Olga Lebedeva

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Dekan:	Dr. Jürgen M. Schneider
Referent:	Professor Ernst Maug, Ph.D.
Korreferent:	Professor Dr. Erik Theissen
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To my parents

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Introduction

1 Overview

This dissertation analyzes the impact of informed trading on the efficiency of financial markets. I refer to the informed traders as the investors who have a temporary informational advantage over other market participants. They obtain this informational advantage, because they either have some private information or they are able to correctly process new public information more quickly than other investors in the market. The term "market efficiency" relates to the Efficient Market Hypothesis (EMH) of Fama (1965). The EMH states that at any point in time security prices should incorporate all public and private information available to market participants. Specifically, the EMH assumes that all investors are fully informed and agree on the same fundamental value for a stock. All transactions take place at this fundamental value, which is only revised subsequently to arrivals of the new information.

The presence of the informed traders introduces a friction in the EMH setup, because the informed investors know some information that is not available, at least temporarily, to other investors in the market. The informed investors usually use their temporary advantage to trade with the uninformed investors and extract profit from these transactions.

The implications of informed trading for the market efficiency are twofold. With each trade, informed investors disclose a part of their private information, because market participants can infer the direction of their trades.[1] As the private information is disclosed over time, the prices become informationally more efficient and approach the fundamental value of the stock. However, this positive effect of informed trading can be outweighed by its negative impact on the incentives of other investors to participate in the trading process. Market makers, who act as dealers and post their quotes to buy and sell the stock, realize the risk of trading against an informed investor and demand additional compensation for the losses they incur from these transactions. Specifically, they set their quote to buy (the bid quote) lower and their quote to sell (the ask quote) higher, which increases the bid-ask spread for the roundtrip transaction. A higher bid-ask spread pushes the transaction price away from its fundamental value and makes the uninformed investors more reluctant to participate. In the extreme case, they might completely withdraw from the market, after which the trading process might temporarily freeze out.

This dissertation contributes to the on-going discussion about the role of informed trading in the formation of efficient security prices. In Chapter II, I examine the pre-announcement periods with the temporary increases in informed trading. The findings suggest that the market can detect the temporary changes in the information environment of a stock in these periods with the standard measures of information asymmetry. In Chapter III, I analyze how the increases in trading aggressiveness by informed and uninformed traders after earnings announcement releases impact the speed of price adjustment to its new equilibrium level. I find that an increased use of aggressive orders

[1] Although the trading process is anonymous, market participants can still observe the total order flow and calculate the imbalance between the buy-initiated and sell-initiated transactions.

slows down the adjustment process, especially in the situations when the majority of aggressive orders are submitted by uninformed traders. Chapter IV investigates different reasons for the current practice of corporate insiders who represent a group of potentially informed investors to spread their trades over time. The findings suggest that the majority of insider trades are not information-related and that insiders time liquidity of the market.

Next, I provide an introduction to the market microstructure approach of price formation in current financial markets, which is followed by the synopsis of main results. The detailed discussion of the relevant literature is relegated to the respective Chapters II to IV.

2 Price Formation in Financial Markets

An informationally efficient price is useful for the broad categories of market agents. Investors are interested in efficient prices, because they care about returns on their financial investments. Market regulators are interested in fully functioning financial markets, because they would like to ensure a level playing field for all participants. Trading exchanges also care for accurate and transparent prices to remain competitive in attracting order flow from the uninformed investors. Corporate decision makers are interested in reference stock prices when they take their investment decisions or managerial compensation decisions. An accurate stock price is also relevant for capital budgeting decisions of the firms, such as new equity issues or share repurchases.

This section explains how prices are formed in current financial markets and how the new information is impounded into the prices. Recall that in the EMH setup all transactions take place at the same price that is immediately revised after the arrival of the new information. This price corresponds to the Walrasian market-clearing price and is set by an invisible auctioneer who matches supply and demand. The implicit assumption here is that demand always equals supply, such that the market-clearing price always exists.

One major difference between the EMH setup and the real world is that demand does not necessarily equal supply in each time interval. Some traders are impatient and prefer to buy or sell immediately, whereas others can wait and are able to postpone their trades. Suppose you are an impatient buyer, but you cannot find a counterparty for your transaction, because demand temporarily exceeds supply. What can you do? Certainly, you can wait until more sellers arrive to the market. Another solution to your problem is to pay a higher price to convince sellers to sell instantly. Thus, in addition to a standard security price, you also incur an immediacy cost.

The market microstructure literature refers to impatient traders as liquidity demanders and to patient traders as liquidity suppliers. Liquidity demanders bear transaction costs in exchange for being able to trade immediately. Liquidity suppliers require compensation in the form of transaction costs in exchange for posting quotes and quantities, at which liquidity demanders' orders can be executed.

Markets are either organized as dealer markets or as limit order markets. In a dealer market, only market makers (dealers) can assume the role of a liquidity supplier. They post bid quotes at which they stand ready to buy immediately, and ask quotes at which they stand ready to sell immediately. The difference between the bid price and the ask price is called the bid-ask spread and represents the dealer's compensation for the order processing costs, the incurred inventory risks and the adverse selection risk of trading against an informed investor. The market maker normally revises his quotes after each transaction. After a series of buy orders, he revises the ask price upwards, because these buy orders might come from the informed traders with private information. Similarly, he revises the bid price downwards after a series of sell orders. Therefore, even in the absence of the information arrivals, the prices fluctuate over time and might deviate from the fundamental stock value.

In limit order markets, any investor can be either a liquidity demander, or a liquidity supplier. Liquidity demanders submit the market orders that set the amount of shares to be purchased or sold (the size of the order). They are executed at the best available quote, but, as in the dealer markets, liquidity demanders incur immediacy costs. Liquidity suppliers submit the limit orders that set not only the order size, but also the limit price, above (below) which the limit buy (sell) order will not be executed. If the limit price is non-binding, the order is immediately executed. Otherwise, it is added to the limit order book that represents the collection of all outstanding limit orders. A limit order remains in the limit order book until it is either exercised against an incoming market order, or canceled.

Figure I.1 presents an example of a limit order book. The first column shows the currently quoted prices and the second column indicates the number of shares available at each price (the depth of the book at each price). The upper part of the limit order book displays ask prices at which liquidity demanders can instantly buy the corresponding amount of shares. The best ask price is \$10.73 with 200 shares available at this price. The lower part of the book displays the bid prices at which liquidity demanders can instantly sell their shares. The best bid price is \$10.70. However, a liquidity demander could only sell 300 shares at this price. The bid-ask spread is the difference between the best bid and the best ask price, and equals \$0.03.

Suppose a market buy order for 400 shares arrives at the market. At which price will it be exercised? The limit order book is organized as a discriminatory auction, which

Figure I.1: **Limit Order Book**

	Price	Shares
	\$10.76	1,000
ask side	\$10.75	500
	\$10.73	200
	\$10.70	300
bid side	\$10.67	600
	\$10.66	1,200

means that a market order can be split, and each portion of it can be exercised at different prices. In our example, the first 200 shares of the market buy order exercise at the best ask price of \$10.73, and the remaining 200 shares go up the limit order book and exercise at \$10.75. After this order is executed, the best ask price increases to \$10.75, and the amount of shares available at this price decreases to 300 (500 - 200). Each point in time new market and limit orders arrive at the market, and the best prices change subsequent to the exercises of market orders or the arrivals of new limit orders.

After the new information is released to the market, market participants update their beliefs about the fundamental value of a stock. In the EMH setup, this update is immediate, and the new information is already incorporated into prices before any investor can trade on it. In contrast with the theory, prior empirical studies document abnormal trading volumes and abnormal volatility after information releases, which indicates that price adjustment does not happen immediately.[2]

Importantly, even though investors have access to the same public information, they still may not reach the consensus about the fundamental value of the stock. On the one hand, some investors, such as market professionals, can process the same public information quicker than unsophisticated retail investors. For instance, Barber and

[2]Bamber, Barron, and Stevens (2011) provide an extensive literature review on the trading volume around corporate information releases.

Odean (2008) and Corwin and Coughenour (2008) argue that the attention of investors is limited and, therefore, they can pay different amounts of attention to different stocks in their portfolios. On the other hand, even after the information has been processed, investors might reach different conclusions about the implications of this new information for the stock price due to their heterogeneous beliefs about the future development of the stock price. As the trading process evolves and investors update their beliefs, we observe a continuous trading process, and the price gradually adjusts towards its new equilibrium value.

To sum up, transaction prices can deviate from the fundamental value of a stock in current financial markets. They deviate more after information releases when not everyone has processed new information yet, and they fluctuate around the fundamental value as soon as investors reach the consensus about the new value of the stock. This dissertation analyzes the role of the informed traders in this price discovery process and examines whether and how informed trading contributes to the formation of efficient security prices.

3 Outline of the Thesis

Chapter II examines whether the market is able to detect the temporary increases in informed trading with the standard measures of information asymmetry. I use the periods before tender offer announcements and the first rumors about bankruptcy filings to identify the temporary increases in informed trading. Prior studies by Agrawal and Nasser (2010), Seyhun and Bradley (1997) and Iqbal and Shetty (2002) show that corporate insiders who represent a group of potential informed traders act on their private information in these periods. I find that the market can detect changes in the information environment of a stock up to six months before a tender offer announcement and up to nine months before the first rumors of the bankruptcy filing. Surprisingly, I find that simple measures of information asymmetry - the relative spread, the Amihud measure and the intraday price impact - consistently outperform more complex measures, specifically constructed to measure "pure" information asymmetry, such as the adverse selection component of the spread and the order imbalance measures.

Chapter III investigates the influence of an increase in investors' trading aggressiveness on the speed of price adjustment after an earnings announcement release. Subsequent to the news release, those traders who can process the new information faster try to exploit their advantage and switch to the most aggressive order type, an intermarket sweep order (ISO). ISOs allow for the quickest possible execution, but potentially at the transaction price inferior to the NBBO (National Best Bid and Offer). However, the uninformed investors might also trade more aggressively because of the decrease in liquidity supply around earnings announcements. Chakravarty et al (2011a) provide empirical evidence in support of the latter explanation.

The implications of abnormal trading aggressiveness on the speed of price adjustment after an information release are twofold. An increase in trading aggressiveness allows for quicker price changes within a given time interval. Quicker price changes can be beneficial, if the majority of aggressive orders are submitted by informed investors and push the price in the direction of its new equilibrium level. However, abnormal trading aggressiveness can also slow down the adjustment process if aggressive orders are mostly used by uninformed investors with heterogeneous beliefs. In this case, quick price changes in different directions just increase intraday volatility and the probability of price overshooting. Empirical findings of my study suggest that the latter negative effect dominates, and it is especially harmful for illiquid stocks. Importantly, adjustment times of these stocks have even increased compared to the period before aggressive ISO orders became available.

Chapter IV analyzes trading strategies of corporate insiders and is a joint work with Ernst Maug and Christoph Schneider. We investigate how and why insiders spread their trades over time in current financial markets. One explanation, which takes its roots in Kyle (1985), is that insiders split their trades to optimally exploit their private information. The second explanation, based on more recent theories of Bertsimas and Lo (1998) and Vayanos (1999, 2001), is that insiders trade for pure liquidity reasons and spread their trades over time to minimize the temporary price impact. We consider situations when multiple insiders are trading in the same direction and find evidence in support of both explanations. Importantly, we find that the vast majority of insider trades (more than 85%) are liqudity-based. Further, insiders time liquidity and exercise a larger portion of their trades on days when liquidity is higher. Overall, our evidence suggests that most of insider trading nowadays is not information-related and can hardly be perceived as detrimental to the efficiency of financial markets.

Chapter II

Measuring and Monitoring Time-Varying Information Asymmetry

1 Introduction

In the recent past, the most striking example of information asymmetry between informed and uninformed investors was, probably, Enron's bankruptcy case. For more than a year before Enron filed for Chapter 11 on December 2, 2001, its top executives started to dispose of their holdings at the share's highest price of $90, while at the same time encouraging uninformed investors to keep buying the stock. After the successful unloading of the insiders' shares, the stock price started to decrease gradually. It abruptly fell below one dollar on November 28, 2001 when the news about millions of dollars in losses became public.[1]

Was the abnormal increase in the informed trading of the Enron stock before the official news reached the market possible to detect? Motivated by this question, I examine whether standard measures of information asymmetry can detect temporary increases in

[1] As described by McLean and Elkind (2003) in their book "*Smartest Guys in the Room: the Amazing Rise and Scandalous Fall of Enron*".

the informed trading prior to unexpected events, such as tender offer announcements and crashes in stock returns that are followed by a subsequent bankruptcy filing. The empirical findings of this paper suggest that the simple measures of the relative spread, the intraday price impact, as well as the Amihud measure show significant positive deviations from their base level at least six months before the corresponding event. Moreover, the monitoring of the time-varying information asymmetry with the above measures can help risk-averse uninformed investors better time the volatility of their portfolios. Overall, these investors should avoid investing in the stocks with the highest increases in information asymmetry during the previous three months, because the portfolios of these stocks exhibit consistently lower Sharpe ratios.

The first main assumption of this study is that two groups of investors exist in the market: those "informed", who possess material non-public information about a firm, and those "uninformed", who represent liquidity traders.[2] The second main assumption is that the informed investors act on their information by submitting buy or sell orders. Thus, the informed investors partially disclose their information through their trades that cause higher permanent price changes, compared to the trades of the uninformed investors.[3]

The information asymmetry between the informed and uninformed investors varies over time as their information sets about the fundamentals of a company change. It increases temporarily with the arrival of new private information about the operational or strategic activities of the company and decreases when at least some of this information is made public. The most suitable setup to test the validity of the time-varying information asymmetry measures are the periods with large differences in the company's valuation be-

[2]Note that "informed" investors include not only the management of a company and other insiders, but also people who are potentially informed through them (e.g., family, friends, brokers etc.)

[3]Importantly, if none of the informed investors uses his or her information to trade on the market, the price does not adjust until after the information becomes public. Therefore, the time-varying information asymmetry is only measurable in cases where informed investors actively trade on the market. Since there are several informed investors for one firm, it is reasonable to assume that at least some of them trade on their private information.

tween informed and uninformed investors. Arguably, these differences attain their highest value prior to unexpected corporate announcements that produce large impacts on the stock price.[4] This setup does not use any benchmark measure but rather directly looks at the changes in the information asymmetry within a firm. Since informed investors would like to take advantage of their private information, they intensify their trading in these periods and the information environment of a stock gradually changes. A valid measure should then detect this temporary change in the information environment of the stock through the abnormal deviation from its base level.

In this paper, I use periods that precede tender offer announcements and crashes in stock returns that are followed by bankruptcy filings to proxy for times of temporarily high information asymmetry. As opposed to regular corporate information releases, such as earnings announcements, these events are not scheduled and are not expected by the market. Further, these events result in a strong price reaction that represents price adjustment towards the stock's new fundamental value, previously known only to the informed investors.

Before a firm publicly announces a tender offer, only a very limited circle of insiders has access to the private information about an upcoming event. Despite the documented evidence on the takeover rumors and the runups of pre-bid target stock prices, a tender offer is mostly unexpected by the market.[5] Further, Agrawal and Nasser (2010) show that corporate insiders act on their information by increasing their net purchases of the stock of a target company in the six months preceding the announcement of a tender offer. As opposed to tender offers, some bankruptcy filings are anticipated by the market

[4]Several prior studies make an assumption about a temporary increase in information asymmetry between informed and uninformed investors before the release of a corporate announcement. A non-exhaustive list of such studies includes Korajczyk, Lucas, and McDonald (1992), Affleck-Graves, Callahan, and Chipalkatti (2002), Vandelanoite (2002), Serednyakov (2002), Aktas et al (2007), and Tetlock (2010).

[5]Pound and Zeckhauser (1990) examine the link between takeover rumors and target stock prices and find that takeover rumors predict a final takeover bid less than half the time.

long in advance. Thus, they do not represent unexpected news to the market and do not cause large changes in the stock price. For this reason, this paper analyzes the information asymmetry measures only in the period preceding first rumors of an upcoming bankruptcy, represented by the first crash in the stock's returns. Similar to periods preceding tender offer announcements, corporate insiders engage in profitable trading of their shares prior to bankruptcy announcements. They increase their sales significantly not only prior to the actual bankruptcy filing date (Seyhun and Bradley, 1997), but also before the market starts expecting the bankruptcy filing (Iqbal and Shetty, 2002).

The major difference between the two setups is the duration of the information asymmetry. The large information advantage of the investors that know about an upcoming tender offer ceases to exist after a relatively short period of three to six months. As in the case of Enron, the information asymmetries in the periods preceding the bankruptcy filings can persist over much longer time periods: up to two years prior to the actual bankruptcy filings. Testing the information asymmetry measures in two different setups also serves as a reliability check that ensures the validity of a measure does not depend on any particular sample or the direction of a price change.

The information asymmetry measures examined in this study belong to four broad categories: (1) the broad measures of transaction costs, such as the relative spread; (2) the daily (intraday) price impact measures that evaluate the change in the daily (intraday) prices; (3) the adverse selection component of the spread and (4) the order imbalance measures.[6] All of the measures, except the daily Amihud price impact measure, are estimated on an intraday basis with high frequency data. I refer to the relative spread and the price impact measures as "mixed" measures of information asymmetry, because

[6]The Probability of Informed Trading (PIN), first proposed by Easley et al (1996), belongs to the last category. However, I exclude PIN from the analysis because only quarterly estimates of this measure are available.

they also include a pure liquidity component and are often used as liquidity measures in the literature. However, when the informed trading in the market temporarily increases, these measures should deviate from their base level largely due to an increase in their information component. The main advantage of these measures are that they are easy to construct. In contrast, the adverse selection component and the order imbalance measures represent more complex "pure" measures, specifically constructed to capture information asymmetry between informed and uninformed traders.

Surprisingly, the results from a difference-in-differences analysis suggest that the simple "mixed" measures - the relative spread, the Amihud measure, and the intraday price impact - consistently outperform the "pure" information asymmetry measures in both the tender offer and bankruptcy samples. In the tender sample, the "mixed" measures deviate significantly from their base level in the previous year starting as early as six months prior to an announcement date. Consistent with prior expectations, the information environment of the stocks with subsequent bankruptcy filings experiences changes even earlier - up to nine months prior to the first rumors about an upcoming bankruptcy filing. In contrast, the adverse selection component and the order imbalance measures do not display any significant deviations in either of the two samples. These results are further confirmed in the subsample analyses. These analyses show that the "mixed" information asymmetry measures deviate more for the stocks with more intensive informed trading in the pre-announcement periods.

The "pure" information asymmetry measures fail because the underlying assumptions for their constructions do not hold empirically. The main assumption of the order imbalance measures is that the informed trading unbalances the order flow either to the buy side if the information is positive or to the sell side if it is negative. Empirically, even though the total trading volume increases in the pre-announcement periods, both the sales and the purchases increase proportionally, which implies that the effect of an increase in the informed trading is camouflaged by an even greater increase in the uninformed trading in both directions. The main problem with the adverse selection component of the spread is that it is mechanically driven by changes in the spread level. In contrast with the theoretical predictions, the correlation between the adverse selection component and the spread is negative: as the spread decreases over time, the adverse selection component increases as a percentage of the spread. This finding implies that the adverse selection component shows only limited time variations *as the percentage of the stock price.*

Further, this paper shows that monitoring the time-varying information asymmetry is especially important for risk-averse uninformed investors. I form a trading strategy that ranks 753 stocks, approximating the market portfolio, at the beginning of each month in an ascending order based on the previous deviations in their information asymmetry level. The results show that the portfolios of the stocks that experience no change or a slight decline in their information asymmetry over the previous three months, have consistently higher Sharpe ratios as compared to the portfolios of the stocks with a large increase in their information asymmetry level. Overall, these results imply that risk-averse uninformed investors can reduce the excess volatility of their portfolios without diminishing their expected returns if they monitor the fluctuations in the informed trading and time their investments accordingly.

Monitoring variations in information asymmetry over time is useful not only for uninformed investors, but also for the broader categories of market agents. Corporate decision makers should consider the information environment of their company's stock before new equity issues and share repurchases. For example, Ausubel (1990) and Manove (1989) make an assumption that a corporate decision maker and a corporate insider, trading on his or her information, are different individuals. The decision maker can then partially learn the private information of the insider by observing the recent trading in the company's stock. Monitoring fluctuations in informed trading is also important for trading venues, such as major stock exchanges or off-exchange trading platforms. With a higher number of informed traders, it is more difficult for a trading venue to attract order flow from uninformed investors, which has a negative effect on its profits.

Surprisingly, only a few studies exist that compare the empirical measures of information asymmetry. Some of them, for example, prior studies by Clarke and Shastri (2000) and Ness, Ness, and Warr (2001), concentrate mainly on cross-sectional differences in the information asymmetry. In particular, they examine the differences between information asymmetry proxies from the corporate finance literature, such as size, R&D expenditure, and the ratio of intangibles to total assets, to more high-frequency proxies from the market microstructure literature used in this study. However, the measures from the corporate finance literature do not suit the purposes of this paper, because they provide only annual or quarterly estimates at best. The second type of studies examines daily or intraday measures that are better suited to detect the fluctuations in the information asymmetry between informed and uninformed investors, but these studies always relate the performances of several measures to one benchmark measure. For example, Lei and Wu (2005) run a horse race between the different information asymmetry measures to predict the bid-ask spread on the next day. Goyenko, Holden, and Trzcinka (2009) and Fong, Holden, and Trzcinka (2011) analyze time-series and cross-sectional correlations of different high-frequency liquidity measures with the effective relative spread. In this paper, I extend the existing literature by testing the validity of the time-varying information asymmetry measures. The advantage of my approach is that I do not assume a benchmark measure, but rather look directly at periods prior to unexpected information releases when informed trading is known to be high *ex post.*[7]

This study contributes to different strands in the finance literature. First, measuring fluctuations in information asymmetry is of high interest to researchers who work in corporate finance. One of the most prominent examples is probably the pecking order theory of capital structure, first proposed by Myers and Majluf (1984) and subsequently tested by Shyam-Sunder and Myers (1999) and several other papers.[8] Further examples include the relation between information asymmetry and the corporate spin-off decision (Krishnaswami and Subramaniam, 1999), the value of cash in the firm (Drobetz, Grüninger, and Hirschvogl, 2010) and the investment-cash flow sensitivity (Ascioglu, Hegde, and McDermott (2008)). Korajczyk, Lucas, and McDonald (1992) theoretically analyze the impact of time-varying information asymmetry on the timing of equity issues by a company. The second strand is the insider trading literature that relates the information asymmetry to the level of insider gains (Aboody and Lev, 2000 and Huddart and Ke (2007)). A further important question from the asset pricing literature is whether information asymmetry affects equity prices (Chan, Menkveld, and Yang (2008)). Several of the studies listed above concentrate on the cross-sectional variations in information asymmetry, but addressing the time variations in the information asymmetry within each firm might help further enrich our previous insights into these questions.

[7] Several studies investigate changes in a particular measure prior to a corporate information release. For instance, Venkatesh and Chiang (1986), Lee, Mucklow, and Ready (1993) and Chae (2005) examine the dealer's bid-ask spread. Korajczyk, Lucas, and McDonald (1992) and Affleck-Graves, Callahan, and Chipalkatti (2002) analyze changes in the bid-ask spread and its components around earnings announcements. Vandelanoite (2002) investigates deviations of the adverse selection component around takeover announcements, and Serednyakov (2002) conducts the same type of analysis for bankruptcy announcements. Aktas et al (2007) provide evidence on the anomalous behavior of a PIN measure before M&A announcements. However, neither of the previous studies compares different measures between each other in the pre-announcement periods.

[8] See, for example, Fama and French (2002), Frank and Goyal (2003), Leary and Roberts (2010). Bharath, Pasquariello, and Wu (2009) provide a full overview of the mixed empirical evidence on the pecking order theory.

The remainder of this paper is organized as follows. Section 2 provides the details of the construction of the final samples and a brief overview of all of the measures used in this study. Section 3 investigates the time-varying information asymmetry measures in the pre-announcement periods. Section 4 demonstrates the importance of monitoring the information asymmetry fluctuations and Section 5 briefly concludes.

2 Data and Sample Construction

2.1 Tender Sample

The data on the tender offer announcements comes from the Security Data Company's (SDC) Mergers & Acquisitions database. The initial sample includes 1,232 tender offer announcements with a publicly traded target firm and a deal value over $1 mln in the US market over the years 1997 to 2008.[9]

[Insert Table II.1 approximately here]

Panel A of Table II.1 presents the details of the construction of the tender offer sample. I lose 54 observations from the initial sample after excluding the repeated tender offer announcements for each firm. After the first tender proposal becomes public, the informed investors lose their informational advantage over the uninformed investors with respect to the identity of the target firm. Although the identity of an acquirer might not be known yet due to the possibility of subsequent tender offers, the highest returns typically accrue to the shareholders of the target firm.[10] I omit another 229 announcements due to the incomplete coverage by CRSP because I require a minimum of twelve months of trading

[9] My access to the NYSE Transactions and Quotes database (TAQ) is limited to years 1996-2008. I omit all announcements from 1996 because I require twelve months of trading data before the announcement date to calculate the long-run means of the information asymmetry measures.

[10] Schwert (1996) shows that the cumulative average abnormal returns (CARs) to target firms' stocks on an announcement day are positive and significant irrespective of the subsequent success of an offer.

data to construct long-run means of information asymmetry measures. Further, I drop all observations with missing data for at least one event month for any of the information asymmetry measures. This requirement assures an equal number of observations for all measures, which is crucial for a comparison study. These filters yield the final sample with 909 tender offer announcements.

[Insert Table II.2 approximately here]

Panel A of Table II.2 reports the summary statistics for size and the financial data of the target firms in the tender sample.[11]

The median target firm is relatively small with a market capitalization of around $129 mln and total assets of around $160 mln. However, the distribution is positively skewed with a few relatively large firms in the sample (the mean of the market capitalization is $516 mln and the mean of the total assets is $709 mln). The financial leverage, defined as the ratio of total liabilities to the total firm value, varies considerably, and is between 10% and 76% with the median firm financing 37% of its investment needs through debt. A median target firm has a positive return on assets (ROA) of 2%.

The majority of the tender offer announcements occur in the years 1998 to 2000 with around 150 tender offers per year. This number gradually declines to 25 in the year 2004 and goes slightly up again to 50 in 2008. The sample is widely distributed across 47 industries in the Fama and French (1997) industry classifications, with the greatest number of tender offers in the sectors of business services (174), drugs & pharmaceuticals (55), retail (51), and wholesale (44) (results not tabulated).

Figure II.1 shows the cumulative average daily abnormal returns (CARs) and the average daily net sales (in basis points of market capitalization) for the target firms

[11] I match firms in the tender sample with Compustat on a quarterly basis. Since Compustat data are available only for 879 out of 909 firms in the tender sample, the number of observations for Compustat variables differs from the total number of observations. Overall, the Compustat variables represent 96% of the tender sample.

in the tender sample from day -120 to day +30 relative to the date of the first public announcement. I use the market model with the CRSP value-weighted portfolio as the market index to estimate the necessary parameters for the calculation of the abnormal returns. The length of the estimation window is 200 days starting from day -321.

Figure II.1 depicts a stylized fact in the literature: the abnormal return of a typical target firm's stock on the announcement day is positive and statistically significant at the 1% level. The mean abnormal return of a target firm in the tender sample is 26%.[12] The price runup starts around 20 days before an announcement date due to takeover rumors or information leakage to the market. However, the information asymmetry between the informed and uninformed investors is probably still very high during this period, because the uninformed investors do not know whether a tender offer will be announced or not.

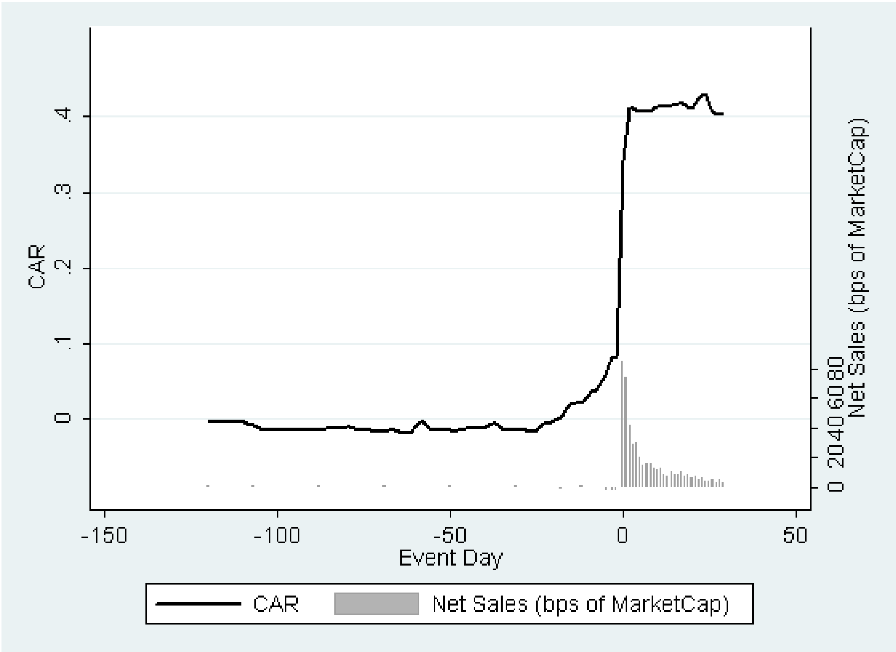
Interestingly, the pre-announcement order flow is almost balanced, with approximately the same volume of purchases and sales of a target stock within a trading day (see Figure II.1). On the announcement day, the net sales of a target stock increase dramatically, reaching almost 1% of the market capitalization. This additional sales increase is most probably due to those shareholders who seek an immediate realization of their profits in the fear of a transaction cancellation.

2.2 Bankruptcy Sample

The source for the bankruptcy announcement dates of public US companies is the BankruptcyData.com website. Since this database provides only the names of the companies, but not their CUSIPs, I manually find the CUSIPs for each company from the CRSP database. Out of the 2,050 firms with bankruptcy announcements in the period

[12] Jensen and Ruback (1983), Jarrell, Brickley, and Netter (1988), Schwert (1996) and Agrawal and Nasser (2010) have similar findings in their samples.

Figure II.1: **CARs and Trading Volume of Stocks in Tender Sample.** The figure displays the cumulative average daily abnormal returns (CARs) and the average daily net sales (in basis points of market capitalization) from day -120 to day +30 relative to the date of the first public announcement for 909 target firm stocks over the years 1997 to 2008. I use the market model with the CRSP value-weighted portfolio as the market index to estimate the necessary parameters for the calculation of the abnormal returns.



from January 1, 1997, until December 31, 2008, an unambiguous name match exists for 1,220 firms, which constitute the initial sample.

The construction of the final bankruptcy sample follows similar steps as in the tender sample (see Panel B of Table II.1). The major difference between the two samples is the identification of an event month. In the tender sample, an event month is the month in which a tender offer is announced. This definition is due to the fact that the information asymmetry continues to stay on a high level up to an announcement date, when the price of a target stock jumps abruptly almost to the offer level.[13] Because a bankruptcy filing might be expected by the market long in advance, a public bankruptcy announcement does not usually cause a large adjustment in the stock price. The price of a typical bankrupt

[13] If the success of an offer were certain, the price of a target stock would equal the offer price. The discount in the price of the target stock reflects the probability that a tender offer might fail.

stock is almost always below $2 in the months preceding a bankruptcy announcement. For the case of bankruptcy filings, the information asymmetry between the informed and uninformed investors is high in the months before the market starts expecting the bankruptcy filing by the company. Iqbal and Shetty (2002) provide empirical evidence that insiders sell their shares prior to the expectation of the bankruptcy by the market. Also, the insiders at Enron started selling their shares as long as one and a half years before the official bankruptcy filing.

