.92

Panel B. Overview of sample firms

	All Firms		Sample with Insider Trading	
	Mean	*σ*	*Mean*	*σ*
Firms				
Mkt Cap (bil)	1.399	4.268	1.747	5.209
Volatility	0.037	0.027	0.036	0.024
# Analysts	8.409	8.169	8.931	8.300
Opacity	0.219	0.199	0.209	0.185
Insider Trading				
# Insider Trades	NA	NA	13.734	25.515
# Insider Buys	NA	NA	4.853	19.414
$ Insider Trades (mil)	NA	NA	14.764	211.112
$ Insider Buys (mil)	NA	NA	2.194	111.807
% Trades by Insiders	NA	NA	0.359	0.855
% Volume by Insiders	NA	NA	2.838	8.910
# Obs	160001		103381	
# Obs with ITNUM			55579	
# Unique Firms	17710		13112	
# Firms per Year	5714		3692	

Panel C. Overview of sample firms by ITNUM quintile

	By ITNUM Quintile									
	Low		2		3		4		High	
	Mean	*σ*	*Mean*	*σ*	*Mean*	*σ*	*Mean*	*σ*	*Mean*	*σ*
Firms										
Mkt Cap (bil)	2.313	5.725	0.589	1.541	0.265	0.562	0.153	0.308	0.085	0.218
Volatility	0.038	0.022	0.043	0.024	0.044	0.025	0.043	0.026	0.044	0.028
# Analysts	11.643	8.862	7.097	6.262	5.490	4.956	4.259	3.869	2.941	2.749
Opacity	0.205	0.184	0.241	0.201	0.255	0.202	0.251	0.200	0.254	0.197
Insider Trading										
# Insider Trades	12.117	16.956	14.713	20.453	12.998	19.364	13.926	24.582	18.210	52.599
# Insider Buys	1.928	3.790	3.221	6.399	3.740	6.740	5.636	16.582	11.208	50.169
$ Insider Trades (mil)	26.680	193.257	12.139	92.085	6.904	166.320	4.564	54.744	2.400	16.231
$ Insider Buys (mil)	2.008	28.682	1.740	44.175	0.975	14.180	1.095	22.074	0.934	8.907
% Trades by Insiders	0.002	0.002	0.017	0.008	0.069	0.024	0.225	0.077	1.484	1.427
% Volume by Insiders	0.621	3.488	1.467	5.823	2.060	7.074	3.446	9.286	7.641	13.720
# Obs										
# Obs with ITNUM	11116		11116		11116		11116		11115	
# Unique Firms										
# Firms per Year										

Panel D: Distribution of Insider Trading Years and Years in Sample

Number of Years with Insider Trading	*# Firms*	*Number of Years in the Sample*	*# Firms*
1	1825	**1**	1962
2	1491	**2**	1716
3	1263	**3**	1540
4	1046	**4**	1468
5	838	**5**	1232
6	741	**6**	1113
7	608	**7**	1044
8	562	**8**	824
9	496	**9**	715
10	488	**10**	644
>10	3754	**>10**	6320
Total	18578	**Total**	13112

Table 2.2 Summary Statistics of Control Samples

This table reports summary statistics of control samples, matched by firm size (market capitalization) or by propensity score (see Appendix 2A). Panel A summarizes size-matched samples with 10%, 5% and 1% maximum size difference allowed. Panel B summarizes propensity score matched samples.

Panel A. Size-matched firms

Max Size Diff:	10%				5%				1%			
	Sample		***Matched***		***Sample***		***Matched***		***Sample***		***Matched***	
	Mean	*σ*	*Mean*	*σ*	*Mean*	*σ*	*Mean*	*σ*	*Mean*	*σ*	*Mean*	*σ*
Mkt Cap	366.811	798.296	364.614	792.926	366.226	800.041	365.574	797.919	363.585	796.147	363.987	799.171
Volatility	0.031	0.022	0.028	0.022	0.031	0.022	0.028	0.022	0.031	0.022	0.028	0.021
# Analysts	5.989	5.987	5.215	5.831	6.021	5.996	5.250	5.889	5.975	5.913	5.395	6.282
Opacity (1y)	0.080	0.094	0.078	0.096	0.080	0.095	0.078	0.096	0.080	0.096	0.076	0.095
Opacity (3y)	0.244	0.219	0.237	0.229	0.245	0.221	0.237	0.229	0.244	0.218	0.234	0.224
R2	0.128	0.172	0.106	0.151	0.128	0.172	0.107	0.151	0.128	0.171	0.107	0.152
# Obs	53821		167566		38531		83482		13042		16798	

Panel B. Propensity score matched firms

	All Sample			
	Sample		***Matched***	
	Mean	*σ*	*Mean*	*σ*
Mkt Cap	1222.827	3664.308	1550.881	4456.160
Volatility	0.040	0.023	0.039	0.025
# Analysts	5.213	7.120	4.822	6.796
Opacity	0.216	0.191	0.206	0.188
R2	0.140	0.173	0.143	0.173
# Obs	71571		128867	

Table 2.3 Univariate Test: Price Informativeness

This table reports the univariate differences in price informativeness, measured by *FSRV*, between sample firms and matched firms. *FSRV* is defined in Section 2.3 as the log-transformed R^2. R^2 is estimated by regressing firm daily stock return on market return and industry return: $r_{i,t} = \alpha_i + \beta_{i,mkt} r_{mkt,t} + \beta_{i,ind} r_{ind,t} + \varepsilon_{i,t}$ for each firm and fiscal year. ***, **, * indicate significance at 1%, 5% and 10%, respectively.

	# Matches	*FSRV*		By *IT_NUM* *Low*		*2*		*3*		*4*		*High*	
Size Matched													
Max Size Diff: 10%	167349												
Sample		3.014		1.726		2.853		3.687		4.248		4.879	
Matched		3.193		2.044		3.002		3.584		3.941		4.311	
Difference		-0.179	***	-0.318	***	-0.149	***	0.104	***	0.307	***	0.569	***
Max Size Diff: 5%	83375												
Sample		3.009		1.699		2.837		3.672		4.228		4.879	
Matched		3.186		2.009		2.961		3.58		3.934		4.291	
Difference		-0.177	***	-0.31	***	-0.124	***	0.092	***	0.294	***	0.587	***
Max Size Diff: 1%	*16780*												
Sample		3.009		1.775		2.801		3.667		4.225		4.868	
Matched		3.172		2.047		2.897		3.541		3.957		4.254	
Difference		-0.164	***	-0.272	***	-0.096	***	0.126	***	0.268	***	0.614	***
Propensity Score	128867												
Sample		2.822		1.504		2.629		3.391		3.887		4.491	
Matched		2.752		1.599		2.472		3.106		3.433		3.891	
Difference		0.069	***	-0.095	***	0.157	***	0.285	***	0.454	***	0.600	***

Table 2.4 Regression Analysis: *FSRV* and Insider Trading Intensity

This table reports regression analysis of stock price informativeness (measured by *FSRV*) on insider trading intensity, using observations with insider trading and match firms with propensity scores close to firms with insider trading. The dependent variable is the transformed R^2, which is defined as $\log[(1-R^2)/R^2]$. IT_NUM is the number of insider trades divided by the total number of trades over the one year period ending three months before the fiscal year end. IT_VOL is the volume of insider trades divided by the total volume of trades over the one year period ending three months before the fiscal year end. IT_DUMMY is a dummy variable that takes value of 1 if the firm has recent insider trading history, and 0 if otherwise. LOGMV is the log value of market capitalization. ANALYSTS is the log value of the number of analysts following the firm plus one. OPACITY is the 3-year opacity measure as described in Hutton et al (2009). All continuous variables are winsorized by 1%. Standard errors are clustered by firm. SIC-2 fixed effects and year fixed effects are included. Robust T statistics are reported in parentheses. ***, ** and * indicate significance levels of 1%, 5% and 10%, respectively.

Panel A. Number of Insider Trading

	(1)	(2)	(3)	(4)
IT_NUM	0.274***	0.234***	0.219***	0.182***
	(23.64)	(20.93)	(13.65)	(11.72)
IT_DUMMY	0.027	0.168***	0.025	0.150***
	(1.33)	(8.12)	(1.16)	(6.75)
LOGMV	-0.639***	-0.554***	-0.626***	-0.555***
	(-143.61)	(-93.27)	(-125.14)	(-82.27)
ANALYSTS		-0.260***		-0.220***
		(-25.29)		(-19.13)
OPACITY			-0.097**	-0.102***
			(-2.49)	(-2.68)
Constant	5.780***	5.599***	5.764***	5.668***
	(26.43)	(28.66)	(16.48)	(17.40)
Industry Effects	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes
Observations	68,590	68,590	49,544	49,544
R-squared	0.587	0.598	0.604	0.612

Panel B. Volume of Insider Trading

	(1)	(2)	(3)	(4)
IT_VOL	0.020***	0.018***	0.019***	0.017***
	(24.63)	(22.56)	(19.21)	(17.59)
IT_DUMMY	-0.017	0.081***	-0.050**	0.038*
	(-0.88)	(4.21)	(-2.47)	(1.88)
LOGMV	-0.653***	-0.581***	-0.635***	-0.576***
	(-192.18)	(-122.88)	(-165.92)	(-110.20)
ANALYSTS		-0.209***		-0.172***
		(-24.69)		(-18.56)
OPACITY			-0.038	-0.040
			(-1.14)	(-1.21)
Constant	5.768***	5.566***	5.914***	5.789***
	(25.74)	(24.44)	(24.34)	(25.08)
Industry Effects	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes
Observations	113,277	113,277	78,975	78,975
R-squared	0.643	0.650	0.663	0.668

Table 2.5 Abnormal returns around SEO announcements

This table reports daily abnormal returns, estimated using a market model, before and after SEO announcements. Day 0 is the event day (announcement). Numbers in this table are reported in percentage numbers (%).

Variable	Obs	Mean	Std. Dev.	Min	Max	Q25	Median	Q75
AR(-5)	4660	0.232	5.683	-30.401	274.104	-1.325	-0.101	1.229
AR(-4)	4659	0.055	3.812	-24.409	93.805	-1.279	-0.059	1.171
AR(-3)	4659	0.036	4.119	-23.658	101.414	-1.380	-0.119	1.143
AR(-2)	4660	0.024	4.890	-35.601	151.082	-1.420	-0.138	1.063
AR(-1)	4660	-0.067	3.924	-35.907	61.708	-1.463	-0.103	1.190
AR(0)	4660	-1.324	5.148	-78.613	109.376	-2.827	-0.705	0.611
AR(1)	4660	-2.208	5.260	-44.104	31.274	-4.128	-1.496	0.417
AR(2)	4660	-0.166	3.610	-40.182	55.135	-1.506	-0.126	1.160
AR(3)	4660	-0.112	3.206	-16.441	32.119	-1.394	-0.123	1.059
AR(4)	4660	-0.117	3.289	-24.214	46.826	-1.334	-0.154	0.975
AR(5)	4660	-0.042	3.403	-51.184	58.316	-1.171	-0.106	1.032
CAR[-1,1]	4660	-3.598	7.899	-94.087	83.944	-6.545	-2.819	0.056
CAR[-1,3]	4660	-3.877	9.475	-98.817	88.707	-7.397	-2.966	0.442
CAR[-1,5]	4660	-4.036	10.543	-97.917	87.168	-8.015	-3.142	0.728

Table 2.6 SEO CAR and Insider Trading Intensity

This table reports regression results with SEO CAR as dependent variables, using observations with insider trading and observations with propensity scores greater than 50% and 60% cutoffs. Four different windows, [0,1], [0,5], [-1, 1] and [-1, 5] are used (day 0 is the announcement date); however, using other windows leads to very similar results. CAR is estimated using a standard market model (250 days of estimation window ending 43 days before event, equal weighted market return). TBQ is the Tobin's q ratio, measured as book assets minus book equity plus market value of equity, and then divided by book assets. Other variables are defined in the same way as in Table 5. All continuous variables are winsorized by 1%. Standard errors are clustered by firm. SIC-2 fixed effects and year fixed effects are included. Robust T statistics are reported in parentheses. ***, ** and * indicate significance levels of 1%, 5% and 10%, respectively.

Panel A. Regressions with IT_NUM

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep Var:	CAR[0,1]	CAR[0,5]	CAR[-1,1]	CAR[-1,5]	CAR[0,1]	CAR[0,5]	CAR[-1,1]	CAR[-1,5]
IT_NUM	0.452	-0.072	1.164*	0.603	1.740**	0.280	1.924***	0.223
	(0.55)	(-0.05)	(1.78)	(0.52)	(2.04)	(0.24)	(2.73)	(0.21)
IT_DUMMY	2.213**	3.550***	2.517**	3.588***	1.123	2.155**	1.630*	2.472**
	(2.14)	(3.04)	(2.56)	(3.23)	(1.42)	(2.19)	(1.89)	(2.43)
OPACITY	-0.530	-1.553	-0.996	-2.101**				
	(-1.12)	(-1.32)	(-1.01)	(-2.02)				
LOGMV	0.676***	0.622	0.633***	0.539**	0.598**	0.667	0.516	0.590
	(2.95)	(1.56)	(3.07)	(2.06)	(2.28)	(1.53)	(1.53)	(1.18)
TBQ	0.046***	0.146***	0.068***	0.174***	0.038***	0.121***	0.040**	0.123***
	(2.99)	(2.78)	(2.72)	(4.78)	(2.84)	(3.61)	(2.39)	(4.16)
ANALYSTS					0.397	0.717	0.715	0.900
					(0.59)	(0.58)	(0.86)	(0.68)
Constant	-10.848***	-17.728***	2.351	3.577*	-11.017***	-14.417***	-8.220***	-11.926**
	(-7.31)	(-7.01)	(1.57)	(2.01)	(-4.94)	(-3.32)	(-3.14)	(-2.64)
Industry Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,117	1,117	1,117	1,117	1,418	1,418	1,418	1,418
R-squared	0.123	0.120	0.110	0.104	0.113	0.100	0.102	0.085

Panel B. Regressions with IT_VOL

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep Var:	CAR[0,1]	CAR[0,5]	CAR[-1,1]	CAR[-1,5]	CAR[0,1]	CAR[0,5]	CAR[-1,1]	CAR[-1,5]
IT_VOL	0.002	0.035	-0.002	0.030	-0.006	0.007	-0.007	0.006
	(0.13)	(1.26)	(-0.08)	(0.96)	(-0.58)	(0.57)	(-0.69)	(0.49)
IT_DUMMY	1.566***	2.181***	1.744***	2.206***	0.874**	1.247**	0.988**	1.243**
	(2.78)	(3.27)	(3.17)	(3.17)	(2.17)	(2.37)	(2.05)	(2.12)
OPACITY	-0.797	-2.187*	-1.203	-2.679***				
	(-1.30)	(-1.86)	(-1.24)	(-3.00)				
LOGMV	0.496***	0.761***	0.529***	0.764***	0.474***	0.678***	0.485***	0.698**
	(3.43)	(4.84)	(4.19)	(6.55)	(4.55)	(2.87)	(3.88)	(2.61)
TBQ	0.072**	0.170***	0.080***	0.177***	0.038**	0.105***	0.029	0.090***
	(2.56)	(3.58)	(3.11)	(6.34)	(2.35)	(5.67)	(1.64)	(5.38)
ANALYSTS					0.241	0.586	0.516	0.776
					(0.74)	(0.96)	(1.34)	(1.21)
Constant	-10.207***	-15.076***	-9.925***	-13.912***	-11.744***	-16.741***	-13.489***	-18.341***
	(-9.14)	(-12.54)	(-10.17)	(-15.83)	(-13.49)	(-14.21)	(-14.46)	(-16.42)
Industry Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,912	1,912	1,912	1,912	2,904	2,904	2,904	2,904
R-squared	0.139	0.146	0.118	0.123	0.130	0.125	0.113	0.109

Table 2.7 Insider Trading Intensity and Long-Term Reversal

This table reports the equal-weighted average monthly returns of reversal portfolios that are cross-sorted into insider trading intensity quintiles. The insider trading intensity and past return sortings are done independently. *IT_NUM* is the annual number of insider trades divided by the annual number of all trades (in hundreds). *IT_VOL* is the annual volume of insider trades divided by the annual total volume (in hundreds). The reversal portfolios' returns are calculated by buying the low past return quintile (losers) and selling the high past return quintile (winners). Numbers in this table are in percents (%). The t-statistics are reported in parentheses. ***, ** and * indicate significance levels of 1%, 5% and 10%, respectively.

.	**Panel A: IT_NUM Quintile**				
Reversal Portfolio	***Low***	***2***	***3***	***4***	***High***
Losers	2.285	2.612	2.844	2.276	1.586
2	1.615	1.726	1.685	1.368	1.141
3	1.204	1.566	1.472	1.540	1.002
4	1.237	1.545	1.617	1.344	1.006
Winners	0.871	1.099	1.420	1.011	1.470
L – W	1.414***	1.513***	1.424***	1.264***	0.116
t-statistic	(4.32)	(5.22)	(4.53)	(3.66)	(0.39)

	Panel B: IT_VOL Quintile				
Reversal Portfolio	***Low***	***2***	***3***	***4***	***High***
Losers	1.543	2.037	2.228	2.400	2.112
2	0.991	1.300	1.437	1.554	1.308
3	0.840	1.125	1.464	1.315	1.314
4	0.732	0.966	1.509	1.484	1.264
Winners	0.253	0.846	1.335	1.488	1.493
L – W	1.290***	1.191***	0.893***	0.911***	0.619***
t-statistic	(3.76)	(4.28)	(2.72)	(3.67)	(2.70)

Appendix 2A: Propensity score matching

This table reports the model estimates used to calculate propensity scores.

Dep Var: IT_DUMMY		
LOGMV	0.0586	***
	(0.0037)	
OPACITY	0.0717	
	(0.0488)	
ANALYSTS	0.5907	***
	(0.0077)	
ITNUM_MATCH	0.0463	***
	(0.0057)	
ITVOL_MATCH	0.0572	***
	(0.0019)	
ABSMOM	0.0937	***
	(0.0145)	
Intercept	-0.4374	***
	(0.0192)	
No Obs:	115716	
Likelihood Ratio	14012.41	***
Wald	11303.71	***
Percent Concordant	72.6	
Percent Discordant	27.0	
Percent Tied	0.4	

Chapter 3. Does Legal Insider Trading Affect Firm Value?

Abstract

If insider trading intensity promotes informational efficiency, it may enhance firm value and lower cost of capital by making stock prices more informative. I find that firms with larger and more frequent insider trading have higher values of Tobin's q, after accounting for other determinants of firm value. The positive associations are robust if only insider purchases or sales are analyzed, and are stronger for firms with higher information asymmetry. Firms with more reported insider trades also have lower implied cost of capital. I also find a negative association between firm-level insider trading restriction and firm value. The results support the view that reported insider trades positively affect firm value by lowering cost of capital.

3.1 Introduction

In Chapter 2, I document a positive association between insider trading intensity and stock price informativeness. A more important question is: how does insider trading affect firm value?

More than 40 years ago, Manne (1966) argued that the informative trading by corporate insiders could benefit shareholders. The new information revealed by reported insider trades make stock prices more informative, and informative stock prices may eventually translate to higher firm valuations. For example, insider trading reveals private information to the public and reduces information asymmetry between corporate insiders and outside investors. This change in information composition may lead to a lower cost of capital (Easley and O'Hara, 2004). When prices reflect more information, corporate resources are also allocated more efficiently (Subrahmanyam and Titman, 1999; Durnev, Morck, and Yeung, 2004), and investment risk is reduced (Roll, Schwartz, and Subrahmanyam, 2009). All these effects eventually lead to a higher firm value and greater shareholder wealth, as predicted by Manne (1966).