When does the market start to expect a bankruptcy filing? Dugan and Forsyth (1995) and Ramaswami (1987) show that the parametric change in the mean and the variance of stock returns is related to the releases of unfavorable news about a company in the *Wall Street Journal*. A period between the first perception of an upcoming bankruptcy and an actual filing can then last for several months. Based on this evidence, I define the month, after which the bankruptcy filing is expected by the market, as the first month in which the return crash occurs. The definition of the return crash comes from Marin and Olivier (2008). The crash in returns occurs in the month when an excess stock return drops below two standard deviations of the average excess monthly return in the past 24 months:

$$Crash = \begin{cases} 1 & if\; r_{i,t} - \overline{r}_{i,t} \leq -2\sigma_{i,t} \\ 0, & otherwise. \end{cases}$$

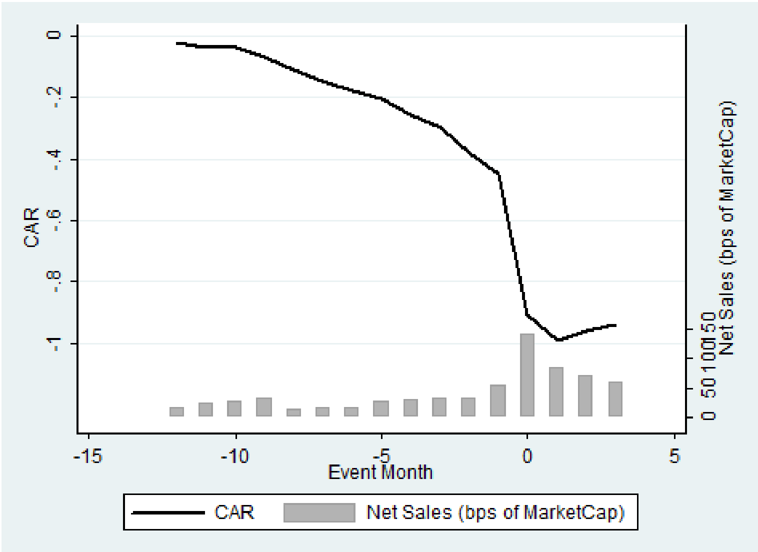
Out of 366 bankruptcy announcements for which up to three years of CRSP data is available, I can clearly identify the month when the market starts to expect a bankruptcy filing for 261 firms. I omit the remaining 105 firms from the analysis, because I cannot define an event month unambiguously. Also, a bankruptcy filing for these companies might have been anticipated long in advance and was not surprising to the market. The mean and median interval between the anticipation time and the eventual bankruptcy date is 9.34 months and 8 months, respectively (results not tabulated). The exclusion of an additional 49 observations with insufficient data yields the final bankruptcy sample of 212 announcements.

The famous examples of Enron's and Worldcom's bankruptcies illustrate the credibility of this approach for identifying the starting point of the bankruptcy expectation by the market. Although Enron's stock had been gradually decreasing in value from the beginning of 2001, it experienced the first crash in late October 2001, when the fraudulent accountant practices began to be divulged. The Securities and Exchange Commission (SEC) started its investigation on October 22 of 2001. On that day the stock price fell by \$5.40 to \$20.65.[14] The further decrease to \$16.41 followed on October 25 with the removal of Enron's CFO from his position.[15] Overall, Enron's stock value had dropped by more than a half in one week. In contrast to the rather unexpected bankruptcy filing of Enron (the time between the first bankruptcy expectation in October 2001 and the bankruptcy filing on December 2, 2001, constitutes barely one month), the first expectation of WorldCom's bankruptcy filing, which occurred in July 2002, was as early as November 2000. On November 1, 2000, WorldCom announced its major restructuring plans and the first earnings warning. As a result, its stock price plummeted by 21.58% to \$18.62, giving the first major concern about the financial stability of the company.[16]

Panel B of Table II.2 presents the summary statistics for the firms in the bankruptcy sample before the market starts expecting an upcoming filing.[17] The median stock price is \$5, but drops below \$2 after the unfavorable information is released to the market (results not tabulated). Because the price of a pre-bankrupt stock gradually decreases

[14] *The New York Times,* 2001, *Where Did The Value Go At Enron?* October 23.
[15] *The New York Times,* 2001, *Enron Ousts Finance Chief As SEC Looks at Dealings*, October 25.
[16] *CNN Money,* 2000, *WorldCom warns, splits in two,* November 1.
[17] Compustat data are available only for 167 out of 212 firms in the bankruptcy sample.

Figure II.2: **CARs and Trading Volume of Stocks in Bankruptcy Sample.** The figure displays the cumulative average monthly abnormal returns (CARs) and the average monthly net sales (in basis points of market capitalization) in the twelve months before and the three months after the market starts expecting an upcoming bankruptcy filing. The final sample consists of 212 bankrupt firm stocks in the period 1997 to 2008. I use the market model with the CRSP value-weighted portfolio as the market index to estimate the necessary parameters for the calculation of the abnormal returns.



over the preceding months, the financial leverage is relatively high, reaching 69% of total assets. As expected, the *ROA* is negative and equals -1% for a median firm in the sample. Overall, the financial characteristics of firms in the bankruptcy sample follow the normal patterns of firms close to financial distress. The number of firms in the bankruptcy sample varies over the years with a maximum of 37 bankruptcy filings in 2001 and a minimum of 3 in 2006. The leader in financially distressed firms is the retail industry (27 firms) followed by business services (17 firms) and transportation services (14 firms) (results not tabulated).

Figure II.2 displays the CARs and the average monthly net sales of the firms in the bankruptcy sample in the year preceding the crash in their returns. By definition, the crash happens in the event month 0, which is also observable from Figure II.2. In contrast to tender offers, I conduct the event study on a monthly basis for bankrupt firms due to the longer duration of the information asymmetry. As previously shown, the informed traders are already selling their shares several months before the market starts anticipating the bankruptcy filing. The estimation window length is 24 months starting from month -36 relative to the event month. As expected, the price declines gradually in the months before the crash with sales slightly dominating purchases in all of the months. The net sales reach almost 1.5% of the market capitalization in the event month and continue to stay at this high level up to the official bankruptcy filing. This evidence provides additional support for the hypothesis that the information asymmetry decreases considerably after the first release of the unfavorable information to the market.

2.3 Information Asymmetry Measures

In this study, I examine the daily or intraday measures of information asymmetry, because only frequently calculated measures can potentially capture changes in the information asymmetry over relatively short time periods. Intraday transaction and quote data come from the TAQ database. The daily returns and the daily trading volumes come from CRSP. I provide the detailed definitions for all of the variables used in this paper in the Appendix A and the technical details of the construction of the information asymmetry measures in the Appendix B.

Relative Spread *(RelSpr).* The broadest measure of transaction costs is the relative spread. The relative spread measures the quoted bid-ask spread as the percentage of the midpoint price:

$$RelSpr_t = (A_t - B_t)/Q_t,$$

where Q_t is the average of the bid and the ask price. The relative spread captures the overall liquidity of the stock, but it can be decomposed into three components that compensate for order processing, inventory and adverse selection costs.[18] When informed trading in the market temporarily increases, the relative spread changes its value due to an increase in its adverse selection component. An increase in informed trading should not influence the order processing component and the inventory component of the spread. Therefore, a temporary increase in the information asymmetry between the informed and uninformed investors should cause a temporary positive deviation in the relative spread from its normal level.[19] [20]

Adverse selection component of the spread *(Lam).* I use the Lin, Sanger, and Booth (1995) approach to decompose the spread and to extract its adverse selection component, *Lam*. In brief, *Lam* represents the regression coefficient of the changes in the midpoint prices on the effective spread:

$$\Delta Midpoint_t = \lambda \cdot (Price_{t-1} - Midpoint_{t-1}) + \varepsilon_{t.}$$

The exact estimation procedure is in the appendix. *Lam* is a reasonable representation of the speed of the incorporation of the information from the previous transaction into quotes that prevail for the next transaction. The adverse selection component is estimated as the percentage of the effective spread.[21]

The Lin, Sanger, and Booth (1995) approach is attractive because it accounts for both the reasonable difficulty of the estimation as well as the plausible estimates. The theoretically appealing Huang and Stoll (1997) model that reconciles all the previous decomposition models provides poor empirical estimates in almost 60% of the cases, as reported by Clarke and Shastri (2000) and Krishnan (2000).

[18] Ness, Ness, and Warr (2001) provide a good survey of different models for the decomposition of the bid-ask spread.

[19] The necessary condition is that informed investors actively trade on their information.

[20] Results do not differ materially if I use the effective relative spread, defined as $2 \cdot |P_t - Q_t| / Q_t$, instead of the relative spread.

[21] By definition, the adverse selection component can take values between zero and one. I delete all estimates that lie outside of this theoretical range.

Price impact measures. The price impact that a trade produces over an interval of time x is measured as the change in the midpoint price of a stock from the transaction time t to the future time point $t+x$. I examine two measures of the price impact: the ***Intraday Price Impact*** *(PrcImp)* that calculates the change in the stock price's midpoints over five-minute intervals, and the ***Daily Price Impact*** measure of *Amihud (2002) (Amihud)* that captures the price impact of all trades in one day. The Amihud measure is defined as the ratio of the daily absolute return to the dollar trading volume on that day and requires only daily trading data, which is available from the CRSP database. The intraday price impact measure is similar to the one used by Riordan and Storkenmaier (2009). I follow their assumption that a five-minute interval is long enough to reflect all the information from the previous trade. Additionally, I scale the intraday price impact by the size of a trade, which makes it equivalent to the Amihud measure, calculated on an intraday basis.

A trade that comes from an informed trader should cause a permanent price impact because it partly reflects his or her private information, and the market subsequently incorporates this information into the price.[22] In contrast, the price changes due to order processing and inventory costs are transitory in their nature, and their impact should vanish after the next few transactions. With an increase in the information asymmetry that precedes a major information release, the trades by informed investors should cause a larger price impact per dollar traded because more information is incorporated into the prices.

Note that the price impact measures are similar in their motivation to the adverse selection component, *Lam*. However, there are several important differences between these two measures. First, both of the price impact measures control for trade size, because

[22]Kyle (1985) is among the first authors to address strategic trading by informed investors. Under the assumption that trading time is finite, he shows that all information will be reflected in prices at the end of the trading period.

larger trades normally cause larger price changes. Second, the price impact measures capture price changes over longer time periods (five minutes to one day) as compared to *Lam,* which is based on a transaction-by-transaction analysis. Further, *Lam* measures price changes as a percentage of the spread, whereas the price impact measures directly address the changes in the midpoint price.

Imbalance measures. The basic reasoning behind the imbalance measures is that with the existence of some private information, all informed traders will trade only on one side of the market, which unbalances the order flow in either the direction of purchases or in the direction of sales. The ***Daily Order Imbalance*** *(OIB)* captures an absolute difference between the number of purchases and the number of sales in one trading day relative to the total number of transactions:

$$OIB = |B - S| / (B + S),$$

where B stands for a number of buys and S for a number of sells in one trading day. Aktas et al (2007) show that the daily order imbalance measure faithfully approximates the Probability of Informed Trading (PIN), as proposed by Easley et al (1996). I do not analyze the PIN because this measure provides only one estimate per quarter and is too infrequent for the purposes of measuring the changes in the information asymmetry over short time intervals.

The weak point in the OIB is that this measure concentrates solely on the difference in the number of trades and does not take the transaction's size or value into account. The ***Trade Value Imbalance*** *(OIBvalue),* defined as an absolute difference between the traded value of purchases and the traded value of sales to the total traded value in one day ($OIBvalue = |B_{VAL} - S_{VAL}| / (B_{VAL} + S_{VAL})$), seeks to overcome this shortcoming.

Summary Statistics. Table II.3 reports the summary statistics for the information asymmetry measures, the volume traded *(Volume),* and the stock volatility *(Volatility)* across the firms in both of the samples. The volatility is defined as the annualized standard deviation of the daily market-adjusted stock returns in the corresponding calendar month (with the CRSP equally-weighted portfolio as the market index). All observations are on a firm-month level. The first three columns of Table II.3 report the mean, the median, and the standard deviation for all of the variables in the twelve months before the corresponding event month (event month -12). The table's last three columns report the same statistics for the month immediately preceding the corresponding event month (event month -1).

[Insert Table II.3 approximately here]

Panel A of Table II.3 shows the differences in the distributions between the two periods for the tender sample. Overall, the stocks in this sample are relatively liquid with an average relative spread of 2.8% and an average five-minute price impact of 2.6%. The relative spread, the intraday price impact, the daily traded volume and the volatility significantly increase in their means in the pre-announcement month. The Amihud measure also increases in its mean and median, but this increase is not significant. Interestingly, the adverse selection component does not change significantly from its mean value of 42%. The mean daily order imbalance is 29%, whereas the mean trade value imbalance reaches up to 37%. However, neither of the imbalance measures changes its mean value significantly in the pre-announcement month as well. Panel A of Table II.4 shows that even though the number of transactions and the dollar value traded overall increased in the pre-announcement month, the number of purchases (and their dollar value) still approximately equals the number of sales (and their dollar value).

[Insert Table II.4 approximately here]

Panel B of Table II.3 displays the summary statistics for the bankruptcy sample. The stocks in this sample exhibit a higher spread (the mean relative spread is 3.5%) and a higher intraday price impact (3.8%) than the stocks in the tender sample. Remarkably, the mean trading volume per day exceeds the volume in the tender sample by more than three times. Such a high volume in the bankruptcy sample is partly explained by the overall lower prices of the financially distressed stocks. The relative spread, the Amihud measure and the intraday price impact significantly increase in their means in the month preceding the crash in the returns. As in the tender sample, the adverse selection component barely varies between the two periods. Neither of the imbalance measures changes its mean value significantly as well, because the number of purchase and sale transactions remains the same in the pre-crash month (see Panel B of Table II.4). Their dollar values also proportionally decrease in both trading directions, due to an overall decrease in the stock prices.

Table II.5 presents a matrix of the Spearman's rank correlation coefficients for the information asymmetry measures, the volume and the volatility of stocks in the tender (Panel A) and bankruptcy samples (Panel B). For brevity, the p-values are not reported. All of the coefficients are statistically significant at the 1% level, except the coefficients for *Lam* in the bankruptcy sample, which is no longer significantly correlated with any of the other variables.

[Insert Table II.5 approximately here]

Overall, the correlations in the tender and bankruptcy samples follow similar patterns. Almost all of the measures except the adverse selection component of the spread have a positive correlation with each other and the excess volatility of the stocks. This finding is in line with prior expectations. On average, the stocks of firms with higher degrees of information asymmetry should exhibit higher volatility, because it is harder for a market to value the operations of these firms correctly.[23] Further, the same set of measures has a negative correlation with the average daily trading volume. This negative correlation is also not surprising, because more frequently traded stocks usually have higher price informativeness and new information is priced in more quickly for these stocks. Surprisingly, the adverse selection component, *Lam,* shows a mostly negative correlation with the remaining measures and the stock volatility. The correlation patterns of the adverse selection component are puzzling, because the component should be higher for more volatile stocks and is expected to have a positive correlation with other information asymmetry measures. Recall that *Lam* measures the changes in the midpoint price as a percentage of the spread. For stocks with larger spreads, the revisions of their price quotes by lower percentages of the spread suffice to achieve the same absolute price change than for stocks with lower spreads, which might explain the negative correlation between *Lam* and *RelSpr.* Other negative correlations are probably driven by the negative correlation of *Lam* with the relative spread.[24]

[23]However, excess volatility can also arise from the general uncertainty about the firm's value, even without any differences in the information sets of insiders and outsiders. Therefore, stock volatility can be regarded only as a noisy measure of information asymmetry.

[24]Note that the very high correlations are mostly mechanical. For example, a high correlation of the Amihud measure with the *OIB* and the *OIBvalue* is due to the fact that all of these three measures are scaled either by the total dollar volume traded during the day or by its close substitutes (e.g., the number of trades during the day). The relative spread also displays very high correlations with the Amihud measure and the OIB measures, partly due to its high negative correlation with the volume traded.

3 Pre-Announcement Changes in Information Asymmetry Measures

Provided that informed investors act on their information in the periods preceding corporate announcements, an unusual trading pattern arises as prices gradually incorporate the new information. A measure of the time-varying information asymmetry can only be valid if it exhibits temporary positive deviations from its normal level during this period of the increased informed trading.

The main difference between the prediction for the tender sample and the prediction for the bankruptcy sample is the duration of a temporary increase in the information asymmetry between the informed and uninformed investors. Whereas Agrawal and Nasser (2010) provide evidence that insiders of the target firms start acting approximately six months before a tender offer announcement is made public, Iqbal and Shetty (2002) detect insider trading in pre-bankrupt firms long before the market expectations about an upcoming bankruptcy filing, up to two years in advance. Therefore, I expect the information asymmetry measures to deviate from their long-run mean for a shorter time period of up to six months before an announcement for the tender sample and for up to twelve months before the first unfavorable information release for the bankruptcy sample.

3.1 Univariate Results

First, I test the significance of the deviations in the information asymmetry measures in a univariate setup. Table II.6 presents the results. The first column indicates the number of months before the corresponding event month, with the event month defined as $t = 0$.

[Insert Table II.6 approximately here]

Columns 2 through 7 in Panels A and B show the cross-sectional averages of the percentage deviations (Δ) of the measures from their long-run means. I construct the deviations for each measure (ΔM) according to the following formula[25]

$$\Delta M_t = \frac{M_t - \frac{\sum_{i=-24}^{-13} M_i}{12}}{\frac{\sum_{i=-24}^{-13} M_i}{12}}. \qquad \text{(II.1)}$$

The $\Delta RelSpread_{t=-1}$, for example, denotes an average percentage deviation of the relative spread from its mean, calculated over t=*-24* to t=*-13*, in the month preceding the corresponding event.

Panel A of Table II.6 shows the univariate results for the tender sample. Almost all of the measures, except the imbalance measures, display statistically significant positive deviations from their long-run means in each of the six months preceding an announcement of a tender offer. The deviations increase gradually over the months and attain their highest values in the three months before an announcement. These results are in line with the previous expectations, because the imbalances in the market should increase as more informed traders arrive in the market. Further, the deviations of these measures decrease in the event month (t=0), and even become negative for the relative spread and the Amihud measure. This result is also plausible under the assumption that the information asymmetry declines considerably in the event month, or even resolves completely in cases where the shareholders accept the offer.

Remarkably, the imbalance measures increase significantly in the event month, but not in the preceding months. Panel A of Table II.4 shows that, although the overall

[25]Please note that I suppress the subscripts for identification of individual stocks for ease of exposition purposes.

number of trades increases in the pre-announcement month, the number of purchase and sale transactions experiences a proportional change. The overall dollar value also increases proportionally for purchases and sales. Thus, both the daily order and trade value imbalances, remain constant. The imbalance measures fail because not only the number (and value) of purchase transactions changes, which presumably come from the informed traders, but the number (and value) of sales transactions does as well. The significant increase in the number of sale transactions potentially reflects the pessimistic beliefs of the uninformed investors about the stock. Aktas et al (2007) find that the *OIB*, closely approximating the *PIN*, even falls before the M&A announcements for the stocks traded on the Paris Stock Exchange. The large deviation of 12% in the daily order imbalance in the event month results from the disproportional increase in the sales of the stock (see Panel A of Table II.4). Retail investors are willing to sell their shares immediately, even at a slight discount to the offer price that reflects the probability of the tender offer's failure. Institutional investors, on the contrary, buy these stocks and hold them until the deal is closed. As a compensation for the incurred risk, they get the difference between the market price and the offer price - a strategy known as "merger arbitrage".

The deviations in the relative spread, the Amihud measure, and the intraday price impact of the bankruptcy sample (Panel B of Table II.6) are much larger than the corresponding deviations of the tender sample. The explanation for this fact might partly be because of the lower prices for the stocks of the financially distressed firms (the average price is \$8 as compared to the average price of \$14 of stocks in the tender sample). The small changes in the absolute prices lead to higher changes in the relative spread and the price impact measures for these stocks.[26] Overall, the measures in the bankruptcy sample

[26]The tick size, defined as the minimum amount by which the quotes of the stock can change, does not play a big role in my analysis, because the bankruptcy sample spans the years 1997-2008. The

display the same patterns as in the tender sample with the highest deviations in the three months before the first crash in the stock returns. However, the market starts perceiving an increase in the information asymmetry much earlier, eight to nine months in advance.

As in the tender sample, the imbalance measures do not deviate significantly from their long-run means. In the event month, both the numbers of purchases and sales proportionally increase, decreasing an overall order imbalance (Panel B of Table II.4). The dollar value of the buy transactions decreases and the dollar value of the sale transactions increases, compared to the pre-crash month, which reduces the trade value imbalance even further.

Panels C and D of Table II.6 illustrate the changes in the information asymmetry measures in the six months before the event for two firms, Enron from the bankruptcy sample and Caminus Corp. from the tender sample. Consistent with the univariate results from Panels A and B, the relative spread and the price impact measures are higher in the month immediately preceding the event than the six months before the event. Interestingly, the changes for Caminus Corp. are more pronounced with an increase in the relative spread from 1.5% in $t = -6$ to 5.2% in $t = -1$ and an increase in the intraday price impact from 5% to 17% over the same period. These higher changes are due to the lower overall liquidity for the stock of Caminus Corp., a relatively small firm as compared to Enron. Again, consistent with Panels A and B the imbalance measures do not reliably capture the change in the informed trading of the stock. The *OIBvalue* decreases in both cases, and the *OIB* decreases for Enron and increases for Caminus Corp.

decimalization of the spreads was finally adopted in April 2001 by all stock exchanges in the US with 135 out of 212 bankruptcies in my sample occurring in the post-decimalization period. The results do not differ materially for the sub-sample of bankruptcies occurring in the post-decimalization period (not tabulated).

3.2 Difference-in-Differences Analysis

One limitation of a pure time-series analysis is that it does not take into account an overall change in the information environment for the stocks with comparable trading characteristics. For example, after the revelation of the massive earnings manipulations of Enron and WorldCom, the overall degree of investor trust decreased, simultaneously increasing the cost of capital for less transparent firms and the transaction costs for their investors.

To circumvent this problem, I conduct a difference-in-differences analysis that controls for both the cross-sectional and the time-series variations in the information asymmetry measures. First, I match each event firm with a similar (in terms of trading characteristics) non-event firm. In the second step, I compare the deviations in the information asymmetry measures between the event and the matched control firms. I expect the deviations in the information asymmetry measures to be higher for the stock of an event firm due to higher levels of informed trading in this stock.

Matching Procedure. For each firm in the event samples (tender and bankruptcy) I find a firm of similar size, trading volume, volatility, and price level from the control group. The control group covers all listed US firms in the CRSP database that have trading data for at least 12 months and belong to neither of the event samples. The matching of the pairs is based on their propensity scores and is done at the beginning of the corresponding event year.[27] Overall, I find a corresponding match for 899 out of 909 firms in the tender sample and for 201 out of 212 firms in the bankruptcy sample.

The propensity score matching (PSM) approach finds a comparable firm in terms of *the observable* trading characteristics, such as price, market capitalization, volume, and

[27] I match stocks with replacements, so that one stock from a control group might serve as a control for several event stocks. Further, I require that a propensity score of a control stock lies within 1% of the propensity score of an event stock.

volatility. Matching on these trading characteristics is important, because they influence the overall level of stock liquidity and informed trading. For example, almost all of the information asymmetry measures are mechanically correlated with an inverse of the stock price. For this reason, I prefer matching on the inverse than on the price itself. Higher trading volume and market capitalization increase the liquidity of the stock and reduce the price impact of the informed trades. Higher stock volatility signals a higher disagreement between the stock's investors about its fundamental value. This disagreement might arise either due to a general uncertainty about the firm's value among all investors or due to the higher information asymmetry between the informed and uninformed investors, or both. Since two matched firms are similar in terms of their *observable* characteristics, they differ only with respect to *the unobservable* factors, like rumors in the market or temporary changes in the informed trading. Differences in the deviations in the information asymmetry measures between an event firm and its control should then reflect these differences in the trading environment of the two stocks.

One criticism of the PSM approach concerns the industry contagion effects. Rumors and informed trading might occur not only for an event stock, but also for the stocks of other potential targets, so that the information asymmetry increases for those stocks as well.[28] However, the presence of other potential targets in the control group should bias the results against finding any significant differences between the event and the matched control firms. Further, this effect is especially weak in this study because only 7% of

[28]See Song and Walkling (2000) for a discussion of the contagion effects in the industries of takeover targets. However, Agrawal and Nasser (2010) show that an increase in the net purchases of insiders from takeover targets is significantly larger than that of insiders from the control firms, which are similar in size and belong to the same industry. Further, Agrawal and Nasser (2010) and Song and Walkling (2000) find that cumulative abnormal returns (CARs) of firms that subsequently become targets are usually larger than those of their rival firms. These findings provide some evidence about existing differences in the information environments of similar firms from the same industry. Even if the degree of information asymmetry increases for the control firms (e.g., due to industry contagion effects or insider trading), the deviations in the information asymmetry measures from their long-run means should be lower than the corresponding deviations of an event stock.

the matched pairs in both samples belong to the same industry (based on the Fama and French (1997) industry classification).[29]

Table II.7 displays the trading characteristics for the stocks in the treated samples and in their corresponding control groups. The last column shows the p-values of a two-sided t-test on the equality of the means between the two groups and the last row reports the p-values of a Hotelling's test on the joint equality of the means for all of the matching variables.

[Insert Table II.7 approximately here]

Overall, the differences in the means between the event firms and their controls are not jointly significant in any of the event samples. The p-values of the Hotelling's test are 83% in the tender sample and 13% in the bankruptcy sample. The bankruptcy firms and their controls are, in general, smaller and more volatile than the corresponding firms from the tender sample. Due to the lower prices of the firms in the bankruptcy sample, their average daily trading volume exceeds the trading volume of the takeover targets (and their controls) by almost five times.

Differences in Deviations Between Event and Non-Event Firms. Table II.8 summarizes the results of the difference-in-differences analysis. Columns 2 through 10 display the cross-sectional averages of the differences in the deviations for all of the measures. The difference in the deviations in the information asymmetry measures ($\Delta^2 M$) between an event stock and a corresponding control stock is defined as

[29] If I require a control firm to belong to the same industry, then matching on trading characteristics, such as volume and volatility is rather poor. For this study, matching two firms on their trading characteristics is more important than matching them on their industry membership, because measures of informed trading are more closely related to the trading environment of the stock than to the operating process of the firm. However, the results do not change materially, when I match event firms to firms from the same industry and with the same market capitalization (results available upon request).

$$\Delta^2 M_t = \frac{M_{t,Event} - \overline{M}_{Event}}{\overline{M}_{Event}} - \frac{M_{t,Control} - \overline{M}_{Control}}{\overline{M}_{Control}}, \qquad \text{(II.2)}$$

where $\overline{M}$ is a long-run mean over $t \epsilon [-24, -12]$. If the deviations of an event stock and its corresponding control do not differ significantly, their difference (Δ^2) should be close to zero.

[Insert Table II.8 approximately here]

Consistent with the univariate results, the relative spread, the Amihud measure, and the intraday price impact show significantly higher deviations in the treated samples than in the corresponding control samples. Although the difference between the two groups is positive for the above measures, it is lower than the stand-alone deviations of the event stocks in Table II.6. This result implies that the relative spreads and the price impact measures of the stocks in the control groups have also increased, but to a lower degree than for the stocks in the treated samples. However, an increase in the above measures for the control stocks is mechanically driven by a decline in their price levels and not by a change in the information asymmetry between the informed and uninformed investors (results not tabulated). Again, as in the previous results, a difference in the deviations of the relative spread, the Amihud and the intraday price impact declines in the event month for stocks in the tender sample (Panel A) and further increases for stocks in the bankruptcy sample (Panel B).[30] The results for the order and trade imbalance measures are also consistent with the univariate results: the imbalance measures do not change significantly for firms in the tender and bankruptcy samples as well as in their corresponding control groups.

[30] A further increase in the relative spread, the Amihud measure and the intraday price impact in the month of the first negative information release for a stock in the bankruptcy sample is driven to a high extent by the crash in its price level.

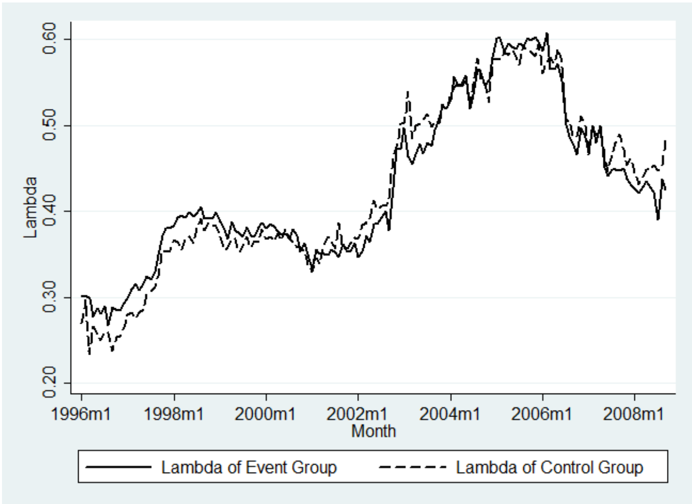
Importantly, the deviation of *Lam* loses its significance after controlling for its cross-sectional variation and even becomes negative. Thus, the adverse selection component increases by the same amount for the stocks in the event samples and their controls. To investigate this issue more closely, I plot the development of *Lam* separately over time for the sample of event firms and for their control group. Panel A of Figure II.3 displays the close time-varying relation between the adverse selection components in the two samples, which suggests that its time variations are similar for all stocks. Specifically, *Lam* monotonically increases in both samples until mid-2006 and declines afterwards. Since *Lam* is measured as a percentage of the spread, the deviations in *Lam* might be mechanically related to the deviations in the spread levels.

Panel B of Figure II.3 compares the development of these two measures over time in the combined samples of the event firms and their controls. The figure displays a strikingly negative relation between the time variations in the two measures: as the spread decreases over time, *Lam* increases as a percentage of the spread. In contrast, as the spreads start increasing in anticipation of the 2008 financial crisis, *Lam* is monotonically decreasing, which suggests that the deviations in *Lam* are mechanically driven by the deviations in the spread levels. The negative and significant correlation between *Lam* and the spread in Table II.5 further supports this explanation. The negative relation between *Lam* and the spread stays in contrast with theory, which predicts that the adverse selection component should increase as a percentage of the spread with higher levels of informed trading. Such contradictory evidence casts doubts on the adverse selection component as a valid measure of the time-varying information asymmetry.

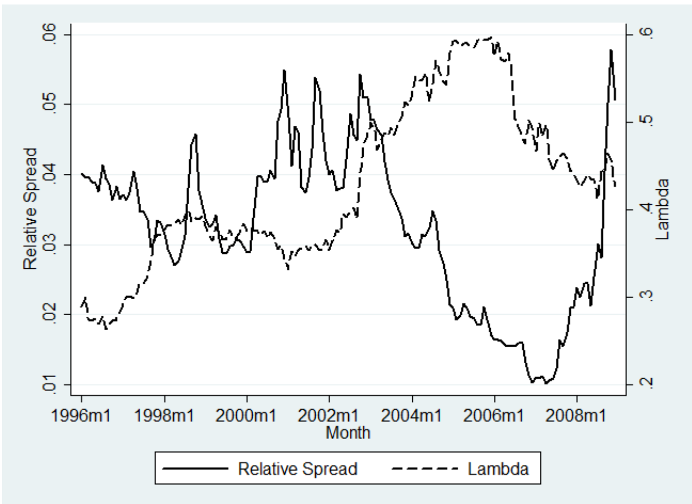
Overall, the results of the difference-in-differences analysis suggest that only the relative spread and the price impact measures (the Amihud measure and the intraday price impact) can consistently capture the changes in the information asymmetry between the

Figure II.3: **Development of relative spread and lambda over time.** Panel A of the figure displays the development of the adverse selection component, *Lam,* over 1996 to 2008 separately for the sample of the event firms (solid line) and their matched controls (dashed line). Panel B of the figure displays the development of the relative spread (solid line) and the lambda (dashed line) over 1996 to 2008 in the combined samples of event firms and their matched controls.

A. Development of Lambda over time



B. Development of Relative Spread and Lambda over time



informed and uninformed investors in both of the samples. The imbalance measures do not display any significant changes in almost every month, and the adverse selection component, *Lam,* loses its significance after controlling for its increase in the sample of the comparable companies.

3.3 Subsamples Analysis

The previous section examines differences in the deviations of the information asymmetry measures in the total samples of the tender offer and bankruptcy announcements. The next step is to examine whether the information asymmetry measures deviate more for stocks with more intensive informed trading prior to an event date. Prior studies by Meulbroek (1992) and Schwert (1996) show that the daily stock returns have a correlation with the insider trading activity and that almost half of the price runup in the month before a tender offer announcement occurs on days when insiders trade. Thus, a higher price runup in pre-announcement periods indicates the leakage of information to the market through the trades of informed investors. In the following, I measure intensity of the informed trading by the degree of the price runup preceding the event.

To differentiate between the high and low price runups, I construct a price runup ratio that calculates the proportion of information that has already been incorporated into the prices prior to an event:

$$\left| \frac{CAR[-x;t-1]}{AR_t + CAR[-x;t-1]} \right| .$$

The AR_t is the abnormal return on the event day (month) t in the tender (bankruptcy) sample. The $CAR[-x;t-1]$ represents the cumulative abnormal return for x days (months) prior to an event, with $x = 120$ days in the tender sample and $x = 12$ months in the bankruptcy sample. The higher the ratio, the higher is the observed price runup in relation to the abnormal return on an announcement day. I expect the deviations in the information asymmetry measures to be higher for the subsample with the above median price runup ratio.

Tables II.9 and II.10 summarize the differences in the deviations across the two sample splits. Panel A presents the results for the subsample with the above median price runup ratio, and Panel B displays the results for the remaining observations.

[Insert Tables II.9 and II.10 approximately here]

Consistent with the prior expectations, the relative spread and the intraday price impact deviate more significantly for the stocks with the higher price runup ratios in the tender sample as well as in the bankruptcy sample. The Amihud measure also deviates more significantly in the bankruptcy sample, but not in the tender sample. The reason is that the higher pre-announcement abnormal returns in the tender sample are accompanied by an abnormal (dollar) volume increase, whereas the overall (dollar) volume significantly drops in the bankruptcy sample. Since the Amihud measure is constructed on a daily basis, it relates the total trading volume, both by the informed and the uninformed investors, to the total price impact over the day. Therefore, it is harder for this measure, as compared to the intraday price impact, to estimate the price impact of the individual trades within a day. As before, the adverse selection component and the imbalance measures do not display significant deviations in any of the subsamples.

4 Monitoring Information Asymmetry by Uninformed Investors

If temporary fluctuations in the information asymmetry between the informed and the uninformed investors can be detected, then the risk-averse uninformed traders should monitor these fluctuations and time their trades accordingly. When a large number of informed traders enters the market for a stock, this signals a higher probability of a price change in the near future after information has been released to the market. However, the uninformed traders do not know *ex ante* the direction of the price change that depends on whether the news released will be positive or negative. Thus, a stock with a high level of informed trading experiences a temporary increase in its volatility, and the risk-averse uninformed investors should prefer to stay temporarily out of the market for this stock.

In the following, I form a trading strategy to test whether monitoring variations in the information asymmetry over time can help uninformed investors to time the volatility of their portfolio.[31] The previous findings suggest that only the relative spread, the Amihud and the intraday price impact can reliably capture the temporary deviations in the information asymmetry of the traded stocks. Therefore, I omit the remaining measures from the following analysis.

[Insert Table II.11 approximately here]

The sample of analyzed stocks includes 753 stocks from the CRSP database, which approximates a market portfolio. The sample period starts in January 2001 and ends in December 2007. Panel A of Table II.11 presents the details of the stock selection. I consider only common stocks that traded on the NYSE, the AMEX or the Nasdaq for at least 24 months. I further exclude all firms from the financial industry and utilities.[32] Due to the computational intensity of the intraday measures, the final sample comprises only 20% of the 3,886 stocks traded as of June 30, 2004. The following procedure is used to approximate a market portfolio. First, all of the stocks are split by industry and by quintiles of the market capitalization within each industry group. Afterward, I randomly draw 20% of the stocks from each industry-market capitalization group to form a sample

[31] The importance of volatility timing is discussed in previous studies by Busse (1999) and Fleming, Kirby, and Ostdiek (2001). Busse (1999) finds that mutual fund managers tend to reduce their market exposure in times of high expected volatility. Fleming, Kirby, and Ostdiek (2001) provide evidence that volatility timing strategies outperform the unconditionally efficient static portfolios.

[32] According to Fama and French (1997) industry classification.

of 764 stocks. Excluding 11 stocks with missing data for several information asymmetry measures yields a final sample of 753 stocks.

At the end of each month all of the stocks in the final sample are ranked in ascending order on the basis of their deviation in the corresponding information asymmetry measures from their 12-month moving averages and are subsequently sorted into deciles. Decile 1 comprises stocks with the lowest increase in information asymmetry, which might also be negative, and Decile 10 consists of stocks for which the information asymmetry has increased the most. At the beginning of the following month, a decile portfolio is formed that comprises all of the stocks sorted into the corresponding decile over the previous three months.[33] Thus, only one third of a decile portfolio is rebalanced each month.[34] A zero-cost trading strategy then buys the stocks with the lowest information asymmetry increase in the previous three months (Decile 1) and sells the stocks with the highest information asymmetry increase (Decile 10) accordingly. The average monthly returns and the Sharpe ratios of the decile portfolios, based on deviations in the corresponding information asymmetry measures, are presented in Panel B of Table II.11. Decile 1-10 shows the average monthly returns of the zero-cost trading strategy. I also report the p-values of a two-tailed t-test with a null hypothesis of an average monthly return being equal to zero.

On average, the monthly returns are slightly higher for the portfolios in the lower deciles that consist of stocks with recent decreases in their information asymmetry levels. These higher returns might be partially explained by the momentum effect, such that price increases in the previous months lead to price increases in the following month as well. However, the returns of the zero-cost trading strategy (Decile 1 - Decile 10) are not

[33]If a stock stays in the same decile over the previous two (three) months, then a double (triple) amount is invested in this stock.

[34]The results are qualitatively the same, and even stronger, if 100% of a decile portfolio is rebalanced monthly. However, a holding period of three months is more plausible in this setting.

statistically significant. The positive average returns of the Decile 10 portfolio represent an interesting result, because they mean that stocks with the highest increase in their information asymmetry level in the past will on average rise in their price, possibly due to some positive news. Although positive on average, the Decile 10 portfolio returns are only marginally significant for the relative spread and not significant for the price impact measures.

To control for the changes in volatility, I calculate Sharpe ratios for each decile.[35] Starting from Decile 2, the Sharpe ratios gradually decrease and attain their lowest values in Deciles 9 and 10 for all measures. This result is crucial, because it confirms the importance of monitoring the variations in the information asymmetry over time. The stocks with the highest increase in the informed trading in the past represent a relatively poor investment in terms of compensation per each unit of risk incurred. This result is driven by a disproportional volatility increase for the stocks in the higher information asymmetry deciles. Although the volatility of the individual portfolios is not tabulated in Table II.11, clearly some portfolios in the higher deciles have lower Sharpe ratios despite having a higher monthly average return, as compared to portfolios in the lower deciles for the same measure.[36]

Puzzling at first glance, the Sharpe ratios for the Decile 1 portfolios are lower than the Decile 2 portfolios for the relative spread and the intraday price impact, and are equal to each other for the Amihud measure. This counterintuitive observation is the result of increased volatility for the stocks that experience a considerable rise in the number of transactions by uninformed traders. Jones et al (1994) confirm a positive volatility-

[35] The Sharpe ratio is calculated as the ratio of the excess return of a portfolio to its total volatility in the current month. Table II.11 reports average Sharpe ratios over 72 months or 6 years for each decile.

[36] For example, compare the Decile 8 and the Decile 4 portfolios for the Amihud measure, the Decile 8 and the Decile 3 portfolios for the intraday price impact, and the Decile 7 and the Decile 4 portfolios for the relative spread.

volume relation and further show that it is mainly driven by an increase in the number of transactions, and not by their size. Overall, it is important to distinguish between different sources for the volatility increase of a stock. The volatility can rise because of an increase either in the number of uninformed traders or informed traders, or both. The Decile 1 portfolio comprises the stocks with the highest decrease in their information asymmetry in the past three months. Thus, although information asymmetry has previously existed for these stocks, it has probably been completely resolved after a corporate information release, causing the arrival of additional uninformed investors to the market in the current month. As in the example with the tender offer announcements, the relative spread and the price impact measures experience a significant decline after an announcement release. Simultaneously, the volume traded and the number of transactions surge, and the daily volatility remains on a relatively high level, even without any information asymmetry between the different investor types.[37]

The overall findings suggest that the risk-averse uninformed traders should avoid investing in stocks that have experienced extreme increases in their information asymmetry level in the recent past. Monitoring the time-varying information asymmetry can thus help them improve the volatility timing of their portfolios.

[37]The volatility argument is also important to demonstrate that the results for the higher deciles are driven by an increase in the information asymmetry level of the stock, and not by the pure liquidity effects. If a stock experiences a pure liquidity decline in the form of an exogenous decrease in the number of the uninformed investors, its volatility should actually decrease due to a lower overall transaction number. The high volatility of the higher decile portfolios rather signals an arrival of the informed traders to the market.

5 Conclusions

This paper tests the validity of the time-varying information asymmetry measures in periods prior to unexpected events, such as tender offer announcements and the first rumors about an upcoming bankruptcy filing. Since the levels of informed trading usually increase in these periods, the information environment of the stock changes. A valid measure should detect this change through the abnormal deviation from its base level of the previous year.

The measures analyzed in this study can be divided into "mixed" measures that include both an information component and a liquidity component, and "pure" measures that extract a pure information component. Specifically, the relative spread, the intraday price impact, and the Amihud measure belong to the "mixed" category, whereas the adverse selection component and the order imbalance measures represent the "pure" information asymmetry measures.

Based on a sample of 909 announcements of tender offers and the return crashes of 212 stocks that subsequently file for bankruptcy, this paper provides evidence that the "mixed" measures consistently outperform the "pure" measures in both of the samples. The relative spread and the price impact measures show significant deviations from their base levels starting six months prior to tender offer announcements and as early as nine months prior to the return crashes of subsequently bankrupt stocks. Further, these measures deviate by a larger amount in periods when informed trading is more intensive, as measured by the higher price runup ratios.

In contrast, the order imbalance measures do not show significant deviations in the periods of increased informed trading, because the number and the value of the purchases and sales increases proportionally. This proportional increase in trades in both directions contradicts the main underlying assumption of these measures - namely, that informed traders unbalance the order flow either to the buy side or to the sell side. The adverse selection component of the spread ceases to capture variations in the information asymmetry over time after controlling for its changes in a group of stocks with similar trading characteristics. Further analysis shows that this measure has similar time variations for all stocks and that the changes in this measure are mechanically driven by the changes in the spread level.

Further, this paper demonstrates that monitoring temporary deviations in the information asymmetry can help the risk-averse uninformed investors better time the volatility of their portfolios. Overall, the decile portfolios of stocks with high deviations in their information asymmetry levels over the previous three months have lower Sharpe ratios as compared to the portfolios of stocks that do not experience any changes or only slight decreases in their informed trading.

The findings of this paper can be of interest for researchers from broad finance and accounting areas, because the suggested "mixed" measures of the information asymmetry are easy to construct and the Amihud measure requires only daily trading data. However, caution needs to be exerted when using the suggested measures to identify changes in informed trading in a particular stock. Additional controls for the changes in price and volume are always necessary, because artificial deviations in the information asymmetry measures can also be caused by exogenous changes in the trading characteristics of a stock, which might occur, for example, after a stock split.

Appendix A

Variable Definitions

Variable	Description	Source
Amihud	The Amihud measure of illiquidity, defined as the ratio of the daily absolute return to the dollar trading volume on that day (Amihud, 2002).	CRSP
Cash	Cash and the short-term investments of the company (in million $)	Compustat
Event, $t = 0$	One for observations in the event month ($t = 0$), which includes the event day and 30 days thereafter, and zero otherwise.	
$Event_t$, $t \epsilon [-1, -6]$	One for observations in the month t, where t is defined as *CurrentMonth-EventMonth.* Event days [-31;-1] are assigned to *t=-1*, event days [-32;-62] to *t=-2* and so on.	
Lam	The adverse selection component of the effective spread, based on the estimation procedure of Lin, Sanger and Booth (1995). For estimation details, please refer to the Appendix B. Observations that lie outside of the range between zero and one are set to missing values.	TAQ

Variable	Description	Source
Leverage	The market leverage of the company, defined as the ratio of the total liabilities to the sum of the total liabilities and the market capitalization of the company.	Compustat
Liabilities	The total liabilities of the company (in million $)	Compustat
MarketCap	The market capitalization of the company (in million $)	CRSP
NumberTrades	The average daily number of trades in a particular stock	TAQ
OIB	The daily order imbalance, defined as the absolute difference between the number of buy- and sell-initiated transactions in one day relative to the total number of transactions.	TAQ
OIBvalue	The trade value imbalance, defined as the absolute difference between the traded value of the buy- and sell-initiated transactions to the total traded value in one day.	TAQ

Variable	Description	Source
PrcImp	The price impact of each trade after five minutes, defined as $PrcImp_t = 2\left\|Q_{t+5} - Q_t\right\|/(Q_t \cdot w_t)$, where Q_{t+5} represents the quote midpoint price of the stock after five minutes and w_t stands for the size of a trade.	TAQ
Price (P)	The closing price of a stock (in $)	CRSP
ROA	Return on assets, defined as the ratio of the operating income after depreciation to the average total assets of the current year and the previous year.	Compustat
RelSpr	The relative spread, defined as the daily average quoted bid-ask spread, scaled by the quote midpoint price; observations with *RelSpr>0.5* are set to missing values.	TAQ
Sharpe	The Sharpe ratio of the portfolio, calculated as $Sharpe_i = (R_{it} - Rf_t)/\sigma_{R_i}$. The R_{it} is the return of a portfolio i in the month t and the Rf_t is the risk free rate in the month t. Data on the risk free rates in the USA comes from the Kenneth French's website.	CRSP
Total Assets	The total assets of the company (in million $)	Compustat

Variable	**Description**	**Source**
Volatility	The annualized standard deviation of daily stock returns over the calendar month	CRSP
Volume	The average daily traded volume of a stock (in thousands of shares)	CRSP

Appendix B

Computational Routines

For all of the high frequency measures, I use the NYSE TAQ database to extract the necessary intraday transaction data. For each trade I assign the bid quote and the ask quote that prevail at least one second before the trade took place.[38] The final data set contains the following items for each transaction:

1. Date and time stamp (up to seconds)
2. Transaction price (P_t)
3. Transaction volume in shares (w_t)
4. Prevailing bid quote (B_t)
5. Prevailing ask quote (A_t)

I calculate the quote midpoint price (Q_t) as the average of the prevailing bid and ask quotes ($Q_t = \frac{A_t+B_t}{2}$). I further use the Lee and Ready's (1991) algorithm to classify trades into the buy-initiated and sell-initiated transactions. Specifically, I classify the trades with a transaction price above the quote midpoint ($P_t > Q_t$) as buy-initiated and those with a transaction price below the quote midpoint ($P_t < Q_t$) as sell-initiated. If a transaction price is equal to the quote midpoint, I compare the current transaction price with the previous transaction price. If $P_t < P_{t-1}$, I consider a trade to be sell-initiated; if $P_t > P_{t-1}$, I consider it to be buy-initiated. Should the two prices be equal, I leave the trade as unclassified.

[38]Henker and Wang (2006) consider this procedure to be more appropriate compared to the classical Lee and Ready (1991) five-second rule. Bessembinder (2003) tries zero- to thirty-second delays in increments of five seconds and does not find any differences in the results.

Relative Spread

I calculate the relative spread for each transaction as the quoted bid-ask spread, scaled by the quote midpoint:

$$RelSpr_t = \frac{A_t - B_t}{Q_t}.$$

To reduce the noise, I average the relative spreads of all transactions for a stock over one month and set observations with $RelSpr > 0.5$ to missing values.

Adverse Selection Component of the Spread

Following the Lin, Sanger, and Booth (1995) approach, I estimate the adverse selection component of the effective spread, Lam, as the coefficient λ from the regression of the change in logs of the quotes on the log of the one-half signed effective spread ($z_t = p_t - q_t$):

$$q_{t+1} - q_t = \lambda \cdot z_t + \varepsilon_{t+1}.$$

The q_t stands for the logarithm of the quote midpoint Q_t for a transaction t, and the p_t denotes the logarithm of the transaction price P_t. In this setup λ represents the adverse selection component as *the percentage* of the effective spread.

Amihud Measure

Amihud (2002) was the first to propose the measure of the daily price impact that requires only daily stock trading data. The Amihud measure is calculated as follows:

$$Amihud_t = \frac{|Return_t|}{Price_t \cdot Volume_t}.$$

For convenience of the coefficients' presentation I multiply this ratio by 10^6.

Intraday Price Impact

This measure is calculated as the five-minute price impact of the trade, scaled by its size:

$$PrcImp_t = 2\left|Q_{t+5} - Q_t\right| / (Q_t \cdot w_t),$$

where Q_{t+5} represents the quote midpoint price of the stock after five minutes (300 seconds). I average the intraday price impact of all trades for a stock over one month.

In principle, this measure corresponds to the Amihud measure. The only difference is that the five-minute price impact is calculated on an intraday basis, whereas the Amihud measure estimates the price impact over the whole day. The five-minute price impact measure builds on the similar measure proposed by Riordan and Storkenmaier (2009), but the measure used in this paper additionally controls for the size of the transaction.

Daily Order Imbalance

The measure of daily order imbalance (OIB), as proposed by Aktas et al (2007), captures the absolute difference between the number of purchases and the number of sales in one day relative to the total number of transactions:

$$OIB = \frac{|B-S|}{B+S},$$

where B stands for the number of buy-initiated transactions and S for the number of sell-initiated transactions in one trading day. I classify each trade as buy- or sell-initiated with the Lee and Ready (1991) algorithm.

Trade Value Imbalance

In contrast to *OIB*, $OIBvalue$ accounts not only for the imbalance in the number of transactions, but also for their value. It is defined as the absolute difference between the traded value of the buy- and sell-initiated transactions to the total traded value in one day:

$$OIBvalue = \frac{|B_{VAL} - S_{VAL}|}{(B_{VAL} + S_{VAL})},$$

where $B_{VAL} = \sum_{t=1}^{m}(P_t^A \cdot w_t^A)$ and $S_{VAL} = \sum_{t=1}^{n}(P_t^B \cdot w_t^B)$.

P_t^A (w_t^A) denotes the transaction price (size) at the ask and $P_t^B(w_t^B)$ is the transaction price (size) at the bid.

Tables

Table II.1: **Construction of Tender and Bankruptcy Samples.** This table shows the details of the sample construction. Panel A presents the steps in the construction of the tender sample that consists of the announcements of tender offers in the USA between January 1, 1997 and December 31, 2008. The data source for the announcement dates of tender offers is the Securities Data Corporation (SDC) M&A database. Panel B presents the steps in the construction of the bankruptcy sample. The bankruptcy filings of the publicly traded US firms between January 1, 1997 and December 31, 2008 are collected from the BankruptcyData.com website.

Panel A: Tender Sample

Criteria	Announcements Dropped	Number of announcements
Tender offer announcements with a publicly traded target firm and a deal value over $1 mln		1,232
No repeat tender offer announcements for one target	57	1,175
Trading data available on CRSP for 12 months before the announcement date	229	946
No missing data for all of the information asymmetry measures	37	909

Panel B: Bankruptcy Sample

Criteria	Announcements Dropped	Number of announcements
Bankruptcy filings of publicly traded firms for which CUSIPs from CRSP could be identified		1,220
No repeat bankruptcy filings by one firm	54	1,166
Trading data available on CRSP for 36 months before the announcement date	800	366
The month of the bankruptcy expectation is clearly identified	105	261
No missing data for all of the information asymmetry measures	49	212

Table II.2: **Firm Characteristics in Tender and Bankruptcy Samples.** This table reports summary statistics on the size and crucial financial variables of the firms in the tender and bankruptcy samples. All statistics are reported on a firm-month level. *MarketCap* and *Price* data are taken from CRSP. Financial statement variables on a quarterly basis come from Compustat. See Appendix A for the exact definition of all variables. Panel A shows the characteristics of 909 firms in the tender sample (879 firms for the Compustat variables). Panel B displays the statistics of 212 firms in the bankruptcy sample (167 firms for the Compustat variables).

Panel A: Tender Sample

	N	Mean	Std	10%	25%	50%	75%	90%
MarketCap (in mln $)	9626	516	1251	21	50	129	399	1192
Total Assets (in mln $)	8228	709	2320	33	65	160	481	1255
Cash (in mln $)	8194	48	107	1	4	14	43	106
Liabilities (in mln $)	8198	461	1752	9	23	73	286	844
Price (in $)	9626	14	13	2	5	10	19	32
Leverage	8198	0.40	0.24	0.10	0.19	0.37	0.57	0.76
ROA	8160	0.00	0.06	-0.06	-0.00	0.02	0.03	0.05

Panel B: Bankruptcy Sample

	N	Mean	Std	10%	25%	50%	75%	90%
MarketCap (in mln $)	1844	503	1520	12	30	80	265	880
Total Assets (in mln $)	1373	1473	4146	36	83	204	753	2867
Cash (in mln $)	1376	60	162	0	2	7	35	130
Liabilities (in mln $)	1373	1223	3530	17	58	154	576	2415
Price (in $)	1844	8	10	1	3	5	9	18
Leverage	1373	0.64	0.24	0.28	0.48	0.69	0.83	0.93
ROA	1351	-0.03	0.07	-0.12	-0.05	-0.01	0.01	0.02

Table II.3: **Information Asymmetry Measures: Summary Statistics.** This table displays summary statistics for the information asymmetry measures, the trading volume (in thousands of shares) and the excess volatility of the stocks. Columns (2) through (4) report summary statistics twelve months before the corresponding event month. Columns (5) through (7) report summary statistics in the month immediately preceding the corresponding event month. The last column displays the p-value of the two-sided t-test for the null-hypothesis that the difference in means between the two months equals zero. * denotes statistical significance at the 10% level, ** denotes statistical significance at the 5% level, *** denotes statistical significance at the 1% level. Panel A summarizes the trading characteristics of 909 firms in the tender sample. Panel B displays the statistics of 212 firms in the bankruptcy sample. *Amihud, Volume* and *Volatility* are calculated from the CRSP data. The remaining variables are constructed from the intraday transaction data in the NYSE TAQ database. See Appendix A for the exact definition of all variables and the Appendix B for construction and estimation details.

Panel A: Tender Sample

	12M before			1M before			t-test
	Mean	Median	Std	Mean	Median	Std	
RelSpr	0.028	0.022	0.02	0.032	0.023	0.03	***
Lam	0.424	0.415	0.19	0.430	0.416	0.17	
Amihud	1.620	0.077	6.20	1.675	0.107	6.36	
PrcImp	0.026	0.008	0.07	0.047	0.010	0.12	***
OIB	0.292	0.287	0.13	0.291	0.292	0.13	
OIBvalue	0.368	0.367	0.16	0.360	0.362	0.16	
Volatility	0.557	0.478	0.32	0.661	0.540	0.46	***
Volume	165	50	460	230	53	731	**

Panel B: Bankruptcy Sample

	12M before			1M before			t-test
	Mean	Median	Std	Mean	Median	Std	
RelSpr	0.035	0.024	0.03	0.050	0.034	0.05	***
Lam	0.404	0.386	0.18	0.404	0.404	0.17	
Amihud	1.714	0.112	7.71	4.658	0.262	12.62	**
PrcImp	0.038	0.016	0.06	0.084	0.032	0.15	***
OIB	0.265	0.267	0.13	0.268	0.266	0.12	
OIBvalue	0.328	0.318	0.17	0.346	0.345	0.15	
Volatility	0.668	0.597	0.36	0.793	0.675	0.46	**
Volume	619	88	1802	589	66	1649	

Table II.4: **Number and Dollar Value of Purchase and Sale Transactions.** This table displays daily averages of the number of purchase and sale transactions and their corresponding dollar value (in billions of dollars). Column (2) reports the corresponding means twelve months before the event month, column (3) reports the statistics in the month immediately preceding the event month, and column (4) reports the statistics for the event month. Panel A shows the results for 909 firms in the tender sample. Panel B shows the results for 212 firms in the bankruptcy sample. All variables are constructed from the intraday transaction data in the NYSE TAQ database. See Appendix A for the exact definition of all variables.

Panel A: Tender Sample

	12M before	1M before	Event Month
Number of Purchases	134	223	284
Number of Sales	133	227	324
Value of Purchases ($ bln)	1.70	2.25	6.74
Value of Sales ($ bln)	1.63	2.25	8.18

Panel B: Bankruptcy Sample

	12M before	1M before	Event Month
Number of Purchases	383	388	538
Number of Sales	358	381	529
Value of Purchases ($ bln)	5.93	4.55	4.32
Value of Sales ($ bln)	5.34	4.20	4.42

Table II.5: **Information Asymmetry Measures: Correlation Matrix.** This table presents the matrix of Spearman's rank correlation coefficients in the tender sample (Panel A) and in the bankruptcy sample (Panel B). For brevity, p-values are not reported. All coefficients are statistically significant at the 1% level, except the coefficients for *Lam* in the bankruptcy sample, which is no longer significantly correlated to any of the other variables. See Appendix A for the exact definition of all variables.

Panel A: Tender Sample

	RelSpr	Lam	Amihud	PrcImp	OIB	OIBvalue	Volat	Volume
RelSpr	1.00							
Lam	-0.13	1.00						
Amihud	0.87	-0.22	1.00					
PrcImp	0.54	-0.12	0.51	1.00				
OIB	0.61	-0.19	0.72	0.25	1.00			
OIBvalue	0.63	-0.06	0.73	0.20	0.86	1.00		
Volatility	0.38	-0.34	0.33	0.46	0.15	0.03	1.00	
Volume	-0.63	0.03	-0.80	-0.17	-0.70	-0.77	0.11	1.00

Panel B: Bankruptcy Sample

	RelSpr	Lam	Amihud	PrcImp	OIB	OIBvalue	Volat	Volume
RelSpr	1.00							
Lam	0.05	1.00						
Amihud	0.85	-0.06	1.00					
PrcImp	0.57	0.02	0.47	1.00				
OIB	0.65	-0.07	0.78	0.27	1.00			
OIBvalue	0.69	0.02	0.80	0.23	0.88	1.00		
Volatility	0.43	-0.24	0.33	0.50	0.13	0.07	1.00	
Volume	-0.64	-0.06	-0.86	-0.19	-0.78	-0.83	0.05	1.00

Table II.6: **Pre-Announcement Changes in Information Asymmetry Measures.** Panels A and B of this table present the cross-sectional averages of deviations in the information asymmetry measures from their long-run means in t months preceding the corresponding event, and for the event month, $t = 0$. The long-run mean for each stock is constructed over t=-24 to t=-12. P-values of a two-tailed t-test with a null-hypothesis of a deviation being equal to zero are reported in form of asterisks to the right of each coefficient. * denotes statistical significance at the 10% level, ** - at the 5% level, and *** - at the 1% level. Panels C and D present the levels of the information asymmetry measures in different months for Enron and Caminus Corp., respectively.

Panel A: Deviations in Tender Sample

t	$\Delta RelSpr$	ΔLam	$\Delta Amihud$	$\Delta PrcImp$	ΔOIB	$\Delta OIBvalue$
0	-0.21 ***	0.10 ***	-0.17 ***	0.81 ***	0.12 ***	0.06 ***
-1	0.19 ***	0.14 ***	0.50 ***	0.87 ***	-0.01	-0.02
-2	0.20 ***	0.12 ***	0.55 ***	0.83 ***	-0.01	-0.01
-3	0.14 ***	0.11 ***	0.51 ***	0.86 ***	-0.01	-0.01
-4	0.13 ***	0.11 ***	0.45 ***	0.74 ***	0.00	-0.01
-5	0.10 ***	0.09 ***	0.43 ***	0.46 ***	-0.00	0.01
-6	0.07 ***	0.08 ***	0.29 ***	0.48 ***	-0.03 ***	-0.02 ***

Panel B: Deviations in Bankruptcy Sample

t	$\Delta RelSpr$	ΔLam	$\Delta Amihud$	$\Delta PrcImp$	ΔOIB	$\Delta OIBvalue$
0	0.90 ***	0.05 *	3.54 ***	3.35 ***	-0.06 ***	-0.05 ***
-1	0.53 ***	0.08 **	2.98 ***	1.53 ***	-0.01	0.04 **
-2	0.31 ***	0.07 **	1.81 ***	1.41 ***	-0.01	-0.01
-3	0.25 ***	0.09 **	1.39 ***	0.76 ***	-0.01	0.02
-4	0.23 ***	0.05	1.24 ***	0.72 ***	-0.01	0.01
-5	0.22 ***	0.08 **	0.78 ***	0.95 ***	0.01	0.02
-6	0.12 ***	0.07 *	0.89 ***	0.56 ***	-0.03	-0.02
-7	0.12 ***	0.11 ***	0.53 ***	0.29 ***	-0.01	-0.01
-8	0.09 ***	0.01	0.31 ***	0.16 *	-0.03	-0.02
-9	0.02	0.06	0.13 *	0.13 *	-0.01	-0.00
-10	0.03	0.02	0.10	0.15	-0.04 **	-0.04 **
-11	-0.02	0.06 **	-0.11 **	-0.13 **	0.03	0.01
-12	-0.01	-0.02	-0.01	-0.16 ***	-0.02	-0.03

Panel C: Enron Example

t	RelSpr	Lam	Amihud	PrcImp	OIB	OIBvalue
0	0.012	0.11	0.0002	0.04	0.16	0.25
-1	0.010	0.12	0.0002	0.06	0.07	0.15
-6	0.008	0.22	0.0001	0.01	0.13	0.17

Panel D: Caminus Example

t	RelSpr	Lam	Amihud	PrcImp	OIB	OIBvalue
0	0.033	0.57	0.0549	0.09	0.26	0.27
-1	0.052	0.49	0.2271	0.17	0.20	0.21
-6	0.015	0.43	0.1248	0.05	0.16	0.23

Table II.7: **Trading Characteristics of Matched Firms.** This table displays the trading characteristics of the event firms and their matched controls with the closest propensity scores. See Appendix A for the exact definition of all variables. All variables used for the propensity score matching are calculated from the CRSP daily stock trading data. The market capitalization, *MarketCap,* and the inverse of the price, $1/P$, are taken at the beginning of the year in which an event has taken place. Volume and volatility represent averages over the year in which an event has taken place. For each variable the table displays the p-value of the two-sided t-test on the equality of the means. I also report the p-value of the Hotelling's F-test on the joint equality of the means of all matching variables in the event sample and the corresponding control sample. Panel A summarizes the trading characteristics of 899 matched pairs from the tender sample. Panel B displays the statistics of 201 pairs from the bankruptcy sample.

Panel A: Tender Sample

		Tender		Control		T-test
	N	Mean	Median	Mean	Median	p-value
MarketCap (in mln $)	899	575	143	592	117	0.52
1/P	899	0.23	0.09	0.21	0.08	0.42
Volume (in 1,000 shares)	899	226	62	207	37	0.51
Volatility	899	0.59	0.52	0.58	0.51	0.32
Hotelling's F-test	899					0.83

Panel B: Bankruptcy Sample

		Bankruptcy		Control		T-test
	N	Mean	Median	Mean	Median	p-value
MarketCap (in mln $)	201	441	69	435	42	0.97
1/P	201	0.48	0.27	0.52	0.24	0.49
Volume (in 1,000 shares)	201	950	134	1322	78	0.33
Volatility	201	1.12	1.05	1.08	0.97	0.20
Hotelling's F-test	201					0.13

Table II.8: **Difference-in-Differences Analysis.** This table presents the cross-sectional averages of the differences in deviations in the information asymmetry measures between the event firm and the corresponding control firm in t months preceding the corresponding event, and for the event month, $t = 0$. The long-run mean for each stock is constructed over t=-24 to t=-13. P-values of the Wilcoxon signed-rank test with a null-hypothesis of equality of both distributions are reported in form of asterisks to the right of each coefficient. * denotes statistical significance at the 10% level, ** - at the 5% level, and *** - at the 1% level. Panel A displays the results of the difference-in-differences analysis for 899 matched pairs in the tender sample. Panel B presents the results of the difference-in-differences analysis for 201 matched pairs in the bankruptcy sample.