Insider trading also has its drawbacks. Since insider trading is not immediately disclosed to the public, it may discourage outside investors from investing (Ausubel, 1990) and information collection (Fishman and Hagerty, 1992; Khanna, Slezak, and Bradley, 1994). Insider trading may also lead to a lower liquidity (Glosten, 1989). These negative effects could also result in a lower firm value.

The two opposite views mentioned above are both theoretically plausible; how reported insider trading affects firm value is thus an empirical question. In this study, I examine how the intensity of reported insider trading affects firm value as measured by Tobin's q, using a sample of reported insider trades in the United States between 1986 and 2010. I find that both the frequency and volume of reported insider trades are positively associated with Tobin's q. The economic significance of the results is large: a one standard deviation increase in the number of reported insider trades is associated with a 10% increase in Tobin's q, while a one standard deviation increase in the volume of reported insider trades is associated with a 3% increase in Tobin's q. The results are not driven by insiders timing their trades as the positive associations are observed when only insider purchases or insider sales are analyzed. Consistent with the view that the positive effect is a result of enhanced informational efficiency, the positive associations are stronger for firms with higher information asymmetry, and weaker for trades by insiders who are less likely to possess firm-specific information. Firms with more insider trades also appear to have more informative stock prices, as they are less affected by long-term return reversal and exhibit higher firm-specific return variation.

This study is distinct from the literature on the effects of insider trading. A few studies find that when a country first enforces its insider trading laws, the cost of equity decreases (Bhattacharya and Daouk, 2002) and stock price informativeness increases (Fernandes and Ferreira, 2009). While these studies shed light on the economic costs of illegal insider trades, few of the illegal trades are reported trades by corporate insiders. Gunny and Zhang (2012) find that the most profitable portion of insider trades (defined as "strategic informed trading" in their paper) has a relatively negative effect on firm value, but it is still not clear how insider trading intensity affects firm value in general. This paper aims to add to the literature and fill the gap.

The contribution of this paper is directly linked to insider trading regulations. Since the Securities Exchange Act of 1934, insider trading regulations have become more and more rigorous. In response, many firms have implemented firm-imposed restrictions against insider trading (Bettis, Coles, and Lemmon, 2000). Open-market trades reported by insiders, though legal, are subject to firm-imposed restrictions, but it is not clear whether these firm-level trading restrictions benefit shareholders. My findings show that reported insider trades enhance firm value and benefit shareholders; the justification of firm-imposed regulations restricting reported insider trading is at doubt.

The rest of the chapter is organized as follows. In Section 3.2, I review the research background. In Section 3.3, I describe the data and key variables. In Section 3.4, I explore the association between reported insider trading intensity and firm value, while in Section 3.5 I directly investigate the association between insider trading intensity and cost of capital, and discuss alternative explanations. Concluding remarks are given in Section 3.6.

3.2 Research background

As discussed in Chapter 2, insider trading laws keep getting more and more stringent, both in the US and world-wide. In the US, the majority of public firms surveyed by Bettis, Coles and Lemmon (2000) have policies restricting reported insider trades, and 78% use blackout periods during which reported insider trading is prohibited. Many of the firms claim that firm-level insider trading restrictions are enacted to protect shareholder value, while it is not clear to me how it works because no research has shown a direct negative association between legal insider trading and shareholder value.

That being said, the justification of such firm-level insider trading restrictions could have some root in studies against insider trading. Ausubel (1990) argues that when insiders have superior information, the adverse selection problem could deter outsiders from investing and may lead to lower valuations of assets. Fishman and Hagerty (1992) show that insider trading may reduce outsider information collection and decrease information efficiency, though

Subrahmanyam and Titman (1999) show that adding more insiders leads to opposite conclusions. Insider trading could also affect firm value by lowering market liquidity (Glosten, 1989; Leland, 1992; Cao, Field and Hanka, 2004) which is positively associated with firm value (Fang, Noe and Tice, 2009).

On the other hand, many other researchers hold the view that insider trading could benefit shareholders and enhance firm value. Manne (1966) is one of the earliest among the group with the view that insider trading benefit shareholders because it makes stock prices more informative. Later studies confirm that insider trades do predict future stock returns (Seyhun, 1986), and the return-predicting ability seems to come from insiders' contrarian strategy and knowledge about future earnings (Lakonishok and Lee, 2001; Piotroski and Roulstone, 2005; Jiang and Zaman, 2010). Insiders also seem to trade against mispricing (Ma and Ukhov, 2013), and their trades accelerate the incorporation of firm-specific information (Piotroski and Roulstone, 2004). As a result, informative stock prices may reduce information asymmetry between corporate insiders and outside investors, facilitate efficient corporate investment, reduce investment risk and make firm value higher (Leland, 1992; Khanna, Slezak and Bradley, 1994; Subrahmanyam and Titman, 1999; Durnev, Morck and Yeung, 2004; Easley and O'Hara, 2004; Roll, Schwartz and Subrahmanyam, 2009).

Given the two contradicting views, how insider trading affects firm value becomes an empirical issue. In this chapter, I continue to use the frequency and volume of insider trading at the firm-year level (*IT_NUM* and *IT_VOL*) to measure insider trading intensity and study how these measures are associated with firm value. The measures are to some extent similar to insider trading measures used in Peress (2010), but different from the commonly used net purchase ratio (defined as the volume of insider purchases minus the volume of insider sales scaled by the total volume of insider trades). This is because the focus of this chapter is the effect of non-directional insider trading intensity on firm value in the long run, rather than how the directional opinion of insider trading affects short-term stock prices. In fact, at the firm-year level, firms with frequent and large insider purchases are also likely to have frequent and large insider sales; as I will discuss later, separating purchases from sales does not qualitatively change my results.

3.3 Data

3.3.1 The sample of insider trading

The insider trading sample in this chapter is largely the same as the sample described in Chapter 2. Specifically, I study reported insider trades by corporate insiders who are subject to SEC filing requirements (Form 3, 4 or 5), including trades by board directors, officers, beneficiary owners (with more than 10% ownership, either directly or indirectly) and affiliated persons. The definition of "insider" is given by SEC under Section 16(a) of the Securities Exchange Act of 1934. The reported insider trades are from Thomson Financial Insider Filing database. To avoid noisy trades that are not informative, I download only open market[11] trades recorded in Table 1[12] from 1986 to 2010. Non-open market transactions, such as stock grants, option-related transactions and bona-fide gifts, are excluded because these trades do not necessarily reflect information. I delete records with the same document control number (DCN) and sequence number to avoid duplicate records. The sample of reported insider trading used in this study differs from illegal insider trades. An illegal insider trade is unlikely reported to the

[11] Similar as in Chapter 2, I download all transactions that are recorded as an open market purchase (with transaction code of "P") or an open market sale (with transaction code of "S").
[12] The Thomson Reuters Insider Filing database consists of Table 1 items and Table 2 items. Table 1 reports insider equity trades, and Table 2 reports insider derivative trades. Trading of derivatives by insiders is more strictly regulated, and there are very limited observations in Table 2.

SEC, while the reported insider trades are presumably legal and not based on material nonpublic information. The sample overview is reported in Table 3.1.

[Insert Table 3.1 here]

Some interesting facts are worth noting in Table 3.1. First, almost three quarters of insider trades are sales. This is probably because insider purchases are more closely watched and are subject to more restrictions[13]. However, the average purchase size is much larger than the average sale size for almost every insider group except for beneficiary owners; the total purchase volume and the total sale volume are not very different though the total sell volume is usually higher. Second, different insider groups exhibit very different trading patterns. Most of the insider trades come from board directors and officers; only 15% of total trades are from beneficiary owners, but their average trading size is larger than that of other insiders. Beneficiary owners seem to be the only group that has similar numbers of purchases and sales.

3.3.2 Insider trading measures

The two measures of insider trading intensity are defined in the same way as in Chapter 2. The frequency measure, *IT_NUM*, is defined as the total number of insider trades scaled by the annual number of trades by all investors (in hundreds); the volume measure, *IT_VOL*, is defined as the total absolute volume of insider trades scaled by the annual trading volume by all investors (in hundreds). Unlike in Chapter 2, now the main dependent variable in this chapter is value. The short-term effects of insider buying and selling on firm value could be opposite. Therefore, it is necessary to further justify the use of non-directional measures. My argument is that if both purchases and sales make stock prices more informative, in the long run they should both have a

[13] For instance, the "short swing" rule requires any insider buy that is sold in less than six months not be profitable; otherwise the profit should be paid back to the company.

positive (or negative) effect on firm value. By aggregating purchases and sales, their opposite short-term effects are canceled out so that I can examine their long-term effect on firm-value. The method is to some extent similar to a study by Roll, Schwartz and Subrahmanyam (2009), in which option volumes are aggregated annually regardless of their directions.

For illustrative purposes, consider the following example. An insider of Firm A buys 10,000 shares in January when the prices are too low, and sells 10,000 shares in July when the prices are too high. The net insider purchase in this year is 0. However, because the two trades correct mispricing to some extent, they both make stock prices more informative in January and in July; thus, they may both have a positive long-term effect on firm value, though their short-term effects are opposite. Now consider Firm B with more frequent insider trades and a net purchase of 0. More frequent insider trading makes Firm B's stock prices more informative, Firm B might have a higher firm value than Firm A does, even though they both have net insider purchases of 0. Therefore, the two non-directional measures capture the common long-term effects in purchases and sales.

3.3.3 Firm value and control variables

I use Tobin's q ratio as the firm value measure. The q ratio is frequently used in studies on firm value such as Fang, Noe and Tice (2009) and Roll, Schwartz and Subrahmanyam (2009). I follow Baker, Stein and Wurgler (2003) and calculate Tobin's q as book assets (COMPUSTAT item AT) minus book value of common equity (COMPUSTAT item CEQ + TXDB) plus market equity value (annual average stock price times number of shares outstanding), then divided by book assets. If a firm has multiple share issues, I calculate market value for each issue and sum them up for the firm market equity value. Dropping those observations does not affect my results.

The control variables are as follows. *LOGAT*[14] is the natural log of total assets, and is a measure of size. Lakonishok and Lee (2001) show that size is an important factor affecting insider trading, and the log value of total assets is used in similar studies like Fang, Noe and Tice (2009) and Gunny and Zhang (2012). *ROA* is the percentage return on assets defined as net income divided by total assets. This term captures investment opportunities, which presumably affects Tobin's q. *ROA* may also be associated with firm maturity, which may affect both Tobin's q and insider trading measures. *DE* is the debt to equity ratio defined as book value of debt divided by book value of equity, which captures the effect of likely financial distress on firm value. All these controls are also used in similar studies such as Roll, Schwartz and Subrahmanyam (2009) and Gunny and Zhang (2012).

I also include some other controls not used in previous studies. *MKTPOWER* is the gross profit margin defined as sales minus costs divided by sales. Peress (2010) finds that firm market power, measured by operating profit margin, may affect both insider trading and firm value. Therefore, I include the market power measure as an additional control. *ILLIQ* is the Amihud (2002) illiquidity measure multiplied by 1000. This captures the potential endogeneity from illiquidity, which affects firm value (see Fang, Noe and Tice, 2009) and insider trading simultaneously. *LOGVOL* is the natural log of total trading volume. *LOGVOL* is another measure of liquidity which affects Tobin's q; more importantly, it is the denominator of my *IT_VOL* measure, so I include the natural log of volume to make sure my results are not driven by the denominator. All variables are winsorized by 1%. Summary statistics are reported in Table 3.2.

[Insert Table 3.2 here]

[Insert Table 3.3 here]

---

[14] Some studies use the natural log of market value as the control. Using the market value instead of book asset value does not change my main results much; however, I use the log value of book asset value because it is less correlated with Tobin's q.

Table 3.3 presents the correlation matrix of variables used in the main analysis. Two insider trading measures, *IT_NUM* and *IT_VOL*, are highly correlated with each other. Since they are both scaled by liquidity measures which are strongly associated with firm value, *IT_NUM* and *IT_VOL* are negatively correlated with *TBQ*. When their denominators are controlled for in regression analysis, the coefficients of the two variables become significantly positive. In results not tabulated here, the numerators of the two insider trading measures (i.e., the total number of insider trades and the total volume of insider trades) are positively correlated with Tobin's q ratio.

3.4 Main results

3.4.1. The association between reported insider trading intensity and firm value

In this section, I examine the effect of reported insider trades on q. As a preliminary check, I sort firm-year observations into quintiles by total number or volume of insider trades and plot the average Tobin's q in Figure 3.1. Figure 3.1 shows that firms with larger and more frequent insider trades seem to have higher firm value measured by Tobin's q, though the monotonic relation is not very strong for the first three number quintiles[15].

[Insert Figure 3.1 here]

Figure 3.1 reveals some positive patterns; however, several important control variables are not added and statistical significance cannot be inferred from the figure. Thus, I continue to examine the associations by including control variables defined in the previous section in regressions. Since Tobin's q varies across industries and may change over time (so are the insider trading measures), I include industry dummies (SIC 2-digit) and year dummies to account for industry and year fixed effects. Standard errors are clustered by firm. Regression results are

[15] The positive association is significant in regressions for the first three number quintiles when control variables are added.

reported in the first two columns of Table 3.4, while the last two columns of Table 3.4 reports regression results with firm fixed effects instead of industry fixed effects.

[Insert Table 3.4 here]

The coefficient of *LOGAT* is negative in each of the models, which is likely because the dependent variable has total assets as the denominator. Firms with bigger total assets are also mature firms with lower Tobin's q. The coefficient of *ROA* is negative, which may appear a bit counter-intuitive but it is consistent with other similar studies (e.g., Roll, Schwartz and Subrahmanyam, 2009). One plausible explanation is that high ROA firms tend to be mature firms with lower Tobin's q ratio, and the explanation could be extended to explain the negative coefficient of *MKTPOWER*. The coefficient of *DE* is not significant in general. Amihud illiquidity measure *ILLIQ* is negatively associated with firm value, which is consistent with Amihud (2002) and Fang, Noe and Tice (2009) as illiquidity costs shareholders. *LOGVOL* is positively associated with firm value, possibly because the total volume could be viewed as another liquidity measure; also, firms with frequent trading may have more informative prices and higher q ratios.

Both of the measures of reported insider trading intensity, *IT_NUM* and *IT_VOL*, are positive and significant in each of the regression specifications. The results suggest that reported insider trades may have a positive effect on firm value; the effect appears to be stronger in cross-sectional analysis, but is also significant when firm fixed effects are included. The economic significance of the results is large. In OLS results, a one standard deviation increase of *IT_NUM* is associated with about 10% increase in Tobin's q, or in other words, an increase of about 10% of the book assets value. A one standard deviation increase in *IT_VOL* is associated with about 3%

increase in Tobin's q. In results with firm fixed effects, a one standard deviation increase in *IT_NUM* (*IT_VOL*) is associated with about 3% (1%) increase in *TBQ*.

3.4.2. Alternative measures of insider trading intensity

To ensure the positive associations documented in Table 3.4 are robust, I use various alternative measures of insider trading intensity in this sub-section. One potential problem with my current measures lies in the denominators. Note that *IT_NUM* is scaled by the total number of trades by all investors, and *IT_VOL* is scaled by the total volume of trades by all investors. The denominators are both positively correlated with Tobin's q and could drive the results.

To address the concern, I examine whether the positive associations in Table 4 primarily come from numerators. Specifically, I use the natural log of total number of insider trades and the natural log of total insider trading volume instead of the scaled measures. The results are reported in columns 1 and 2 of Table 3.5, with identical control variables as in Table 3.4. Industry and year fixed effects are also included, and standard errors are clustered by firm. Results in Table 3.5 are largely similar as the associations between alternative measures and q are positively significant.

While annual insider trading measures are noisy, moving averages of these measures may better reflect the intensity of reported insider trading. Averaging insider trading measures over the prior three years removes a great portion of annual fluctuations and may capture the effect of regular insider trades on firm value. In columns 3 and 4 of Table 3.5, I use the average frequency and average volume of insider trading estimated in the prior three years as measures of insider trading intensity. The results are virtually the same as the results reported in Table 3.4.

[Insert Table 3.5 here]

A few other measures of reported insider trades have been examined and the results are largely similar. Those alternative measures include lagged insider trading measures, changes in insider trading measures, insider trading measures scaled by the number of shares outstanding, and industry-adjusted measures. The results reported in Table 3.4 are also robust when small firms or regulated industries are dropped, when standard errors are clustered by two dimensions (including time), and when year-by-year cross-sectional regressions are used. These results are not reported here for brevity but are available upon request. All these additional tests suggest that the positive associations between the intensity of reported insider trades and firm value are robust.

3.4.3. Separating purchases from sales

One may argue that aggregating purchases and sales creates problems because they have opposite short-term price effects. Insiders may choose to sell more when the firm value is higher, and the positive associations documented in Table 3.4 may be caused by sales alone and only manifest insiders' market timing activities. To address the concern, in Table 3.6 I separate insider purchases from sales, and analyze only insider buying intensity or selling intensity in regressions. Specifically, *IT_NUM* is the annual number of insider purchases divided by the annual number of all trades (in hundreds) in column 1, and the annual number of insider sales divided by the annual number of all trades (in hundreds) in column 3. *IT_VOL* is the annual volume of insider purchases divided by the annual number of all trades (in hundreds) in column 2, and the annual number of insider sales divided by the annual number of all trades (in hundreds) in column 4. Control variables in Table 3.6 are the same as in Table 3.4, and industry and year fixed effects are also included in regressions. Standard errors are clustered by firm.

[Insert Table 3.6 here]

If the positive associations in Table 3.4 are driven by insider sales alone, then the coefficients of insider trading intensity measures should only be significant in column 2 and column 4 of Table 3.6. However, that is not the case. In Table 6, insider buying intensity measures and selling intensity measures are both positively associated with q, suggesting that purchases and sales may both have a positive effect on q by making stock prices more informative.

Note that the coefficients of purchase measures are smaller than the coefficients of sales measures, possibly due to a buy-low-sell-high effect. It raises another concern that the positive coefficients of insider buying intensity measures could be caused by the correlation between buying intensity and selling intensity. In results not tabulated here, I also include insider buying intensity measures and insider selling intensity measures at the same time. Both of them are positively significant. In general, the main results reported in Table 3.4 are not caused by only insider purchases or sales, and aggregating purchases and sales does not seem to generate biased results.

3.4.4. Endogeneity

Endogeneity is an important issue in this study. Reported insider trades and q could be affected by many factors, and an exogenous shock which only affects reported insider trading seems difficult to find. Though including firm fixed effects or lagged independent variables address the issue to some extent, it is ideal to use instruments that are inherently unrelated to q. I consider two instruments that are arguably less related to q: the average insider trading intensity in the prior three years and the insider trading intensity in firms matched by industry and book assets. The three-year average insider trading intensity is strongly correlated with insider trading intensity at t through auto-correlation, but should be less correlated with other variables at time t. The insider trading intensity in a peer firm matched by industry and book assets is comparable to the insider trading intensity of the sample firm, but should be less correlated with q of the sample firm.

Two-stage least squares (2SLS) estimates with the aforementioned two instruments are reported in Table 3.7. The instrumented variables are *IT_NUM* and *IT_VOL*. In general, results with instrument variables are largely similar to the main results reported in Table 3.4.

[Insert Table 3.7 here]

The validity of instrument variables is often difficult to establish particularly when the dependent variable is Tobin's q. Therefore, the endogeneity issue is not entirely addressed by Table 3.7. I consider an indirect way to further address endogeneity. Some firms have self-imposed insider trading restrictions, and the likelihood of firm-level insider trading restrictions is less endogenous compared to insider trading measures. If reported insider trades have a positive effect on firm value, firms that are more likely to have insider trading restrictions should have lower q, *ceteris paribus*.