Panel A: Tender Sample

t	$\Delta^2 RelSpr$	$\Delta^2 Lam$	$\Delta^2 Amihud$	$\Delta^2 PrcImp$	$\Delta^2 OIB$	$\Delta^2 OIBvalue$
0	-0.26 ***	-0.03	-0.65 ***	0.15	0.12 ***	0.08 ***
-1	0.10 ***	-0.01	0.05	0.32 **	-0.00	0.02
-2	0.13 ***	-0.01	0.13 *	0.25 *	-0.00	0.02
-3	0.09 ***	-0.01	0.14 **	0.32 **	-0.01	0.02
-4	0.09 ***	-0.01	0.18 ***	0.25 **	0.00	0.02 *
-5	0.08 ***	-0.01	0.19 ***	0.05	0.02	0.04 ***
-6	0.03	0.03	0.11 **	0.17 *	-0.01	0.01

Panel B: Bankruptcy Sample

t	$\Delta^2 RelSpr$	$\Delta^2 Lam$	$\Delta^2 Amihud$	$\Delta^2 PrcImp$	$\Delta^2 OIB$	$\Delta^2 OIBvalue$
0	0.53 ***	-0.11 ***	0.85 ***	0.92 ***	-0.04	-0.07
-1	0.27 ***	-0.02	0.69 ***	0.18 **	-0.02	0.01
-2	0.18 ***	-0.01	0.44 ***	0.42 ***	-0.03	-0.03
-3	0.12 ***	-0.01	0.29 ***	0.09	0.01	-0.02
-4	0.12 ***	-0.04	0.22 ***	0.35 **	-0.01	-0.03
-5	0.11 ***	-0.01	0.20 *	0.05	0.03	0.04
-6	0.07 *	-0.02	0.16 **	0.18 ***	-0.04	0.01
-7	0.07 *	-0.01	0.21 ***	0.05	-0.07	-0.02
-8	0.09 *	-0.01	0.14 *	0.19 *	0.01	-0.00
-9	0.07 *	-0.02	0.10	0.05	0.05	-0.00
-10	0.04	0.04	0.07	0.14	-0.04	-0.00
-11	0.01	-0.01	0.12 *	0.05	-0.03	-0.01
-12	0.07 *	-0.07 **	0.02	0.11 *	-0.04 **	-0.05 *

Table II.9: **Subsamples Analysis: Tender Sample.** This table presents the cross-sectional averages of the differences in deviations in the information asymmetry measures between the event firm and the corresponding control firm in t months preceding the corresponding event, and for the event month, $t = 0$. The long-run mean for each stock is constructed over t=-24 to t=-13. Panel A presents the results for 450 firms in the tender sample with the above median price runup ratio, constructed as the ratio of CAR[-120;-1] to CAR[-120;0]. Panel B presents the results for the remaining 449 firms for which the price runup ratio lies below the sample median. The CARs are calculated on a daily basis with the help of the market model and the CRSP value-weighted portfolio used as the market index. P-values of the Wilcoxon signed-rank test with a null-hypothesis of equality of both distributions are reported in form of asterisks to the right of each coefficient. * denotes statistical significance at the 10% level, ** - at the 5% level, and *** - at the 1% level.

Panel A: Higher Price Runup Ratio

t	$\Delta^2 RelSpr$	$\Delta^2 Lam$	$\Delta^2 Amihud$	$\Delta^2 PrcImp$	$\Delta^2 OIB$	$\Delta^2 OIBvalue$
0	-0.24 ***	0.00	-0.78 ***	0.31	0.08 ***	0.05 *
-1	0.10 **	-0.02	-0.12	0.50 ***	-0.03	-0.02
-2	0.11 **	-0.01	-0.09	0.09	-0.03	0.01
-3	0.08 *	0.04	-0.03	0.39 **	-0.03	0.01
-4	0.11 ***	0.01	0.00	0.28	-0.00	0.01
-5	0.10 ***	-0.01	0.01	0.05	0.01	0.04 *
-6	0.06	0.03	0.01	0.26 *	0.00	0.01

Panel B: Lower Price Runup Ratio

t	$\Delta^2 RelSpr$	$\Delta^2 Lam$	$\Delta^2 Amihud$	$\Delta^2 PrcImp$	$\Delta^2 OIB$	$\Delta^2 OIBvalue$
0	-0.32 ***	-0.04	-0.67 ***	-0.20	0.16 ***	0.11 ***
-1	0.07	0.01	0.10	0.12	0.02	0.05 **
-2	0.09 *	-0.01	0.23 **	0.05	0.02	0.02
-3	0.07	-0.02	0.16	0.04	-0.01	0.02
-4	0.04	0.00	0.19 **	0.09	0.00	0.03
-5	0.04	-0.03	0.24 ***	0.06	0.02	0.04 *
-6	-0.01	0.07 *	0.14 *	0.07	-0.02	0.00

Table II.10: **Subsamples Analysis: Bankruptcy Sample.** This table presents the cross-sectional averages of the differences in deviations in the information asymmetry measures between the event firm and the corresponding control firm in t months preceding the corresponding event, and for the event month, $t = 0$. The long-run mean for each stock is constructed over t=-24 to t=-13. Panel A presents the results for 100 firms in the bankruptcy sample with the above median price runup ratio, constructed as the ratio of CAR[-12;-1] to CAR[-12;0]. Panel B presents the results for the remaining 99 firms for which the price runup ratio lies below the sample median. The CARs are calculated on a monthly basis with the help of the market model and the CRSP value-weighted portfolio used as the market index. P-values of the Wilcoxon signed-rank test with a null-hypothesis of equality of both distributions are reported in form of asterisks to the right of each coefficient. * denotes statistical significance at the 10% level, ** - at the 5% level, and *** - at the 1% level.

Panel A: Higher Price Runup Ratio

t	$\Delta^2 RelSpr$	$\Delta^2 Lam$	$\Delta^2 Amihud$	$\Delta^2 PrcImp$	$\Delta^2 OIB$	$\Delta^2 OIBvalue$
0	0.87 ***	-0.17 **	3.97 ***	2.64 ***	-0.07	-0.02
-1	0.55 ***	-0.17 **	2.71 ***	1.67 ***	-0.05	0.05
-2	0.31 ***	-0.08	1.18 ***	1.17 **	-0.02	0.01
-3	0.23 **	-0.11	1.00 ***	0.69	-0.02	0.04
-4	0.19 **	-0.08	1.03 **	0.45	-0.03	0.01
-5	0.17 *	-0.05	0.46 *	0.32	0.02	0.06
-6	0.13 *	0.05	0.44 *	0.94 **	-0.01	0.08
-7	0.12	0.04	0.53 ***	0.13	-0.05	0.03
-8	0.09	0.01	0.16	-0.33	0.04	0.06
-9	0.08	-0.04	0.10	-0.09	-0.02	-0.03
-10	0.04	0.11 *	-0.13	0.17	-0.09 *	-0.04
-11	-0.02	0.04	0.12	-0.22	-0.06 *	-0.05
-12	0.03	-0.07	0.04	0.20	-0.09 **	-0.08 **

Panel A: Lower Price Runup Ratio

t	$\Delta^2 RelSpr$	$\Delta^2 Lam$	$\Delta^2 Amihud$	$\Delta^2 PrcImp$	$\Delta^2 OIB$	$\Delta^2 OIBvalue$
0	0.48 ***	-0.07	1.13 ***	2.59 ***	-0.07	-0.09 **
-1	0.18 *	0.09	0.68 *	0.41	-0.06	-0.02
-2	0.08	-0.04	0.55 *	0.46	-0.06	-0.07 *
-3	0.08	0.01	0.39	-0.21	-0.03	-0.07
-4	0.06	-0.03	0.01	0.02	-0.00	-0.02
-5	0.09	0.03	-0.03	0.34	-0.06	-0.02
-6	0.02	-0.03	0.28	0.11	-0.06	-0.08 *
-7	0.01	-0.05	-0.09	0.22	-0.05	-0.05
-8	-0.00	0.03	0.14	0.10	-0.04	-0.04
-9	0.01	-0.04	0.01	0.27 **	0.04	0.03
-10	-0.01	-0.02	0.06	0.15	0.03	0.04
-11	0.02	0.10	-0.12	0.06	0.02	-0.01
-12	0.02	-0.11 *	-0.07	-0.01	-0.05	-0.01

Table II.11: **Returns and Sharpe Ratios of Risk Averse Trading Strategy.** Panel A of this table presents the details of the stock selection for the risk averse trading strategy. The sample period covers years 2001 to 2007. Panel B presents the average monthly returns and the Sharpe ratios of the decile portfolios that are formed by the risk averse trading strategy. The risk averse strategy buys the stocks with the lowest increase in the information asymmetry in the previous month (Decile 1) and sells the stocks with the highest increase in the information asymmetry (Decile 10). The holding period for the risk averse strategy comprises 3 months. Decile 1-10 shows the average monthly returns of a zero-cost portfolio (Buy-Sell). The Sharpe ratio is calculated as the ratio of the excess return of a portfolio to its total volatility in the current month. Panel B reports the average monthly returns and the Sharpe ratios over 72 months, or 6 years, for each of the deciles. P-values of a two-tailed t-test with a null-hypothesis of an average monthly return equaling zero are reported in form of asterisks.

Panel A: Selection of Stocks

Criteria	**Firms**	**Observations**
All common stocks from the CRSP database traded between January 1, 2001 and December 31, 2007 on NYSE, AMEX or Nasdaq	8,082	426,798
Trading data available on CRSP for a minimum of 24 months	6,007	403,808
Exclude Financials and Utilities	4,865	324,418
Random 20% of the market portfolio as of June 30, 2004	764	57,683
No missing data for all of the information asymmetry measures	753	44,363

Panel B: Returns and Sharpe Ratios

	RelSpr		Amihud		PrcImp	
Decile	Ret, %	Sharpe	Ret, %	Sharpe	Ret, %	Sharpe
1	0.76	0.11	2.02 ***	0.29	1.24 **	0.22
2	1.48 **	0.24	1.66 ***	0.29	1.49 **	0.26
3	1.46 **	0.23	1.38 **	0.24	1.11 *	0.18
4	1.29 **	0.21	1.21 **	0.21	1.19 **	0.19
5	1.44 **	0.22	1.09 **	0.19	1.35 **	0.22
6	1.25 **	0.20	1.18 **	0.20	1.25 *	0.19
7	1.29 *	0.18	0.93	0.13	1.27 *	0.19
8	1.26 *	0.17	1.26 *	0.17	1.32 *	0.18
9	1.22 *	0.16	0.95	0.11	1.05	0.13
10	1.17 *	0.16	0.93	0.09	1.34	0.15
1-10	-0.41		1.09		-0.10	

Chapter III

Trading Aggressiveness and its Implications for Market Efficiency

1 Introduction

This paper analyzes the influence of abnormal trading aggressiveness on the speed of price adjustment after earnings announcement releases. An investor is trading aggressively if he prefers quicker execution of his limit order over a better execution price. Such a situation is most likely to arise when investors expect immediate changes in the value of a stock, and therefore the speed of order execution is of primary importance. Two recent examples of abnormal trading aggressiveness on the market are the Flash Crash (May 6, 2010), when the Dow Jones Industrial Average index (DJIA) dropped by more than 1,000 points in less than one hour, and the release of erroneous information about the United Airlines bankruptcy from Bloomberg on September 8, 2008. In both of these events, traders switched to the most aggressive orders on the market as soon as they realized that they were better off by having their orders executed immediately, even at inferior prices.[1] Waiting for execution at the best quoted price in such moments is costly, because the best quote might change by a large amount within the next second.

Quick action also pays off in periods immediately following corporate information releases. New information makes investors revise their beliefs, which leads to a subsequent increase in trading aggressiveness. What implications does abnormal trading aggressiveness have on the speed of price adjustment after a corporate information release? A higher execution speed of an aggressive order ensures that a larger portion of this order is executed within a given time interval, as compared to a standard limit order. Thus, aggressive trading enables quicker price changes over relatively short time intervals. Quicker changes are beneficial if aggressive trading is informative and, thus, pushes the stock price more quickly towards its new equilibrium value. In contrast, if aggressive trades are mostly submitted by uninformed traders, who are just as likely to buy or to sell, then quick price changes in different directions might increase intraday volatility and the probability of price overshooting. An abnormal increase in intraday volatility may slow down the stabilization of a price at its new equilibrium value.[2]

Empirical results of this paper show that, on average, the negative effect of increased trading aggressiveness dominates. Abnormal trading aggressiveness is especially harmful for stocks with low liquidity levels, because the adjustment times of illiquid stocks with abnormal trading aggressiveness are significantly longer compared to the time period before aggressive orders became available. However, the negative effect declines if aggressive trades are more informative and move the stock prices in the correct direction.

[1] As documented by Chakravarty et al (2011b) for the Flash Crash day and Lei and Li (2010) for the false announcement of the United Airlines bankruptcy.

[2] Fleming and Remolona (1999) analyze a two-stage adjustment process in the U.S. Treasury market upon arrival of macroeconomic announcement releases. They identify the first stage as an almost immediate price reaction with a reduction in trading volume. The second "stabilization" stage lasts for more than an hour with abnormal price volatility, trading volume, and bid-ask spreads.

I measure trading aggressiveness as a proportion of the total volume that is executed through aggressive orders within a particular interval of time. To differentiate aggressive orders from non-aggressive ones, I use a new order type, called an intermarket sweep order (ISO), that represents the most aggressive trading instrument on U.S. equity markets. If an order is marked as an ISO, a trading venue has to give this order an immediate execution - even if this execution leads to a trade-through of the best quoted price.[3] Since an ISO is marked as such at the time of its submission, I can *ex post* observe investor preferences for the speed of order execution.

Earnings announcements are the most natural choice for this study, because they represent the most common type of information release for any stock. Further, earnings announcements are released regularly for a broad cross-section of firms in the market in the short period of time since ISOs became available in October 2007.

The major findings of this paper are as follows. First, I show that ISO trades have higher intraday price impacts than non-ISO trades and the difference in the price impacts between ISO and non-ISO trades is larger for illiquid stocks. The reason is that illiquid stocks have a thin order book with a lower number of shares quoted at each price, and, therefore, aggressive orders can move the prices of these stocks more easily. Further, I investigate the intraday changes in trading aggressiveness on earnings announcement days and document a significant 15% increase in the proportion of ISO volume in the first 15 minutes after an announcement release. Afterward, the proportion of the volume traded with aggressive orders steadily decreases, but it continues to deviate significantly from its base level until the end of the trading day. Additional analysis shows that the post-announcement jump in trading aggressiveness can be explained by a significant increase in the proportion of the sell volume of ISOs after the negative earnings surprises.

[3] Chakravarty et al (2010) provides an excellent overview of ISO characteristics and their use on the current financial markets.

This result suggests that investors trade more aggressively when confronted with negative news. For positive news releases, ISOs are largely uninformative in the first two hours after announcement releases with large increases in the proportions of ISO volume in both trading directions.

Further, this paper establishes the link between increases in investors' trading aggressiveness and the speed of price adjustment after earnings announcement releases.[4] The length of the price adjustment period is defined as the number of five-minute intervals from an announcement release until the interval in which the realized volatility of the one-minute midpoint returns is no longer abnormal.[5] For identification, I use a difference-in-differences approach that controls for differences in the speed of price adjustment of the stocks in the pre-Regulation National Market System (Reg NMS) period, when aggressive orders were not yet available.

The results of the difference-in-differences analysis suggest that the relation between the changes in trading aggressiveness and the speed of price adjustment is rather weak for liquid stocks, but exhibits a pronounced U-shape for stocks with low liquidity levels. Since liquid stocks have a deep limit order book, the adverse effects from increases in trading aggressiveness do not have a significant impact on the adjustment process of these stocks. By contrast, high increases in aggressive trading significantly slow down price adjustment of illiquid stocks: doubling the proportion of ISO volume on an announcement day results in a 78-minute delay in the adjustment of illiquid stocks relative to its benchmark level of

[4] Note that only changes in trading aggressiveness, as opposed to its levels, are suitable for the analysis of its effect on the speed of price adjustment. The reason is that the adverse effect on intraday volatility, and thus on the price stabilization process, only arises if the proportion of aggressive trades actually increases. By contrast, if trading aggressiveness is high, but stays at its pre-announcement level, there is no additional increase in the intraday volatility of a stock. In fact, the speed of price adjustment might be quicker for this stock than for a stock that experiences a rise in its intraday volatility due to the increased use of aggressive orders on the announcement day.

[5] I prefer the volatility criterion over measuring abnormal returns or the serial correlation in returns, because it covers both stages of price adjustment: the initial price reaction and the subsequent stabilization period.

4 hours and 40 minutes when the level of trading aggressiveness remains constant. This overall negative effect of aggressive trading is more pronounced after positive earnings surprises, when aggressive trading is largely uninformative. After negative earnings surprises, when the majority of aggressive trades is submitted in the direction of the earnings surprise, the impact is less pronounced and no longer statistically significant. Interestingly, large decreases in trading aggressiveness can be even more harmful for illiquid stocks. With low trading aggressiveness, price changes of illiquid stocks are not sufficiently quick, which slows down the adjustment process.

This paper contributes to the on-going debate on the efficiency of financial markets. Specifically, it examines how the investors' trading process directly influences price adjustment. There is a vast amount of literature that investigates investor trading around information releases.[6] Surprisingly, the overlap between this literature and the price adjustment literature is relatively small.[7] To the best of my knowledge, only two studies exist that examine the relation between the trading process and the speed of price adjustment after information releases. Woodruff and Senchack (1988) find that stocks with large positive earnings surprises experience quicker adjustments than stocks with large negative earnings surprises. They further show that a large number of smaller trades occurs after positive earnings surprises and relatively few but larger trades after negative earnings surprises. However, they do not establish the causal relation between differences

[6]One of the first studies to analyze investor trading around information releases is Lee (1992), which examines differences in the clustering of small and large trades around earnings announcements. Recent studies examine the informativeness of institutional (Ali, Klasa, and Li (2008)) and individual trades (Kaniel, Saar, and Titman (2008), Kaniel et al (2012)) around earnings announcements. Also, Sarkar and Schwartz (2009) document a post-announcement increase in two-sided trading, especially when the news surprises are large.

[7]Prior empirical studies on the speed of price adjustment investigate the duration of the adjustment process for different announcement types (Patell and Wolfson (1984) for earnings announcements; Ederington and Lee (1993) for macroeconomic releases; Busse and Green (2002) for releases of analysts' opinions; Brooks, Patel and Su (2003) and Coleman (2011) for unanticipated events) and relate it to the degree of earnings surprise (Jennings and Starks (1985)), firm and report characteristics (Defeo (1986), Damodaran (1993)), timing of an announcement (Francis, Pagach, and Stephan (1992)), and differences in market structures (Greene and Watts (1996), Masulis and Shivakumar (2002)).

in trading processes and the speed of price adjustment. Ederington and Lee (1995) examine the short-run dynamics of price adjustment in interest rate and foreign exchange futures markets. They find that prices adjust in a series of small price changes, and not in few large price jumps, which also suggests that there is intensive trading immediately after an information release. Whereas both of the previous studies concentrate mainly on trade size and transaction frequency, the main focus of this paper is the effect of investors' trading aggressiveness, disclosed by their preference for the speed of order execution, on the price adjustment process.

Following the pioneering work of Chakravarty et al (2010), this paper also sheds light on the use and characteristics of intermarket sweep orders on the current financial markets. In addition to Chakravarty et al (2011a), who analyze changes in market breadth and daily trading aggressiveness on an announcement day, I investigate intraday changes in the use of aggressive orders. Further, I examine the informativeness of ISO trades by testing whether the proportion of ISO volume increases more in the direction of the earnings surprise right after an announcement release.

The remaining part of the paper is organized as follows. Section 2 provides details of the relevant institutional framework and develops the main hypotheses of this study. Section 3 describes the construction of the data set. Section 4 analyzes the use and characteristics of aggressive orders in the base period and around earnings announcements. Section 5 investigates how abnormal trading aggressiveness affects the speed of price adjustment after an announcement release. Section 6 briefly concludes.

2 Institutional Background and Hypothesis Development

2.1 Overview of Intermarket Sweep Orders

On August 29, 2005, the Securities and Exchange Commission (SEC) adopted a new set of rules, known as the Regulation National Market System (Reg NMS). The SEC designed the new regulation to modernize US equity markets and to promote their efficiency. Due to technical difficulties with the implementation of several changes required by this new regulation, markets achieved full compliance with Reg NMS first in October 2007.[8]

The most important change introduced by Reg NMS is the adoption of the Order Protection Rule (Rule 611) that requires execution of any incoming order at the best available price. The best available price is defined as the lowest ask or the highest bid price quoted over the previous one second among all equity trading venues in the US. If the trader sends a limit order to a venue that does not currently quote the best price, then this venue has to re-route the order to the venue with the best price. The Order Protection Rule caters mainly to the interests of retail investors. The best-price execution guarantee increases the retail investors' confidence and decreases their search costs for the best available price. Further, protection of the best-priced limit orders minimizes the investors' transaction costs, because the number of trade-throughs automatically declines.[9]

Although appealing to retail investors with a long-term investment horizon, the Order Protection Rule is less attractive for short-term and institutional investors. Suppose an institutional investor wants to sell 3,200 shares at a price not lower than \$10.67. For simplicity, suppose only two trading venues exist: A and B. Figure III.1 shows the bid

[8]See Regulation NMS, SEC Release No. 34-51808.

[9]A trade-through occurs when the best available bid or the best available offer quotation is ignored, or in other words, "traded-through".

Figure III.1: **Bid Side of Limit Order Book**

Price	Shares A	Shares B
\$10.75	500	
\$10.73		500
\$10.70	2,000	
\$10.67	3,500	
\$10.66		3,000

sides of limit order books in two venues. The first column shows the currently quoted bid prices, the second column indicates the number of shares available at each price for venue A and the third column displays the corresponding number of shares for venue B.[10] Assume that an investor submits his order to A. However, A's depth at the best available quote, \$10.75, is too small for the order to be fully executed: only 500 shares can be sold at the best price. Venue B quotes the next best bid price at \$10.73. Under the Order Protection Rule the outstanding part of the order (2,700 shares) has to be re-routed by venue A to venue B. After an execution of 500 shares at \$10.73 on venue B, the remaining part (2,200 shares) has to be re-routed to A again. However, re-routing takes time and the best bid offer can change while the order is being re-routed. Thus, the execution of large-sized orders under the Order Protection Rule takes longer and might end up at an inferior average price as compared to having the whole order executed at a single venue.

To avoid such situations, the Order Protection Rule makes an exemption for a specific order type, an intermarket sweep order (ISO). An ISO is a marketable limit order (Immediate-or-Cancel) and it provides an opportunity for institutional investors to trade large blocks quickly. Specifically, when an ISO arrives at a particular trading venue, it is executed as if this venue stands alone, ignoring the other venues. An ISO simply walks down the limit order book until either the order is completely filled or the limit price of

[10]Note that total depth at each price is equal to the sum of the number of shares quoted at this price and the cumulative number of shares quoted above this price for the bid side of the book (or, equivalently, below this price for the ask side of the book). Thus, total depth for $P = \$10.70$ on trading venue A equals 2,500 shares (500 shares quoted at \$10.75 and additional 2,000 shares quoted at \$10.70).

the order is reached (the outstanding part of an ISO is then canceled). Importantly, there is no re-routing requirement, even if some parts of the order are executed at inferior prices as compared to the best national bid offer. To comply with the principles of the Order Protection Rule, an investor submitting an ISO is obliged to send additional limit orders, also marked as ISOs, with the same limit price to all other venues quoting the stock. The total size of these additional ISOs should equal the total number of shares available at quotes superior to the limit price at the time of the submission of the ISO. Therefore, an ISO represents a series of marketable limit orders with the same limit price sent across all trading venues quoting the stock. The total size of all simultaneously sent ISOs equals the total number of shares available at prices better than the indicated limit price plus any additional number of shares at the limit price.[11]

Suppose that an institutional investor wants to sell another 3,200 shares at the limit price of \$10.67 with an ISO. Thus, the investor sends two limit orders, marked as ISO, with the same limit price of \$10.67 simultaneously to both venues, A and B. The total size of the order is then optimally split between the two venues: an ISO sent to A has the total size of 2,700 and an ISO sent to B has a total size of 500. Since trading venues can recognize both orders as ISOs, they do not re-route either of them. Both venues instantaneously execute ISOs against the outstanding orders up to a limit price of \$10.67. An investor instantly sells 3,200 shares and the new best price drops to \$10.67 on venue A. Note that the institutional investor satisfies its obligations with respect to the Order Protection Rule because the investor has extracted all available shares that are quoted at prices better than \$10.67 from both venues.

[11] Paragraph (b)(30) of Rule 600 gives a formal definition of an intermarket sweep order as a limit order that satisfies the following requirements: (1) when routed to a trading venue, the limit order is identified as an intermarket sweep order; and (2) simultaneously with the routing of the limit order identified as an intermarket sweep order, one or more additional limit orders, as necessary, are routed to execute against the full displayed size of all protected quotations with a superior price.

2.2 Hypothesis Development

Speed of price adjustment. Prior empirical studies document an increase in trading aggressiveness, measured as the proportion of ISO volume, following companies' information releases.[12] What implications does an increased use of ISOs have on the speed of price adjustment? With their ability to sweep liquidity almost instantly up to a particular price level, ISOs on average produce a higher change in the best quoted bid/ask price (the price impact) *within a given trading interval*, as compared to the standard limit order. To illustrate this point, assume that if an investor trades one share, then the best quoted bid/ask price changes by σ. In other words, *the price impact per share traded* equals σ. The trading day consists of a finite number of T intervals. During a given interval *t,* an order can either be submitted to one trading venue (or several trading venues in the case of an ISO), be (fully or partially) executed at one of the venues, or be re-routed from one venue to another.

Suppose that a standard limit order and an aggressive limit order of an identical size s and with an identical limit price are submitted in t. In *t+1,* they arrive to the market and are ready for execution. Since the aggressive order is split at t across different exchanges as a series of limit orders, these exchanges do not need to search for the best quoted prices. Instead, all of the ISOs get immediate executions across all exchanges and the total size s of the aggressive order is executed at *t+1.* The full price impact of the aggressive order, $\sigma \cdot s$, is then realized within one trading interval *t+1.*

There are three possible execution scenarios for the standard limit order:

1) If the investor sends the limit order to the exchange with the best price quotes and the number of shares available at the best quotes is greater than *s,* then the venue fully

[12] Chakravarty et al (2011a) report an increase in the proportion and volume of ISOs after earnings announcements. Lei and Li (2010) document the increased use of ISOs after the erroneous information on a bankruptcy announcement of the United Airlines on September 8, 2008.

executes the limit order. In this case, the limit order also produces the full price impact, $\sigma \cdot s$, within *t+1.*

2) If the investor sends the limit order to the exchange that does not quote the best price, it searches for the exchange with the best available quotes and re-routes the order to that exchange. No shares are executed and the price impact for *t+1* equals 0.

3) If the investor sends the limit order to the exchange with the best price quotes, but the number of shares available at the best quotes, y, is smaller than s $(y < s)$, then the exchange only executes y shares and re-routes the outstanding part of the order, $s - y$, to another exchange with the next best available price. The price impact within *t+1* equals $\sigma \cdot y < \sigma \cdot s$.

Dependent on the liquidity of the stock, some scenarios are more prevalent than others. For example, for liquid stocks, the first scenario probably dominates, because there is large depth at each price level for these stocks. For illiquid stocks with a low number of shares available at each price, the last scenario occurs more frequently. However, on average, the price impact of a standard limit order is lower than the price impact of an aggressive order within *t+1*, because the full price impact does not get necessarily realized within one trading interval.

Consider the previous numerical example. Figure III.2 summarizes the number of shares executed and the price impact of both orders in each trading interval. Price impact is calculated as the difference between the best bid price prior to the execution and the best bid price after the execution.

Note that in *t=1* the price impact of the standard order equals only \$0.02 when the venue executes the first 500 shares at the best available price, whereas the price impact of the aggressive order, \$0.08, is fully realized, because the total size of the order (3,200 shares) is immediately executed at both venues. If the limit order book does not change

Figure III.2: **Price Impact Interval-by-Interval: Limit Order versus ISO**

		Limit order				**ISO**			
t	Action	Shares executed	Best Price before	Best Price after	Price Impact	Shares executed	Best Price before	Best Price after	Price Impact
0	Submission								
1	Execution	500	\$10.75	\$10.73	\$0.02	3,200	\$10.75	\$10.67	\$0.08
2	Re-routing								
3	Execution	500	\$10.73	\$10.70	\$0.03				
4	Re-routing								
5	Execution	2,200	\$10.70	\$10.67	\$0.03				
	Total	3,200			\$0.08	3,200			\$0.08

over time, the cumulative price impact of both orders is the same after $t{=}5$. The standard limit order just takes a longer time to execute because of the re-routing between the two different exchanges in search of the best execution price.

Since an aggressive order has on average a higher price impact within a given trading interval, the higher proportion of aggressive orders in the order flow subsequent to an announcement release enables quicker price movements within short time intervals. Quicker price movements are beneficial for price adjustment if the majority of traders are informed in the following sense: they have already correctly processed new information and know the true equilibrium value of a stock. They can then purchase the stock if it is undervalued or sell the stock if it is overvalued, pushing the stock price towards its new equilibrium value. In this case, an increase in trading aggressiveness might speed up price adjustment due to a quicker movement of the price in the correct direction.

However, quicker price movements might also slow down the adjustment process if the majority of aggressive traders are uninformed, in the sense that they do not observe the true equilibrium value of a stock and can only form their subjective beliefs about it. Some uninformed investors will purchase the stock and push the price temporarily upwards, whereas the other uninformed investors will sell the stock and push the price downwards. As the stock price continuously experiences quick upward changes, followed by quick downward changes, it might be constantly over- and undershooting its true equilibrium value. Thus, large increases in aggressive trading by uninformed investors with heterogeneous beliefs produce additional abnormal volatility and make the stabilization of a price at its new level harder.

Overall, the positive effect of quicker price movements towards the new equilibrium value should dominate in situations with the higher proportion of informed traders, whereas the negative effect of increased intraday volatility should dominate when the majority of aggressive traders are uninformed and have heterogeneous beliefs about the true value of the stock.

Liquid versus illiquid stocks. Does the influence of trading aggressiveness on the speed of price adjustment differ for stocks with high and low liquidity? Since illiquid stocks have a lower depth of the limit order book at each price level (their limit order book is "thinner"), *the price impact per share traded* is overall higher for these stocks.

Importantly, *the difference in price impact within a given trading interval* between an aggressive order and a standard order should be higher for an illiquid stock than for a liquid stock. The effect of the aggressive order should be larger on the price of an illiquid stock, because a larger number of shares is executed within a given trading interval and, additionally, the price changes by a larger amount per each traded share. Basically, the effect of a thinner book for illiquid stocks is additionally multiplied with the effect of faster trading with aggressive orders, and an aggressive order thus goes faster through a thinner limit order book. Therefore, I expect the positive and negative effects of increased aggressive trading on the speed of price adjustment to be more pronounced for illiquid stocks.

3 Data and Sample Construction

3.1 Earnings Announcements Sample

The data source for the earnings announcements is the Institutional Brokers Estimate System (I/B/E/S) database. I collect announcements between January 2006 and December 2009 that happen within the trading hours of US equity trading exchanges (9:30 a.m. to 16:00 p.m. EST).[13] Each record has an exact date and a time stamp (up to a minute). Further, I require that each firm exists in the intersection set of I/B/E/S and CRSP. Table II.1 provides details of the sample construction.

[Insert Table II.1 approximately here]

The initial sample comprises 10,334 announcements by 3,361 firms. I omit 647 announcements by 88 firms for which a stock is not traded on the announcement day, and another 967 announcements by 267 firms for which intraday transaction data are not available. Following Jegadeesh and Titman (1993), I further eliminate very illiquid stocks for which the closing price is less than $5 at the beginning of the base period. The reasoning behind this elimination is that the large deviations in intraday volatility of these stocks on their announcement days might be biased upwards by the virtue of their low price levels. Excluding days with multiple announcements and announcements with less than 40 days of trading data previously available leaves 5,944 announcements by 2,307 firms.[14] To ensure that the differences in results between the pre-Reg NMS period and the post-Reg NMS period are not driven by differences in the characteristics of the underlying stocks, I require that each stock in the sample has at least one announcement in

[13] I use earnings announcements from the pre-Reg NMS period to form the control group of stocks, needed for the difference-in-differences analysis.

[14] I require at least 40 days of trading data to be available prior to an announcement, because I use these days to calculate values in the base period that consists of days [-38;-2].

each period. The final sample consists of 3,613 announcements by 675 firms, out of which 1,818 announcements happen prior to the adoption of Reg NMS and 1,795 afterward.

One of the requirements for the data set's construction is that an announcement should happen within trading hours. Out of the 6,536 firms for which I/B/E/S reports earnings announcement releases over 2006 to 2009, 3,175 firms do not announce within trading hours. The remaining 3,361 firms constitute the initial sample out of which 58 firms release their earnings information exclusively within trading hours and 3,303 announce both within and outside trading hours. Overall, firms announcing both within and outside trading hours are smaller than the firms announcing only outside trading hours, with the median market capitalization of $239 million and $482 million, respectively (results not tabulated). Even though there is a bias towards smaller firms, the initial sample still covers more than 50% of all of the firms with earnings announcement releases. Table III.2 summarizes the main firm characteristics in the final sample and the initial sample. All variable definitions are in the appendix.

[Insert Table III.2 approximately here]

The median firm in the final sample has a larger market capitalization of $256 million, as compared to $239 million of the median firm in the initial sample. Since I exclude small and illiquid stocks with closing prices below $5 from the final sample, the median firm in this sample is more liquid than the median firm in the initial sample, as measured by the daily relative spread and the daily Amihud measure.[15]

3.2 Intraday Transaction and Quote Data

The source for the intraday transaction data is the NYSE Transaction and Quote database (TAQ). In the first step, I extract data on the number and trading volume ex-

[15] The Amihud (2002) measure is defined as the ratio of the daily absolute return to the dollar trading volume on that day: $Illiq_{i,t} = |Ret|_{i,t} / Dollar\,Volume_{i,t}$.

ecuted with the ISOs and standard limit orders (non-ISOs) for each stock in the final sample on their announcement days as well as 40 trading days preceding the announcements. The ISOs are marked with the code "F" in the condition field of the TAQ database. The base period consists of 39 trading days preceding an announcement day, starting on day -40 and ending on day -2. I collapse transaction-by-transaction data over 15-minute intervals and extract the number of trades and traded volume in each 15-minute interval separately for the ISOs and non-ISOs. I use a modified Lee and Ready's (1991) algorithm to identify the direction of a trade, with the bid (B_t) and the ask quote (A_t) that prevail one second before the trade takes place.[16]

The quoted relative spread for a transaction is defined as the difference between the corresponding ask and the corresponding bid, scaled by the midpoint price ($RelSpr_t = (A_t - B_t)/Q_t$). The midpoint price ($Q_t$) is calculated as the average of the prevailing bid and ask quotes ($Q_t = \frac{A_t+B_t}{2}$). I set the observations with $RelSpr > 0.5$ to the missing values. The effective relative spread of each transaction is calculated as twice the absolute difference between the transaction price and the midpoint price, scaled by the midpoint price ($EffSpr_t = 2\left|P_t - Q_t\right|/Q_t$). Observations with $EffSpr > 0.5$ are also set to missing values. The price impact of each trade after five minutes is defined as $PrcImp_t = 2\left|Q_{t+5} - Q_t\right|/(Q_t \cdot w_t)$ where Q_{t+5} represents the midpoint price for a stock after five minutes (300 seconds), and w_t is the size of the transaction (in shares). Note that this measure is similar to the daily Amihud measure, but it is calculated on an intraday basis.

The intraday one-minute returns are computed from the closing midpoint price for each minute from the TAQ Consolidated Quotes database. Closing midpoints better serve the

[16] Henker and Wang (2006) consider this procedure to be more appropriate compared to the classical Lee and Ready (1991) five-second rule. Bessembinder (2003) tries zero- to thirty-second delays in increments of five seconds and does not find any differences in the results.

purposes of the price adjustment analysis, because they exclude the bid-ask bounce that is present in the transaction prices.

4 Trading Aggressiveness around Earnings Announcements

Definition of Trading Aggressiveness. I define trading aggressiveness as the proportion of total volume traded with ISOs within a particular time interval (the proportion of ISO volume, $\%ISO\,Volume$). Daily trading aggressiveness is the proportion of daily volume that is executed through ISOs. Intraday trading aggressiveness is measured as the proportion of ISO volume over a respective time interval within a day, for example 15 minutes, 1 hour etc.[17] In the remainder of the paper I use the terms "trading aggressiveness" and "trading with aggressive orders" interchangeably.

The median proportion of ISO volume in my sample is 36%. However, the variation is quite significant with 22% of the volume traded with ISOs for firms in the lowest decile and 56% in the highest decile (not tabulated).

Trading characteristics of aggressive orders. Panel A of Table III.3 summarizes the differences in the characteristics of ISOs and non-ISOs in the base period and in the hours immediately following the release of an earnings announcement.

[Insert Table III.3 approximately here]

Columns 1 and 2 display the bootstrapped means for the ISOs and non-ISOs from the base period, correspondingly.[18] Columns 3 and 4 report the cross-sectional mean of the

[17]The proportion of the total number of trades executed with ISOs is highly correlated with the proportion of ISO volume (correlation coefficient of 93%). None of my results is materially affected if I use the proportion of ISO trades to measure trading aggressiveness.

[18]Since the base period is rather short (38 days) and proportions of the number of trades and of their volume are not normally distributed, I estimate their means with a bootstrap procedure. Specifically, I draw with replacement one observation from the base period that happened between the time of an

respective variables starting from an announcement release until the end of the trading day. Column 5 displays the difference-in-differences (or simply the difference between the base period and the event day for variables, calculated as proportions) and tests their significance with a standard t-test.

The proportion of trades, executed with aggressive orders, $\%Trades$, equals 40.8% in the base period. It increases significantly by 4.6% in hours immediately following an information release. The proportion of the total volume executed with aggressive orders, $\%Volume$, (37.8%) is lower than $\%Trades$ in the base period, but it also significantly increases to 42.4% on announcement days. The reason for the lower proportion of ISO volume is the overall smaller size of the ISOs. The average size of an ISO in the base period equals 176 shares, as compared to 256 shares for a non-ISO.[19] Overall, the ISO characteristics in my sample are similar to the ISO characteristics in the Chakravarty et al (2010) sample.[20]

Interestingly, investors use ISOs approximately as much for purchases as for sales. The proportion of ISO purchase volume, $\%Purchases$, and the proportion of ISO sales volume, $\%Sales$, both increase significantly by around 4% on announcement days. Further, the effective relative spread, $EffSpr$, is marginally lower for ISOs in the base period, 1.73%, as compared to 1.82% for non-ISOs. However, it does not differ significantly from the non-ISO effective spread on event days. As liquidity around information releases declines, all traders, including uninformed ones, become more aggressive, and the effective relative spread increases accordingly to the level of non-ISOs. The price impact of ISO

announcement release and the end of the trading day for each stock-announcement and repeatedly calculate the mean across all stock-announcements in this bootstrapped sample. I repeat this step for 1,000 bootstrapped samples.

[19]The size of an ISO is smaller, because the TAQ database does not record a cumulative size for all ISOs sent simultaneously across all exchanges, but rather the size of each individual order sent and executed on a particular stock exchange.

[20]The proportion of ISO trades is 46% and the proportion of ISO volume equals 41% in their sample. The average size of an ISO equals 178 shares and is also significantly smaller than the average size of a standard limit order.

trades, $PrcImp$, is higher than the price impact of non-ISOs, and even more so in hours following an information release (the difference-in-differences equals 0.11% and is statistically significant at the 5% level). This finding is important, because it provides the first supportive evidence for the assumption that ISO trades have a higher price impact within a given trading interval, as compared to non-ISO trades.

Next, I examine changes in the use of aggressive orders at the intraday level. Figure III.3 displays mean percentage deviations in the proportion of ISO volume throughout an announcement day. The deviations from the bootstrapped means are measured in 15-minute intervals relative to the 15-minute interval with an earnings announcement release (interval 0). The dashed line shows the 1% significance level for the mean percentage change in the proportion of ISO volume, which is equal to 3.8%.

[Insert Figure III.3 approximately here]

The proportion of ISO volume experiences a jump of up to 15% ($\%ISOVolume =$ 43.47%) in the first 15 minutes after an information release. Afterward, it steadily decreases, but does not drop below its 1% significance level of 3.8% until the end of the trading day.

The reasons for an increase in trading aggressiveness on an announcement day are twofold. First, investors have different rates of information processing. Those investors who are able to process new information more quickly try to exploit their advantage. The 15% jump immediately after a release indicates the increase in pressure from traders with quicker rates of information processing. Second, uninformed investors might also trade more aggressively because of the decreasing liquidity supply around earnings announcements. Chakravarty et al (2011a) provide empirical evidence in support of this explanation.

Intraday analysis of the effective relative spread and price impact. The results from Panel A of Table III.3 confirm that the ISO trades have an overall higher price impact within a given trading interval than the non-ISO trades. However, I expect the difference in the intraday price impact between the ISO trades and non-ISO trades to be higher for illiquid stocks, because an aggressive order goes faster through a thinner limit order book of an illiquid stock, which produces an even higher price change.

To investigate this hypothesis more closely, I report the intraday price impact of ISO trades in post-announcement hours separately for liquid and illiquid stocks (Panel B of Table III.3). The stock is classified as liquid if its daily quoted relative spread is above the median for all of the stocks in the sample in the base period, and it is classified as illiquid otherwise. The last line in Panel B of Table III.3 confirms this prediction, because the difference in the intraday price impact between the ISO and the non-ISO trades for illiquid stocks is higher than the corresponding difference for liquid stocks by 0.45% and is statistically significant at the 1% level. Note that investors trade illiquid stocks more aggressively in the post-announcement hours than liquid stocks, because the proportion of their volume traded with aggressive orders (43.4%) exceeds the proportion of ISO volume for the liquid stocks by a significant 2%.

Table III.4 additionally investigates differences in the effective relative spread and the intraday price impact between the ISO and the non-ISO trades in a multivariate setup. The main variable of interest is the *ISO,* which equals one for ISO trades, and zero otherwise. One observation represents a ten-minute trading interval for a stock. All models are panel OLS regressions and include firm-, year-, daytime- and weekday-fixed effects. In addition, I control for the inverse of the mean stock price in a ten-minute period, which is mechanically related to the two dependent variables; the total volume executed within a 10-minute trading interval; and the listing exchange of a stock.

[Insert Table III.4 approximately here]

The effective relative spreads of the ISO and non-ISO trades exhibit no significant differences in the base period as well as on announcement days, as captured by the indicator variable *ISO* and its interaction with the indicator variable *Event* that denotes the announcement day. These results are in line with prior univariate analyses and continue to hold if I additionally control for the liquidity of a stock with an indicator variable *Illiquid* (Model 2). All control variables have their expected signs.

In line with univariate findings, the intraday price impact is higher for the ISO trades in the base period and even more so on announcement days. However, the latter effect disappears if I add the indicator variable *Illiquid*, which means that an additional increase in the intraday price impact on announcement days is driven by illiquid stocks, consistent with the univariate results from Table III.3. After controlling for liquidity as well as other control variables, the additional intraday price impact of an aggressive order constitutes 0.187% for an illiquid stock, which is statistically and economically significant (e.g., 3.74 cent for an average illiquid stock with a price of $20 and a quoted spread of 96.4 cent).

Informativeness of ISO trades after earnings announcements. Prior results show that trading aggressiveness increases significantly in the hours following earnings announcement releases. The next step is to analyze whether the increased use of aggressive orders in post-announcement hours represents informed or uninformed trading. Recall that the effect of trading aggressiveness on the speed of price adjustment depends on the informativeness of the ISO trades. The effect should be positive (higher trading aggressiveness speeds up price adjustment) if informed investors submit the majority of the ISOs and trade in the direction of the new equilibrium value. The effect should be negative (higher trading aggressiveness slows down price adjustment) if the ISOs are mostly submitted by uninformed investors who are just as likely to buy or sell a stock.

I analyze the informativeness of ISO trades by testing whether the proportion of ISO volume increases more in the direction of the earnings surprise. For positive earnings surprises, aggressive trading is more informative if the change in the proportion of ISO buy volume ($\Delta ISOBuyVol$) is overall higher than the change in the proportion of ISO sell volume ($\Delta ISOSellVol$). For negative earnings surprises, the opposite relation should hold. I measure an earnings surprise as a 24-hour stock return after an announcement release.[21]

If prices overshoot, then trading in the opposite direction of the earnings surprise is also informative. For this reason, I additionally classify trades on an intraday basis: I define an ISO trade as informative if it is buyer-initiated and the current price is below the equilibrium price, or if it is seller-initiated and the current price is above the equilibrium price. The proxy for an equilibrium price is the price in 24 hours after an announcement release, which is reasonable to assume, because the short-term price adjustment happens on average within 2.5 hours of an announcement release (as the next section documents). I find that after positive earnings surprises 80.7% of all informative trades are buyer-initiated and after negative earnings surprises 86.8% of all informative trades are seller-initiated. None of my results is materially affected if I define informativeness of an ISO trade on an intraday basis.

In the first step, I examine the imbalance between the proportions of ISO buy and ISO sell volumes on announcement days. Figure III.4 displays both proportions for each 15-minute event interval relative to the 15-minute interval with an earnings announcement release (interval 0). The dashed line marks the event interval 0.

[21]The results do not differ materially, if CAR(0;1) or I/B/E/S analyst earnings forecasts are used to measure earnings surprises. In the case of analyst earnings forecasts, I lose around 50% of observations in my final sample due to missing data in I/B/E/S.

[Insert Figure III.4 approximately here]

Panel A shows the imbalance in the proportions of ISO volumes for positive earnings surprises. Interestingly, the proportions of the ISO sell and ISO buy volumes increase in the first hour after an announcement release. The proportion of the ISO buy volume begins to dominate only after two hours. These preliminary results suggest that the majority of ISO trades are mostly uninformative in the first hour after a positive earnings announcement release. Although investors realize that higher earnings are good news, their initial opinions might diverge on how good this news is. As time passes by, traders correctly process the information from an announcement release and ISO trades increase their informativeness. The situation is different for negative earnings surprises (Panel B). The proportion of the ISO sell volume experiences a jump of up to 3% (from 47% to 50%) in the first 15 minutes after an announcement and significantly dominates the proportion of ISO buy volume for at least three hours after an announcement release. Thus, investors react quickly to the negative news and increase their aggressiveness on the sell side almost immediately.

Table III.5 examines the informativeness of the ISO trades separately for the subsamples of liquid and illiquid stocks. In addition to the direction of the earnings surprise, I differentiate between large and small surprises. An earnings surprise is defined as large if a 24-hour stock return is above its median for positive earnings surprises and below its median for negative earnings surprises. The first column shows the number of hours after an announcement release. The remaining columns report the difference in means between the increases in the proportion of the ISO buy and ISO sell volumes for the corresponding hour:

$$\Delta = \Delta_{Buy} - \Delta_{Sell},$$

where $\Delta_{Buy} = \%ISOBuyVol_{Event} - \%ISOBuyVol_{Base}$, and $\triangle_{Sell}$ is calculated in a similar way.

[Insert Table III.5 approximately here]

On average, investors increase their trading aggressiveness in the predicted direction: they increase the proportion of the ISO buy volume by a larger amount if an earnings surprise is positive ($\Delta > 0$), and by a smaller amount if it is negative ($\Delta < 0$). As expected, the differences in proportions are higher for larger earnings surprises.

Consistent with Figure III.4 (A), the ISO trades are quite uninformative in the first hour after a positive announcement release for both liquid and illiquid stocks. Over time aggressive trading becomes more informative, but none of the coefficients is statistically different from zero. For large positive surprises, an increase in the proportion of the ISO buy volume is on average higher and becomes statistically significant at the 10% level for liquid stocks four hours after an announcement release. For negative earnings surprises, the ISO trades are largely uninformative for liquid stocks, but they are strongly informative for illiquid stocks for up to five hours after an announcement release. All differences are negative and significant either at the 5% or the 1% levels. These findings suggest that a significant jump in the proportion of ISO sell volume immediately after an announcement release, observed in Figure III.4 (B), is mainly driven by an increase in the aggressiveness of informed traders of illiquid stocks.

Overall, even though investors increase their trading aggressiveness mostly in the correct direction, ISO trades are largely uninformative for positive earnings surprises and are strongly informative for negative earnings surprises, but only for the subsample of illiquid stocks.

5 Trading Aggressiveness and the Speed of Price Adjustment

How does an increase in trading aggressiveness after an earnings announcement release influence the speed of price adjustment to the new equilibrium value? An increase in trading aggressiveness by traders with quicker rates of information processing might increase the speed of the initial price reaction, by pushing the price more quickly towards its new equilibrium value. However, if the majority of the aggressive traders are uninformed, because they cannot predict the new equilibrium value, their increased trading aggressiveness might also prolong the subsequent stabilization stage and unnecessarily increase the post-announcement intraday volatility. Figure III.5 provides evidence in support of both statements. Panel A shows that stocks with higher increases in trading aggressiveness on announcement days experience larger jumps in their cumulative absolute returns during the first minutes after the information releases. However, these stocks also have higher increases in their intraday volatilities, which persist up to four hours after the announcement releases (as reported by Panel B). This section examines which of these two countervailing effects dominates.

The definition of the end of the price adjustment process. The speed of price adjustment can be theoretically measured as the difference in time between an announcement release and the time when the price reaches its new equilibrium value. Since the new equilibrium price level is not observable, I have to empirically determine the time period when the price ends its adjustment process. I consider that the price ends its adjustment process if the intraday volatility returns to its pre-announcement level. Prior studies by Patell and Wolfson (1984) and Jennings and Starks (1985) analyze post-announcement abnormal returns and abnormal serial correlations in price changes, in addition to abnormal volatility. However, the volatility criterion is more appropriate for this study, because it captures both stages of price adjustment: the initial price reaction as well as the subsequent period of price stabilization.[22]

Andersen et al (2001) show that the realized variance, calculated as the sum of the squared high-frequency returns over a particular time interval, represents the most unbiased and efficient estimator of daily as well as intraday volatilities. As illustrated by Martens and van Dijk (2007), the realized variance is also robust in the presence of infrequent trading and non-trading intervals. I calculate the realized volatility as the square root of the sum of the squared one-minute closing midpoint returns within each five-minute interval according to the following formula:

$$RV_{ti} = \sqrt{\sum_{j=1}^{5} (log\, C_{ti,j} - log\, C_{ti,j-1})^2},$$

where $C_{ti,j}$ represents the closing midpoint of a minute j within a five-minute interval i on day t. Further, I use the non-parametric test, proposed by Smith et al (1997), to compare the realized volatility within each five-minute interval during an announcement period (event days 0 to 2) with the realized volatility within the same five-minute interval in the base period (event days -40 to -3). Volatility is considered to be abnormal if it exceeds the 75% cutoff value in the same five-minute period calculated over days $[-40; -3]$. I also report the multivariate results for a more conservative definition of the abnormal volatility for which volatility is defined as abnormal if it exceeds the median volatility in the same five-minute period on the non-announcement days.[23]

[22]Patell and Wolfson (1984) and Jennings and Starks (1985) show that abnormal returns disappear in 5 to 15 minutes after an earnings announcement release. However, abnormal volatility of intraday returns persists for several hours and can even extend to the following trading day. The recent study by Brooks, Patel and Su (2003) provides similar evidence for unanticipated events with abnormal returns lasting for 15 minutes and abnormal variance for at least three hours after an event.

[23]The non-parametric test of Smith et al (1997) is more appropriate for high-frequency intervals, especially for illiquid stocks with thin trading. Prior studies by Patell and Wolfson (1984) and Woodruff and Senchack (1988) use parametric tests to compare distributional properties between announcement and non-announcement samples, because they use much longer one-hour sampling intervals.

To identify the end of the adjustment period, I order all intervals in the event window relative to the first five-minute post-announcement interval (interval 0). The ordering is consecutive for all days in the event window. For example, if an announcement time was 3 p.m. on day 0, then a period from 9:30 a.m. until 9:35 a.m. on the next day is numerated as period 13. I define the end of the adjustment period as the first interval for which the realized volatility is no longer abnormal.[24]

Univariate results. Panel A of Table III.6 displays the distribution of the length of price adjustment periods (in minutes) across the pre- and post-Reg NMS periods, separately for the subsamples of liquid and illiquid stocks. Thus, the median length of a price adjustment period for a liquid stock prior to the Reg NMS is 125 minutes after an announcement release. After the Reg NMS the median adjustment time for liquid stocks significantly decreases by 25 minutes as reported by the non-parametric Mann-Whitney test. Surprisingly, the median length of the price adjustment period for an illiquid stock (178 minutes or ca. 3 hours) does not change significantly in the post-Reg NMS period. The standard deviation of the length of the price adjustment period has even increased for these stocks, which suggests that the adjustment process has become quicker for some illiquid stocks in the post-Reg NMS period and slower for the others.

[Insert Table III.6 approximately here]

To investigate this issue more closely, I sort all announcements into terciles of changes in trading aggressiveness on announcement days (TA1 - TA3) in the post-Reg NMS period. The TA3 comprises announcements with the highest increases in trading aggressiveness

[24]Patell and Wolfson (1984), Brooks, Patel, and Su (2003), Masulis and Shivakumar (2002), analyze the post-announcement volatility in a univariate setup and test up to which interval it exhibits significant increases, but they do not explicitly define the length of the adjustment period. In addition to 5-minute intervals, I use 10-minute, 15-minute and 30-minute intervals to identify the end of the adjustment period. All results stay robust and are available upon request.

on event days, whereas the TA1 comprises stocks with the lowest increases.[25] To compare the change in the length of the adjustment period between two regulation regimes, I also assign "pseudo"-terciles of trading aggressiveness for all announcements in the pre-Reg NMS period. For this purpose, I calculate the median TA tercile for each stock after the Reg NMS and assign this TA tercile for all announcements of this stock that happen prior to the Reg NMS.[26] Panel B of Table III.6 displays the median length of the adjustment period (in minutes) for each TA tercile. The last two rows report the p-values of the Mann-Whitney test on the equality of medians across different terciles of trading aggressiveness.

Consistent with the previous results from Panel A, the price adjustment process is quicker in the post-Reg NMS period for each TA tercile in the sample of liquid stocks. However, there is no significant relation between an increase in trading aggressiveness and the speed of price adjustment for these stocks. By contrast, this relation has a striking U-shape in the sample of illiquid stocks, which gets even more pronounced in the post-Reg NMS period. Whereas the adjustment time for illiquid stocks in the TA1 group decreases in the post-Reg NMS period, it stays constant for stocks with moderate increases in trading aggressiveness (TA2) and even increases for stocks with excess trading aggressiveness in post-announcement hours (TA3). The 75-minute difference in medians between the second and the third tercile of trading aggressiveness in the post-Reg NMS period is also statistically significant at the 5% level.

[25] Recall that trading aggressiveness is measured as the change in the proportion of ISO volume traded after an announcement release relative to its mean in the base period ($\Delta ISOvol$). Although on average trading aggressiveness increases in hours after the release, changes in the proportion of ISO volume can take negative values for some stocks in the TA1 sample.

[26] Normally, there is almost no within-stock variation in liquidity and trading aggressiveness and I can correctly assign the "pseudo"-TA tercile for almost 90% of all of the stocks in my final sample. I omit the remaining 10% from the univariate analysis in Table III.6, but add these observations later in my multivariate analysis.

Figure III.6 further illustrates the relation between the mean length of the price adjustment period, measured in minutes, and the mean change in the proportion of ISO volume in the subsamples of liquid and illiquid stocks.

[Insert Figure III.6 approximately here]

Overall, the patterns are consistent with those reported in Table III.6. Large increases in trading aggressiveness slow down the speed of price adjustment for illiquid stocks, but seem to have no effect for liquid stocks. A more surprising finding is that decreases in trading aggressiveness have different implications for liquid and illiquid stocks. Higher decreases in trading aggressiveness are beneficial for liquid stocks, but they slow down the adjustment process of illiquid stocks.

Regression analysis. In this subsection, I estimate the negative binomial regressions with the length of the adjustment period as the dependent variable.[27] The identification strategy is a difference-in-differences analysis, because I am interested in the effect of changes in trading aggressiveness on the speed of price adjustment after controlling for the differences in the speed of price adjustment in the pre-Reg NMS period. For this reason, all of the regressions include earnings announcements from the pre- and the post-Reg NMS period. Since each stock in the final sample has at least one announcement in each of the regulation periods, the results are not influenced by differences in the underlying subsamples.

Models (1) to (3) of Table III.7 report the results for the benchmark definition of abnormal volatility: volatility is abnormal if the realized volatility lies in the upper quartile of the volatility distribution in the non-announcement period.

[27]Since the dependent variable is the number of five-minute intervals until the price ends its adjustment, it represents the count data. Thus, the sample consists of discrete values and is skewed to the right. Negative binomial regressions account for these problems and for the overdispersion present in the data.

[Insert Table III.7 approximately here]

The vector of the explanatory variables consists of the following variables: *Post Reg* that equals one if an announcement happens after the adoption of the Reg NMS, and zero otherwise; *Illiq* that equals one if the relative spread of the stock is above the median of all of the stocks in the sample, and zero otherwise; the interaction of the previous two variables, *Illiq* $\cdot$ *Post Reg;* the positive change in the proportion of the ISO volume for liquid stocks, $Liq \cdot |\Delta ISOvol|_{\Delta>0}$; the positive change in the proportion of ISO volume for illiquid stocks, $Illiq \cdot |\Delta ISOvol|_{\Delta>0}$; and the two corresponding variables for negative changes in the proportion of the ISO volume. I examine separately the influence of the positive and negative deviations in the proportion of ISO volume on the length of the adjustment period, because the relation between trading aggressiveness and the speed of price adjustment might be non-monotonic (as suggested by the univariate results).

The vector of the control variables consists of the mean turnover on event days $[0;2]$, *Turnover;* the average size of a firm that is calculated as the log of its market capitalization at the beginning of the base period, *LnMCap;* the stock market volatility on an announcement day that is measured by Chicago Board Options Exchange Market Volatility Index, *VIX*; and the absolute value of the earnings surprise, *Earn Surp.* I expect the coefficient for *Turnover* and *LnMCap* to be negative, because more frequently traded stocks should adjust more quickly to their equilibrium value. By contrast, higher stock market volatility on the announcement day and larger earnings surprises should slow down the adjustment process. I also add year-fixed effects and control for the weekday and the time of an announcement.

The benchmark value of the dependent variable equals the mean length of the price adjustment period for liquid stocks before the adoption of the Reg NMS (218 minutes or around 3.63 hours, according to Panel A of Table III.6). All of the coefficients should be interpreted as relative changes to the length of the price adjustment period from this benchmark value: for one unit change in the explanatory variable, the difference in the logs of the expected counts of the dependent variable is expected to change by β. For example, the coefficient of -0.20 on the *Post Reg* means that the length of the price adjustment period has on average decreased by $e^{-0.20} - 1 = -0.18$ or 18% from the benchmark value for liquid stocks in the Post-Reg NMS period (from around 3.63 hours to around 3 hours). As expected, the price adjustment period is significantly longer for illiquid stocks by approximately 42%. It does not differ significantly between the two regulation subperiods. All control variables, except *LnMCap,* are significant and have their expected signs.

Consistent with the univariate results, the relation between trading aggressiveness and the speed of price adjustment is rather weak for liquid stocks: negative changes in the proportion of the ISO volume contribute to quicker price adjustment, whereas positive changes do not play a significant role. For illiquid stocks, this relation continues to display a pronounced U-shape, even if I add other control variables. A 100% change in the proportion of the ISO volume slows down the adjustment process by 28% (ca. 78 minutes) for positive changes and by 36% (ca. 100 minutes) for negative changes from its mean value of 4 hours and 40 minutes. This change is statistically and economically significant.

Why do large decreases in trading aggressiveness have different implications for stocks with different levels of liquidity? Aggressive orders induce quicker price changes within a given time interval. Since liquid stocks are traded more frequently by definition, their prices adjust quickly, and thus, an additional increase in the speed of the price changes is not necessary. A decrease in trading aggressiveness speeds up the adjustment process of liquid stocks, because it leads to a reduction in the abnormal volatility and does not produce a negative effect on the speed of the price changes. By contrast, illiquid stocks are infrequently traded. Therefore, a large decrease in trading aggressiveness adversely affects the speed of their price changes and slows down the adjustment of the stock price towards its new equilibrium value.

Informativeness of ISO trades and the speed of price adjustment. The previously formulated hypotheses suggest that the negative effect of trading aggressiveness on the speed of price adjustment should dominate if investors who submit ISOs are largely uninformed and trade in different directions. In such a case, aggressive trades produce very quick upward price changes following purchase transactions and very quick downward price changes following sales transactions. Thus, an increase in aggressive trading raises the probability of price overshooting and intraday volatility of the stock. In the following, I test this hypothesis in the subsample of illiquid stocks, because, according to the previous results, trading aggressiveness has a large and significant impact on these stocks. Table III.5 shows that aggressive trading is largely uninformative for illiquid stocks after positive earnings surprises, and it is strongly informative for these stocks after negative earnings surprises. Therefore, I expect the negative influence of excess trading aggressiveness on the speed of price adjustment of illiquid stocks to be stronger in the subsample of positive earnings surprises.

Models (2) and (3) of Table III.7 present the results for the subsamples of the positive and negative earnings surprises, respectively. In line with previous expectations, the negative effects of trading aggressiveness for illiquid stocks dominate only in the subsample with positive earnings surprises. A 100% change in the proportion of ISO volume slows down the adjustment process of the illiquid stocks by 36% for positive changes and by 75% for negative changes. Thus, an extreme decrease in trading aggressiveness can be even more harmful than an excess increase in the situations when majority of investors are uncertain about the new equilibrium value of an illiquid stock. A large decrease in trading aggressiveness might suggest that the majority of the investors are uninformed, and they prefer to stay out of the market, which increases the probability that the trading process freezes out completely. The negative effect of trading aggressiveness gets reduced and loses its statistical significance in the sample of negative earnings surprises, when ISO trades are on average more informative (Model 3).

Robustness checks. Models (4) to (6) of Table III.7 repeat the previous analysis with a less conservative definition of abnormal volatility: volatility is defined as abnormal if the realized volatility exceeds its median level in the same five-minute period on non-announcement days. Although slightly lower in absolute value, all of the previous results for illiquid stocks still hold. The previous marginally significant effect of decreases in trading aggressiveness disappears for the subsample of liquid stocks, which again demonstrates that there is no significant impact of trading aggressiveness on the speed of price adjustment for these stocks.

Since the average price of the illiquid stocks, \$20.1, is lower than the average price of the liquid stocks, \$32.8, the larger deviations in the intraday volatility of the one-minute returns of the illiquid stocks on the announcement days might be just mechanical. Therefore, the lower price of the illiquid stocks could bias the adjustment time upwards and overestimate the influence of trading aggressiveness on the speed of the price adjustment of these stocks. To account for the price level of the illiquid stocks, I use the realized price range measure, proposed by Martens and van Dijk (2007):

$$RR_{ti} = \frac{(log\, H_{ti} - log\, L_{ti})^2}{4\, log\, 2},$$

where H_{ti} represents the maximum closing midpoint price within a five-minute interval i on day t and L_{ti} represents the corresponding minimum price. Models (1) to (3) of

Table III.8 report the results with the modified dependent variable. All of the previous findings are robust.

[Insert Table III.8 approximately here]

Next, I measure the liquidity of the stock with the daily Amihud (2002) measure. An indicator variable *Illiq* now equals one if the mean Amihud measure of the stock in the base period is above the median for all of the stocks in the sample, and equals zero otherwise. Models (4) to (6) of Table III.8 display the corresponding results, which are again consistent with those of Table III.7.