Bettis, Coles and Lemmon (2000) find black-out periods are the most common insider trading restrictions. Roulstone (2003) estimate insider trading restrictions by calculating the percentage of insider trades occurring within trade-safe windows, e.g. within one month following quarterly earnings announcements. Following Roulstone (2003), I measure the likelihood of insider trading restrictions by estimating the percentage of insider trades occurring within one-month trade-safe windows (denoted by *SAFE_NUM*), and the percentage of insider trading volume occurring within trade-safe windows (denoted by *SAFE_VOL*[16]). The intuition is that when insiders are allowed to trade freely, their trades should evenly distribute over time; but if insiders are only allowed to trade in safe windows, *SAFE_NUM* and *SAFE_VOL* should approach 100% and higher values proxies for a higher likelihood of firm-level insider trading restrictions. Besides these continuous variables, I also construct two dummy variables following Roulstone (2003): *RES_NUM* is a dummy which takes value of 1 if *SAFE_NUM* is greater than 75%[17] and 0 otherwise; *RES_VOL* is a dummy which takes value of 1 if *SAFE_VOL* is greater than 75% and 0 otherwise. If the intensity of reported insider trades is positively associated with q, all these variables should be negatively associated with q.

[Insert Table 3.8 here]

Regression results including these measures are shown in Table 3.8. Consistent with the previous postulations, all four regulation measures are negatively associated with Tobin's q, suggesting that insider trading regulations have a negative effect on firm value as they block information channels from insiders. The coefficients are of economic significance: every one percent change in *SAFE_VOL* will lead to a 0.14% change in Tobin's q, and every one percent change in *SAFE_NUM* will lead to a 0.23% change in Tobin's q. Other things equal, firms more likely to have self-imposed insider trading regulations are valued about 10% lower than firms unlikely to have self-imposed insider trading regulations.

Though it is not possible to consider every source of endogeneity, it helps to consider some important endogeneity sources that have been documented to affect both insider trading and firm value. Insider trading behavior may be affected by firm size (Lakonishok and Lee, 2001) as smaller firms typically have more severe information asymmetry. Insiders are more likely to

[16] Following Roulstone (2003), I use only trades by officers, because firm-imposed regulations usually only work for officers.
[17] The threshold of 75% is close to the estimate reported in Bettis, Coles and Lemmon (2000).

trade when liquidity is affluent (Collin-Dufresne and Fos, 2013), so they may trade more in firms with better liquidity and higher Tobin's q. Peress (2010) shows that firms with greater market power may have more insider trading and higher Tobin's q. All of the three factors have been included in my regressions and including those variables or not does not affect my results much.

In Section 3.5, I investigate what causes the positive associations between reported insider trading measures and q, and by doing that I further address the issue of causality. I also discuss several important alternative explanations which may cause endogeneity at the end of Section 3.5.

3.5. Further analysis

3.5.1 When are reported insider trades valuable?

The positive association between insider trading intensity and firm value is consistent with the story that reported insider trades add to firm value by making stock prices more informative. If that is the case, reported insider trades should be more valuable for firms with greater degrees of information asymmetry. The information story predicts that the interactions of insider trading intensity measures and information asymmetry measures are positively associated with q. On the other hand, if corporate insiders trade more in response to higher firm value, there is no reason to expect those interaction terms to be positive in regressions.

Following Lakonishok and Lee (2001) and Frankel and Li (2004), I use firm size (measured by market capitalization) and number of analysts following (obtained from I/B/E/S) as measures of information asymmetry. To make the coefficients easy to interpret, I construct two dummy variables: *SMALL* is a dummy variable that equals one if the observation's market value is below the sample median and zero otherwise; *NOANALYS* is a dummy variable that equals one if the observation is not covered by any analyst and equals zero if the observation has at least one analyst following. Regression results with interactions of insider trading measures and the two dummy variables are reported in Table 3.9.

[Insert Table 3.9 here]

Consistent with the information role of insider trading, Table 3.9 shows that the positive effect of insider trading on firm value is more pronounced in firms with greater information asymmetry, i.e., firms that are smaller than median and are not covered by analysts. In fact, the effect of insider trading is three times stronger in firms with market capitalizations below the sample median, and two times stronger in firms that are not covered by analysts. The results are robust to how the dummies are constructed. Using continuous size and analysts following in interactions does not change the results. In results not tabulated here, other alternative measures of information asymmetry are used, including illiquidity and probability of informed trading (PIN). The results with these alternative proxies are weaker and sometimes not significant, but the coefficients of the interaction terms are always positive.

The value of reported insider trades may also vary after policy changes which affect the timeliness of insider trading information. After 2002, insiders are required to file their trades to the SEC within two business days, and the new requirement may significantly accelerate the speed of information incorporation process. Thus, reported insider trades may become more valuable for firms. Consistent with it, I find that the positive associations between insider trading intensity measures and firm value are significantly stronger after 2002.

Reported insider trades are also more valuable if they are more likely to contain firm-specific information. Not all insider trades are equally informative. Some corporate insiders (for example, board directors and officers) are likely to possess more information compared to others (like beneficiary owners). I hypothesize that trades by board directors and officers have a greater effect on firm value compared to trades by beneficiary owners; this is because directors are officers are more likely to know undisclosed firm-specific information and more aware of how the firm is performing, while beneficiary owners are less involved in daily operations of firms and have less firm-specific information. I classify insiders into four groups by insider role[18]: all insiders (ALL), directors (DIR), officers (OFF) and beneficiary owners (BEN). Group ALL consists of all insider trades. Group DIR consists of trades by board directors. Group OFF consists of trades by corporate officers defined by SEC[19]. Group BEN consists of trades by beneficiary owners holding at least 10% of the firm's shares. *IT_NUM* and *IT_VOL* are then constructed for each group and used in regressions with the same control variables as Table 3.4. 2-digit SIC industry fixed effects and year fixed effects are included. Standard errors are clustered by firm.

[Insert Table 3.10 here]

Table 3.10 presents the results by insider groups. The positive effect of insider trading intensity on firm value is only observed for trades by board directors (DIR) and officers (OFF), and is not observed for trades by beneficiary owners (BEN). The results suggest that only insider trades that are likely to contain firm-specific information are positively associated with firm value.

Cohen, Malloy and Pomorski (2012) propose a way to separate "routine" insider trades from "opportunistic" insider trades. They argue that routine insider trades are in general not informative, while opportunistic insider trades are informative and profitable. In results not

---

[18] Insider positions are not mutually exclusive. Some insiders hold more than one position in a firm. The database records up to 4 positions of any insider in a firm.

[19] The group includes: CEO, CFO, CIO, COO, CTO, president, vice president, senior vice president, assistant vice president, secretary, officer, officer of parent/subsidiary companies, and divisional officer.

tabulated here, I find that both the intensity of routine trades and the intensity of opportunistic trades are positively associated with Tobin's q.

3.5.2 Cost of capital and insider trading intensity

Tobin's q is often argued to be too noisy. In this section, I examine the association between insider trading and cost of capital instead of Tobin's q. Compared to Tobin's q, cost of capital has several advantages: first, it is not affected by expectation of future cash flows and is thus less affected by endogeneity; second, it has a solid theoretical connection with informational efficiency (see Easley and O'Hara, 2004). The main drawback of using cost of capital is that it has very demanding data requirements and will usually result in a much smaller sample.

Following Hail and Leuz (2006), I use stock prices and analyst forecasts to estimate implied cost of capital (ICC hereafter). ICC is very sensitive to model and data used in the estimation process; to ensure my results are robust, I use four different models to estimate ICC (Claus and Thomas, 2001; Gebhardt et al., 2001; Easton, 2004; Ohlson and Juettner-Nauroth, 2005, as implemented by Gode and Mohanram, 2003). Specifically, we estimate the implied cost of capital measures r_{ct}, r_{gls}, r_{peg1} and r_{oj} from the following models:

Claus and Thomas (2001):

$$P_t = bv_t + \sum_{\tau=1}^{T} \frac{(\hat{x}_{t+\tau} - r_{ct} * bv_{t+\tau-1})}{(1+r_{ct})^{\tau}} + \frac{(\hat{x}_{t+T} - r_{ct} * bv_{t+T-1})(1+g)}{(r_{ct}-g)(1+r_{ct})^{T}}$$

Gebhardt, Lee and Swaminathan (2001):

$$P_t = bv_t + \sum_{\tau=1}^{T} \frac{(\hat{x}_{t+\tau} - r_{gls} * bv_{t+\tau-1})}{(1+r_{gls})^{\tau}} + \frac{\left(\hat{x}_{t+T+1} - r_{gls} * bv_{t+T}\right)}{r_{gls}(1+r_{gls})^{T}}$$

Ohlson and Juettner-Nauroth (2005):

$$P_t = \frac{\hat{x}_{t+1}}{r_{oj}} * (g_{st} + r_{oj} * \frac{\hat{d}_{t+1}}{\hat{x}_{t+1}} - g_{lt})/(r_{oj} - g_{lt})$$

Modified PEG ratio model by Easton (2004):

$$P_t = (\hat{x}_{t+2} + r_{peg1} * \hat{d}_{t+1} - \hat{x}_{t+1})/r_{peg1}^2$$

Botosan and Plumlee (2005) use a slightly different modified PEG model. I also estimate r_{peg2} from the following model:

$$P_t = (\hat{x}_{t+5} - \hat{x}_{t+4})/r_{peg2}^2$$

In the models above, P_t is the market price of the firm's stock at time t; bv_t is the book value per share at the beginning of the fiscal year t; $bv_{t+\tau}$ is the expected future book value per share at time t+ τ, where $bv_{t+\tau} = bv_{t+\tau-1} + \hat{x}_{t+\tau} - \hat{d}_{t+\tau}$; $\hat{x}_{t+\tau}$ is the expected future earnings per share for period (t+τ-1, t+τ) using either explicit analyst forecasts or future earnings derived from growth forecasts; $\hat{d}_{t+\tau}$ is the expected future net dividends per share for period (t+τ-1, t+τ), derived from the dividend payout ratio times the earnings per share forecast $\hat{x}_{t+\tau}$; g, g_{st} and g_{lt} are expected perpetual, short-term and long-term future growth rates, respectively.

I obtain estimates of earnings and estimates of growth rates from I/B/E/S. The forecasts data is then merged with CRSP and Compustat for stock price data and financial data. For an observation to have valid estimates of implied cost of capital, I require current stock price data (P_t), analyst earnings per share forecasts for two periods ahead ($\hat{x}_{t+1}$ and $\hat{x}_{t+2}$), and either forecasted earnings per share for period t+3 ($\hat{x}_{t+3}$) or an estimate of long-term earnings growth (ltg). Following Hail and Leuz (2006), I measure stock prices and earnings forecasts as of month +10 after the fiscal year end. I also use $(1+r)^{10/12}$ as a discount factor to account for the 10-month misalignment. If the estimation process does not converge, I set the implied cost of capital estimate to missing. To avoid extreme estimates, I winsorize all ICC estimates by 1%.

Since the ICC is evaluated at month t+10 rather than at the end of the fiscal year (t), I use [t-5, t+6] as the new window to evaluate *IT_NUM* and *IT_VOL*. As a first test, I match firms with insider trading to firms without insider trading in the last three years by propensity score. The propensity score model is the same as in Chapter 2, and is described in Appendix 2A. T test results of propensity score matching are reported in Table 3.11.

[Insert Table 3.11 here]

Table 3.11 shows that ICC estimates for firms with recent insider trading are significantly lower than ICC estimates for firms without recent insider trading. Of the 5 different models used, only the OJ model does not give consistent results, and all other 4 models lead to the same conclusion. In Table 3.12, I report regression results using ICC as dependent variable and insider trading measures as variables of interest. Because the dependent variable is no longer Tobin's q ratio but ICC, many of the control variables used in previous sections of Chapter 3 are no longer necessary; instead, I continue to use the same control variables used in Chapter 2: LOGMV, ANALYSTS and OPACITY. The results in Table 3.12 are largely consistent with the hypothesis, with most of the insider trading variables having negative coefficients. The findings suggest that firms with higher insider trading intensity tend to have lower implied cost of capital.

[Insert Table 3.12 here]

3.5.3 Alternative explanations

In this subsection I discuss several important alternative explanations to the positive associations reported in Section 3.4. I do not list size, information asymmetry, liquidity and market power in this subsection because they have been discussed in previous sections.

3.5.3.1 Market timing, volatility, and managerial ability

Section 3.3 shows that the positive associations between reported insider trades and firm value are not only driven by insider sales when q is high or by insider purchases when q is low. However, the positive associations may still be interpreted as consequences of market timing. For example, if insiders can time the market well, they may discover a lot of trading opportunities when stock volatility is high. That could eventually translate to a positive correlation between insider trading intensity and firm value because volatility is positively associated with q.

The argument above is in fact an omitted variable problem and could be accounted for by including volatility measures in regressions. The results are virtually unchanged when I include price volatility, return volatility or idiosyncratic volatility in regressions.

Another problem associated with market timing is managerial ability. If insiders' ability to time the market is correlated with their ability to manage firms, the correlation may cause a spurious association between insider trading intensity and firm value because high-ability managers may trade intensely while maintaining a high level of firm value. Though the argument is consistent with the results of regressions by insider roles (Table 10), it cannot explain why the positive associations are stronger for firms with greater degrees of information asymmetry. Furthermore, the association between insider profit and insider trading intensity is negative, suggesting that high-ability insiders do not necessarily trade more intensely.

3.5.3.2 Value of intangible assets and growth opportunities

Tobin's q captures the difference between market value and accounting value; naturally, q should be higher in firms with more intangible assets. Those firms may also have high information asymmetry and intense insider trades, and the associations between q and insider trading measures are possibly caused by omitting measures of intangible assets and growth opportunities.

This argument is to some extent plausible because my results are slightly weaker in low-intangible or low-R&D industries defined in Cheng (2004), and stronger for firms with greater degrees of information asymmetry (these firms also tend to have greater growth potentials). But even for low-intangible or low-R&D industries and for mature and large firms, the positive associations between q and insider trading intensity measures are still significant at the 5% level. Adding R&D or advertising expenses to regressions does not change my main results much either. The results suggest that the positive associations are not entirely driven by intangible assets and growth opportunities.

3.5.3.3 Executive compensation and ownership

The intensity of reported insider trading is associated with executive compensation or ownership. Insiders are likely to sell more shares if they receive shares from incentive plans or own a large number of shares. They are also likely to buy shares when they receive bonuses or discount plans (Cohen, Malloy and Pomorski, 2012). Thus, if executive compensation or ownership is associated with firm value, the results in this study may be a manifestation of valuable compensation plans rather than information in reported insider trades.

If my results are primarily driven by effective compensation, the results should be strong for routine trades but not significant for other opportunistic trades defined by Cohen, Malloy and Pomorski (2012). I use non-routine trades only and find virtually the same results. Besides, when I include measures of compensation or insider ownership in regressions (for example, stock awards, option awards, exercisable unexercised options, and average shares an insider owns during the year), my results are not significantly affected. The measures of reported insider trading intensity are constantly significant when these control variables are included.

3.6. Concluding remarks

Theoretical models have opposite predictions on how insider trading affects firm value. However, no comprehensive empirical study has been done to investigate the topic. This paper fills the gap by exploring the effect of reported insider trades on firm value. I find a positive association between insider trading intensity and firm value, supporting the view that reported insider trading increases firm value and benefits shareholders. The channel of the positive association is likely through insider trades making stock prices more informative as insider trading measures are also positively associated with measures of price informativeness.

Will insiders trade unlimitedly if they know their trades may have a positive effect on firm value? There are a few reasons for why they wouldn't do so. Even though reported insider trades earn significant raw profits on average, not all of them are profitable. In my sample, more than 40% of those trades do not successfully predict future returns in the following 6 months. In addition, transaction costs and potential litigation costs further lower insiders' profits. Another important reason is that when insiders trade unlimitedly, at some point their trades will become uninformative and the positive effect on firm value will disappear.

This study has practical implications. Insider trades seem to play an important role in incorporating new information into stock prices, and the information role further leads to higher firm valuation and shareholder welfare. Restrictions of reported insider trading may undermine stock price informativeness and lead to lower firm values.

The positive association between the scale of reported insider trading and firm value does not necessarily contradict previous studies which find enforcement of insider trading laws has positive effects (see Bhattacharya and Daouk, 2002; Fernandes and Ferreira, 2009). Nor should the results be extended to illegal insider trades. A key difference between reported insider trades and illegal insider trades (and in general, unreported informed trades) lies in transparency. Reported insider trades are disclosed to the public; they are more transparent and may reduce information asymmetry between corporate insiders and outside investors. Illegal insider trades, on the other hand, are hard to detect and may exacerbate the problem of information asymmetry. Besides, illegal insider trades are more likely based on solid undisclosed information rather than mispricing. If illegal insider trades are permitted, firm insiders may have incentive to "create" information just like what happened in the US before the SEA of 1934.

Findings in this study also suggest the importance of insider trading disclosures. The positive effect of insider trading channels through incorporating information into stock prices, and laws or regulations that accelerate the information incorporation process (like the 2002 SEC requirement which shortens disclosure deadline of insider trades to two business days) may increase the positive effect on firm value. Policies increasing the transparency of insider trades may have positive effects on firm value and benefit shareholders.

As discussed before, there seems to be a gray area between clear-cut legal insider trading and illegal insider trading. It is natural to worry whether legal insider trading and illegal insider trading are different: do corporate insiders also profit themselves by trading ahead of important corporate events such as mergers? If so, wouldn't that result in higher Kyle type of information asymmetry? In the next chapter, I focus on one of the most high-profile corporate events: mergers. Specifically, I explore the price formation prior to M&A announcements. I will investigate whether legal or illegal insider trading causes the significant price run-up prior to M&A announcements.

References

Agrawal, A., and J. F. Jaffe, 1995, Does Section 16b Deter Insider Trading by Target Managers? *Journal of Financial Economics* 39, 295-319.

Agrawal, A., and T. Nasser, 2012, Insider Trading in Takeover Targets, *Journal of Corporate Finance* 18, 598-625.

Amihud, Y., 2002, Illiquidity and Stock Returns: Cross-Section and Time-Series Effects, *Journal of Financial Markets* 5, 31-56.

Ausubel, L. M., 1990, Insider Trading in a Rational Expectations Economy, *The American Economic Review* 80, 1022-1041.

Baker, M., J. C. Stein, and J. Wurgler, 2003, When does the Market Matter? Stock Prices and the Investment of Equity-Dependent Firms, *The Quarterly Journal of Economics* 118, 969-1005.

Barberis, N., A. Shleifer, and R. Vishny, 1998, A Model of Investor Sentiment, *Journal of Financial Economics* 49, 307-343.

Bettis, J. C., J. L. Coles, and M. L. Lemmon, 2000, Corporate Policies Restricting Trading by Insiders, *Journal of Financial Economics* 57, 191-220.

Bhattacharya, U., and H. Daouk, 2002, The World Price of Insider Trading, *The Journal of Finance* 57, 75-108.

Cheng, S., 2004, R&D Expenditures and CEO Compensation, *The Accounting Review* 79, 305-328.

Cohen, L., C. Malloy, and L. Pomorski, 2012, Decoding Inside Information, *The Journal of Finance* 67, 1009-1043.

Collin-Dufresne, P., and V. Fos, 2012, Do Prices Reveal the Presence of Informed Trading? *NBER Working Paper*.

Durnev, A., R. Morck, and B. Yeung, 2004, Value-Enhancing Capital Budgeting and Firm-Specific Stock Return Variation, *The Journal of Finance* 59, 65-105.

Fang, V. W., T. H. Noe, and S. Tice, 2009, Stock Market Liquidity and Firm Value, *Journal of Financial Economics* 94, 150-169.