Overall, the findings in this section show that the relation between trading aggressiveness and the speed of price adjustment is not significant for liquid stocks and exhibits a pronounced U-shape for illiquid stocks. Thus, both large increases and large decreases in the proportion of aggressive trades slow down the adjustment process of illiquid stocks. For excess increases in trading aggressiveness, the adverse effect of the additional intraday volatility dominates, especially after positive earnings surprises when the aggressive trading is overall uninformative. However, when the majority of ISO trades are submitted in the direction of the earnings surprise, the negative effect of the excess trading aggressiveness is reduced and becomes largely insignificant. Interestingly, although less common, large decreases in trading aggressiveness can be even more harmful for the adjustment process of illiquid stocks, because they prevent their stock price from moving towards its new equilibrium value and can even signal a complete freeze-out of the trading process.

6 Conclusions

This paper analyzes how abnormal trading aggressiveness after earnings announcement releases influences the speed of price adjustment of stocks on US financial markets. I measure trading aggressiveness as the proportion of volume that is traded with the most aggressive limit orders available, intermarket sweep orders, over a particular time interval. Intermarket sweep orders represent an exemption from the Order Protection Rule of the Regulation National Market System and are executed more quickly than other limit orders, but possibly at an inferior price. They produce larger intraday price impact and contribute to quicker price changes within a given time interval.

The major result of this study is that excess trading aggressiveness after earnings announcements is overall harmful to the speed of price adjustment of illiquid stocks. As compared to the pre-Reg NMS period, the adjustment time after an earnings announcement release has increased for illiquid stocks with large deviations in the proportion of ISO volume. The effect is more pronounced after positive earnings announcements when aggressive trades are mostly conducted by uninformed investors who do not observe the new equilibrium value of the stock. Since uninformed investors are just as likely to buy or to sell, quick price changes in different directions unnecessarily increase intraday volatility and make the price stabilization process more difficult.

The findings in this paper suggest that the excessive use of intermarket sweep orders produces adverse effects on the adjustment process of illiquid stocks after information releases. Thus, market efficiency for these stocks can be even further reduced in situations where traders become too aggressive - something, that needs to be taken into account by stock exchanges and market regulators if they are interested in the promotion of accurate and transparent prices.

Appendix

Variable Definitions

Variable	Description	Source
$1/P$	The inverse of the stock price (in $)	TAQ
$\Delta ISOvol$	The change in the proportion of daily volume that is executed with aggressive intermarket sweep orders (ISOs) after an announcement release relative to its mean in the base period	TAQ
Amihud	The Amihud's measure of illiquidity, defined as the ratio of the daily absolute return to the dollar trading volume on that day (Amihud, 2002).	CRSP
Big Neg Surp	One, if a 24-hour post-announcement return is negative and below the median of all of the negative earnings announcements, and zero otherwise	TAQ
Big Pos Surp	One, if a 24-hour post-announcement return is positive and above the median of all of the positive earnings announcements, and zero otherwise	TAQ
Earn Surp	The absolute value of a 24-hour post-announcement return	TAQ

Variable	Description	Source
EffSpr	The effective relative spread, calculated as twice the absolute difference between the transaction price and the midpoint price, scaled by the midpoint price ($EffSpr_t = 2\left\|P_t - Q_t\right\|/Q_t$). Observations with $EffSpr > 0.5$ are set to missing values	TAQ
Event$_i$, $i \,\epsilon\, [-2;+2]$	One for observations on the event day i, where i is calculated as *Current Day - Announcement Day*	I/B/E/S
Illiquid (Illiq)	One, if the relative spread of the stock is above the median value of all of the stocks in the sample, and zero otherwise	TAQ
ISO	One, if an order is marked as ISO, and zero otherwise	TAQ
Leverage	The market leverage, defined as the ratio of the total liabilities to the sum of the total liabilities and the market capitalization of the company	Compustat
Liquid (Liq)	One, if the relative spread of the stock is below the median value of all of the stocks in the sample, and zero otherwise	TAQ
LnMCap	The natural logarithm of market capitalization	CRSP
MCap	The market value of equity (in million $)	CRSP
Nasdaq	One, if the stock is listed on Nasdaq, and zero otherwise	TAQ
Neg Surp	One, if a 24-hour post-announcement return is negative, and zero otherwise	TAQ

Variable	Description	Source
Pos Surp	One, if a 24-hour post-announcement return is positive, and zero otherwise	TAQ
Post-Reg NMS, (*Post Reg*)	One, if an announcement happens after the final implementation of the Regulation NMS (October 2007), and zero otherwise	
Pre-Reg NMS	One, if an announcement happens before the final implementation of the Regulation NMS (October 2007), and zero otherwise	
Prc	Stock price (in $)	CRSP
PrcImp	The measure of the five-minute price impact of a trade, defined as $PrcImp_t = 2\left\|Q_{t+5} - Q_t\right\| / (Q_t * w_t)$, where Q_{t+5} is the midpoint price of the stock after five minutes and w_t is the size of the trade	TAQ
Proportion of ISO trades, %Trades	The ratio of the number of intermarket sweep orders to the total number of orders executed within a given time interval	TAQ
Proportion of ISO volume, %ISOvol	The ratio of the volume that is executed with intermarket sweep orders to the total volume traded within a given time interval	TAQ

Variable	Description	Source
Proportion of ISO purchases, %Purchases	The ratio of the number of purchase transactions that are executed with intermarket sweep orders to the total number of purchase transactions within a given time interval	TAQ
Proportion of ISO buy volume, $\%ISOBuyVol$	The ratio of the volume of purchase transactions that are executed with intermarket sweep orders to the total volume of purchase transactions within a given time interval	TAQ
Proportion of ISO sales, %Sales	The ratio of the number of sale transactions that are executed with intermarket sweep orders to the total number of sale transactions within a given time interval	TAQ
Proportion of ISO sell volume, $\%ISOSellVol$	The ratio of the volume of sale transactions that are executed with intermarket sweep orders to the total volume of sale transactions within a given time interval	TAQ
RelSpr	Intraday relative spread, defined as the difference between the ask and the bid, scaled by their average; observations with *RelSpr*$>$*0.5* are set to missing values.	TAQ
RelSpr (daily)	Daily relative spread, defined as the difference between the closing ask and the closing bid, scaled by their average; observations with *RelSpr (daily)*$>$*0.5* are set to missing values.	CRSP
ROA	Return on assets, defined as the ratio of the operating income after depreciation to the average total assets of the current year and the previous year.	Compustat

Variable	Description	Source
Size	Size of a transaction (in shares)	TAQ
TA_i	ith tercile of trading aggressiveness (TA1 - the lowest tercile of trading aggressiveness and TA3 - the highest tercile of trading aggressiveness)	Own calculations
Total Assets	Total assets (in million $)	Compustat
Total Liabilities	Total liabilities (in million $)	Compustat
Turnover	The average daily traded volume divided by the number of shares outstanding	CRSP
VIX	Chicago Board Options Exchange Market Volatility Index, a measure of the implied volatility of S&P 500 index options that represents the market's expectation of the stock market volatility over the next 30 day period	Chicago Board Options Exchange
Volatility	The annualized standard deviation of daily stock returns over the calendar month	CRSP
Volume	The total volume traded within a 10-minute interval (in shares)	TAQ

Figures

Figure III.3: **Changes in Proportion of ISO volume on Announcement Day.** This figure displays the mean percentage deviations in the proportion of ISO volume throughout the announcement days. The deviations from the bootstrapped means are measured in 15-minute intervals relative to the 15-minute interval with an earnings announcement release (interval 0). The dashed line shows the 1% significance level for the mean percentage change in the proportion of ISO volume, which is equal to 3.8%.

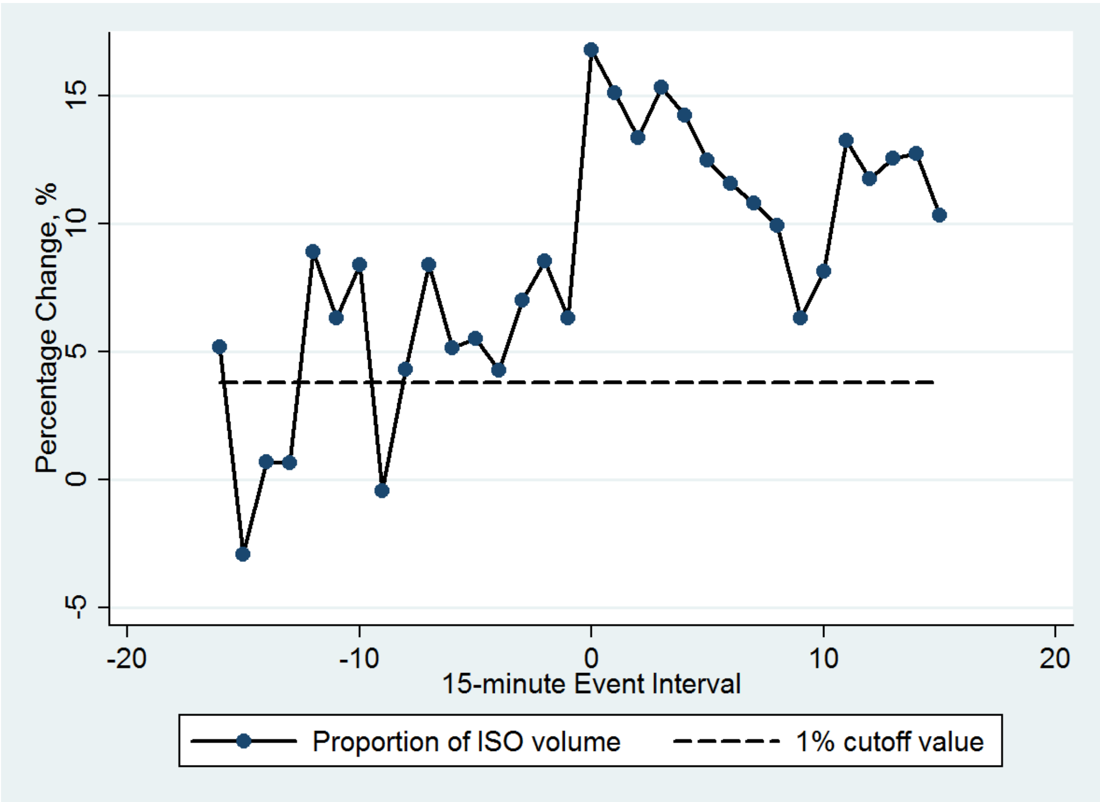
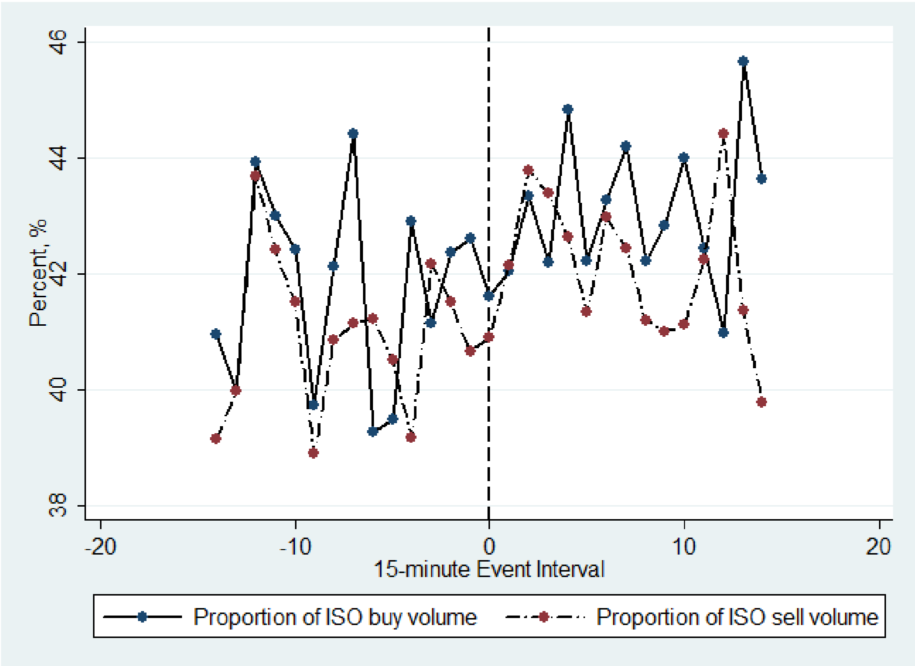


Figure III.4: **Trading Imbalances in ISO volume on Announcement Day.** This figure displays the mean proportion of ISO buy volume, defined as $ISObuyvolume/Totalbuyvolume$, and the mean proportion of ISO sell volume, defined as $ISO\ sell\ volume/Total\ sell\ volume$, throughout the announcement days. Both proportions are measured in 15-minute intervals relative to the 15-minute interval with an earnings announcement release (interval 0). The dashed line marks the event interval.

A. Positive Earnings Surprises



B. Negative Earnings Surprises

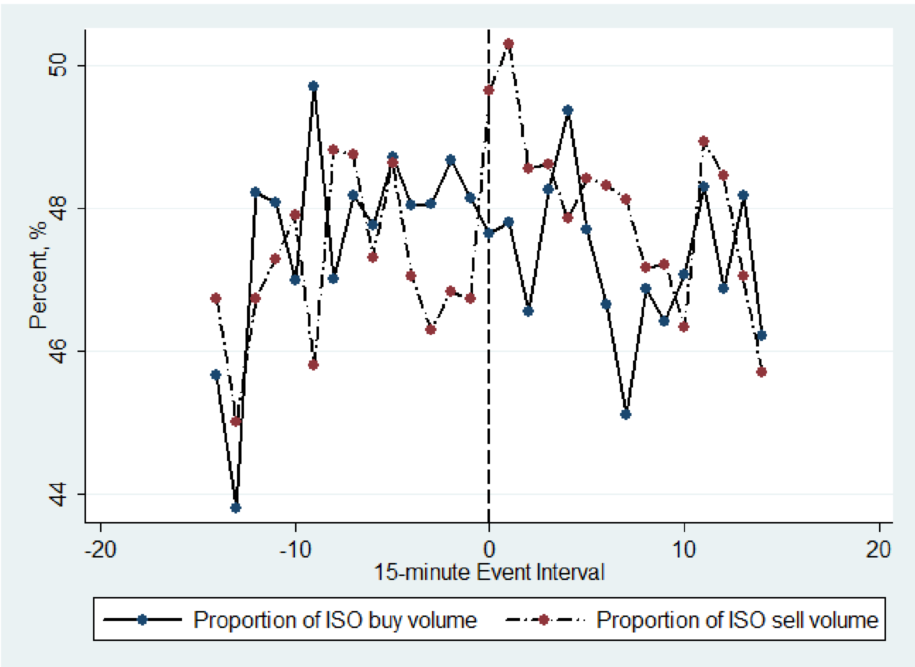
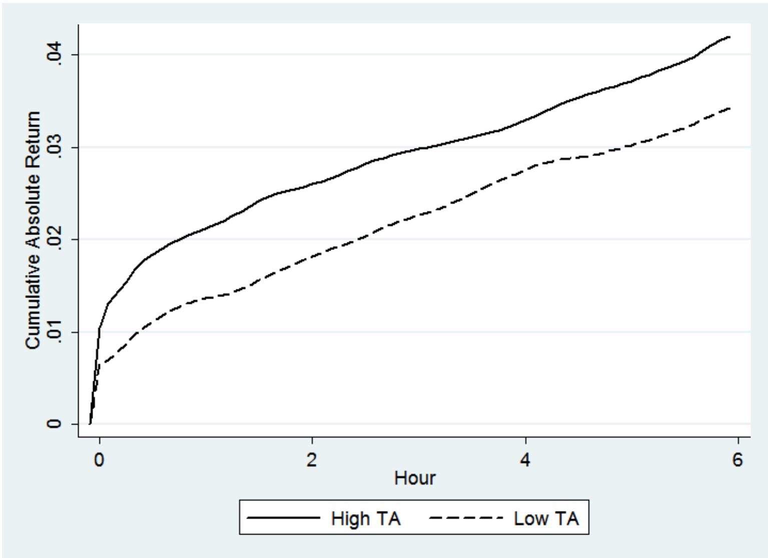


Figure III.5: **Cumulative Intraday Returns and Abnormal Volatility.** Panel A of this figure depicts the development of the cumulative five-minute absolute returns within the first six hours since an earnings announcement release (interval 0). I aggregate positive and negative earnings surprises, and multiply all of the returns for negative earnings surprises by -1. The solid line represents the subsample of the stocks with the above median increases in trading aggressiveness on the announcement day. The dashed line represents the subsample of the stocks with the below median increases in trading aggressiveness on the announcement day. Panel B presents the percentage increases in the realized volatility on the announcement days from its base level, calculated as the mean realized volatility over the same five-minute interval on the non-announcement days [-40;-3]. The realized volatility within each five-minute interval is calculated as the standard deviation of the sum of the squared one-minute closing midpoint returns.

A. Cumulative intraday post-announcement returns



B. Abnormal post-announcement volatility

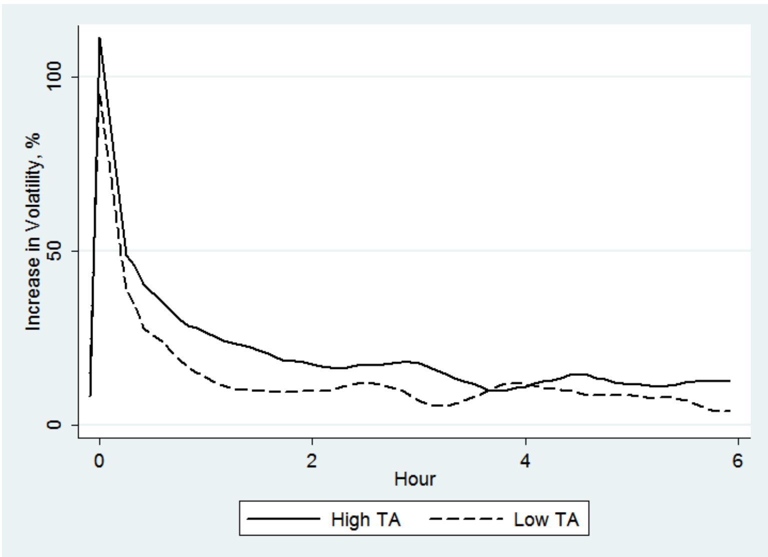
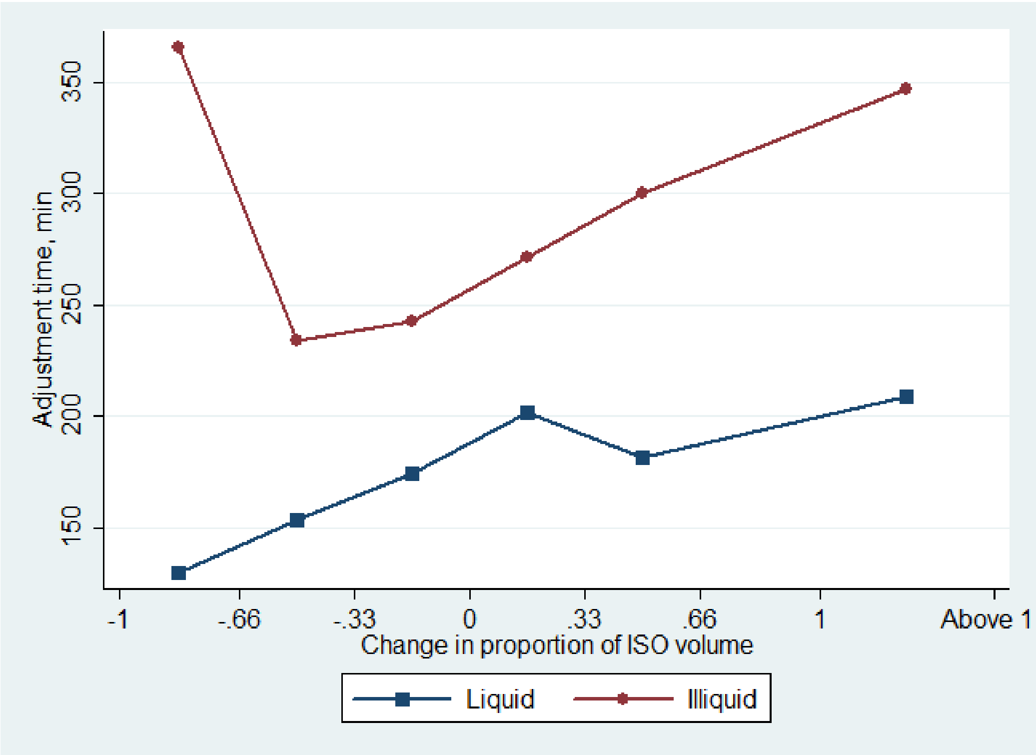


Figure III.6: **Adjustment Time and Trading Aggressiveness.** This figure depicts the relationship between the mean length of the price adjustment period and the mean change in the proportion of ISO volume after an information release, separately for the subsamples of liquid and illiquid stocks. The length of the price adjustment period is measured as the number of five-minute time intervals until the realized volatility of one-minute midpoint returns is no longer abnormal.



Tables

Table III.1: **Sample Construction.** This table shows the sample selection of the earnings announcements of US firms that happened within trading hours (from 9:30 a.m. till 16:00 p.m. EST) from 2006 to 2009. The data source for dates and times of the earnings announcements is the Institutional Brokers Estimate System (I/B/E/S) database. I require each firm to exist in the intersection set of I/B/E/S and CRSP.

Criteria	**Announcements**	**Lost obs.**	**Firms**
Initial sample	10,334		3,361
Stock traded on an announcement day	9,687	647	3,273
Intraday transaction data available on TAQ	8,720	967	3,008
Closing price not less than $5	6,126	2,594	2,334
Not more than one announcement per day	6,040	86	2,322
Trading data exists for previous 2 months	5,944	96	2,307
At least one announcement before and one announcement after Reg NMS, out of which:	3,613	2,331	675
- Before Reg NMS	1,818		675
- After Reg NMS	1,795		675

Table III.2: **Sample Distributions.** This table displays the distributions of firm characteristics in the final sample (Columns 1 to 3) and the initial sample (Columns 4 to 6). The differences in the means and medians are statistically significant at the 5% level for all of the variables, except the market capitalization, *MCap*, which is statistically significant at the 10% level. See the Appendix for the exact definition of all variables.

	Final			**Initial**		
	N	Mean	50%	N	Mean	50%
	(1)	(2)	(3)	(4)	(5)	(6)
Total Assets (in mln $)	666	8672	686	3300	6220	477
Total Liabilities (in mln $)	666	5990	507	3300	4309	274
MCap (in mln $)	675	2670	256	3361	2254	239
Prc (in $)	675	26	21	3361	20	14
ROA	654	0.07	0.05	3054	-0.01	0.04
Leverage	666	0.54	0.55	3290	0.46	0.41
RelSpr (daily)	675	0.01	0.00	3361	0.01	0.01
Amihud	675	0.95	0.04	3361	1.93	0.06
Volatility	675	0.44	0.41	3361	0.59	0.53
Turnover	675	0.006	0.003	3361	0.007	0.005

Table III.3: **Differences in Characteristics of ISOs and non-ISOs.** Panel A of this table summarizes the differences in trading characteristics between intermarket sweep orders (ISOs) and standard limit orders (non-ISOs) in the base period and after earnings announcement releases. Columns (1) and (2) display the mean of the bootstrapped distribution for ISOs and non-ISOs from the base period, correspondingly. Columns (3) and (4) report the cross-sectional mean of the respective variables starting from an announcement release until the end of the trading day (16:00 p.m. EST). I also report the p-value of the t-test for the null-hypothesis that the difference in means between ISOs and non-ISOs equals zero. * denotes statistical significance at the 10% level, ** - at the 5% level, and *** - at the 1% level. Column (5) displays the difference-in-differences results. For proportions, Column (5) displays the difference between the base period and the event day. Panel B summarizes the differences in trading characteristics between ISOs and non-ISOs after earnings announcement releases for stocks with different liquidity levels. The variables are calculated from the intraday transaction data in the NYSE TAQ database. See the Appendix for the exact definition of all variables.

Panel A: Base Period vs Announcement Day

	Base Period			Event Day			Diff-in-Diff	
	(1) ISO	(2) Non-ISO	Δ_1	(3) ISO	(4) Non-ISO	Δ_2	(5) Δ_2-Δ_1	
%Trades	40.8			45.4			4.6	***
%Volume	37.8			42.4			4.6	***
%Purchases	40.5			44.4			4.0	***
%Sales	41.3			45.5			4.2	***
Size	176	256	***	180	226	***	33	***
EffSpr, %	1.73	1.82	*	1.84	1.86		0.08	
PrcImp, %	1.29	1.20	**	1.47	1.27	***	0.11	**

Panel B: Liquid vs Illiquid on Event Day

	Liquid			Illiquid			Diff-in-Diff	
	(1) ISO	(2) Non-ISO	Δ_1	(3) ISO	(4) Non-ISO	Δ_2	(5) Δ_2-Δ_1	
%Trades	45.0			45.9			0.9	*
%Volume	41.6			43.3			1.8	***
Size	163	200	***	200	257	***	-20	***
EffSpr, %	0.57	0.56		3.43	3.38		0.05	
PrcImp, %	0.64	0.62		2.51	2.04	***	0.45	***

Table III.4: **Intraday Analysis of Effective Spread and Price Impact.** This table presents the results of panel OLS regressions with the effective relative spread as the dependent variable for Models (1) and (2) and the price impact as the dependent variable for Models (3) and (4). One observation represents a ten-minute trading interval for a stock. All regressions include firm-, year-, daytime- and weekday-fixed effects. See the Appendix for the exact definition of all variables. P-values of the two-tailed t-test with the null-hypothesis of a coefficient equaling zero are reported in form of asterisks to the right of each coefficient. * denotes statistical significance at the 10% level, ** - at the 5% level, and *** - at the 1% level. I also report the number of observations (N) and R^2 for each regression.

	(1) EffSpr	(2) EffSpr	(3) PrcImp	(4) PrcImp
ISO	-0.003	-0.003	0.053 ***	0.016 ***
Illiquid		0.664 ***		0.623 ***
ISO · Illiquid		0.001		0.187 ***
Event_{-2}	0.000	0.003	0.004	0.007
Event_{-1}	0.062 ***	0.064 ***	0.064 ***	0.066 ***
Event	0.049 ***	0.051 ***	0.091 ***	0.097 ***
Event_{+1}	-0.015	-0.011	0.004	0.009
Event_{+2}	-0.034 ***	-0.030 **	-0.000	0.005
ISO · Event_{-2}	0.010	0.010	-0.007	-0.007
ISO · Event_{-1}	-0.012	-0.011	0.002	0.004
ISO · Event	0.020	0.021	0.036 **	0.028
ISO · Event_{+1}	0.001	0.001	0.003	-0.000
ISO · Event_{+2}	-0.003	-0.003	-0.014	-0.015
$1/P$	7.504 ***	6.768 ***	19.374 ***	18.593 ***
Volume	-0.000 ***	-0.000 ***	0.000 ***	0.000 ***
Nasdaq	1.413 ***	1.352 ***	1.197 ***	1.122 ***
N	1489118	1489118	1489118	1489118
R-squared	0.33	0.34	0.31	0.32
Weekday FE	Yes	Yes	Yes	Yes
Daytime FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

Table III.5: **Informativeness of ISO Trades.** This table reports the differences in the means between an increase in the proportion of ISO buy volume and an increase in the proportion of ISO sell volume on the announcement days, separately for the liquid stocks (Panel A) and the illiquid stocks (Panel B). The first column shows the number of hours since an announcement release. Columns (2) and (3) report the results for the positive surprises and the large positive surprises, respectively. Columns (4) and (5) report the corresponding results for the negative surprises. An earnings surprise is measured as a 24-hour stock return since an announcement release, and is classified as large if a 24-hour stock return is above the median for all of the stocks in the sample for the positive earnings surprises and below the median for the negative earnings surprises. The t-statistics of the two-tailed t-test with the null-hypothesis of a difference in means equaling zero are in parentheses below each coefficient. P-values are reported in form of asterisks to the right of each coefficient. * denotes statistical significance at the 10% level, ** - at the 5% level, and *** - at the 1% level.

Panel A: Liquid Stocks

(1) Hour	(2) Pos Surp	(3) Big Pos Surp	(4) Neg Surp	(5) Big Neg Surp
1	0.47%	0.80%	-0.45%	-0.51%
	(0.49)	(0.69)	(-0.45)	(-0.43)
2	0.86%	0.74%	-0.13%	-0.11%
	(1.09)	(0.76)	(-0.17)	(-0.12)
3	0.90%	1.22%	-0.33%	-0.39%
	(1.23)	(1.43)	(-0.44)	(-0.45)
4	0.79%	1.43% *	-0.13%	-0.17%
	(1.15)	(1.79)	(-0.19)	(-0.20)
5	0.55%	1.45% *	0.03%	-0.27%
	(0.82)	(1.84)	(0.05)	(-0.34)

Panel B: Illiquid Stocks

(1) Hour	(2) Pos Surp	(3) Big Pos Surp	(4) Neg Surp	(5) Big Neg Surp
1	-0.73%	1.85%	-6.13% **	-5.21%
	(-0.34)	(0.59)	(-2.12)	(-1.43)
2	0.91%	3.61%	-6.51% ***	-7.11% **
	(0.44)	(1.26)	(-2.76)	(-2.41)
3	1.72%	3.76%	-4.95% **	-7.32% **
	(0.90)	(1.42)	(-2.21)	(-2.59)
4	1.27%	3.74%	-6.03% ***	-7.00% ***
	(0.73)	(1.53)	(-2.95)	(-2.75)
5	0.86%	3.03%	-5.67% ***	-6.86% ***
	(0.50)	(1.28)	(-2.78)	(-2.70)

Table III.6: **Price Adjustment: Summary Statistics and Univariate Analysis.** Panel A of this table presents the distributions of the length of the price adjustment period (in minutes), separately for the subsamples of liquid and illiquid stocks, in the pre- and the post-Reg NMS periods. See the Appendix for the exact definition of all variables. Columns (3) and (6) report the p-values of the Mann-Whitney test on the equality of medians between the pre- and post-Reg NMS periods for liquid and illiquid stocks, respectively. Panel B displays the mean adjustment time across different terciles of trading aggressiveness (TA1 to TA3) in the post-Reg NMS period. Trading aggressiveness is measured as the change in the proportion of ISO volume that is traded after an announcement release relative to its mean in the base period ($\Delta ISOvol$). The TA1 comprises the stocks with the lowest increases in trading aggressiveness on an announcement day and the TA3 comprises the stocks with the highest increases. The announcements in the pre-Reg NMS period are sorted in "pseudo" - TA terciles that equal the median TA tercile in the post-Reg NMS period. The last two rows report the p-values of the Mann-Whitney test on the equality of the medians across different terciles of trading aggressiveness.

Panel A: Pre-Reg NMS vs Post-Reg NMS

	Liquid			Illiquid		
	Pre-Reg NMS (1)	Post-Reg NMS (2)	MW-test p-value (3)	Pre-Reg NMS (4)	Post-Reg NMS (5)	MW-test p-value (6)
5%	0	0		0	0	
25%	35	35		60	50	
50%	125	100	0.04	178	175	0.97
75%	300	240		480	585	
95%	810	730		955	1020	
Mean	218	188		308	331	
Std	257	234		317	345	

Panel B: Liquidity and Aggressiveness Terciles

	Liquid			Illiquid		
	Pre-Reg NMS (1)	Post-Reg NMS (2)	MW-test p-value (3)	Pre-Reg NMS (4)	Post-Reg NMS (5)	MW-test p-value (6)
TA1	130	105	0.22	235	200	0.78
TA2	115	95	0.14	148	150	0.88
TA3	145	115	0.55	195	225	0.44
TA1-TA3	0.78	0.27		0.31	0.82	
TA2-TA3	0.57	0.22		0.12	0.05	

Table III.7: **Price Adjustment: Difference-in-Differences Analysis.** This table presents the results of the negative binomial regressions that include observations from the pre- and post-Reg NMS periods. The dependent variable in each model is the length of the adjustment period. Models (1) to (3) report the results for the benchmark definition of abnormal volatility: volatility is abnormal if the realized volatility in a five-minute interval exceeds the 75% cutoff value in the same five-minute interval calculated over days $[-40; -3]$. Models (4) to (6) report the multivariate results for an alternative definition of abnormal volatility: volatility is abnormal if it exceeds the median volatility in the same five-minute period on the non-announcement days. Models (1) and (4) report the results for the total sample, Models (2) and (5) for the positive earnings surprises, and Models (3) and (6) for the negative earnings surprises. See the Appendix for the exact definition of all variables.

	AV: Upper Quartile			AV: Above Median		
	(1) Total	(2) Pos Surp	(3) Neg Surp	(4) Total	(5) Pos Surp	(6) Neg Surp
Adj Time						
Post Reg	-0.20 *	-0.05	-0.35 **	-0.15 *	-0.06	-0.26 **
Illiq	0.35 ***	0.35 ***	0.39 ***	-0.01	-0.01	-0.01
Illiq· Post Reg	-0.07	-0.19	0.01	0.03	-0.01	0.07
Liq· $\lvert\Delta ISOvol\rvert_{\Delta>0}$	-0.01	-0.08	0.08	0.18	0.07	0.31 *
Liq· $\lvert\Delta ISOvol\rvert_{\Delta<0}$	-0.51 *	-0.95 **	0.01	-0.20	-0.27	-0.10
Illiq· $\lvert\Delta ISOvol\rvert_{\Delta>0}$	0.25 ***	0.31 ***	0.18	0.16 ***	0.22 ***	0.08
Illiq· $\lvert\Delta ISOvol\rvert_{\Delta<0}$	0.31 **	0.56 ***	-0.01	0.17 *	0.37 ***	-0.05
Turnover	-9.78 **	-15.84 ***	-5.38	-2.78	-1.58	-3.77
LnMCap	0.00	-0.00	0.01	0.02 *	0.02	0.03
VIX	0.70 ***	0.70 **	0.71 **	0.54 ***	0.47 **	0.62 **
Earn Surp	1.38 ***	1.00	1.95 **	1.62 ***	1.45 ***	1.84 ***
N	3,613	1,826	1,762	3,613	1,826	1,762
P(Chi-Squared)	0.000	0.000	0.000	0.000	0.026	0.005
Weekday FE	Yes	Yes	Yes	Yes	Yes	Yes
Daytime FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table III.8: **Price Adjustment: Robustness Checks.** This table presents the results of the negative binomial regressions that include observations from the pre- and post-Reg NMS periods. The dependent variable in each model is the length of the adjustment period. Models (1) to (3) use an alternative definition of intraday volatility that is now measured as the realized price range in each five-minute interval. Models (4) to (6) use the benchmark definition of the realized volatility, but differentiate between the samples of liquid and illiquid stocks with the Amihud (2002) illiquidity measure. Models (1) and (4) report the results for the total sample, Models (2) and (5) for the positive earnings surprises, and Models (3) and (6) for the negative earnings surprises. See the Appendix for the exact definition of all variables.

	Price Range			Amihud		
	(1) Total	(2) Pos Surp	(3) Neg Surp	(4) Total	(5) Pos Surp	(6) Neg Surp
Adj time						
Post Reg	-0.20 *	-0.15	-0.21	-0.19	-0.06	-0.28 *
Illiq	0.45 ***	0.46 ***	0.48 ***	0.37 ***	0.39 ***	0.39 ***
Illiq· Post Reg	-0.01	-0.17	0.11	-0.09	-0.16	-0.08
Liq· $\|\Delta ISOvol\|_{\Delta>0}$	0.10	0.05	0.12	-0.06	-0.08	-0.05
Liq· $\|\Delta ISOvol\|_{\Delta<0}$	-0.49 *	-0.88 **	-0.15	-0.71 ***	-1.02 ***	-0.35
Illiq· $\|\Delta ISOvol\|_{\Delta>0}$	0.25 ***	0.37 ***	0.13	0.25 ***	0.29 ***	0.21 *
Illiq· $\|\Delta ISOvol\|_{\Delta<0}$	0.37 ***	0.55 ***	0.14	0.34 ***	0.56 ***	0.06
Turnover	-12.19 ***	-24.96 ***	-3.64	-9.17 **	-14.48 ***	-5.77
LnMCap	-0.04 **	-0.03	-0.04 *	0.01	0.00	0.01
VIX	0.67 ***	0.74 **	0.61 *	0.70 ***	0.70 **	0.73 **
Earn Surp	1.44 ***	1.33 *	1.79 **	1.38 ***	0.95	1.99 **
N	3,589	1,808	1,756	3,613	1,826	1,762
P(Chi-Squared)	0.000	0.000	0.000	0.000	0.000	0.000
WeekdayFE	Yes	Yes	Yes	Yes	Yes	Yes
DaytimeFE	Yes	Yes	Yes	Yes	Yes	Yes
YearFE	Yes	Yes	Yes	Yes	Yes	Yes

Chapter IV

Trading Strategies of Corporate Insiders

1 Introduction

In this paper we analyze the trading strategies of corporate insiders. Our particular focus is on the competing roles of liquidity and information. Two distinct but complementary theoretical approaches in the literature develop models of insiders' trading strategies. The first approach is based on the notion that insiders possess private information and that their trading strategies are primarily designed to optimally exploit their informational advantage. Theoretical formulations of this information-based view of insider trading go back to Kyle (1985), who shows how insiders could optimally profit from their informational advantage by spreading their transactions dynamically over time.[1] The second approach analyzes block traders who trade for liquidity reasons and spread their trades over time to minimize price impact, especially temporary price impact. The analysis of

[1] While many authors have expanded on Kyle's original analysis, very few have taken up its dynamic aspect and analyze strategies for how traders with long-lived information break up their trades over time. The most important extension for our purposes is Holden and Subrahmanyam (1993) and Foster and Viswanathan (1994, 1996), who consider multiple competing traders. We discuss their model and later extensions in more detail below.

these liquidity-based trading strategies is more recent and goes back to Bertsimas and Lo (1998) and Vayanos (1999, 2001).[2]

Both theories can only be distinguished empirically in a context in which multiple block traders trade simultaneously. However, the theories are indistinguishable in environments where one block trader is assumed to trade only with small traders. Then both theories predict that traders break up their trades and spread their transactions over time. By contrast, for environments in which multiple block traders trade simultaneously, the empirical predictions of information-based theories and liquidity-based theories differ. Holden and Subrahmanyam (1993) extend Kyle's model to a setting with multiple informed traders and show that insiders trade more aggressively if other insiders trade on the same long-lived information at the same time. The intuition is that they become competitors for the exploitation of the informative signal and enjoy an informational advantage only as long as the information has not been incorporated into prices through the trades of other insiders.[3] By contrast, liquidity-based arguments imply the opposite: traders extend their trading horizons and trade more slowly if they know that others trade in the same direction at the same time.[4] In this scenario, other traders demand liquidity in the same market at the same time, which increases temporary price impact and makes trading more costly. This reduction in liquidity shifts the trade-off between

[2]Other approaches include Almgren (2003), Almgren and Chriss (2001), He and Mamaysky (2005), Obizhaeva and Wang (2005), Huberman and Stanzl (2005), and Schied and Schöneborn (2009). The papers differ with respect to the assumed objective of the insider and with respect to the details of the price formation process, which is typically assumed to be an exogenous process that combines temporary as well as permanent price impact. Vayanos (1999) derives prices and price impact endogenously from the model.

[3]See also Foster and Viswanathan (1994, 1996), who also investigate the case in which the signals of two competing insiders are not perfectly correlated. Then the prediction mentioned above holds only for the common component of insiders' signals. Important extensions of this framework allow for the possibility that information is disclosed (Huddart, Hughes, and Levine (2001)) and that it becomes stale (Bernhardt and Miao (2004)).

[4]Note that the opposite happens in Vayanos' (1999) model, because in his framework additional traders supply liquidity and reduce price impact since their endowment shocks are uncorrelated, whereas in our setting the opposite is the case. To the best of our knowledge, no model in the literature extends the liquidity-based argument to a multiple-trader context. We provide such an extension in Appendix B.

immediacy and the desire to avoid price impact towards the second objective, resulting in less aggressive trading strategies and longer completion times for executing trades.

We analyze the transactions of corporate insiders in order to test these theories. Insider trading provides an ideal testing ground for these models. Insider transactions are well documented and allow us to identify multiple transactions by the same insider. Importantly, insiders' filings allow us to separate situations in which insiders compete with each other from situations in which only one insider trades. In addition, the motives identified by both theories play an important role: A significant part of the trades of corporate insiders is based on informational advantages; at the same time, trades are typically large, which creates liquidity motivations to spread transactions over time.

We study a sample of 1.85 million transactions by more than 99.000 insiders in the United States. We first show that most of these transactions indeed form sequences that result from breaking up larger trades and not just from random clustering of transactions. We then analyze the length of transaction sequences in terms of calendar time (trade duration). Based on event-study methodology, we classify about one in seven trades as informed. We then distinguish days on which multiple insiders trade in the same direction at the same time from those days on which only one insider trades.

We find support for both theories. On average, insiders trade more slowly and break up trades into longer sequences whenever multiple insiders trade at the same time, which is consistent with the predictions of liquidity-based models of strategic trading. By contrast, informed trades, which are associated with large abnormal disclosure day returns, are completed faster. Competition from other insiders reduces the trade duration for informed trades, in line with the predictions of information-based models. We conclude that both classes of models have significant explanatory power, although information-related effects tend to be economically smaller than liquidity-related effects. Competition for the use of privileged information is somewhat more prevalent before the passage of the Sarbanes-Oxley act (SOX) than in the later period of our sample.

In addition to the baseline predictions from the models in the literature, we formulate several other hypotheses and investigate a range of other variables that capture the liquidity of the market or informational advantages. We group trades by the category of insiders (CEO, other officers, etc.), which is most likely related to the amount of information insiders possess. Interestingly, the least informed insiders who have no operational role in the firm take the longest to complete their trades, which supports liquidity-based theories more than information-based theories. If insiders are trading on the short side of the market, i.e. they buy when the market moves up or sell when the market moves down, then they trade over longer periods of time. Insiders take longer to complete trades in less liquid markets, independently of the measure we chose to proxy for market liquidity. We conclude that overall, the motive to avoid temporary price impact is more important for insiders' trading strategies compared to informational motives.

Next, we investigate how insiders adapt their trading strategies in response to changes in the liquidity of the firm's stock. The models of optimal liquidation strategies for large blocks discussed above assume that the price impact of transactions is constant over time. By contrast, we hypothesize that insiders do not simply follow mechanical trading strategies, but respond to changes in market liquidity by avoiding low-liquidity days and trading more on days on which liquidity is high. We find strong evidence for this liquidity-timing hypothesis. The effective spread and the Amihud illiquidity measure are higher by a factor of about two on days when insiders do not trade compared to days when they trade. Additionally, within the subsample of days on which insiders trade, insiders trade more on those days on which liquidity is higher. These findings are not driven by reverse causality.

We contribute to the literature in several ways. To the best of our knowledge, we are the first to analyze strategic trading by corporate insiders empirically, and also the first to provide empirical tests for the contrasting implications of information-based and liquidity-based strategic trading models.[5] Keim and Madhavan (1995) analyze trading strategies for a sample of 21 institutions and find a positive relationship between trade duration and block size. However, they do not analyze how traders compete for the use of information or liquidity. Chan and Lakonishok (1995) analyze how 37 institutions spread their trades over several days and how their strategies affect price impact and execution costs. There is a large later literature on the price impact and the information content of large block trades, but this literature does not explicitly analyze the determinants of trading strategies and does not contrast liquidity motives with information-related motives.[6] All these papers study small proprietary data sets provided by institutions that include identifiers for individual traders, information that is normally not available, whereas we can rely on a large, comprehensive data set.

The remainder of the paper is organized as follows. The following section briefly describes the institutional framework of insider trading in the United States and how we construct our data set. Section 2 shows that insiders break up large trades into sequences of smaller transactions. Section 3 analyzes the determinants for trade duration and forms the core of our analysis. Section 4 tests the liquidity-timing hypothesis and Section 5 concludes. The appendix contains the descriptions of our variables and a theoretical model that analyzes competition for liquidity.

[5] Our definition of strategic trading is different from that in Betzer, Gider, Metzger and Theissen (2011), who analyze the relationship between insider trades and trade reporting.

[6] See Holthausen, Leftwich, and Mayers (1987, 1990) and Keim and Madhavan (1996). Later papers focus in particular on price impact and the slope of demand curves, e.g. Kaul, Mehrotra, and Morck (2000) and Wurgler and Zhuravskaya (2002). For a recent empirical analysis of trading strategies and price impact see Almgren, Thum, Hauptmann and Li (2005).

2 Construction of the Data Set and Methodology

According to Section 16 of the Securities Exchange Act of 1934, all insiders have to disclose their transactions to the SEC. Insiders are direct and indirect beneficial owners of more than ten percent of any class of equity securities and any director or officer of the issuer of equity securities (Section 16(a)(1) of the Securities Exchange Act of 1934, SEC rule 16a-2). Until August 2002, insiders had to report their transactions on a monthly basis within 10 days after the end of each calendar month in which the transaction occurred (Form 4), which gave insiders up to forty days to disclose their trades. The Sarbanes-Oxley Act (SOX) changed this practice. Since August 29, 2002, insiders had to report their trades within two business days (SEC rule 16a-3(g)). Small purchases or sales that do not add up to more than $10,000 within six months are exempt from these reporting requirements (SEC rule 16a-6). These small acquisitions are not reported on Form 4 as usual insider transactions but on Form 5, which has to be filed only within 45 days after the issuer's fiscal year end (SEC rule 16a-3(f)).

2.1 Construction of the Data Set

Our data source for insider transactions is the Insider Filing Data Feed (IFDF) provided by Thomson Reuters. IFDF collects information on three forms insiders have to file with the SEC: Form 3 ("Initial Statement of Beneficial Ownership of Securities"), Form 4 ("Statement of Changes of Beneficial Ownership of Securities"), and Form 5 ("Annual Statement of Beneficial Ownership of Securities"). We include all open market purchases and sales as well as private transactions between January 1, 1996 and December 31, 2008 with complete data (including CUSIP, transaction date, and disclosure date) on IFDF.

Table 1 provides the details of the construction of our data set. We extract 3,272,073 transactions for 151,523 insiders from 18,380 firms. We match the transactions to CRSP and lose 9.2% of the transactions because the firm is not listed on CRSP and another 9.1%

because the stock price data available on CRSP are insufficient to compute abnormal returns. We also delete all transactions for which the number of shares in the transaction as reported on IFDF exceeds the number of shares traded on the exchange on the same day as reported by CRSP; these transactions form 3.9% of the original sample and are most likely privately negotiated and therefore not of interest for our analysis. We have a small number of cases in which insiders trade in different directions on the same day (0.8% of the original sample) and for which the transaction data on IFDF are incomplete (0.3%). We delete these transactions. We are concerned that our analysis may be influenced by computer-executed trades. We therefore exclude transactions for which the number of shares traded is not a multiple of ten, which are most likely initiated by computerized algorithms. These odd-numbered trades form 14.4% of our original sample. Excluding them probably biases our results against liquidity-based theories because trading in multiples of 500, 1000, or 5000 shares has been associated with stealth trading (Alexander and Peterson (2007)), but we find that our results remain unaffected by excluding odd-numbered trades. Furthermore, we do not have time stamps and can therefore not analyze trading sequences that are completed within one day. We therefore aggregate all transactions of the same insider, in the same stock, in the same direction, on the same day that are executed at the same price. In unreported regressions, we check whether out results are affected by the choice of this or several other aggregation rules and find that they have no impact on the results. We are left with 1,849,513 transactions by 99,413 insiders of 11,013 firms, or 56.5% of the raw data. Of these 20.3% are purchases and 79.7% are sales.

For all microstructure variables, we use the TAQ database to extract the necessary intraday transaction data. For each trade we assign the bid and ask quotes prevailing one second before the trade took place.[7]

2.2 Constructing Transaction Sequences

Definition of a transaction sequence. In our baseline analysis, we regard a transaction as a part of a sequence of transactions from a split trade if there is a subsequent transaction in the same direction and by the same insider before or on the same day on which the first transaction is disclosed. If two trades in the same direction are separated by a trade in the opposite direction, or if the first trade has been disclosed, we start a new sequence. The motivation for this definition is that trade splitting only helps insiders to conceal information as long as the transaction has not been disclosed. Later we show that our results are robust to this definition and that we can omit the requirement that the first transaction has not been disclosed. Our definition is probably conservative. Huddart, Hughes, and Levine (2001) analyze a model in which insiders have to disclose their trades after every trading round and find that this disclosure requirement induces insiders to play mixed strategies and to garble the information from disclosures by trading in the opposite direction. In their model, insiders may interrupt a sequence of transactions in the same direction with a transaction in the opposite direction to mislead the market. However, we find hardly any evidence for this prediction and conclude that the theoretical possibility highlighted by Huddart, Hughes, and Levine (2001) is not relevant for our analysis.[8]

[7] Henker and Wang (2006) consider this procedure to be more appropriate compared to the classical Lee and Ready (1991) five-second rule. Bessembinder (2003) tries zero- to thirty-second delays in increments of five seconds and does not find any differences in the results.

[8] In our sample, we observe 128,137 cases in which insiders trade more than once during one week. There are only 121 cases in which insiders change the direction of their trades within a week. We therefore conclude that insiders do not try to camouflage the information of disclosures by trading in the opposite direction.

Disclosure requirements changed with SOX on August 29, 2002. However, insiders did sometimes not comply with these regulations before and after the passage of SOX. We therefore use the actual rather than the mandated disclosure date to identify transaction sequences. We define the maximum length of a transaction sequence to be 40 days. If the first transaction of a sequence is not reported within 40 days, then we consider this sequence to be finished to avoid sequences that stretch over extremely long periods. These 40 days define the upper legal bound for reporting most insider trades before SOX became effective. We consider alternative definitions of trade sequences. In particular, we reran our regressions with shorter time limits (7 days instead of 40 days) and find qualitatively and quantitatively very similar results (results not tabulated).

Figure 1 displays some characteristics of transaction sequences according to our definition. Panel A of Figure 1 shows a secular trend throughout our sample period towards more transaction sequences, which account for about 70% of all trades at the beginning of our sample period and for 90% before the onset of the financial crisis, which then led to a sharp drop in split trades. There is also a drop in August 2002 that continues until January of the following year. Panel B of Figure 1 displays the number of transactions per sequence, which shows a similar pattern. There are about two transactions per sequence in 1996; the number increases steadily, with a short interruption after Sarbanes-Oxley, to about ten transactions per sequence. The financial crisis caused a dramatic drop in the number of transactions per sequence.

Definition of trade duration. The trade duration of transaction sequences is defined as the weighted number of days between the first and the last transaction of the sequence, where the weights are the number of shares traded in sequence s on date t:

$$Trade\,Duration(s) = \sum_{t=1}^{T} t \cdot SharesTraded_{s,t} / \sum_{t=1}^{T} SharesTraded_{s,t}.$$

This definition takes into account not only the number of days between the beginning and the end of the transaction sequence but also the number of shares traded on each day. Under this definition, trade duration decreases if the insider trades larger volumes during the first days of the sequence compared to situations when the insider splits her transactions equally throughout the sequence. The trade duration of a single trade is equal to one. Average trade duration increases from about three to five days in the period before Sarbanes-Oxley. After Sarbanes-Oxley, trade duration sharply decreases to two days, largely for mechanical reasons, and stabilizes at about one and a half after 2004 (Panel C of Figure 1).

Next, we show that transaction sequences constitute trades that were broken up and do not result from random clustering. We consider the clustering of transactions by the same person in the same direction as evidence for trade splitting. Absent trade splitting, the direction of insiders' transactions should be uncorrelated over time, i.e., if an insider executes purchases with probability p and sales with probability *1-p*, then this unconditional probability should be equal to the conditional probability given the direction of the last transaction. Trade splitting may be active, if insiders post a sequence of market orders, or passive, if they post limit orders that are executed against other orders over a period of time. The only relevant aspect for our analysis is that a sequence of transactions should be regarded as the execution of one larger trade. We first perform univariate tests to see whether the unconditional probability and the conditional probability of a sale are the same, given the direction of the previous transaction.

Panel A of Table 3 reports the results for univariate tests. We calculate the proportion of transactions that have the same sign as the previous transaction. Since we need the sign of the previous transaction, the calculations do not include the first transaction for each person. In our baseline case, we do not impose a time limit within which the next transaction has to occur. Table 3 shows that trades cluster not just randomly. In total, 20.3% of all transactions are purchases and 79.7% are sales (see Table 2). Conditional on the previous transaction being a sale (purchase), the next transaction is also a sale (purchase) in 98.8% (96.8%) of all cases, which is significant at the 0.01%-level using standard tests. We repeat the analysis by requiring that the next transaction occurs within a certain period of time, which we assume to be 183 days, 40 days, and 2 days of the first transaction. The six-month restriction is motivated by the short-swing rule, the 40-day restriction by pre-SOX disclosure regulation, and the 2-day restriction by post-SOX disclosure regulation (see above). We find higher probabilities for insiders to trade in the same direction if we restrict the length of a transaction sequence more, although the differences are economically insignificant.

In Panel B of Table 3 we address the same question with a standard Probit model to make sure that transaction clustering cannot be attributed to exogenous factors that influence the direction of trade. The dependent variable equals one if the transaction is a purchase, and regress it on the same dummy variable for the previous transaction (*LagPurchase*). We control for other factors that may drive trade clustering. Many papers document the influence of investor sentiment on investment decisions of retail investors and asset prices. In regression (2) in Table 3B we control for investor sentiment (e.g., Lee, Shleifer, and Thaler (1991)), by including *Sentiment*, the investor sentiment measure of Baker and Wurgler (2006), as an independent variable. The insider trading literature has shown that insiders often act like contrarian investors.[9] We therefore include two additional independent variables in models (3) and (4): *RunupCAR*, the abnormal return

[9]Rozeff and Zaman (1988), Lakonishok and Lee (2001), Jenter (2005), and Fidrmuc, Goergen, and Renneboog (2006) find that insiders on aggregate are contrarian investors.

over the 20 trading days before the transaction, and *StockTercile*, which is the tercile of the stock return in the calendar month before the transaction of all sample companies with sufficient data for this period. Both variables measure the relative development of firm's stock price in the month before an insider transaction. Model (5) includes all four control variables.

Across all these regressions, the coefficient of *LagPurchase* is between 92% and 94%, which means that the conditional probability that the next transaction is again a purchase is at least 92% if we evaluate the impact at the mean of all independent variables. This is economically significantly different from its unconditional probability of 20.3% and statistically significant at all conventional significance levels. All controls have the predicted signs and suggest that some trade clustering responds to investor sentiment and contrarian motives. We conclude that trade splitting is pervasive. Insiders are much more likely to purchase (sell) shares if the previous transaction was also a purchase (sale), even after controlling for all factors that influence trade clustering.

We aggregate sequences of transactions and refer to them as aggregate trades. If we analyze individual trades of a transaction sequence, we refer to them as single transactions. The average trade duration for transaction sequences is 2 days (3.4 days pre-SOX and 1.4 days post-SOX) and varies between 1 and 20.6 days. Single transactions in a trading sequence are only about one third as large as single trades (median size: \$26,300 vs. \$72,200 or 0.002% vs. 0.013% as a percentage of all shares outstanding). Aggregate trades are almost four times larger than single trades (median size: \$255,300 vs. \$72,200, or 0.047% vs. 0.013% of all shares outstanding).

Table 2 provides summary statistics of all variables for our sample. We report summary statistics of trades instead of single transactions because these are the unit of our analysis. The 1,849,513 insider transactions in our data set map into 471,241 trades. We identify 260,438 single trades and 210,803 aggregate trades (transaction sequences). For all variables, which can change over a transaction sequence, we assign the value of the first transaction to the whole sequence. We aggregate only *Stake* and *Volume* over trading sequences.

2.3 Event Study Analysis

We apply standard event study analysis to disclosure day returns to measure the information content of insider trades, which is an established methodology in the insider trading literature (e.g., Lakonishok and Lee (2001); Fidrmuc, Goergen, and Renneboog (2006)). We calculate cumulative abnormal returns (CARs) by using the market model for different event windows between 2 to 41 trading days starting at the disclosure day. The market return is proxied by the CRSP equally weighted return index, and the estimation window ranges over 200 trading days from 220 until 21 trading days prior to the disclosure day. We require at least 100 stock return observations for the parameter estimation.

The results for the event study are presented in Table 4. Similar to the prior literature on insider trading we find that insider trades are informative. Disclosure day returns are significant across all event windows for the pooled sample. We can also confirm the finding of Brochet (2010) that post-SOX the CARs after disclosing purchases increased significantly, whereas the reaction to sales became less negative. In line with the prior literature we find that purchases usually lead to stronger market reactions, although this observation does not apply to the longer event windows pre-SOX (e.g. Lakonishok and Lee (2001); Jeng, Metrick, and Zeckhauser (2003)).

3 What Influences Trade Duration?

Since we analyze trade duration, the main unit of analysis for this section is a sequence of transactions and not an individual transaction itself. In a setting in which only one insider trades, both, information-based theories and liquidity-based theories, imply that insiders stretch their trades over time. We generate contrasting predictions of these theories of optimal trading strategies in two ways. First, as mentioned in the Introduction, our main strategy is to focus on situations when several insiders trade simultaneously. Second, we identify moderating factors that influence optimal trading strategies and that differ depending on the motive for trading.[10] We therefore test the implications for competition by insiders first and then develop additional hypotheses about how the economic environment influences the execution of information-based and liquidity-based trading strategies.

3.1 Hypothesis Development

Holden and Subrahmanyam (1993) show in the context of a Kyle (1985) model that insiders trade more intensely or more aggressively if they compete for the use of the same information at the same time. Foster and Viswanathan (1996) refine this argument by considering the possibility that insiders have information that is positively, but not perfectly correlated. Then insiders compete more intensely for the component of their information they have in common. We therefore have:

Hypothesis 1 (Informed trading with competition): *Trade duration decreases if several insiders compete for exploiting the same long-lived information.*

[10]It may be possible to generate implications about the dynamic profiles of trades. Kyle (1985) predicts that monopolistic insider trades result in a constant speed of information resolution. Optimal liquidation strategies without privileged fundamental information imply that insiders sell their stakes at a decreasing rate (e.g., Vayanos (2001)). However, these predictions seem to be highly model-dependent and do not easily lend themselves to empirical testing.

By contrast, liquidity-based arguments predict the opposite. We develop this argument more formally in the context of a highly stylized model in Appendix B and provide the intuition here. Assume two or more insiders wish to sell a block of shares for liquidity reasons in order to diversify their portfolios. They intend to trade simultaneously and their trades have a temporary impact on transaction prices.[11] All insiders have a need to trade, for example because they wish to reduce their exposure to the long-term uncertainty about the fundamental value of the stock.[12] Then trading faster implies larger benefits from diversification as well as costs from incurring additional temporary price impact. Consequently, each insider trades less and stretches her transactions over a longer period of time if other insiders trade simultaneously in the same direction. The intuition for this result is that simultaneous trading by other insiders increases the slope of the residual demand function for each insider. The increased price impact increases the costs of immediacy and therefore slows down trading by each insider. The fundamental risk of the stock increases insiders' demand for immediacy; hence, they should trade the asset faster if the stock is more volatile.

Hypothesis 2 (Liquidity trading): *(1) Trade duration increases if several insiders trade simultaneously in the same direction for liquidity reasons. (2) Trade duration decreases with the volatility of the stock if insiders sell for liquidity reasons.*

Comparing Hypotheses 1 and 2 shows that information-based and liquidity-based explanations have contrasting implications in a context in which multiple insiders trade at the same time.

[11]In our model and in the argument in the text we abstract from permanent price impact based on the notion that insiders trade for liquidity reasons and have no privileged information. Including permanent price impact would complicate but not change the basic argument.

[12]The model is in the spirit of Almgren and Chriss (2001), He and Mamaysky (2005), and Huberman and Stanzl (2005), who all use some variant of a mean-variance framework to generate a trade-off between price impact and immediacy. Our model can be understood as a reduced-form version of these models, because our model summarizes the costs from trading in a quadratic penalty function.

Testing the implications of the two theoretical approaches requires us to distinguish information-based trades from liquidity-based trades and days on which insiders compete from days on which this is not the case. We measure the information content of trades using the two-day cumulative abnormal announcement return on the day of and the day after the disclosure of the first transaction in a sequence (*CAR(0,1)*). If an insider exploits private information, we should see a stronger market reaction at the disclosure date. We define a dummy variable *Informed*, which equals one if the two-day cumulative abnormal return is greater in absolute value than the standard deviation of stock returns in the month prior to the trade. Additionally, we require that the CAR is positive (negative) for purchases (sales).[13] Our results are robust to alternative definitions of *Informed*. In the robustness section (Section 3.2) we report results using *CAR(0,5)*. We measure competition between insiders by defining the dummy variable *MultipleInsiders*, which is one if more than one insider trades in the same direction on the same day, and zero otherwise.

We formulate additional hypotheses that motivate the inclusion of additional explanatory variables below. We enter all these variables in one regression in order to avoid omitted variable bias and collect the results in Table 5. Our baseline regression is model (1), which regresses *TradeDuration* on the independent variables associated with our hypotheses. Models (2) to (5) perform two sample splits based on the direction of trade and on the passage of the Sarbanes-Oxley act (SOX). The sample split into purchases and sales is motivated by the notion in the insider trading literature that purchases have a larger information content compared to sales (e.g., Lakonishok and Lee (2001)). The sample split into the pre- and post-SOX period recognizes that SOX changed disclosure

[13]We also investigated other measures of asymmetric information (e.g., earnings quality, R&D). However, these measures are only available annually or quarterly on the firm level and exhibit very low correlations with our measure *Informed*. We believe that the asymmetric information component is most accurately measured using ex post realized returns.

standards for insider trades (see Section 2.1 above). The substantial reduction in the disclosure requirement from a maximum of 40 days to only two business days reduces insiders' ability to spread transactions over time without disclosing their trades. We group variables in Table 5 by the associated hypothesis and order them in the order in which we discuss them in the text. As an additional check, models (6) and (7) in Table 5 regress the cumulative abnormal disclosure-date returns on the same independent variables. These regressions allow us to identify which of the explanatory variables are systematically associated with more information. This analysis is performed separately for purchases and for sales in accordance with standard procedures in the insider trading literature.

3.2 Analysis

3.2.1 Competition for Liquidity vs. Competition for Information

The main variable of interest in Table 5 is *MultipleInsiders*. The coefficient on *MultipleInsiders* is always positive and highly significant at all conventional levels with t-statistics ranging from 27.3 to 48.4. The presence of at least one additional insider who trades in the stock in the same direction increases trade duration on average by 5.3% in the baseline regression (1). The effect has a similar strength for purchases and for sales, but is about three times stronger in relative terms in the pre-SOX period (7.6% increase) compared to the post-SOX period (2.7% increase). Since *TradeDuration* is much larger before SOX than after, the economic effect is correspondingly even stronger in the pre-SOX period. The evidence therefore strongly supports the prediction of Hypothesis 2 that insiders compete for the same liquidity and spread their trades over longer periods if other insiders trade at the same time. By contrast, the coefficient on *MultipleInsiders* does not support the predictions of Hypothesis 1 and information-based models for the whole sample, because then we should find a negative coefficient.