Fernandes, N., and M. A. Ferreira, 2009, Insider Trading Laws and Stock Price Informativeness, *The Review of Financial Studies* 22, 1845-1887.

Fishe, R. P. H., and M. A. Robe, 2004, The Impact of Illegal Insider Trading in Dealer and Specialist Markets: Evidence from a Natural Experiment, *Journal of Financial Economics* 71, 461-488.

Fishman, M. J., and K. M. Hagerty, 1992, Insider Trading and the Efficiency of Stock Prices, *The Rand journal of economics* 23, 106-122.

Frankel, R., and X. Li, 2004, Characteristics of a Firm's Information Environment and the Information Asymmetry between Insiders and Outsiders, *Journal of Accounting and Economic*s 37, 229-259.

Glosten, L. R., 1989, Insider Trading, Liquidity, and the Role of the Monopolist Specialist, *The Journal of Business* 62, 211-235.

Harlow, W. V., and J. S. Howe, 1993, Leveraged Buyouts and Insider Nontrading, *Financial Management* 22, 109-118.

Huddart, S., B. Ke, and C. Shi, 2007, Jeopardy, Non-Public Information, and Insider Trading Around SEC 10-K and 10-Q Filings, *Journal of Accounting and Economics* 43, 3-36.

Jiang, X., and M. A. Zaman, 2010, Aggregate Insider Trading: Contrarian Beliefs Or Superior Information? *Journal of Banking & Finance* 34, 1225-1236.

Khanna, N., S. L. Slezak, and M. Bradley, 1994, Insider Trading, Outside Search, and Resource Allocation: Why Firms and Society may Disagree on Insider Trading Restrictions, *The Review of Financial Studies* 7, 575-608.

Lakonishok, J., and I. Lee, 2001, Are Insider Trades Informative? *The Review of Financial Studies* 14, 79-111.

Leland, H. E., 1992, Insider Trading: Should it be Prohibited? *Journal of Political Economy* 100, 859-887.

Ma, Q., and A. Ukhov, 2013, What is Common Among Return Anomalies? Evidence from Insider Trading Decisions, *Working Paper*.

Manne, H., 1966, *Insider Trading and the Stock Market*, New York: Free Press.

Morck, R., B. Yeung and W. Yu, 2000, The Information Content of Stock Markets: Why do Emerging Markets have Synchronous Stock Price Movements? *Journal of Financial Economics* 58, 215-260.

Peress, J., 2010, Product Market Competition, Insider Trading, and Stock Market Efficiency, *The Journal of Finance* 65, 1-43.

Piotroski, J. D., and D. T. Roulstone, 2004, The Influence of Analysts, Institutional Investors, and Insiders on the Incorporation of Market, Industry, and Firm-Specific Information into Stock Prices. *The Accounting Review* 79, 1119-1151.

Piotroski, J. D., and D. T. Roulstone, 2005, Do Insider Trades Reflect both Contrarian Beliefs and Superior Knowledge about Future Cash Flow Realizations? *Journal of Accounting and Economics* 39, 55-81.

Roll, R., E. Schwartz, and A. Subrahmanyam, 2009, Options Trading Activity and Firm Valuation, *Journal of Financial Economics* 94, 345-360.

Roulstone, D. T., 2003, The Relation between Insider-Trading Restrictions and Executive Compensation, *Journal of Accounting Research* 41, pp. 525-551.

Seyhun, H. N., 1986, Insiders' Profits, Costs of Trading, and Market Efficiency, *Journal of Financial Economics* 16, 189-212.

Seyhun, H. N, and M. Bradley, 1997, Corporate Bankruptcy and Insider Trading, *The Journal of Business* 70, 189-216.

Seyhun, H. N., 1992, Why does Aggregate Insider Trading Predict Future Stock Returns, *The Quarterly Journal of Economics* 107, 1303-1331.

Subrahmanyam, A., and S. Titman, 1999, The Going-Public Decision and the Development of Financial Markets, *The Journal of Finance* 54, 1045-1082.

Table 3.1 Sample Overview

This table reports an overview of all open market insider trades recorded in Thomson Financial Insider Filing database from 1986 to 2010. Only trades recorded either as "open market purchases" or "open market sales" are included. Group ALL consists of all insider trades. Group DIR consists of trades by board directors. Group OFF consists of trades by corporate officers defined by SEC. Group BEN consists of trades by beneficiary owners holding at least 10% of the firm's shares. Panel A reports trade-level information including number of trades and average trade volumes. Panel B reports firm-year level information including number of insider trades, total volume of insider trades (in millions), and the number of insiders who trade in the year.

Panel A. Trade-level

	Total		***Purchases***		***Sales***	
	Number	*Avg. Vol.*	*Number*	*Avg. Vol.*	*Number*	*Avg. Vol.*
ALL	4053120	46534.567	1122846	71945.290	2930274	36797.481
DIR	2119782	40148.747	604196	70603.130	1515586	28007.954
OFF	2008496	25651.898	346893	81394.721	1661603	14014.464
BEN	611975	137585.956	291253	118115.437	320722	155267.459

Panel B. Firm-year level

	Obs	*Mean*	*Std. Dev.*	*Obs*	*Mean*	*Std. Dev.*	*Obs*	*Mean*	*Std. Dev.*
		Number of Trade			***Volume (mil)***			***Number of Insiders***	
ALL	114696	29.096	139.382	114696	0.818	10.412	114696	4.648	3.738
DIR	114696	15.785	100.400	114696	0.333	6.581	114696	2.292	2.008
OFF	114696	15.359	106.071	114696	0.151	1.686	114696	2.452	2.682
BEN	114696	5.117	65.467	114696	0.424	5.866	114696	0.307	1.035

Table 3.2 Summary Statistics

This panel reports summary statistics for the main variables used in this study. *TBQ* is the Tobin's Q ratio and is defined as market value of assets divided book value of assets, where market value of assets is market value of equity plus book value of total assets minus book value of equity. *IT_NUM* is the total number of insider trades divided by the annual number of trades. *IT_VOL* is the total volume of insider trades divided by the annual volume of trades. *LOGAT* is the natural log of total assets. *ROA* is the percentage return on assets defined as net income divided by total assets. *DE* is the debt to equity ratio defined as book value of debt divided by book value of equity. *MKTPOWER* is the profit margin defined as sales minus costs divided by sales. *ILLIQ* is the Amihud (2002) illiquidity measure multiplied by 1000. *LOGVOL* is the natural log of total trading volume. All variables are winsorized by 1%.

Variable	*Obs*	*Mean*	*Std. Dev.*	*Q1*	*Median*	*Q3*
TBQ	160444	1.867	1.675	1.022	1.283	1.984
IT_NUM	64167	0.400	0.827	0.023	0.102	0.363
IT_VOL	113672	3.471	10.642	0.094	0.444	1.929
LOGAT	164451	5.315	2.396	3.594	5.217	6.910
ROA (%)	158872	-5.238	27.389	-3.992	1.808	6.325
DE	164317	2.657	5.356	0.416	1.104	2.640
MKTPOWER	97209	-0.111	1.489	0.047	0.126	0.240
ILLIQ	160707	0.558	1.880	0.001	0.017	0.198
LOGVOL	160585	9.058	2.114	7.592	9.055	10.521

Table 3.3 Variable Correlation

This table reports correlation between key insider trading measures and control variables. *TBQ* is the Tobin's Q ratio, defined as book value of debt plus market value of equity divided by total assets. *IT_NUM* is the annual number of open market insider trades divided by the annual number of all trades (in hundreds). *IT_VOL* is the annual volume of open market insider trades divided by the annual total volume (in hundreds). *LOGAT* is the natural log of total assets. *ROA* is the percentage return on assets defined as net income divided by total assets. *DE* is the debt to equity ratio defined as book value of debt divided by book value of equity. *MKTPOWER* is the profit margin defined as sales minus costs divided by sales. *ILLIQ* is the Amihud (2002) illiquidity measure multiplied by 1000. *LOGVOL* is the natural log of total trading volume. All variables are winsorized by 1%. *, **, and *** indicate significance (clustered at firm level) at the 10%, 5%, and 1% levels, respectively.

	TBQ	***IT_NUM***	***IT_VOL***	***LOGAT***	***ROA***	***DE***	***MKTPOWER***	***ILLIQ***
IT_NUM	-0.161***							
IT_VOL	-0.045***	0.345***						
LOGAT	-0.260***	-0.122***	-0.115***					
ROA	-0.319***	0.058***	-0.024***	0.284***				
DE	-0.252***	0.178***	0.019	0.411***	0.071***			
MKTPOWER	-0.300***	0.065***	-0.001*	0.215***	0.509***	0.118***		
ILLIQ	-0.119***	0.269***	0.193***	-0.268***	-0.081***	0.039	-0.001***	
LOGVOL	0.354***	-0.523***	-0.201***	0.322***	-0.104	-0.277***	-0.114***	-0.324***

Table 3.4 The Effect of Reported Insider Trading on Firm Value

This table reports regression results on the effect of insider trading on firm value. Columns 1 and 2 show ordinary least squares (OLS) regression results with 2-digit SIC fixed effects and year fixed effects. Columns 3 and 4 show panel regression results with firm fixed effects and year fixed effects. The dependent variable is Tobin's Q. *IT_NUM* is the annual number of open market insider trades divided by the annual number of all trades (in hundreds). *IT_VOL* is the annual volume of open market insider trades divided by the annual total volume (in hundreds). *LOGAT* is the natural log of total assets. *ROA* is the percentage return on assets defined as net income divided by total assets. *DE* is the debt to equity ratio defined as book value of debt divided by book value of equity. *MKTPOWER* is the profit margin defined as sales minus costs divided by sales. *ILLIQ* is the Amihud (2002) illiquidity measure multiplied by 1000. *LOGVOL* is the natural log of total trading volume. All variables are winsorized by 1%. T statistics are in parentheses and clustered by firm. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
IT_NUM	0.126***		0.034***	
	(13.72)		(4.66)	
IT_VOL		0.003***		0.001***
		(6.53)		(4.00)
Control Variables				
LOGAT	-0.432***	-0.375***	-0.602***	-0.535***
	(-31.63)	(-41.74)	(-26.31)	(-32.68)
ROA	-0.006***	-0.007***	-0.002***	-0.003***
	(-7.87)	(-10.54)	(-3.14)	(-5.09)
DE	-0.002	-0.002*	-0.002	-0.002**
	(-1.10)	(-1.70)	(-1.03)	(-2.35)
MKTPOWER	-0.090***	-0.110***	-0.035***	-0.046***
	(-7.31)	(-10.32)	(-2.79)	(-3.93)
ILLIQ	-0.081***	-0.085***	-0.036***	-0.047***
	(-15.69)	(-20.22)	(-7.50)	(-11.62)
LOGVOL	0.456***	0.400***	0.433***	0.389***
	(40.59)	(48.35)	(35.21)	(42.57)
Constant	-1.052***	0.139	1.147***	1.313***
	(-9.90)	(0.77)	(10.64)	(16.25)
Observations	55,938	95,357	55,938	95,357
R-squared	0.374	0.375	0.169	0.158

Table 3.5 Alternative Measures of Reported Insider Trades

This table reports regression results on the effect of alternative insider trading measures on firm value. The dependent variable is Tobin's Q. *IT_NUM* is the natural log of the annual number of insider trades in column 1, and in column 3 is the prior three years' moving average of *IT_NUM* defined in Table 3. *IT_VOL* is the natural log of the annual volume of insider trades in column 2, and in column 4 is the prior three years' moving average of *IT_VOL* defined in Table 4. *LOGAT* is the natural log of total assets. *ROA* is the percentage return on assets defined as net income divided by total assets. *DE* is the debt to equity ratio defined as book value of debt divided by book value of equity. *MKTPOWER* is the profit margin defined as sales minus costs divided by sales. *ILLIQ* is the Amihud (2002) illiquidity measure multiplied by 1000. *LOGVOL* is the natural log of total trading volume. All variables are winsorized by 1%. 2-digit SIC industry dummies and year dummies are included in regressions and are not reported. T statistics are in parentheses and clustered by firm. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Unscaled		**3-Year Average**	
	(1)	(2)	(3)	(4)
IT_NUM	0.118***		0.065***	
	(22.62)		(3.35)	
IT_VOL		0.040***		0.005***
		(13.17)		(5.18)
Control Variables				
LOGAT	-0.377***	-0.367***	-0.387***	-0.343***
	(-42.04)	(-40.67)	(-19.26)	(-26.26)
ROA	-0.008***	-0.007***	-0.002	-0.002
	(-11.38)	(-10.79)	(-1.43)	(-1.49)
DE	-0.002	-0.003**	-0.007**	-0.009***
	(-1.62)	(-2.06)	(-2.55)	(-4.61)
MKTPOWER	-0.109***	-0.110***	-0.108***	-0.121***
	(-10.37)	(-10.34)	(-3.96)	(-5.17)
ILLIQ	-0.079***	-0.085***	-0.050***	-0.058***
	(-18.92)	(-20.32)	(-6.14)	(-8.64)
LOGVOL	0.377***	0.374***	0.435***	0.396***
	(47.07)	(45.83)	(28.27)	(32.49)
Constant	0.293	0.022	0.128	0.408
	(1.34)	(0.11)	(0.37)	(1.27)
Observations	95,357	95,357	28,618	46,922
R-squared	0.383	0.377	0.371	0.360

Table 3.6 Purchases and Sales

This table reports regression results on the effect of purchases and sales on firm value. The dependent variable is Tobin's Q. *IT_NUM* is the annual number of insider purchases divided by the annual number of all trades (in hundreds) in columns 1, and the annual number of insider sales divided by the annual number of all trades (in hundreds) in columns 3. *IT_VOL* is the annual volume of insider purchases divided by the annual number of all trades (in hundreds) in columns 2, and the annual number of insider sales divided by the annual number of all trades (in hundreds) in columns 4. *LOGAT* is the natural log of total assets. *ROA* is the percentage return on assets defined as net income divided by total assets. *DE* is the debt to equity ratio defined as book value of debt divided by book value of equity. *MKTPOWER* is the profit margin defined as sales minus costs divided by sales. *ILLIQ* is the Amihud (2002) illiquidity measure multiplied by 1000. *LOGVOL* is the natural log of total trading volume. All variables are winsorized by 1%. 2-digit SIC industry dummies and year dummies are included in regressions and are not tabulated. T statistics are in parentheses and clustered by firm. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Purchases		**Sales**	
	(1)	(2)	(3)	(4)
IT_NUM	0.077***		0.313***	
	(7.41)		(15.17)	
IT_VOL		0.001**		0.003*
		(2.11)		(1.85)
Control Variables				
LOGAT	-0.429***	-0.429***	-0.374***	-0.374***
	(-31.33)	(-31.37)	(-41.70)	(-41.69)
ROA	-0.006***	-0.006***	-0.007***	-0.007***
	(-7.81)	(-8.02)	(-10.58)	(-10.59)
DE	-0.002	-0.002	-0.002*	-0.002*
	(-1.26)	(-1.04)	(-1.66)	(-1.68)
MKTPOWER	-0.090***	-0.090***	-0.110***	-0.110***
	(-7.33)	(-7.33)	(-10.32)	(-10.32)
ILLIQ	-0.078***	-0.072***	-0.083***	-0.083***
	(-15.14)	(-13.51)	(-19.82)	(-19.55)
LOGVOL	0.441***	0.449***	0.397***	0.398***
	(39.92)	(41.47)	(48.30)	(48.28)
Constant	-0.900***	-1.007***	0.164	0.162
	(-8.63)	(-9.90)	(0.91)	(0.90)
Observations	55,938	55,938	95,357	95,357
R-squared	0.372	0.375	0.375	0.375

Table 3.7. Regressions with Instrumental Variables

This table reports regression results with insider trading measures in size-matched firms and 3-year average insider trading measures as instrumental variables. The dependent variable is Tobin's q. Instrumented variables are *IT_NUM* and *IT_VOL*. *LOGAT* is the natural log of total assets. *ROA* is the percentage return on assets defined as net income divided by total assets. *DE* is the debt to equity ratio defined as book value of debt divided by book value of equity. *MKTPOWER* is the profit margin defined as sales minus costs divided by sales. *ILLIQ* is the Amihud (2002) illiquidity measure multiplied by 1000. *LOGVOL* is the natural log of total trading volume. All variables are winsorized by 1%. 2-digit SIC industry dummies and year dummies are included in regressions and are not reported. T statistics are in parentheses and clustered by firm. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)
IT_NUM	0.424***	
	(10.21)	
IT_VOL		0.028***
		(3.88)
Control Variables		
LOGAT	-0.463***	-0.384***
	(-19.70)	(-24.78)
ROA	-0.001	0.001
	(-0.79)	(0.18)
DE	-0.007**	-0.009***
	(-2.30)	(-4.01)
MKTPOWER	-0.079***	-0.115***
	(-2.59)	(-4.22)
ILLIQ	-0.049***	-0.047***
	(-4.01)	(-3.82)
LOGVOL	0.525***	0.438***
	(26.60)	(26.64)
Constant	-0.001	0.001
	(-0.01)	(0.02)
Observations	16,071	27,185
R-squared	0.379	0.349

Table 3.8 Insider Trading Restrictions and Firm Value

This table reports regression results on the effect of firm-imposed insider trading restrictions on firm value. The dependent variable is Tobin's Q. *SAFE_NUM* is the percentage of insider trades in trade-safe windows. *SAFE_VOL* is the percentage of insider trading volume in trade-safe windows. *RES_NUM* is a dummy that takes value of 1 if *SAFE_NUM* is greater than 75%, and 0 otherwise. *RES_VOL* is a dummy that takes value of 1 if *SAFE_VOL* is greater than 75%, and 0 otherwise. *LOGAT* is the natural log of total assets. *ROA* is the percentage return on assets defined as net income divided by total assets. *DE* is the debt to equity ratio defined as book value of debt divided by book value of equity. *MKTPOWER* is the profit margin defined as sales minus costs divided by sales. *ILLIQ* is the Amihud (2002) illiquidity measure multiplied by 1000. *LOGVOL* is the natural log of total trading volume. All variables are winsorized by 1%. 2-digit SIC industry dummies and year dummies are included in regressions and are not reported. T statistics are in parentheses and clustered by firm. *, **, and *** denote significantly different from zero at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
SAFE_NUM	-0.182***			
	(-8.82)			
SAFE_VOL		-0.112***		
		(-6.96)		
RES_NUM			-0.112***	
			(-9.65)	
RES_VOL				-0.085***
				(-7.80)
Control Variables				
LOGAT	-0.381***	-0.381***	-0.382***	-0.381***
	(-40.67)	(-40.63)	(-40.68)	(-40.64)
ROA	-0.004***	-0.004***	-0.004***	-0.004***
	(-5.31)	(-5.27)	(-5.33)	(-5.29)
DE	-0.002	-0.002	-0.002	-0.002
	(-1.55)	(-1.59)	(-1.53)	(-1.59)
MKTPOWER	-0.109***	-0.110***	-0.109***	-0.110***
	(-9.23)	(-9.27)	(-9.25)	(-9.28)
ILLIQ	-0.067***	-0.067***	-0.066***	-0.067***
	(-12.67)	(-12.68)	(-12.67)	(-12.67)
LOGVOL	0.415***	0.415***	0.415***	0.415***
	(46.15)	(46.09)	(46.15)	(46.10)
Constant	-0.179	-0.204	-0.224	-0.233
	(-0.97)	(-1.13)	(-1.25)	(-1.30)
Observations	76,576	76,552	76,576	76,552
R-squared	0.364	0.363	0.364	0.363

Table 3.9 Interaction of Reported Insider Trades and Information Asymmetry

This table reports regression results on the effect of insider trading on firm value with information asymmetry measures interacted with insider trading measures. The dependent variable is Tobin's Q. *IT_NUM* is the annual number of insider trades divided by the annual number of all trades (in hundreds). *IT_VOL* is the annual volume of insider trades divided by the annual total volume (in hundreds). *SMALL* is a dummy variable that equals one if the observation's market value is below the sample median and zero otherwise. *NOANALYS* is a dummy variable that equals one if the observation is not covered by any analyst and equals zero if the observation has at least one analyst following. Control variables are defined as in Table 4. All variables are winsorized by 1%. T statistics are in parentheses and clustered by firm. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
IT_NUM	0.044*		0.074***	
	(1.65)		(4.84)	
IT_VOL		0.002**		0.002***
		(2.17)		(3.02)
SMALL	-1.206***	-0.925***		
	(-32.84)	(-36.92)		
IT_NUM*SMALL	0.095***			
	(3.63)			
IT_VOL*SMALL		0.002**		
		(1.97)		
NOANALYS			-0.153***	-0.081***
			(-5.84)	(-4.55)
IT_NUM* NOANALYS			0.075***	
			(4.56)	
IT_VOL* NOANALYS				0.002**
				(2.21)
Control Variables				
LOGAT	-0.622***	-0.488***	-0.444***	-0.379***
	(-35.51)	(-46.26)	(-31.59)	(-41.91)
ROA	-0.007***	-0.009***	-0.006***	-0.007***
	(-10.35)	(-13.03)	(-7.97)	(-10.65)
DE	0.011***	0.007***	-0.002	-0.002
	(5.78)	(5.58)	(-0.85)	(-1.62)
MKTPOWER	-0.076***	-0.100***	-0.089***	-0.109***
	(-6.61)	(-9.73)	(-7.25)	(-10.28)
ILLIQ	-0.086***	-0.074***	-0.078***	-0.083***
	(-15.50)	(-18.17)	(-15.13)	(-19.61)
LOGVOL	0.353***	0.337***	0.448***	0.397***
	(29.84)	(41.78)	(39.44)	(47.53)
Constant	1.247***	1.572***	-0.875***	0.215
	(7.75)	(7.68)	(-7.75)	(1.16)
Observations	55,938	95,357	55,938	95,357
R-squared	0.432	0.414	0.375	0.375

Table 3.10 The Effect of Insider Trades: By Insider Roles

This table reports regression results on the effect of insider trading on firm value. The dependent variable is Tobin's Q. *IT_NUM* is the annual number of insider trades divided by the annual number of all trades (in hundreds). *IT_VOL* is the annual volume of insider trades divided by the annual total volume (in hundreds). Control variables are as defined in Table 4 and all variables are winsorized by 1%. Group ALL consists of all insider trades. Group DIR consists of trades by board directors. Group OFF consists of trades by corporate officers defined by SEC. Group BEN consists of trades by beneficiary owners holding at least 10% of the firm's shares. 2-digit SIC industry dummies and year dummies are included in regressions and are not reported. T statistics are in parentheses and clustered by firm. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Insider Group	(1) ALL	(2) DIR	(3) OFF	(4) BEN	(5) ALL	(6) DIR	(7) OFF	(8) BEN
IT_NUM	0.126***	0.173***	0.209***	-0.014				
	(13.72)	(13.55)	(10.59)	(-0.40)				
IT_VOL					0.003***	0.010***	0.034***	-0.001
					(6.53)	(9.01)	(11.54)	(-0.06)
Control Variables								
LOGAT	-0.432***	-0.430***	-0.430***	-0.427***	-0.375***	-0.374***	-0.374***	-0.374***
	(-31.63)	(-31.45)	(-31.35)	(-31.00)	(-41.74)	(-41.70)	(-41.64)	(-41.69)
ROA	-0.006***	-0.006***	-0.006***	-0.006***	-0.007***	-0.007***	-0.007***	-0.007***
	(-7.87)	(-7.87)	(-7.91)	(-7.84)	(-10.54)	(-10.56)	(-10.69)	(-10.59)
DE	-0.002	-0.002	-0.002	-0.002	-0.002*	-0.002*	-0.002*	-0.002*
	(-1.10)	(-1.21)	(-1.15)	(-1.32)	(-1.70)	(-1.73)	(-1.71)	(-1.68)
MKTPOWER	-0.090***	-0.090***	-0.090***	-0.090***	-0.110***	-0.110***	-0.110***	-0.110***
	(-7.31)	(-7.33)	(-7.33)	(-7.35)	(-10.32)	(-10.31)	(-10.33)	(-10.32)
ILLIQ	-0.081***	-0.080***	-0.078***	-0.073***	-0.085***	-0.087***	-0.087***	-0.083***
	(-15.69)	(-15.63)	(-14.87)	(-13.76)	(-20.22)	(-20.73)	(-20.62)	(-19.53)
LOGVOL	0.456***	0.452***	0.445***	0.430***	0.400***	0.403***	0.404***	0.397***
	(40.59)	(40.45)	(40.53)	(40.53)	(48.35)	(48.45)	(48.60)	(48.31)
Constant	-1.052***	-1.022***	-0.946***	-0.805***	0.139	0.121	0.093	0.165
	(-9.90)	(-9.70)	(-9.15)	(-8.07)	(0.77)	(0.67)	(0.50)	(0.92)
Observations	55,938	55,938	55,938	55,938	95,357	95,357	95,357	95,357
R-squared	0.374	0.374	0.373	0.372	0.375	0.375	0.376	0.374

Table 3.11 Univariate Test: Implied Cost of Capital

This table reports the implied cost of capital estimates using different models, and the univariate differences in implied cost of capital between sample firms and match firms. Five different models for implied cost of capital are used: CT (Claus and Thomas, 2001), GLS (Gebhardt, Lee and Swaminathan, 2001), OJ (Ohlson and Juettner-Nauroth, 2005), PEG (Easton, 2004) and Modified PEG (Botosan and Plumlee, 2005). A detailed description of estimation models can be found in the data section. The implied cost of capital numbers are in percentages, and are winsorized by 1% to exclude extreme estimates. Further dropping extreme values (e.g., deleting negative estimates and estimates greater than 100%) does not change the test results in a significant way.

Model:	**CT**		**GLS**		**OJ**		**PEG**		**MPEG**	
Sample	8.249		6.836		12.409		10.438		10.381	
Matched	9.489		8.739		12.006		14.538		12.310	
Difference	-1.240	**	-1.904	***	0.403		-4.100	***	-1.929	***
# Matches: 9891										

Table 3.12 Regression Analysis: Implied Cost of Capital and Insider Trading Intensity

This table reports regression results with implied cost of capital estimates as dependent variables, using observations with insider trading and match firms with propensity scores close to firms with insider trading. Five different models are used (CT, GLS, OJ, PEG and MPEG), and the models are described in the data section. We multiply the implied cost of capital estimates by 100 in regressions to make coefficients easier to interpret. Variables are defined in the same way as described in Table 5. All continuous variables are winsorized by 1%. Standard errors are clustered by firm. SIC-2 fixed effects and year fixed effects are included. Robust T statistics are reported in parentheses. ***, ** and * indicate significance levels of 1%, 5% and 10%, respectively.

Panel A.

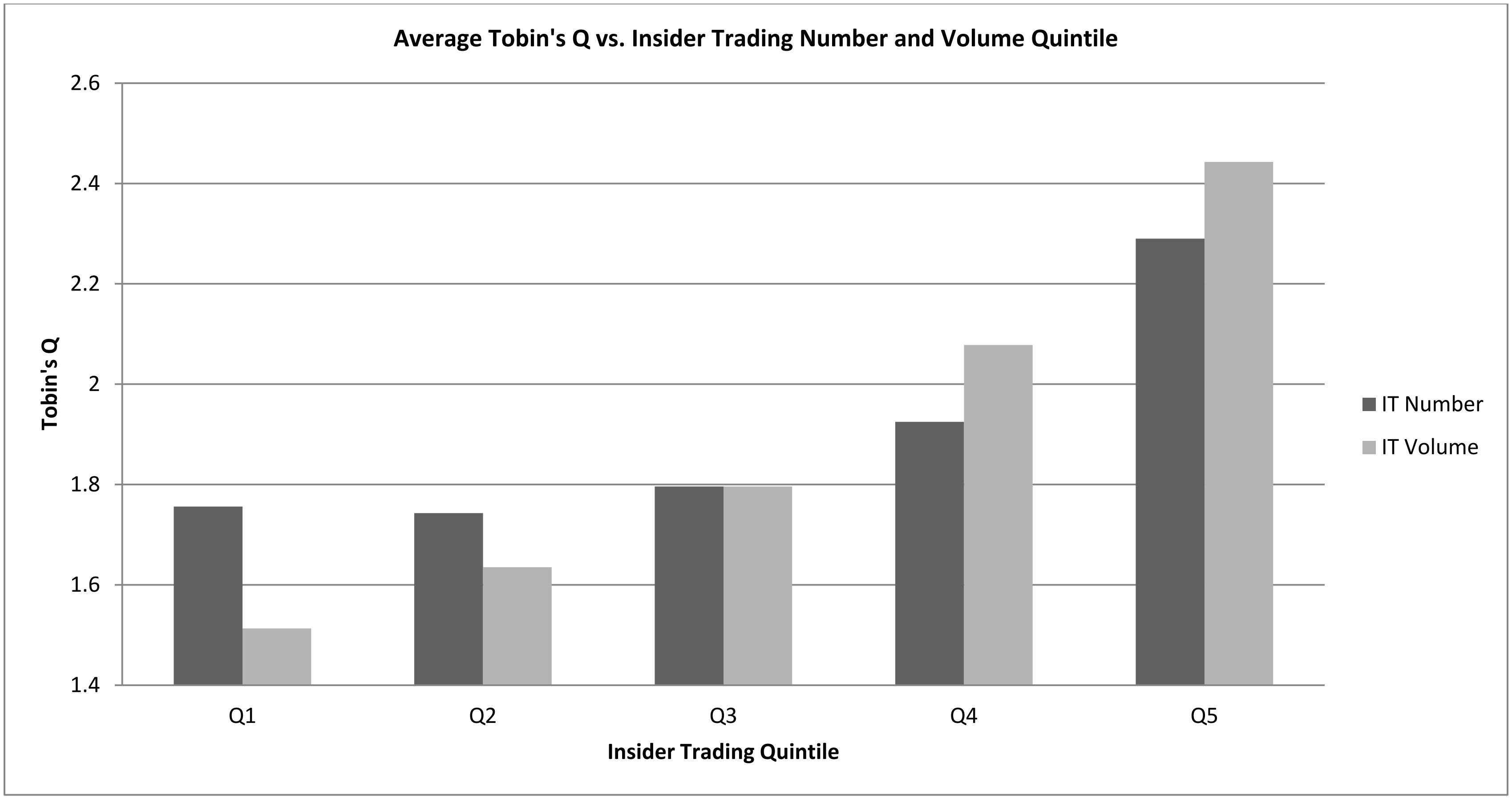
VARIABLES	(1) CT	(2) GLS	(3) OJ	(4) PEG	(5) MPEG
IT_NUM	-0.745	0.120	-1.950**	-0.480	0.203
	(-0.59)	(0.41)	(-2.19)	(-0.61)	(0.52)
IT_DUMMY	4.615***	-1.385***	0.693	-2.262***	-0.618
	(3.28)	(-3.88)	(1.28)	(-3.51)	(-1.39)
LOGMV	-0.785**	-0.835***	-0.342**	-2.247***	-1.230***
	(-2.04)	(-10.58)	(-2.42)	(-15.65)	(-12.86)
ANALYSTS	0.949*	-0.128	0.027	0.114	-0.149
	(1.79)	(-0.98)	(0.13)	(0.48)	(-0.94)
OPACITY	14.641***	3.127***	2.969**	5.971***	6.131***
	(4.61)	(4.78)	(2.20)	(4.81)	(7.38)
Constant	-4.963	10.551***	17.781***	22.518***	11.191***
	(-1.03)	(4.52)	(2.99)	(4.27)	(2.99)
Observations	5,988	6,214	4,908	5,895	6,190
R-squared	0.091	0.173	0.030	0.168	0.167

Panel B.

VARIABLES	(1) CT	(2) GLS	(3) OJ	(4) PEG	(5) MPEG
IT_VOL	0.049	-0.033**	-0.058*	-0.065***	-0.011
	(0.50)	(-2.31)	(-1.76)	(-2.99)	(-0.56)
IT_DUMMY	0.229	-0.745**	-0.077	-1.184**	-0.461
	(0.18)	(-2.48)	(-0.19)	(-2.42)	(-1.28)
LOGMV	-1.762***	-0.704***	-0.476***	-1.824***	-1.142***
	(-6.10)	(-11.82)	(-4.75)	(-17.41)	(-15.67)
ANALYSTS	0.657*	-0.237**	0.018	-0.143	-0.294**
	(1.71)	(-2.47)	(0.15)	(-0.96)	(-2.56)
OPACITY	20.602***	2.191***	3.692***	3.951***	5.656***
	(7.55)	(3.91)	(3.33)	(3.87)	(7.88)
Constant	12.711***	11.675***	18.398***	22.492***	14.744***
	(2.92)	(5.38)	(4.82)	(5.53)	(4.00)
Observations	10,448	10,856	8,135	10,310	10,811
R-squared	0.083	0.150	0.025	0.152	0.191

Figure 3.1 Average Tobin's Q vs. Insider Trading Number and Volume Quintile

Firms are sorted into quintiles by total insider trading number and volume, and the mean value of Tobin's Q in each quintile is depicted below. IT Number is the total number of insider trades for the firm-year observation. IT Volume is the total volume of insider trades for the firm-year observation.



Chapter 4. What Causes the Target Stock Price Run-Up Prior to M&A Announcements?

Abstract

This chapter studies the magnitude and determinants of the target stock price run-up prior to M&A announcements. About one third of the total price run-up occurs before announcements, and the pre-announcement run-up does not seem to be caused by market anticipation of M&As, toehold acquisitions or reported insider trading by corporate insiders. Instead, the pre-announcement run-up is significantly larger when media attention on insider trading is lower, when institutional ownership is lower, and when probability of informed trading is higher. The results suggest that the target stock price run-up prior to M&A announcements may be a result of unreported insider trading.

4.1. Introduction.

Target firms usually experience dramatic stock price run-up when they are acquired. However, a great portion of the run-up occurs prior to M&A announcements. Keown and Pinkerton (1981) find that stock prices react to future mergers about one month before announcements; Halpern (1973) and Mandelker (1974) find the price run-up may start several months before M&A announcements. The pre-announcement run-up is significant and is often accompanied by abnormal trading volumes; not surprisingly, it draws suspicion towards illegal insider trading. The 2012 Nexen insider trading case is a good example, where several traders from Asia are accused of buying Nexen shares before an acquisition announcement which resulted in a 50% stock price increase.

Some researchers argue that the pre-announcement run-up is a proxy for illegal insider trading (Keown and Pinkerton, 1981; Bris, 2005; Beny and Seyhun, 2012). A study by Bhattacharya, Daouk, Jorgenson and Kehr (2000) finds that in some developing countries, insider trading makes significant pre-announcement abnormal returns and leaves no significant post-announcement abnormal returns. The argument is consistent with Meulbroek (1992) and Cornell and Sirri (1992) who find that illegal insider trading significantly moves stock prices. On the other hand, some researchers argue the pre-announcement run-up is not necessarily an outcome of illegal insider trading. In an efficient market for corporate control, takeovers can be anticipated by sophisticated investors. Besides, toehold acquisitions before M&A announcements may also be the reason for the pre-announcement run-up (Mikkelson and Ruback, 1985; Choi, 1991). Jarrell and Poulsen (1989) find the pre-announcement run-up is associated with prevailing rumors and toe-hold acquisitions. Sanders and Zdanowicz (1992) argue the run-up may simply be a measurement error; once the announcement dates are corrected, the pre-announcement run-up becomes insignificant. King (2009) finds that the price-volume dynamics before M&A announcements are more consistent with market anticipation hypothesis rather than insider trading hypothesis.

This paper aims to provide a comprehensive study on what causes the target stock price run-up before M&A announcements. The findings do not support the views that the run-up is caused by market anticipation, toehold acquisition or reported insider trading; instead, the run-up is strongly associated with proxies of unreported insider trading. The pre-announcement price run-up is significantly greater when media attention on insider trading is lower, when institutional ownership is lower, and when probability of informed trading (PIN) is higher. Overall, the findings suggest that pre-announcement run-ups are mainly caused by non-corporate insiders not subject to SEC reporting requirements.

The paper contributes to the literature by documenting associations between the target price run-up before M&A announcements and measures of unreported insider trading. The economic and policy implications are important. Target stock price run-up before M&A announcements makes acquisitions much more expensive and imposes significant transaction costs to the market for corporate control[20]. If the run-up is caused by illegal insider traders, more stringent laws on illegal insider trading may mitigate transaction costs in the market for corporate control and lead to better corporate governance. The magnitude of the pre-announcement run-up may also motivate insiders to enact acquisition barriers to exploit more profits, which may eventually lead to poor corporate governance.

[20] In the sample, about a third of the total run-up occurs before M&A announcements, and the pre-announcement run-up is negatively associated with the post-announcement run-up.

The rest of the paper is organized as follows. Section 2 describes the target stock price run-up prior to M&A announcements and the competing hypotheses explaining the run-up. Section 3 describes the data. Section 4 presents empirical results. Section 5 concludes.

4.2. The pre-announcement price run-up

The target stock price run-up before M&A announcements has been documented in many previous studies[21], along with changes in volume and price volatility[22]. Such price-volume anomaly often results in trading halts and investigations, and sometimes insider trading lawsuits[23]. Though many people suspect unreported illegal insider trading the reason behind the price run-up, it is extremely difficult to detect unreported trades and confirm the suspicion.

Insider trading nowadays has gone beyond its original concept. Any person trading on material non-public information may be accused of insider trading, even though he or she is not a corporate insider subject to SEC filing requirements. The infamous case of Ivan Boesky is one such example: though Boesky was not a corporate insider of the stocks he traded, he was accused of illegal insider trading for receiving tips and trading on private information. There are many traders like Boesky, from big hedge funds to individuals, who are not subject to SEC filing requirements and may trade on inside information secretly. While corporate insiders are found to abstain from trading before M&A activities[24], unreported insider trading is more likely to come into play and move prices prior to announcements.

On the other hand, a pre-announcement run-up is not necessarily caused by insider trades. In a mature and efficient market for corporate control, sophisticated investors might be able to

[21] See Keown and Pinkerton (1981), Jabbour, Jalilvand and Switzer (2000) and Beny and Seyhun (2012).
[22] See Bris (2005) and King (2009).
[23] Meulbroek (1992) finds a direct link between pre-announcement run-up and illegal insider trading cases.
[24] See Agrawal and Nasser (2012).

figure out potential M&A targets. Those potential targets' stock prices may experience pre-announcement run-up due to takeover speculation. For example, fast-growing and cash-rich companies like Apple and Google are often linked to smaller firms in a certain industry with acquisition rumors. Some analysts also predict M&As in their reports based on price levels and strategic considerations. If an acquisition is successfully predicted by the market, a pre-announcement price run-up may be interpreted as a proof of market efficiency rather than an outcome of insider trading.

Investors may also anticipate an acquisition when the potential target is trading at a low price. In an extreme case, a financially distressed firm may actively seek a buyer, which makes the acquisition no secret at all. Many of such firms spend a long time to seal a deal, but some deals are done in less than a month. Therefore, the price run-up before the final announcement may not be a surprise.

Some researchers argue that the pre-announcement run-up is a result of toehold acquisitions (Mikkelson and Ruback, 1985; Choi, 1991). According to SEC Schedule 13D requirements, a bidder may start cumulating stakes long before a takeover is announced. Though Schedule 13D requires that a bidder must update 13D filings when her ownership passes the 5% threshold, there is still a gap of up to ten days before a filing must be made. The toehold acquisition explanation could overlap with the market anticipation explanation because the market could anticipate a takeover once investors learn that a potential bidder is acquiring a toehold. Therefore, the run-up before M&A announcements may also be driven by toehold acquisitions rather than unreported insider trading.

It is worth noting that I do not consider "rumors" as a separate explanation. Based on the news search on Factiva, rumors usually follow existing abnormal price movements or other signs of insider trading (such as trading halts). This makes sense because insiders have no incentive to spread information to other investors at the risk of being sued, and most of the rumors are probably born after abnormal trading activities are observed. Besides, rumors do not always lead to positive abnormal returns. Pound and Zeckhauser (1990) report trading on takeover rumors in a Wall Street Journal column “Heard on the Street” do not yield positive returns, and rumors often come after price run-ups[25]. As a result, I consider rumors as byproducts of the pre-announcement price run-up, rather than what causes the run-up.

A branch of literature focuses on reported insider trading before M&As, but the findings are in general weak[26] as corporate insiders appear to refrain from trading before takeovers. This is probably because corporate insiders are under strict scrutiny particularly around M&As, and they are unlikely to file abnormal trades just before M&A announcements. However, unreported insider trades elude eyes of the general public as non-corporate insiders are not always subject to insider filings. Unreported insider trading is involved in many of the most infamous insider trading scandals including the Boesky case and the recent Galleon case. Under some circumstances, corporate insiders may intentionally seek to hide their trades and avoid reporting their trades to the SEC (see Berkman, Koch and Westerholm, forthcoming).

While it is not possible to directly observe unreported insider trades, I employ an indirect approach. I first hypothesize that unreported insider trading is negatively associated with media attention on insider trading. Barber and Odean (2008) find the buying behavior of individual and institutional investors is affected by news; for illegal insider trading, the story is slightly different. When public attention towards insider trading is high, illegal insider trades are more likely to get caught and thus are more costly. When public attention is low, insiders may become audacious

[25] Ironically, the column was involved in an insider trading case as the columnist Foster Winans was convicted in 1987.
[26] See Seyhun (1990) and Agrawal and Nasser (2012).

with their illegal trading activities. The second proxy for unreported insider trading is institutional ownership. I hypothesize that unreported insider trading is negative associated with institutional ownership. Fidrmuc, Goergen and Renneboog (2006) find the monitoring effect of blockholders reduce insider trading informativeness; the monitoring role of institutional owners may help reduce unreported insider trading prior to M&A announcements. The third measure of unreported insider trading is the probability of informed trading (PIN) defined in Easley, Hvidkjaer and O'Hara (2002). Unreported insider trading is a kind of informed trading and should be included in *PIN*; therefore, the intensity of unreported insider trading should be positively associated with *PIN*.

4.3. Data

I obtain a sample of 22,920 M&A events from Thomson SDC Platinum after cleaning out non-M&A corporate deals[27]. The sample is then merged with CRSP and COMPUSTAT for stock data and accounting data, and the final sample size is 10,202. My sample is big given the time span, and is representative as it is not biased in any specific year. Most of the M&As are done by US domestic acquirers, though I also have 1,378 foreign acquirers in the sample. Comparable to other studies, only a small portion of the observations are hostile M&As, while the majority are friendly or neutral M&As. Sample description is reported in Table 4.1.

[Insert Table 4.1 here]

To measure the pre-announcement run-up, I estimate the 30-day cumulated abnormal returns (CAR) before M&A announcements for all events in the sample. Specifically, I use a market model with coefficients estimated over a one-year window ending two months before the M&A announcement ([t-295, t-45]). The market return is approximated by S&P 500 index return

[27] I only keep deals that are marked "merger" or "acquisitions of partial/major/remaining interest".

but the results are robust to other market returns. Consistent with Keown and Pinkerton (1981), positive price reactions are detected up to 30 days before announcements, which gradually increase all the way to the event announcement day. Panel A of Table 4.2 reports abnormal returns from day t-10 to day t-1, along with cumulated abnormal returns of several representative windows. As can be seen in the table, prices start to react to future M&A events as early as 30 trading days prior to M&A announcements. From ten trading days before announcements, abnormal returns become significantly positive on a daily basis, and the magnitude increases all the way to the announcement day. The pre-announcement run-up is about 5.2% in window [-30, -1], and is as large as 4.8% in a shorter window of [-20, -1]. Compared to the post-announcement of 10.5%, the pre-announcement run-up represents more than one third of the total market reaction to M&A announcements. In this paper, I use CAR[-30, -1] as the main measure of pre-announcement run-up; however, the results are largely the same if other event windows are used.

[Insert Table 4.2 here]

Thomson SDC provides details of the deals, including target attitude, acquirer location, percents of shares owned by acquirers before the deals, and payment form (i.e., how many percents of the payments are made in cash). I take advantage of the information and include a list of control variables that are likely to affect the pre-announcement run-up. Tobin's Q ratio (*TBQ* hereafter) is defined as total assets minus book value of common equity plus market value of shares outstanding at the end of the fiscal year, and then scaled by total assets. This Q approximation is also used Baker, Stein and Wurgler (2003). *SIZE* is defined as the log value of total assets. I define *FRIENDLY* as a dummy variable which equals 1 if target attitude is marked "friendly" and 0 if otherwise. A friendly deal is more likely to be pre-negotiated and is exposed to more insiders, while a neutral or hostile deal may be more sudden to targets. Therefore, *FRIENDLY* is hypothesized to have a positive association with pre-announcement run-up. *FOREIGN* is a dummy variable which equals 1 if the acquirer is a foreign firm. A target in an international deal is less likely to expect the acquisition and may have lower pre-announcement run-up compared to targets in domestic deals. *BEFPCT* is defined as the percentage of shares owned by the acquirer before the announcement. When acquirers own a large percentage of shares before acquisitions, other investors are more likely to anticipate the acquisition; as a result, *BEFPCT* is negatively associated with the pre-announcement run-up. *CASH* is a dummy variable which takes value of 1 if the deal is all paid in cash, and 0 if otherwise. If a deal is paid in 100% cash, the acquirer may cash rich prior to the acquisition and it is more likely for investors to anticipate the acquisition.

As introduced in Section 4.2, I use three variables as indirect measures of unreported insider trading: news about insider trading (*IT_NEWS*), institutional holdings (*INST*), and probability of informed insider trading (*PIN*). For each month I search news articles with keywords "insider trading" or "insider trade"[28] on Factiva and *IT_NEWS* is defined as the monthly number of news articles I found. Most of those articles are about illegal insider trading scandals and trials, and the number of these articles could be a measure of public attention on illegal insider trading. The more news articles there are, the higher media attention on insider trading is and the more aware insiders may become of the risks in their opportunistic trading. As a result, higher media attention may be associated with a lower pre-announcement run-up, if the run-up is caused by unreported insider trading. Institutional holdings data is obtained from Thomson 13F database via WRDS, and is defined as the percentage of reported 13F ownership at the end of the year. Firms with high institutional ownership are usually larger and more closely watched by other investors and SEC, and are thus less likely to have illegal pre-announcement

[28] I also tried other related keywords but the majority of news articles use the phrase "insider trading".

trading; besides, firms with higher institutional ownership are usually better monitored and have better governance, which could potentially limit the profitability and intensity of insider trading (Fidrmuc, Goergen and Renneboog, 2006). Consequently, *INST* should have a negative association with the pre-announcement run-up if unreported insider trading causes the pre-announcement run-up. *PIN* is the probability of informed trading as estimated in Easley, Hvidkjaer and O'Hara (2002). If the pre-announcement run-up is driven by unreported insider trading, the run-up should be greater in firms with higher probability of informed trading. The *PIN* data from 1983 - 2001 is downloaded from Dr. Hvidkjaer's website.

I winsorize all continuous variables by 1% to eliminate outliers. The variables are reported in Table 4.3. Panel A reports summary statistics of variables, and Panel B reports the correlation matrix. Since *PIN* data is only available from 1983 – 2001, only a small portion of observations have available *PIN*. The pre-announcement run-up measure CAR[-30, -1] is significantly correlated with many of the variables as hypothesized. Other CAR measures are highly correlated with CAR[-30, -1] and using other event windows does not change the results much.

[Insert Table 4.3 here]

4.4. Main results

4.4.1 Market anticipation

I first test whether the pre-announcement run-up is caused by market anticipation of acquisitions. Specifically, I examine price movements of comparable companies in the same industry with the final target: if the pre-announcement run-up is caused by market anticipation, other potential targets should also experience price run-ups before the final announcement is made. On the announcement day, the stock price of the final target will go up even more, while the stock prices of other speculated targets are likely to go back to normal levels.

For every target firm, I select a comparable match firm from the same industry. I delete firms that have M&As from the pool of all companies to avoid contaminated match, and then match the remaining "non-target" companies to my sample based on the following criteria: 1, the match firm and the sample firm are in the same SIC 2-digit industry; 2, the combined difference in log total assets and Tobin's Q is not greater than 5% in the year before the event year, e.g. |difference in log total assets|+|difference in Tobin's Q|<0.05. The combined difference of 5% threshold is selected so that the match firm sample size is roughly equal to the original sample size (13,487 compared to 10202). I also tried other thresholds and the results are basically unchanged. Deleting unlikely target firms (e.g., firms with high anti-takeover index and firms with controlling shareholders) does not change the results much either.

Panel B of Table 4.2 reports statistics of abnormal returns for match firms. In general, the match firms do not show any price increases before announcements, and their prices do not go down after the M&A announcements. The results are also illustrated in Figure 1: while the sample firms experience price run-up prior to M&A announcements, match firms do not have significant changes in price. I find no evidence supporting the market anticipation hypothesis.

[Insert Figure 1 here]

I continue to examine other possible market anticipation explanations. Market anticipation can occur to a particular firm, not other comparable rivals in the same industry, when the target is actively looking for buyers or financially distressed. If the pre-announcement run-up is primarily caused by this kind of targets, market anticipation story could be true even when no run-up is observed in match firms. I test whether this explains the pre-announcement run-up by categorizing my sample into quintiles by Tobin's Q ratio and examine whether the pre-announcement run-up only exists in low-Q quintiles. The idea is that most firms looking for buyers are poorly-run or distressed firms; as a result, if the market anticipation story is true, the pre-announcement run-up should only be observed in low-Q quintiles but not in high-Q quintiles.

[Insert Table 4.4 here]

Table 4.4 Panel A presents pre-announcement run-ups categorized by Q quintiles. There is a monotonic relationship between Q and the run-up, but the run-up does not only exist in low Q quintiles. In an event window of [-30, -1], even the highest Q quintile (with a *TBQ* average of 3.6) has a significant pre-announcement run-up. In other two event windows, [-30, -6] and [-30, -11], the top quintiles do not show significant run-up, but the run-up exists in all other quintiles including the second-to-highest quintile with a Q average of 1.5. It is hard to imagine that firms with a Tobin's Q ratio of 1.5 (which is slightly higher than the average of all listed firms) is anticipated to be acquired while the stock prices of peer firms do not change much. The results do not support the story that the run-up is primarily caused by distressed targets. Panel B of Table 4.4 reports run-ups categorized by size. The pre-announcement run-up is significant across all size groups, suggesting it is not a manifestation of size effect. I still do not find any support for the anticipation hypothesis. In fact, if the acquisition could be fully anticipated before announcements, no abnormal returns should be observed when the acquisition is announced.

I also consider the effect of toeholds on stock price before the announcement. It is possible that acquirers start buying target shares before official announcements, and the run-up can be a result of the toehold acquisition. To test this possibility, I select a clean sub-sample which is not likely influenced by toehold acquisition. The official M&A announcements usually precede Schedule 13D filings. Schedule 13D requires that acquirers report to SEC within 10 days immediately after they reach an ownership of 5% threshold of the targets' stocks; besides, Schedule 13D also requires that all acquirers who hold more than 5% of targets' shares update their filings "promptly" to reflect any "material change[29]" in the ownership. Hence, acquirers who hold more than 5% target shares are not allowed to buy more shares without making a prompt Schedule 13D update. The term "prompt" is a bit ambiguous in law, but I take a conservative estimation that this should not be longer than the 10-day reporting period when acquirers reach the reporting threshold for the first time. I create a subsample in which all acquirers have more than 5% target ownership before takeovers, and examine target stock abnormal returns in a [t-30, t-10] window. If the pre-announcement run-up is caused by toehold acquisition, it should not be observed in the [t-30, t-11] window when acquirers initially hold more than 5% target shares[30].

I find the average CAR[t-30, t-11] is 1.404% for the sub-sample; this is not significantly different from the total sample mean of 1.556%. Besides, the sub-sample run-up is significant with a t-value of 4.926. This suggests that the run-up is not entirely driven by toehold acquisition.

4.4.2 Reported Insider Trading

I further conjecture that the run-up could be a result of reported insider trading or unreported insider trading. The effect of reported insider trading is easier to test as corporate insiders are subject to SEC filings. I obtain reported insider trading data from Thomson Financial Insider Filing Data Files. Only open market purchases and sales (with transaction code of "P" or "S") are kept as other types of trades are less informative.

---

[29] Any acquisition of more than 1% target shares is considered material, but a material change is not limited to the 1% ownership change.
[30] The conservative window actually introduces a bias in favor of the toehold acquisition hypothesis.

I track reported insider trades around M&A announcements; specifically, I calculate the number of total insider trades, the number of insider buys, the number of insider sells, the volume of total insider trades, the volume of insider buys, and the volume of insider sells on both daily and monthly levels, and then normalize the data so that I can directly compare different series. Figure 4.2A and Figure 4.2B show normalized insider trades over time on a monthly basis and on a daily basis, respectively. Consistent with previous literature, I do not find significant increase in reported insider trading until only a few days before the announcements. Table 4.5 gives a detailed 30-day daily change of reported insider trading (normalized from day t-30 to day t+30) prior to M&A announcements. Both Figure 4.2 and Table 4.5 show that reported insider trades do not significantly increase until only a few days before the announcement, suggesting that the price run-up up to 30 days before the announcement is not likely a result of reported insider trading.

[Insert Figure 4.2 here]

[Insert Table 4.5 here]

4.4.3 Unreported Insider Trading

Finally, I use an indirect way to test whether unreported insider trading leads to pre-announcement run-up, despite the invisibility of unreported insider trades. As mentioned before, there are three key measures of unreported insider trading, along with some other variables that are likely to be associated with the pre-announcement run-up. The first measure is public attention on insider trading, measured by the monthly number of news articles on insider trading in Factiva (*IT_NEWS*). In the text search, I find most of the news articles are associated with insider trading scandals, ongoing trials and court decisions about previous insider trading cases;

hence, the number of articles about insider trading to some extent reflects the degree of insider trading law enforcement and the likelihood that an illegal insider gets caught. If the pre-announcement run-up is caused by unreported insider trading, *IT_NEWS* should be negatively associated with the run-up. The second measure is institutional ownership (*INST*). Firms with higher institutional ownership are more closely monitored, and are thus less likely affected by illegal insider trading. Therefore, *INST* is negatively associated with the pre-announcement run-up if unreported insider trading leads to the run-up. The third measure is the probability of informed trading (*PIN*). If the pre-announcement run-up reflects the degree of unreported insider trading, the run-up should be greater in firms with higher *PIN*.

In a preliminary test, I sort *IT_NEWS*, *INST* and *PIN* into quintiles and report the mean and t-statistic of CAR[-30, -1] in each quintile. Results are reported in Table 4.6. Consistent with my prior hypotheses, the pre-announcement run-up is significantly lower in the quintile with the highest number of insider trading news articles, the quintile with the highest institutional ownership, and the quintile with the lowest PIN. The results suggest that stock prices are more likely to react to undisclosed future takeovers in firms more likely to have unreported insider trading.

I move on to formal regression analysis before I make a conclusion. *PIN* is a bounded variable with small standard deviation, so I create a dummy variable *PIN_HIGH* which equals 1 if *PIN* is above its median and 0 if otherwise[31]. *IT_NEWS* and *INST* are the same as defined in Table 4.6.

There are other variables that are likely to be associated with price run-ups before takeover announcements. If M&As are not easy to predict, fewer insiders have access to the

[31] If I put *PIN* in regressions directly, its coefficient is significantly positive in some windows and only marginally significant in other windows, possibly due to limited observations and its low variance. Log transformation of *PIN* does not change the results much.

information and thus unreported insider trading is reduced. If unreported insider trades cause pre-announcement run-ups, I should observe a small run-up or even no run-up at all. Variables of this kind include *FRIENDLY* and *FOREIGN*. Friendly deals are more likely to be pre-negotiated before announcements, while foreign deals are likely to be more sudden due to geographical distance. As a result, *FRIENDLY* is likely to be positively associated with the run-up, and *FOREIGN* is likely to be negatively associated with the run-up, if the run-up is caused mainly by unreported insider trading.

SIZE and *TBQ* are included as control variables for obvious reasons. They are shown to be associated with CAR calculated in a market model; besides, they are usually highly correlated with most corporate variables. It is intuitive to think size and Tobin's Q both predict a lower pre-announcement run-up, as small firms and low-Q firms are more likely to be poorly monitored and vulnerable to unreported insider trading. Other control variables include *BEFPCT* and *CASH*. As discussed in Section 4.3, they are associated with the likelihood that an acquisition is anticipated. Besides, a high percentage of pre-announcement ownership indicates a low percentage of ownership transferred in the M&A, so the total market reaction is small. M&As paid in cash are very different from those paid in shares (Loughran and Vijh, 1997), and an acquisition paid with equity may signal the equity prices are too high.

Table 4.7 presents multi-variate regressions with the dependant variable of CAR[-30, -1]. As M&As come in waves and are often clustered in certain industries (Jarrell and Poulsen, 1989), I include 2-digit target SIC industry dummies and year dummies to adjust for industry and year effects. All regressions are clustered by 2-digit target SIC industry.

[Insert Table 4.7 here]

The results, in general, are consistent with results in Table 4.6 and in favor of the hypothesis that unreported insider trades lead to the pre-announcement run-up. My primary measures of unreported insider trading – *IT_NEWS*, *INST* and *PIN_HIGH* – are significantly associated with the pre-announcement price run-up. With year fixed effects controlled, every additional 100 news articles about insider trading results in a 2.3% decrease in the pre-announcement run-up, and every one percent change of institutional ownership reduces the run-up by 0.05%. Target firms with above-median PIN have 3.1% higher pre-announcement run-up compared to target firms with below-median PIN. The economic significances are also large: a one standard deviation increase in both *IT_NEWS* and *INST* corresponds to about a 1% decrease in pre-announcement run-up. In results not tabulated here, dummy variables constructed based on *IT_NEWS* and *INST* are also significant in regressions, and various transformations of *IT_NEWS* and *INST* lead to similar results.

Other variables are also consistent with the unreported insider trading story. Friendly M&As appear to have about 3% lower run-ups compared to hostile M&As and others, and the difference is very significant. M&As with high pre-announcement acquirer ownerships exhibit significantly low run-ups. High-Q firms have low run-ups compared to low-Q firms.

4.4.4 Robustness

Several robustness tests are done to ensure the results are not caused by statistical problems. I first try different event windows to ensure the results are robust. CAR estimated in a market model is volatile. Therefore, I try other event windows to see if my results are sufficiently robust. Good candidates include CAR[-30, -6] and CAR[-30, -11]. These two windows are more rigorous than the [-30, -1] window because the majority of the pre-announcement run-up occurs just a few days before day 0. I report multi-variate regressions with the two alternative event windows in Table 4.8. As shown in the table, the results are virtually unchanged as the coefficients of the three key variables are significant in most regressions, though *IT_NEWS* becomes insignificant in the [-30, -11] window. Dummy variables based on *IT_NEWS* are still significant even in the [-30, -11] window in results not tabulated here.

Another way to measure public attention towards insider trading is to look at how many searches people make about insider trading. Similar to the number of news articles, the number of searches on insider trading also reflects public attention on insider trading. I obtain data from Google Trend, which records insider-trading-related searches on Google from 1994 and normalize the search numbers. Normalized monthly Google searches are then merged with my sample; this gives us a small sample of 1,764 observations.

I regress the pre-announcement run-up on monthly Google searches about insider trading and a dummy variable defined as 1 if the monthly Google search number is greater than 1 (one standard deviation above average) and 0 otherwise. In results not tabulated here, I find a significant negative association between the run-up and the number of Google searches. However, the results are not robust and become insignificant when standard errors are clustered by industry, possibly due to the limited number of observations.

4.5 Conclusion

The big magnitude of target price run-up before M&A announcements makes people wonder what causes the run-up. While some researchers believe the run-up is caused by market anticipation or toehold acquisition, I find neither of the two is able to explain the target stock price run-up prior to M&A announcements. Instead, variables that are associated with unreported insider trading are significantly associated with the run-up. At the end of the day, I may find that Keown and Pinkerton (1981) are right after all in explaining the pre-announcement run-up as insider trading.

While reported insider trades are mostly legal and believed to increase market efficiency (Leland, 1992; Lakonishok and Lee, 2001), unreported insider trades based on material information are considered illegal in almost every country in the world (Bhattacharya and Daouk, 2002). However, due to the low expected cost (as only a small portion of insider trades are caught each year), non-corporate insiders still have a great incentive to get tips from corporate insiders and make profits. These trades are different from reported insider trades partly because they are not visible to the public; therefore, even though these trades still improve ex-post price accuracy, they may not promote general market efficiency as reported insider trades do.

The finding that the target price run-up before M&A announcements is associated with unreported insider trading measures raises the concern that rampant illegal insider trading may undermine corporate governance. Mergers and acquisitions are important in motivating managers as they work as alternative mechanisms for corporate control (Morck, Shleifer and Vishny, 1988). The pre-announcement run-up could add significant costs to mergers and acquisitions, which may have a negative effect on corporate governance.

How to get rid of unreported insider trades? My results indicate that high media attention and institutional ownership can reduce unreported insider trades, or at least make them less profitable. However, things do not seem to improve over time. Beny and Seyhun (2012) observe that insider trading is getting even more rampant over time. Unreported insider trading and the price run-up before M&A announcements are not likely to cease soon.

References

Agrawal, A. and T. Nasser, 2012, Insider trading in takeover targets, *Journal of Corporate Finance* 18, 598-625.

Baker, M., J. C. Stein, and J. Wurgler, 2003, When Does the Market Matter? Stock Prices and the Investment of Equity-Dependent Firms, *The Quarterly Journal of Economics* 118, 969-1005.

Barber, B. M., and T. Odean, 2008, All That Glitters: The Effect of Attention and News on the Buying Behavior of Individual and Institutional Investors, *Review of Financial Studies* 21, 785-818.

Beny, L. N., and H. N. Seyhun, 2012, Has Insider Trading Become More Rampant in the United States? Evidence from Takeovers, *U of Michigan Law and Econ Research Paper* No. 12-012.

Berkman, H., P. D. Koch, and P. J. Westerholm, 2014, Informed Trading through the Accounts of Children, *The Journal of Finance* 69, 363-404.

Bhattacharya, U. and H. Daouk, 2002, The World Price of Insider Trading, *The Journal of Finance* 57, 75-108.

Bhattacharya, U., H. Daouk, B. Jorgenson, and C. Kehr, 2000, When an event is not an event: the curious case of an emerging market, *Journal of Financial Economics* 55, 69-101.

Bris, A., 2005, Do Insider Trading Laws Work? *European Financial Management* 11, 267-312.

Choi, D., 1991, Toehold Acquisitions, Shareholder Wealth, and the Market for Corporate Control, *The Journal of Financial and Quantitative Analysis* 26, 391-407.

Cornell, B. and E. R. Sirri, 1992, The Reaction of Investors and Stock Prices to Insider Trading, *The Journal of Finance* 47, 1031-1059.

Easley, D., S. Hvidkjaer, and M. O'Hara, 2002, Is information risk a determinant of asset returns? *The Journal of Finance* 57, 2185-2221.

Fama, E. F. and K. R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3-56.

Fidrmuc, J. P., M. Goergen, and L. Renneboog, 2006, Insider Trading, News Releases and Ownership Concentration, *The Journal of Finance* 61, 2931-2973.

Halpern, P. J., 1973, Empirical Estimates of the Amount and Distribution of Gains to Companies in Mergers, *The Journal of Business* 46, 554-575.

Jabbour, A. R., A. Jalilvand, and J. A. Switzer, 2000, Pre-bid price run-ups and insider trading activity: Evidence from Canadian acquisitions, *International Review of Financial Analysis* 9, 21-43.

Jarrell, G. A. and A. B. Poulsen, 1989, Stock Trading before the Announcement of Tender Offers: Insider Trading or Market Anticipation?, *Journal of Law, Economics, and Organization* 5, 225-248.

Jensen, M. C. and R. S. Ruback, 1983, The market for corporate control: The scientific evidence, *Journal of Financial Economics* 11, 5-50.

Keown, A. J. and J. M. Pinkerton, 1981, Merger Announcements and Insider Trading Activity: An Empirical Investigation, *The Journal of Finance* 36, 855-869.

King, M. R., 2009, Prebid Run-Ups Ahead of Canadian Takeovers: How Big Is the Problem? *Financial Management* 38, 699-726.

Lakonishok, J. and I. Lee, 2001, Are Insider Trades Informative? *The Review of Financial Studies* 14, 79-111.

Leland, H. E., 1992, Insider Trading: Should It Be Prohibited? *Journal of Political Economy* 100, 859-887.

Loughran, T. and A. Vijh, 1997, Do Long-Term Shareholders Benefit From Corporate Acquisitions? *The Journal of Finance* 52, 1765-1790.

Mandelker, G., 1974, Risk and return: The case of merging firms, *Journal of Financial Economics* 1, 303-335.

Meulbroek, L. K., 1992, An Empirical Analysis of Illegal Insider Trading, *The Journal of Finance* 47, 1661-1699.

Mikkelson, W. H. and R. S. Ruback, 1985, An Empirical Analysis of the Interfirm Equity Investment process, *Journal of Financial Economics* 14, 523-553.

Morck, R., A. Shleifer, and R. W. Vishny, 1988, Alternative Mechanisms for Corporate Control, *American Economic Review* 79, 842-852.

Pound, J. and R. Zeckhauser, 1990, Clearly Heard on the Street: The Effect of Takeover Rumors on Stock Prices, *The Journal of Business* 63, 291-308.

Sanders, R. W. Jr., and J. S. Zdanowicz, 1992, Target Firm Abnormal Returns and Trading Volume Around the Initiation of Change in Control Transactions, *The Journal of Financial and Quantitative Analysis* 27, 109-129.

Schwert, G. W., 1996, Markup pricing in mergers and acquisitions, *Journal of Financial Economics* 41, 153-192.

Seyhun, H. N., 1990, Do Bidder Managers Knowingly Pay Too Much for Target Firms? *The Journal of Business* 63, 439-464.

Table 4.1 Sample Description

This table reports the sample composition by target attitude, bidder location and event year.

			Observations
US M&A activities from 1981 to 2011			22920
with available CRSP data to calculate CAR			11918
with available COMPUSTAT data			10202
Final Sample Size:			10202
Panel A. Sample by Attitude and Bidder Location			
	Domestic Bidder	Foreign Bidder	Total
Friendly	5,839	1,027	6,866
Hostile	337	36	373
Neutral	2,236	284	2,520
Other	412	31	443
Total	8,824	1,378	10,202
Panel B. Sample by Year			
		Pct. (%)	Obs.
	1981	0.74	75
	1982	0.95	97
	1983	1.95	199
	1984	2.84	290
	1985	2.19	223
	1986	2.72	277
	1987	3.82	390
	1988	4.46	455
	1989	5.44	555
	1990	3.4	347
	1991	3.23	330
	1992	3.01	307
	1993	3.77	385
	1994	5.17	527
	1995	6.34	647
	1996	6.18	630
	1997	5.74	586
	1998	5.03	513
	1999	4.58	467
	2000	4.56	465
	2001	2.66	271
	2002	1.96	200
	2003	1.98	202
	2004	1.52	155
	2005	1.78	182
	2006	2.31	236
	2007	2.3	235
	2008	3.19	325
	2009	2.74	280
	2010	1.93	197
	2011	1.51	154
	Total	100	10,202

Table 4.2 Pre-Merger Announcement Price Run-up

This table reports abnormal returns and cumulated abnormal returns over representative windows. Panel A reports statistics of the original sample, and Panel B shows statistics of the match firms constructed as in the data section. *, ** and *** represents significance levels of 10%, 5% and 1%, respectively.

	Mean	*Std. Dev.*	*Min*	*Max*	*T*
Panel A. Sample					
CAR[-30, -21]	0.415***	12.466	-99.184	131.298	3.364
CAR[-20, -11]	1.141***	13.296	-110.580	201.334	8.667
AR[-10]	0.096**	4.955	-48.630	89.038	1.962
AR[-9]	0.091*	5.190	-76.100	100.522	1.762
AR[-8]	0.257***	5.083	-59.182	132.438	5.102
AR[-7]	0.299***	4.749	-44.461	99.750	6.358
AR[-6]	0.244***	4.829	-55.787	69.853	5.106
AR[-5]	0.241***	5.087	-60.600	72.247	4.782
AR[-4]	0.345***	5.144	-61.985	89.021	6.765
AR[-3]	0.427***	5.698	-51.648	112.340	7.572
AR[-2]	0.566***	5.594	-38.708	99.970	10.212
AR[-1]	1.105***	6.224	-48.603	107.243	17.938
CAR[-30, -1]	5.226***	23.656	-172.394	256.911	22.315
CAR[0, 5]	10.572***	21.977	-99.459	434.722	48.429
	Panel B. Match Firms				
CAR[-30, -21]	-0.116	9.685	-133.253	113.791	-1.333
CAR[-20, -11]	-0.182**	10.207	-161.672	163.885	-1.986
AR[-10]	-0.018	4.374	-36.742	188.963	-0.457
AR[-9]	-0.070*	4.468	-61.477	127.088	-1.763
AR[-8]	0.066	5.069	-53.443	189.080	1.458
AR[-7]	0.089**	4.517	-38.423	126.876	2.198
AR[-6]	-0.027	4.617	-41.445	189.229	-0.669
AR[-5]	-0.105***	4.205	-62.438	126.785	-2.770
AR[-4]	-0.006	4.364	-56.816	189.304	-0.146
AR[-3]	0.044	4.077	-33.772	126.715	1.207
AR[-2]	0.021	4.240	-41.970	189.586	0.546
AR[-1]	-0.005	4.243	-56.504	126.623	-0.142
CAR[-30, -1]	-0.312**	15.985	-185.785	156.326	-2.172
CAR[0, 5]	-0.202**	8.746	-83.179	275.080	-2.566

Table 4.3 Variables Description

This table reports key variables used in this paper. Panel A reports summary statistics, and Panel B reports correlation matrix. *SIZE* is log value of total assets. *TBQ* is Tobin's Q defined in the data section. *IT_NEWS* is number of Factiva news hits of insider trading in the event month. *INST* is institutional ownership reported in Form 13F. *PIN* is the probability of informed trading as in Easley, Hvidkjaer and O'Hara (2002). *FRIENDLY* is a dummy which equals 1 if the deal is a friendly M&A and 0 otherwise. *FOREIGN* is a dummy which equals 1 if the acquirer is a non-US firm and 0 otherwise. *BEFPCT* is the percents of shares owned by the acquirer before the announcement. *CASH* is a dummy which equals 1 if the acquisition is 100% paid with cash and 0 otherwise. All continuous variables are winsorized by 1%.

Panel A. Variable Summary Statistics

	Obs	**Mean**	**Std. Dev.**	**Min**	**Max**
SIZE	10202	5.539	1.960	1.399	10.632
TBQ	10179	1.623	1.373	0.548	9.837
IT_NEWS (in hundreds)	9541	0.449	0.471	0.000	3.850
INST (%)	9367	35.029	28.661	0.117	100.00
PIN	3456	0.218	0.074	0.024	0.761
FRIENDLY	10202	0.673	0.469	0.000	1.000
FOREIGN	10202	0.135	0.342	0.000	1.000
BEFPCT (%)	7398	5.694	14.859	-0.050	99.680
CASH	10202	0.473	0.499	0.000	1.000

Panel B. Correlation Matrix

	CAR[-30, -1]	*SIZE*	*TBQ*	*IT_NEWS*	*INST*	*PIN*	*FRIENDLY*	*FOREIGN*	*BEFPCT*
SIZE	-0.053***								
TBQ	-0.037***	-0.311***							
IT_NEWS	-0.037***	0.119***	0.017						
INST	-0.089***	0.430***	-0.028	0.150***					
PIN	0.022*	-0.456***	-0.145***	-0.176***	-0.143**				
FRIENDLY	0.072***	0.009	0.041	0.270***	-0.129***	-0.070			
FOREIGN	0.018	-0.022	0.057***	0.039**	-0.028	-0.035	0.089***		
BEFPCT	-0.029***	-0.022	-0.036	-0.053***	-0.082***	0.148***	-0.011	0.012	
CASH	-0.043***	-0.070	-0.057**	-0.123***	0.060**	0.147***	-0.462***	-0.003	0.104***

Table 4.4 Pre-announcement Run-up by Size and Tobin's Q

This table reports pre-announcement run-ups categorized on Tobin's Q quintiles and size quintiles. Q quintiles are reported in Panel A, and size quintiles are reported in Panel B. Quintile mean reports the mean of *TBQ* or *SIZE* in the quintile. Three event windows are reported, respectively [-30, -1], [-30, -6] and [-30, -11]. *, ** and *** stand for significance levels of 10%, 5% and 1%, respectively.

		CAR[-30, -1]		CAR[-30, -6]		CAR[-30, -11]	
	Quintile Mean	CAR	T	Mean	T	Mean	T
Panel A: TBQ							
Q1	0.827	7.136***	14.71	4.337***	10.41	3.131***	8.57
Q2	1.012	5.958***	13.55	3.279***	8.51	2.422***	7.35
Q3	1.159	4.432***	9.93	1.786***	4.72	0.950***	2.88
Q4	1.519	4.518***	9.99	2.151***	5.46	1.076***	3.14
Q5	3.597	3.427***	6.36	0.709	1.53	-0.223	-0.54
Panel B: Size							
Q1	2.921	7.721***	11.44	4.136***	7.33	2.758***	5.48
Q2	4.382	5.987***	10.93	2.719***	5.70	1.475***	3.65
Q3	5.409	4.632***	9.82	2.197***	5.37	1.181***	3.39
Q4	6.514	3.950***	9.06	1.834***	4.59	0.907***	2.51
Q5	8.427	3.876***	8.60	1.849***	4.83	1.474***	4.42

Table 4.5 Reported Insider Trades by Day

This table reports reported 30-day daily reported insider trades before M&A announcements, normalized to the 60-day daily average (from day t-30 to day t+30). Both the number and the volume of trades are reported.

Day	*Total Trades*	*Buys*	*Sells*	*Total Volume*	*Buy Volume*	*Sell Volume*	*AR*
-30	-49.943%	-35.423%	-57.969%	-68.033%	-43.026%	-72.414%	0.077%
-29	-23.707%	-35.072%	-0.812%	-19.547%	-35.048%	-11.814%	0.059%
-28	-2.791%	2.741%	6.925%	1.280%	2.248%	5.922%	0.052%
-27	0.961%	12.447%	-3.760%	-3.054%	2.017%	-3.416%	0.010%
-26	-37.521%	-36.469%	-33.259%	-34.828%	-40.899%	-23.444%	0.109%
-25	-36.820%	-24.651%	-35.305%	-45.752%	-25.104%	-33.907%	0.078%
-24	-43.134%	-32.816%	-43.866%	-38.831%	-25.717%	-43.156%	-0.075%
-23	-51.399%	-49.666%	-29.915%	-60.087%	-66.971%	-24.751%	-0.008%
-22	-15.920%	-9.060%	-27.319%	-22.172%	1.107%	-36.288%	0.027%
-21	-8.537%	22.154%	-10.806%	-4.377%	40.590%	-18.760%	0.087%
-20	-14.223%	-24.139%	-12.680%	-20.075%	-39.239%	-11.322%	0.078%
-19	-27.635%	-1.254%	-29.900%	-22.236%	12.610%	-27.052%	0.091%
-18	-28.931%	-2.020%	-20.961%	-27.231%	9.289%	-27.476%	0.147%
-17	-37.314%	-17.516%	-27.177%	-35.492%	-23.268%	-32.765%	0.103%
-16	-40.429%	-28.235%	-19.520%	-34.733%	-35.266%	-9.206%	0.105%
-15	-18.892%	-29.080%	-10.805%	-2.770%	-25.947%	8.150%	0.108%
-14	0.885%	43.935%	2.543%	30.968%	51.862%	8.556%	0.013%
-13	-26.601%	-9.954%	-28.925%	-8.039%	13.647%	-29.141%	0.193%
-12	-29.341%	-26.392%	-4.162%	-3.755%	-19.476%	-0.372%	0.102%
-11	-31.388%	-23.886%	-47.641%	-21.042%	2.242%	-47.031%	0.202%
-10	-29.851%	-16.858%	-24.439%	-4.025%	-21.955%	-7.460%	0.096%
-9	-42.796%	-35.900%	-28.683%	-32.126%	-33.434%	-32.773%	0.091%
-8	-23.312%	-0.221%	-18.722%	-6.931%	14.706%	-24.494%	0.257%
-7	11.786%	21.444%	11.278%	74.654%	55.142%	29.116%	0.299%
-6	-12.156%	-5.209%	-15.826%	36.227%	30.057%	1.896%	0.244%
-5	-18.719%	-5.807%	-28.688%	61.258%	28.302%	22.703%	0.241%
-4	-24.293%	-10.581%	-16.441%	42.318%	40.338%	18.358%	0.345%
-3	-16.989%	-19.886%	-13.973%	53.770%	18.335%	17.438%	0.427%
-2	-34.251%	-18.677%	-27.463%	-4.794%	21.379%	-18.235%	0.566%
-1	10.951%	33.134%	6.929%	226.618%	191.070%	67.978%	1.105%

Table 4.6 Univariate Results

This table reports CAR[-30, -1] by quintiles of *IT_NEWS*, *INSPCT* and *PIN*. *IT_NEWS* is number of Factiva news hits of insider trading in the event month. *INST* is institutional ownership reported in Form 13F. *PIN* is the probability of informed trading as in Easley et al. (2002). Robust t statistics clustered by firm are reported in parentheses.

	Low	Q2	Q3	Q4	High	High - Low
IT_NEWS						
Mean	5.395***	4.725***	5.330***	5.028***	3.933***	-1.461*
T	(11.58)	(11.10)	(8.06)	(9.66)	(6.68)	(-1.95)
INST						
Mean	6.450***	5.776***	5.718***	3.181***	2.295***	-4.155***
T	(10.56)	(9.22)	(10.98)	(6.44)	(4.84)	(-5.37)
PIN						
Mean	2.830***	3.463***	3.694***	6.211***	5.819***	2.989**
T	(4.48)	(4.54)	(4.87)	(7.58)	(5.60)	(2.46)

Table 4.7 Multi-Variate Regressions

This table reports multi-variate regressions. *IT_NEWS* is number of Factiva news hits of insider trading in the event month. *INST* is institutional ownership reported in Form 13F. *PIN_HIGH* is a dummy variable which equals 1 if *PIN* is above its median and 0 otherwise. *SIZE* is log value of total assets. *TBQ* is Tobin's Q defined in the data section. *BEFPCT* is the percents of shares owned by the acquirer before the announcement. *FOREIGN* is a dummy which equals 1 if the acquirer is a non-US firm. *FRIENDLY* is a dummy which equals 1 if the deal is a friendly M&A. *CASH* is a dummy which equals 1 if the deal is completely financed by cash. *INST50* is a dummy which equals 1 if *INST* is greater than 50%. All continuous variables are winsorized at 1%. The dependent variable is CAR[-30, -1]. Year fixed effects and SIC-2 industry fixed effects are included. T-statistics are reported in parentheses; *, ** and *** indicates significance levels of 10%, 5% and 1%, respectively. Results are clustered by 2-digit SIC industry.

	(1)	(2)	(3)
IT_NEWS	-0.023*		
	(-1.92)		
INST		-0.052***	
		(-3.88)	
PIN_HIGH			0.031***
			(2.97)
SIZE	-0.006**	-0.002	-0.001
	(-2.60)	(-0.70)	(-0.07)
TBQ	-0.011***	-0.010***	-0.011
	(-3.88)	(-3.09)	(-1.22)
BEFPCT	-0.001***	-0.001***	-0.001**
	(-3.58)	(-4.03)	(-2.51)
FOREIGN	0.013	0.010	0.013
	(1.59)	(1.21)	(1.08)
FRIENDLY	0.033***	0.030***	0.019**
	(4.42)	(3.87)	(2.26)
CASH	-0.005	-0.004	-0.004
	(-0.87)	(-0.58)	(-0.48)
Constant	0.134***	0.124***	-0.014
	(6.08)	(4.64)	(-0.39)
Observations	6,830	6,194	2,205
R-squared	0.041	0.044	0.095

Table 4.8 Multi-Variate Regressions: Alternate Windows

This table reports multi-variate regressions with alternative event windows. *IT_NEWS* is number of Factiva news hits of insider trading in the event month. *INST* is institutional ownership reported in Form 13F. *PIN_HIGH* is a dummy variable which equals 1 if *PIN* is above its median and 0 otherwise. *SIZE* is log value of total assets. *TBQ* is Tobin's Q defined in the data section. *BEFPCT* is the percents of shares owned by the acquirer before the announcement. *FOREIGN* is a dummy which equals 1 if the acquirer is a non-US firm. *FRIENDLY* is a dummy which equals 1 if the deal is a friendly M&A. *CASH* is a dummy which equals 1 if the deal is completely financed by cash. *INST50* is a dummy which equals 1 if *INST* is greater than 50%. All continuous variables are winsorized at 1%. The dependent variables are CAR[-30, -6] and CAR[-30, -11]. Year fixed effects and SIC-2 industry fixed effects are included. T-statistics are reported in parentheses; *, ** and *** indicates significance levels of 10%, 5% and 1%, respectively. Results are clustered by 2-digit SIC industry.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.		CAR[-30, -6]			CAR[-30, -11]	
IT_NEWS	-0.017*			-0.011		
	(-1.73)			(-1.30)		
INST		-0.030***			-0.017**	
		(-3.04)			(-2.17)	
PIN_HIGH			0.031***			0.021***
			(3.71)			(2.75)
SIZE	-0.005**	-0.002	0.002	-0.003	-0.002	0.003
	(-2.28)	(-0.98)	(0.68)	(-1.56)	(-0.78)	(0.87)
TBQ	-0.011***	-0.010***	-0.008	-0.009***	-0.008***	-0.006
	(-4.26)	(-3.61)	(-1.12)	(-3.82)	(-3.04)	(-1.16)
BEFPCT	-0.000**	-0.000***	-0.000***	-0.000	-0.000	-0.000**
	(-2.40)	(-2.66)	(-2.77)	(-0.44)	(-0.76)	(-2.15)
FOREIGN	0.007	0.009	0.013	0.009*	0.009*	0.016
	(1.11)	(1.38)	(1.17)	(1.71)	(1.67)	(1.36)
FRIENDLY	0.016**	0.014**	0.004	0.012***	0.011***	0.002
	(2.60)	(2.32)	(0.44)	(2.85)	(2.83)	(0.32)
CASH	-0.002	-0.000	0.003	-0.005	-0.003	-0.004
	(-0.43)	(-0.04)	(0.33)	(-1.07)	(-0.58)	(-0.71)
Constant	0.086***	0.092***	-0.083**	0.046***	0.051***	-0.105***
	(4.30)	(3.99)	(-2.58)	(3.25)	(3.16)	(-4.16)
Observations	6,830	6,194	2,205	6,830	6,194	2,205
R-squared	0.029	0.032	0.076	0.026	0.028	0.053

Figure 4.1 Price Run-ups around M&A Announcements

The figure shows price run-ups before and after M&A announcements. The horizontal axis represents days relative to the announcement day, while the vertical axis represents cumulated abnormal return. The solid line represents the original sample, while the dash line represents the match firms constructed as described in the data section.

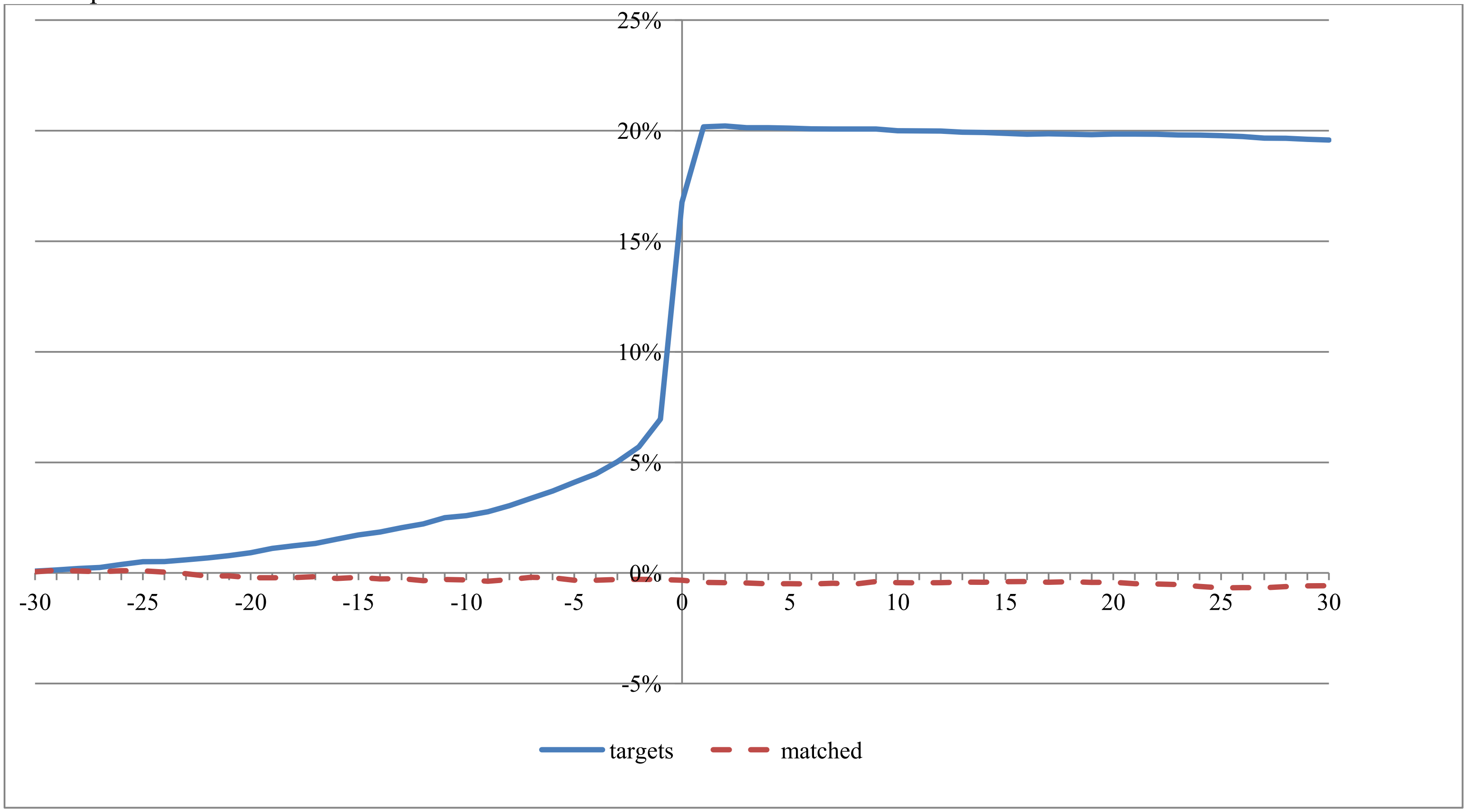


Figure 4.2A Reported Insider Trades Before M&A Announcements: Monthly

This figure shows insider trades normalized by month. The horizontal axis is month relative to the event month. The vertical axis represents normalized trade number or volume relative to the two-year monthly average.

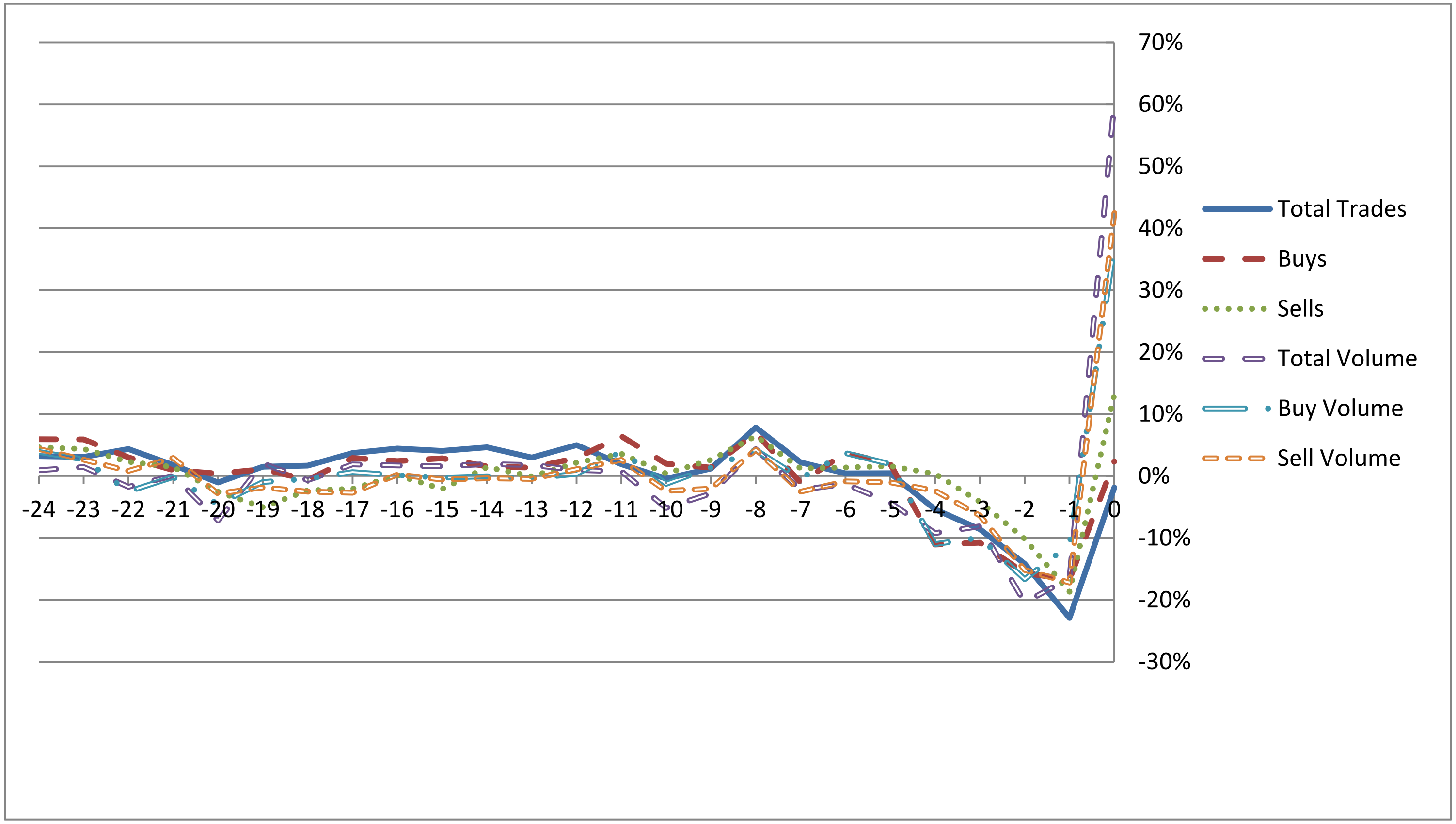
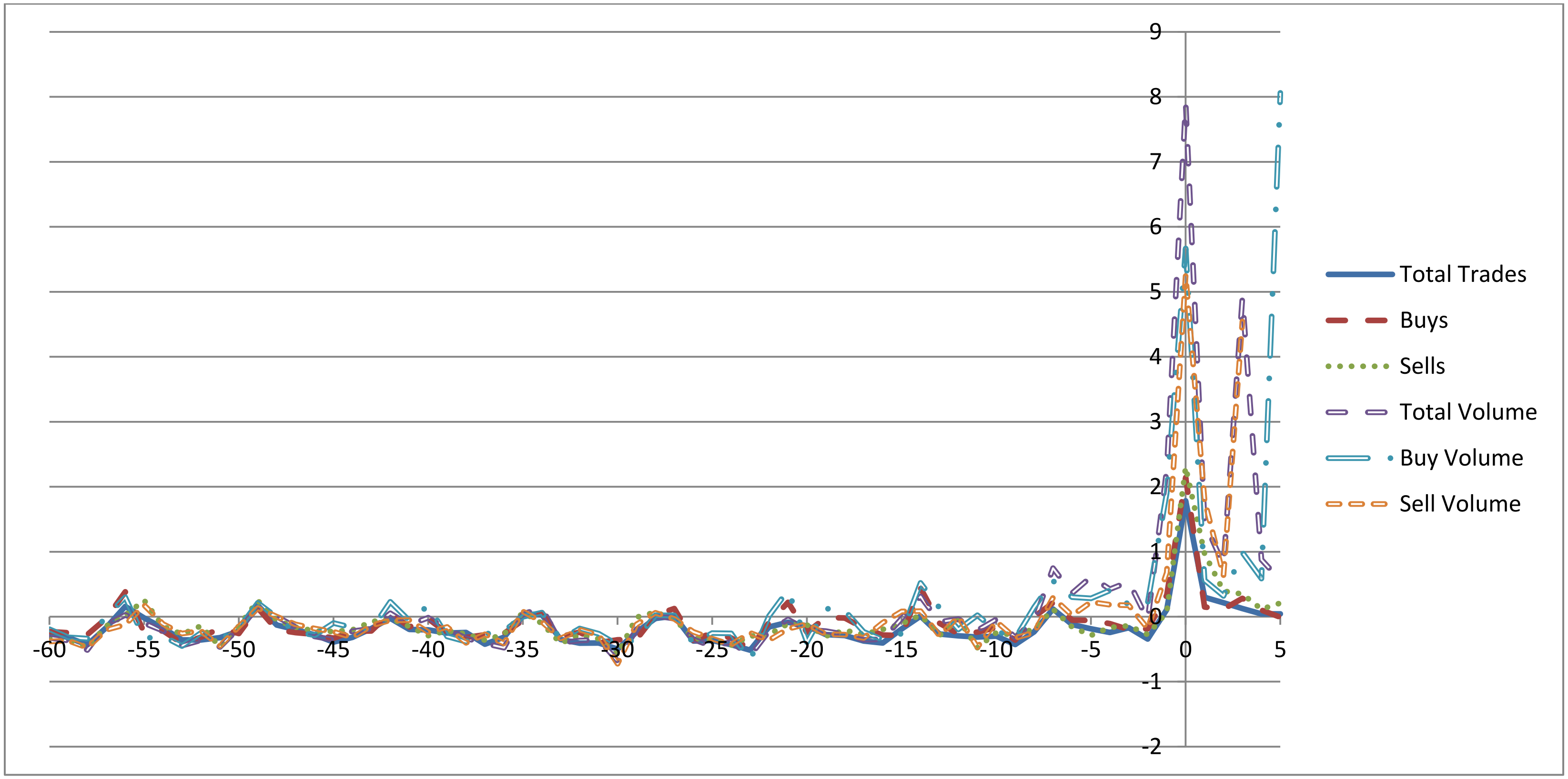


Figure 4.2B Reported Insider Trades Before M&A Announcements: Daily

This figure shows insider trades normalized by day. The horizontal axis is day relative to the event day. The vertical axis represents normalized trade number or volume relative to the 60-day daily average.



Chapter 5. Conclusion

The thesis examines insider trading from three perspectives. As discussed in Chapter 1, legal insider trading could alleviate the Myers and Majluf type of information asymmetry, and could potentially make stock prices more informative, enhance firm value and reduce cost of capital. Illegal insider trading, on the other hand, does not reduce the Myers and Majluf type of information asymmetry because it is not reported to the public. Even though illegal insider trading is also based on information, it only exacerbates the Kyle type of information asymmetry.

Starting from the informational efficiency perspective, three essays explore different aspects of insider trading. In Chapter 2, I answer a very fundamental question: does insider trading increase stock price informativeness? The question, despite its importance, is not formally answered in previous literature. I find a significantly positive association between insider trading intensity and firm-specific return variation. Besides, I find that stocks of firms with higher insider trading intensity have less negative abnormal returns following SEO announcements and are less affected by long-term return reversal. The findings are all consistent with the view that legal insider trading reduces information asymmetry between corporate insiders and outside investors. I conclude at the end of Chapter 2 that insider trading does increase stock price informativeness.

In Chapter 3, I continue with a more important question: does insider trading enhance firm value? Maximizing firm value is the ultimate goal of corporate finance, and the answer to that question is critical to insider trading law makers and business practitioners. I find a robust and positive association between insider trading intensity and firm value, which is measured by Tobin’s q ratio. Following the main analysis, I try various robustness tests to make sure that my results are not driven by alternative explanations other than the informational content in insider trading. I show that the positive association is stronger in firms with poorer information environment, and the positive association becomes stronger when the filing of insider trading becomes timelier. Besides, firms with higher insider trading intensity have lower cost of capital; firms with self-imposed insider trading restrictions have lower firm value. The findings in Chapter 3 suggest that firm-level insider trading restrictions may not fulfill their goals of protecting shareholder value.

In Chapter 4, I focus on an important corporate event: M&A. It has been documented that stock prices experience dramatic run-up prior to M&A announcements, but researchers do not agree on the reason behind the run-up. I find evidence inconsistent with view that the run-up is caused by market anticipation or reported insider trading by corporate insiders. However, the findings are consistent with the view that the pre-merger price run-up is caused by unreported insider trading. The run-up is significantly smaller in periods when media attention on illegal insider trading is high and when institutional ownership is low. When probability of informed trading is high, the run-up is significantly more pronounced.

The three essays in Chapter 2 – 4 confirm that legal insider trading and illegal insider trading are very different animals. Current insider trading laws in the US seem to be working very well because the legal conduct of insider trading appear to be promoting informational efficiency and enhancing firm value in general, while the illegal conduct of insider trading works in a different way. If data on illegal insider trading becomes available one day, it would be an interesting task to continue research along the line and further investigate the difference between legal insider trading and illegal insider trading, especially how they affect firms in different ways.