However, Hypotheses 1 and 2 are not mutually exclusive because some insider trades may be motivated by information whereas others are motivated by liquidity reasons and the result on *MultipleInsiders* then only shows that liquidity motivations dominate on average. The interaction of *Informed* and *MultipleInsiders* shows that this seems to be the case. The coefficient is highly significant and negative, which suggests that insiders trade more aggressively if there is competition from other insiders *and* their trades are motivated by the use of privileged information. The coefficient on the interaction terms is between 20% and 50% of the coefficient on *MultipleInsiders* for all regressions. The mean of *Informed* is 14% from Table 2, which means that we classify about one in seven trades as information-based. In the presence of competition, these information-based trades complete significantly faster compared to liquidity-motivated trades in the presence of competition. Hence, we find strong predictions for the models of Holden and Subrahmanyam (1992) and Foster and Viswanathan (1996) that competition by insiders for the use of the same information leads them to trade more aggressively. However, this observation applies only to a minority of the insider trades in our sample so that liquidity-based arguments have more explanatory power on average.[14]

Trades associated with several insiders are on average more informative. Regressions (6) and (7) show that the coefficient on *MultipleInsiders* is always highly significant for the regressions in which the dependent variable is the disclosure-day return. For purchases, the effect is also economically significant with a 0.52% stronger increase of the stock price for the announcement of purchases when more than one insider purchases at the same time. By contrast, the effect is negligible for sales with a 0.04% stronger decrease of the stock price. This corroborates the notion in the insider trading literature that purchases

[14]Informed equals one if the CAR(0,1) exceeds one standard deviation of the previous month's stock returns in absolute value. The results do not change if we increase the hurdle to two or three standard deviations (results not reported) or if we use CAR(0,5) (reported below).

tend to be more information-motivated than sales. Similarly, 18.8% of insider purchases in our sample, but only 11.7% of insider sales, are classified as informed trades.

The coefficient on *Informed* shows that trade duration for informed trades is generally shorter by about 0.5%. This effect is similar for purchases and sales and concentrated entirely in the period after Sarbanes-Oxley. As we explained above, the models we compare do not make direct predictions on trade duration but only on how trade duration responds to competition. The post-SOX regulatory environment might have led insiders to complete information-based trades faster whereas there was no corresponding need to accelerate liquidity-motivated trades.

Hypothesis 2 also predicts that liquidity-motivated trades complete faster if insiders are exposed to more risk because the benefits of immediacy increase if the risk of the fundamental value of the shares is larger. We do not find much evidence for this prediction. The coefficient on *Volatility* is in fact positive but statistically and economically insignificant in the baseline regression (1). It has the predicted negative sign only in the post-SOX period and then it becomes statistically highly significant, although the economic effect is still small: the coefficient of -0.0078 implies that a one-standard deviation increase in *Volatility* reduces *TradeDuration* by only 0.3%. We conclude that the connection between volatility and the benefits from immediacy is weak and suspect that the benefits from immediacy arise from other considerations.

3.2.2 Liquidity Effects

Next, we investigate the impact of several variables that are associated with the liquidity of the market and with insiders' desire to trade on certain days but not on others. Based on the model in the appendix, we hypothesize that trade splitting is also a strategy to optimize liquidity. Insiders trade over longer intervals of time if the market is less liquid or if they trade on the short side of the market, i.e., they buy when other investors want to buy and sell when other investors want to sell.

Hypothesis 3 (Stock liquidity): *(1) Trade duration increases in the illiquidity of the stock. (2) Trade duration increases if insiders trade on the short side of the market.*

Liquidity is a somewhat elusive concept and the literature has developed different measures.[15] We wish to use a measure that can be calculated on a daily basis. To conserve space we only report results for the effective relative spread (*EffectiveSpread*) in Table 5. The results for other liquidity measures (*Amihud*, *Turnover*, *PriceImpact*) are discussed in Section 3.2. *EffectiveSpread* is defined as $2 \cdot |P_t - Q_t| / Q_t$, where Q_t is the midpoint of the quotes and P_t is the transaction price (see Chordia, Roll, and Subrahmanyam (2001)). We average the measure for all trades during the day and assign the *EffectiveSpread* of the first day of a trading sequence to the whole sequence.

Consistent with Hypothesis 3, we observe significantly longer trading sequences for firms with less liquid stocks. The effects are somewhat stronger for purchases and for the post-SOX period. However, economic significance is small: A one standard deviation change in *EffectiveSpread* increases trade duration only by about 0.1% on average.

The variable *ShortSide* intends to capture periods during which insiders want to buy when other investors buy and sell when other investors sell. We cannot measure the direction in which other traders want to trade directly and infer it from recent price movements instead. We conduct this analysis at the firm level and classify insider transactions according to the recent share price performance of the firm, assuming that it is more difficult for insiders to buy (sell) shares if the stock of their company has over (under) performed compared to all other stocks in the market. We capture this idea by defining the dummy variable *ShortSide*, which equals one for purchases (sales) if the stock return of the firm

[15]See Goyenko, Holden, and Trzcinka (2009) for a recent analysis of liquidity measures.

in the previous calendar month was in the upper (lower) tercile of the stock returns of all firms in the sample. Hypothesis 3 predicts a positive sign for *ShortSide*. In Table 5 the coefficient for *ShortSide* is positive as predicted and highly significant, which supports the notion that insiders adapt their trading strategies to manage liquidity. Trade duration increases on average by about 2.3% if the insider is on the short side of the market. Comparison of regressions (2) and (3) shows that this effect is driven mostly by sales in a falling market (3.12% impact) rather than by purchases in a rising market (0.42% impact).

Both effects, that of the effective spread and that of *ShortSide*, cannot be associated with information effects. For both variables, CARs are smaller in absolute value, i.e., CARs are lower for purchases and higher for sales: insiders realize lower trading profits from trades on the short side of the market and when the market is illiquid, whereas an information-based explanation would have to associate higher effective spreads with more information asymmetry, which would give the opposite sign.

3.2.3 Information Hierarchies and the Role of Insiders

Several papers in the insider trading literature investigate the so-called "information hierarchy hypothesis," which holds that those insiders who are closer to the firm have more information and their trades have therefore more information content and are more profitable (Seyhun (1986)). The empirical evidence on this hypothesis is mixed.[16] Based on our data we can distinguish between the CEO, officers other than the CEO, directors who are not officers, the chairperson of the board, and other insiders who hold none of these roles. Other insiders are mostly large shareholders, who have to file their transactions if their ownership exceeds 10% of the outstanding shares.

[16]Seyhun (1986) shows that the directors and officers trade on more valuable information than other insiders. Lin and Howe (1990) show that trades by the CEO and the officers and directors of the firm have a higher information content than those of unaffiliated shareholders. Fidrmuc, Goergen, and Renneboog (2006) find no evidence for the information hierarchy hypothesis.

The univariate analysis in Table 4 above supports the information hierarchy hypothesis for purchases: we observe the following ranking in terms of the absolute size of cumulative abnormal returns for CAR(0,1) and CAR(0,5): *CEO* > *Chairman* > *Officer* > *Director* > *Other*, although the return differences between these groups are not always statistically significant. For CARs measured over longer event windows the ranking between Chairmen and Officer is reversed; for sales, we cannot observe a clear ranking. The ranking for purchases is in line with predictions based on the information hierarchy hypothesis. In particular, we would always expect CEOs to be best informed and other insiders to be least informed.

Based on this observation, we expect that those insiders who trade for information reasons trade faster when they expect competition for the use of the same information from other insiders, whereas they trade more slowly if they do not expect competition. Insiders at the top of the information hierarchy should face less competition than those at the bottom. To see this, consider a simplified situation in which insiders can observe three independent signals: $\varepsilon_{CEO\&Chair}$ is observed only by the CEO and the chairman, $\varepsilon_{D\&O}$ is observed by the CEO, chairman, and also by directors and officers, and ε_{Other} is observed by all, including other insiders. Accordingly, there is little competition for the exploitation of $\varepsilon_{CEO\&Chair}$, some competition for $\varepsilon_{D\&O}$, and the most intense competition for ε_{Other}. Based on the theory of Foster and Viswanathan (1994), we therefore expect that insiders at the top of the information hierarchy trade less intensely and spread their trades over longer periods, whereas insiders at the bottom of the information hierarchy, who are subject to more competition, trade more aggressively over shorter periods of time.

Hypothesis 4 (Information hierarchy): *Insiders at the bottom of the information hierarchy who trade on less information trade more aggressively, whereas those at the top of the information hierarchy spread their trades over longer periods.*

The multivariate regressions in Table 5 include dummy variables for all categories of insiders except the CEO, so the coefficients for the four remaining insider groups have to be interpreted relative to the CEO of the company. We focus on the results for purchases in regression (2) in Table 5, because the event study returns discussed above reveal that the informativeness of sales does not conform to the information hierarchy hypothesis, so that Hypothesis 4 cannot be applied to sales.

The results for regression (2) partially support Hypothesis 4. We do observe large and negative coefficients for *Officer* and *Director*, showing that this group trades faster than the CEO, in line with Hypothesis 4. The coefficient on *Chairman* is positive and significant, although economically small. This result is difficult to explain as it would suggest that the chairman typically expects less competition than the CEO. Contrary to the predictions of Hypothesis 4, the largest and positive coefficient obtains for *Other*, which suggests that other insiders mostly trade for reasons not related to the exploitation of information.

In Table 5, we control for actual competition because we include *MultipleInsiders* in the regressions. In unreported robustness checks we interact each of the insider-role dummies with *MultipleInsiders* to account for differences in the degree to which they are subject to competition from others. We find qualitatively similar but statistically and economically weaker results. Overall, we conclude that there is partial support for Hypothesis 4.

3.2.4 Control Variables

We control for several other factors that may influence trade duration beyond those on which we form explicit hypotheses. The most obvious source of price impact is the size of the stake an insider intends to trade. It is not possible to assign trade size unambiguously to either information-based or to liquidity-based explanations. Insiders may wish to trade larger stakes because they have stronger informative signals or because of liquidity shocks.

In both cases, they may want to spread their trades over a longer period. We control for trade size by including dummy variables for each decile of *Stake*. *Stake* is defined as the number of shares traded scaled by the number of shares outstanding. This non-parametric approach seems rather general and capable of capturing a range of different relationships between aggregate trade size and trade duration.[17] We do not report the coefficients in our tables to conserve space. The impact of trade size is positive as expected. Trade duration increases by about 50% from the first decile to the tenth decile.

We control for firm size using *LogMarketCap*, the logarithm of the market capitalization of the company and observe that trade duration increases significantly with firm size. We include *Purchase*, a dummy variable that equals one for purchases and zero for sales in all regressions where we do not split the sample into purchases and sales. Completing purchase transactions takes about 4% longer compared to sales in the pre-SOX period.

We control for the impact of earnings announcements because we expect that insiders will adapt their trading strategies around major corporate news events like earnings announcements. Most firms have black-out periods before earnings announcements or only allow insiders to trade in the two-week window after an earnings announcement (Bettis, Coles, and Lemmon (2000)). We define *BeforeEarn* to equal one in the 14-day period before an earnings announcement and *AfterEarn* to equal one in the 14-day period after an earnings announcement. Table 2 shows that insiders avoid trading before earnings announcements: Whereas 3.8% of insiders' transactions occur in the two-week period before earnings announcements, 21% of transactions occur in the two-week period after earnings announcements. If trades would be distributed evenly throughout the year then we would expect that the means of both variables are 8/52=15.4% with quarterly announcements. Regression (7) in Table 5 shows that insiders avoid informed selling before

[17] We obtain very similar results if we use *StakeDecile* or the continuous variables *Stake* and $Stake^2$. We opt to use stake decile dummies because some regressions do not converge if we use *Stake* and $Stake^2$.

earnings announcements, probably to avoid violating insider-trading laws: trading profits as measured by disclosure day returns are lower by 0.19% and the profit from selling is only 0.14% from the event study results in Table 4. There is no corresponding result for purchases though. Trade duration is longer by 2.62% before earnings announcements and this effect is driven entirely by sales and by transactions in the pre-SOX period.

SOX has only a limited impact on the factors that influence trade duration. The coefficients of *Informed*, *Volatility*, and *AfterEarn* change their signs, but the former two are insignificant before SOX. For most variables the post-SOX coefficient is smaller in absolute value by a factor of two to three compared to the pre-SOX period; the exceptions are *EffectiveSpread* and *Officer*.

3.3 Robustness Checks

We perform a number of robustness checks to see if our results are sensitive to (1) the listing exchange (NYSE/AMEX vs. NASDAQ), (2) the level of market liquidity (low vs. high effective spread), (3) whether more than one insider trades at the same time in the same direction, and (4) different measures of liquidity. In Panel A of Table 6 we therefore run regression (1) from Table 5 separately for the three pairs of subsamples. In Panel B of Table 6 we rerun the same regression for different liquidity measures and alternative definitions for trading sequences and *Informed*.

The most notable differences obtain for the effect of *Volatility*. The coefficient for NYSE-firms supports the prediction of Hypothesis 2 that more risk reduces trade duration, whereas the same coefficient for NASDAQ firms implies the opposite. The effect of liquidity (*EffectiveSpread*) on trade duration is about three times larger for NASDAQ- than for NYSE-firms.

Many effects are much stronger in the sample with competition between insiders than in the sample without competition. Hence, insiders react much more sensitively to a range of factors in their trading environment whenever there is competition from other insiders. If the information content of trades is high and there is competition, trade duration shortens by 2.18%, about four times more than if there is no competition. We do not observe major differences between low and high spread firms.

Panel B of Table 6 presents results on robustness tests using different liquidity measures. The results are very similar independently of the liquidity measure used. All liquidity measures, except *PriceImpact*, yield the same result: Higher stock illiquidity leads to longer trading sequences, as predicted by Hypothesis 3. Economic and statistical significance vary greatly and we find the strongest effects for the *Amihud* liquidity measure. The other coefficients are almost unaffected, only for *Volatility* we observe different results depending on the liquidity measure used.

Secondly, we use an alternative definition of trading sequences. Our baseline definition requires that all transactions of the sequence be executed before the disclosure of the first trade. This definition is natural with respect to information-based explanations of trading, but not with respect to liquidity-based explanations. Accordingly, we change the definition of trading sequences by omitting the disclosure requirement. At the same time, we set the maximum length of a sequence to 7 days instead of 40 days as in our baseline definition. Table 6 Panel B shows that most coefficients are not affected. We observe noticeable differences only for *Volatility* and *EffectiveSpread*. *Volatility* has now the predicted negative sign and becomes significant, whereas *EffectiveSpread* becomes insignificant. Finally, we use an alternative definition for *Informed*. Instead of our baseline definition using *CAR(0,1)* we define *Informed* based on *CAR(0,5)*, which classifies 15.1% of all trades as informed (see Table 2). None of our results is materially affected by this change.

4 Do Insiders Time the Liquidity of the Market?

The previous section shows that liquidity concerns are of primary importance for the decision of corporate insiders to split their trades and to spread their transactions over time. In this section we analyze if and to what extent insiders adapt their trading strategies to fluctuations in market liquidity.

Illiquidity is expensive for insiders, so they should avoid trading on days when the stock is less liquid and trade more if the stock is more liquid. Furthermore, if they trade, they should trade larger quantities on days on which liquidity is higher. This argument assumes that insiders can observe liquidity measures and time their trades accordingly. In Appendix B we formally derive this argument in the context of a highly stylized model and derive the liquidity-timing hypothesis.

Hypothesis 5 (Liquidity timing): *Insiders trade more on days with higher stock liquidity and less on days with lower liquidity.*

We first perform univariate tests and then conduct multivariate regressions to test Hypothesis 5. For the univariate tests we compare the equally-weighted and the trade-size-weighted means of four liquidity measures over all days on which an insider actually trades during a transaction sequence. Trade-size-weighting gives more weight to those days of the trading sequence on which the insider trades more. Hence, if insiders optimize their trades with respect to the liquidity of the market, then we should observe that the trade-size-weighted average for each liquidity measure implies a higher liquidity than the equally-weighted average.

The results in Panel A of Table 7 show that trade-size-weighted averages of *EffectiveSpread* and *Amihud* (*Turnover*) are significantly lower (higher) than equally weighted averages, which indicates that insiders trade larger quantities on days where liquidity is higher. For *PriceImpact* we observe the opposite, but this result is statistically insignificant. In Panel B of Table 7 we compare insider-trading days with all days during a trading sequence on which insiders do not trade. We include up to 20 non-trading-days before and after the transaction sequence in this analysis. We observe for all four liquidity measures the predicted signs and that the differences between trading and non-trading days are economically large and statistically highly significant. The *EffectiveSpread*, *PriceImpact*, and *Amihud* are two times larger, and *Turnover* is about 22% less on non-trading days compared to trading days. The univariate tests are in line with the predictions of Hypothesis 5 and support the notion that insiders optimize their trades with respect to market liquidity.

In Table 8 we perform multivariate OLS regressions to test the liquidity-timing hypothesis. Again, we include all insider-trading days and all days during a sequence on which insiders do not trade plus up to 20 non-trading days before and after the trading sequence.[18] The dependent variable is the percentage of shares outstanding the insider trades on the respective day, which is zero for all non-trading days.[19] The independent variable of interest is the liquidity measure and we use four different liquidity measures, one in each regression. We expect more insider trading on days with high stock liquidity; hence, we expect this coefficient to be negative for all measures but *Turnover*.

We control for a number of effects: The *Stake* traded on the day before the day in question, the absolute return of the stock on the same day, which is a day-to-day proxy for market volatility, the abnormal market volume proxied by the percentage deviation in U.S. market equity trading volume on that day from the average daily equity trading volume in that month, *BeforeEarn*, and *AfterEarn*. We do not include the absolute stock

[18]In a not tabulated robustness check, we rerun all regressions from Tables 8 and 9 without the non-trading days before the first and the last day of a trading sequence and find qualitatively very similar results.

[19]Researchers sometimes run Tobit regressions in similar contexts where the dependent variable has many observations at zero and no non-negative observations. We follow the advice of Angrist and Pischke (2009) and use OLS regressions, because the dependent variable is not censored or truncated.

return in regression (2), which uses *Amihud* as a liquidity measure, because *Amihud* is mechanically related to the absolute stock return. Additionally, we control for calendar months, day-of-the-week and firm fixed effects. The results in Panel A of Table 8 support the liquidity-timing hypothesis: The coefficients have the predicted signs for all four liquidity measures, although the coefficient on *Amihud* is insignificant and the coefficient on *Turnover* is only marginally significant at the 10%-level.

In a second step we repeat the same analysis in first differences. The dependent variable in Panel B of Table 8 is the change in *Stake* between two consecutive days. The control variables are the same as in Panel A, we only omit the lag of *Stake* and firm fixed effects. All continuous independent variables also enter in first differences. Again, the coefficients on all four liquidity variables have the predicted signs and are significant, although the coefficient on *Amihud* is significant only at the 10%-level. Hence, if liquidity improves (deteriorates) insiders trade more (less), in line with the liquidity timing hypothesis.

There is a potential endogeneity concern here, because informed trading may demand liquidity and increase spreads, whereas insider trading that provides liquidity would reduce spreads. Informed insider trades would then imply a positive correlation between insider trading and spreads, which is the opposite of Hypothesis 5. However, insider trades that provide liquidity would imply the same correlation as Hypothesis 5. We reason that if reverse causality drives our results, then the results should be stronger on days on which insiders account for a larger proportion of the daily trading volume, but become weaker or vanish on days on which they account only for a small proportion of daily trading volume. Hence, we split the sample at the median ratio of *Stake* over *Turnover* and present the results for days with a below median ratio of *Stake* to *Turnover* in Panel C. Here we only use those days on which insiders actually trade because otherwise our sample split would only measure the difference between days with and without insider trading. The results contradict the notion that our results are driven by reverse causality. If we restrict the sample to days on which insiders account for a smaller part of trading volume and our results become economically and statistically stronger. Hence, if anything, reverse causality works in the opposite direction and without reverse causality our results would be even stronger: Insiders may consume liquidity and the results in Panel B show only the net impact of their liquidity-induced trading according to Hypothesis 5 after subtracting the opposite effect from insiders' liquidity demand.

Finally, in Table 9 we perform probit regressions in which the dependent variable equals one if an insider trades on a certain day and zero otherwise. The sample and the control variables are identical to those in Table 8. We find strong support for the liquidity-timing hypothesis. The coefficients on all four liquidity measures have the predicted signs and are highly significant, at least at the 0.01%-level. Hence, insiders trade on days with higher stock market liquidity and avoid trading on days with low liquidity. We also confirm earlier findings that insiders trade less before and more after earnings announcements. Additionally, we observe that insiders trade more on days on which the volatility of the stock as measured by absolute stock returns is high as well as on days on which the market volume is high. Insiders also prefer to trade at the beginning of the week. Taking the evidence of Tables 7 and 9 together, we find strong support for the liquidity-timing hypothesis. Insiders seem to adapt their trading strategies to changes in market liquidity on a day-to-day basis, as predicted by our model.

5 Conclusions

We analyze the trading strategies of corporate insiders on two dimensions: the duration of their trades and if and how they adapt their trading strategies to the liquidity of the market. We compare information-based theories with liquidity-based theories and focus on situations where several insiders compete, i.e., insiders trade in the same direction at the same time. Information-based theories predict that insiders trade faster if they compete with other insiders, whereas liquidity-based theories predict the opposite.

We find strong evidence for both theories. Insiders trade more slowly if they compete with other insiders. They do the same if they sell shares in falling markets and if the market is less liquid. We interpret all these findings as evidence supporting liquidity-based explanations.

We identify trades that are based on more private information as the more profitable trades. These trades are completed significantly faster if multiple insiders compete for exploiting the same long-lived information, which provides strong support for the predictions of information-based models with competition between insiders.

Further theoretical work is needed to address the issues of competition among traders in a more elaborate framework compared to extant theories and compared to the simple model we develop in the appendix. In particular, liquidity-based models should allow for multiple traders with correlated liquidity shocks who simultaneously demand liquidity in the same market. It would be desirable to have models that endogenously derive how informed as well as uninformed traders choose trade duration optimally.

Appendix A

Variable definitions

This table defines all variables used in this paper. Insider trading data are taken from IFDF, accounting data from Compustat, market data from CRSP and intraday transaction data from TAQ.

Variable	**Description**	**Source**
%Change in Market Volume	Percentage deviation in U.S. market equity trading volume on a particular day from an average daily equity trading volume in that month	Datastream
Absolute Return	Absolute daily stock return	CRSP
AfterEarn	1 for all transactions executed in the 14 days after an earnings announcement (if available), zero otherwise	Compustat
Amihud	Amihud's measure of illiquidity, defined as the ratio of the daily absolute return to the dollar trading volume on that day (Amihud (2002))	CRSP
BeforeEarn	1 for all transactions executed in the 14 days before an earnings announcement (if available), zero otherwise	Compustat
CEO	1 if trade is executed by the CEO, zero otherwise	IFDF
Chairman	1 if trade is executed by the chairman of the supervisory board, who is not an officer, zero otherwise	IFDF
Director	1 if trade is executed by a member of the board (not including the chairman) who is not an officer, zero otherwise	IFDF
EffectiveSpread	Daily average of $2\left|P_t - Q_t\right|/Q_t$, where Q_t is the quote mid-point and P_t is the price at which a transaction is executed; observations with *EffectiveSpread*>0.5 are set to missing values	TAQ
Informed	1 if the CAR(0,1) is greater in absolute value than the standard deviation of residuals from the market model multiplied by $\sqrt{2}$. The market model is estimated over days -220 to -21	CRSP
LogMarketCap	Natural logarithm of market capitalization	CRSP
LogTradeDuration	Natural logarithm of *TradeDuration*	IFDF
MarketCap	Market value of equity at the transaction date in million $	CRSP
MultipleInsiders	1 if more than one insider trades on the same day in the same direction, zero otherwise	IFDF
Officer	1 if trade is executed by an officer (not including the CEO)	IFDF

Variable	Description	Source
Other	1 for all insiders who are not classified as an officer, chairman, director, or CEO	IFDF
PriceImpact	The measure of price impact of each trade after 5 minutes, defined as $2\,\vert Q_{t+5} - Q_t \vert / Q_t$, with Q_{t+5} representing the quote midpoint price of the stock after five minutes.	TAQ
Purchase	1 if the transaction is a purchase, zero otherwise	IFDF
RunupCAR	Cumulative abnormal return over a 20-day event window (-20,-1) ending one day before the trading day for sales and purchases; CARs of sales are multiplied by -1	CRSP
Sentiment	Monthly sentiment index, taken from Baker and Wurgler (2006); based on first principal component of six (standardized) sentiment proxies over 1966-2005 data.	Baker and Wurgler
ShortSide	1 for purchases if *StockTercile*=3; 1 for sales if *StockTercile*=1; zero otherwise	CRSP
SOX	1 if trade is executed after August 28, 2002, zero otherwise	IFDF
Stake	Number of shares traded by insider / total number of shares	IFDF/ CRSP
StakeDecile	Decile of the *Stake* traded in the transaction of all sample transactions, ranging between 1 (lowest) and 10 (highest)	IFDF/ CRSP
StockTercile	Tercile of the firm's stock return in the previous calendar month of all sample firms' stock returns, ranging from 1 (lowest) to 3 (highest)	CRSP
TradeDuration	The volume weighted number of days between the first and the last transaction of a trading sequence	IFDF
TradeSplitting	1 for all transactions of a trading sequence, where all trades are in the same direction. The last transaction is always before or on the day the first transaction is disclosed or within 40 days of the first transaction, whichever is earlier.	IFDF
Trading	A dummy variable, equal to 1 on days, when an insider trades, and 0 otherwise	IFDF
Turnover	Total number of shares traded on the transaction day / total number of shares outstanding	CRSP
Volatility	Annualized standard deviation of daily stock returns over the preceding calendar month	CRSP
Volume	Volume of the transaction in thousand U.S. $	IFDF

Appendix B

A Model of Simultaneous Trading by Multiple Insiders

Consider a highly simplified model of a market with I insiders indexed $i = 1, ..., I$ and two periods t=*1,2*. Each insider wishes to sell a block of Q shares over the two periods and we denote by q_t^i the quantity sold by insider i in period t. The number of shares each insider intends to trade is identical so that the game is entirely symmetric. The fundamental value of the shares is p_0 in both periods, but market makers respond to increased sales by insiders by temporarily reducing the price. The price of the shares in period t is established as a function of the quantity traded by all insiders at that point:

$$p_t = p_0 - \lambda_t \sum_{i=1}^{i=I} q_t^i,\ t = 1, 2. \quad (1)$$

Hence, we focus on temporary price changes and abstract from changes in the fundamental value.[20] The pricing rule resembles that of a call auction more than of a continuous market. This assumption rules out the possibility that an insider gains an advantage by trading slightly ahead of other insiders and thereby avoids the price impact induced by other traders. The fundamental value p_0 and the slope parameters are known to all insiders at the beginning. Each insider maximizes the following objective:

$$p_1 q_1^i + p_2 q_2^i + p_0 \left(Q - q_1^i - q_2^i\right) - \frac{\varrho}{2} \left(Q - q_1^i - q_2^i\right)^2. \quad (2)$$

The first part of the objective consists of the trading revenues across the two periods, $p_1 q_1^i + p_2 q_2^i$. After the two trading rounds insider i has $Q - q_1^i - q_2^i$ shares left, which have a fundamental value p_0, so the second term represents the fundamental value of her

[20] Models that analyze optimal strategies to trade large blocks usually employ price impact functions that feature temporary price changes attributable to microstructure reasons with permanent prices changes, which are due to changes in the fundamental value of the stock. See Almgren and Chriss (2001), Huberman and Stanzl (2005) and Schied and Schöneborn (2009). Bertsimas and Lo (1998) assume a pricing rule for which the price impact of trades is permanent.

remaining shares after the two periods. Finally, we add a penalty term, which introduces the notion that insiders have some urgency to trade, which may be motivated by risk considerations. In a richer model with uncertainty about the fundamental value, such a risk-premium would result if insiders are risk averse and exposed to the uncertainty about the long-term fundamental value of the shares after the two trading periods.[21] In such a context, the parameter ρ would reflect the product of the variance of the long-term fundamental value and insiders' risk aversion. We therefore assume that insiders bear a cost proportional to the square of the number of shares they still own after the two trading periods. We do not introduce a penalty for the stock insiders hold after the first period, but sell in the second period. This simplification has the additional advantage that the optimal trading strategies chosen at time 0 are time-consistent.[22]

Define by $Q_t^{-i} \equiv \sum_{j=1, j\neq i}^{j=I} q_t^j$ the quantity traded by traders other than trader i in period t and inserting the definition for p_t from (1) into (2):

$$\sum_{t=1}^{t=2} \left(p_0 - \lambda_t \left(q_t^i + Q_t^{-i}\right)\right) q_t^i + p_0 \left(Q - q_1^i - q_2^i\right) - \frac{\rho}{2} \left(Q - q_1^i - q_2^i\right)^2. \quad (3)$$

The first order conditions for maximizing this objective with respect to the quantity q_t^i traded by insider i at time t become:

$$p_0 - \lambda_t Q_t^{-i} - 2\lambda_t q_t^i - p_0 + \rho \left(Q - q_1^i - q_2^i\right) = 0,\ t = 1, 2. \quad (4)$$

From symmetry we have that the quantities traded by all insiders are the same. We can therefore drop the superscript i and use $q_t^i = q_t$ for all i and t. We can therefore simplify the first order conditions as:

[21] Almgren and Chriss (2001) and Huberman and Stanzl (2005) use a mean-variance framework, whereas Schied and Schöneborn (2009) analyze an expected-utility model. Some authors employ a mean-standard deviation framework in order to embed the question in a value-at-risk framework, see e.g., Hisata and Yamai (2000) and Dubil (2002).

[22] We considered an alternative specification with a penalty for shares held after the first period and an additional penalty for shares held after the second period. Our conclusions are unchanged but the mathematical derivations become more complex.

$$-\left(I+1\right)\lambda_t q_t + \rho\left(Q - q_1^i - q_2^i\right) = 0,\ t = 1,2. \quad (5)$$

Upon solving we obtain:

$$q_1 = \frac{\lambda_2 \rho Q}{\lambda_1 \lambda_2 (I+1) + \rho(\lambda_1 + \lambda_2)},\ q_2 = \frac{\lambda_1 \rho Q}{\lambda_1 \lambda_2 (I+1) + \rho(\lambda_1 + \lambda_2)}\ . \quad (6)$$

Observe that the quantities traded in both periods increase in ρ, which is consistent with our interpretation of ρ as a parameter that measures insiders' urgency to trade.

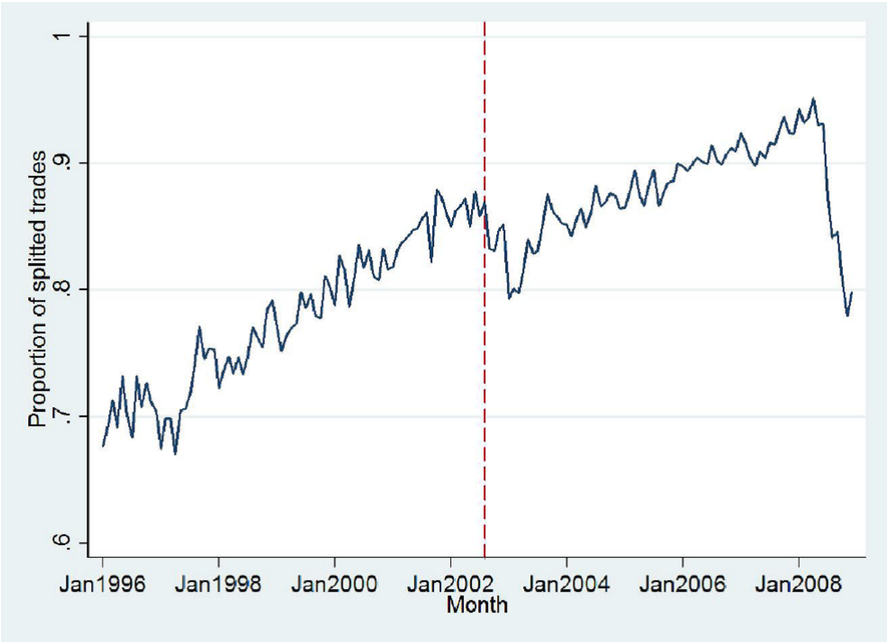
Liquidity timing. The number of shares traded in period t decreases in λ_t, i.e., it decreases if the market at time t becomes less liquid. This is intuitive because illiquidity is expensive for insiders, so they will either trade in the more liquid period or not trade at all if trading becomes more costly. Also, the number of shares traded in period t increases in the slope of the pricing function in the other period, i.e., insiders trade more in period 1 if the market at $t{=}2$ becomes less liquid. Hence, insiders trade more in the period in which the market is more liquid. This is the *liquidity timing effect* to which we refer in the text.

Competition for liquidity. If the number of insiders I increases and more insiders wish to trade at the same time, then each insider trades less. The reason is that each insider perceives that for her, the market has become less liquid and trading more costly if many other insiders trade at the same time.

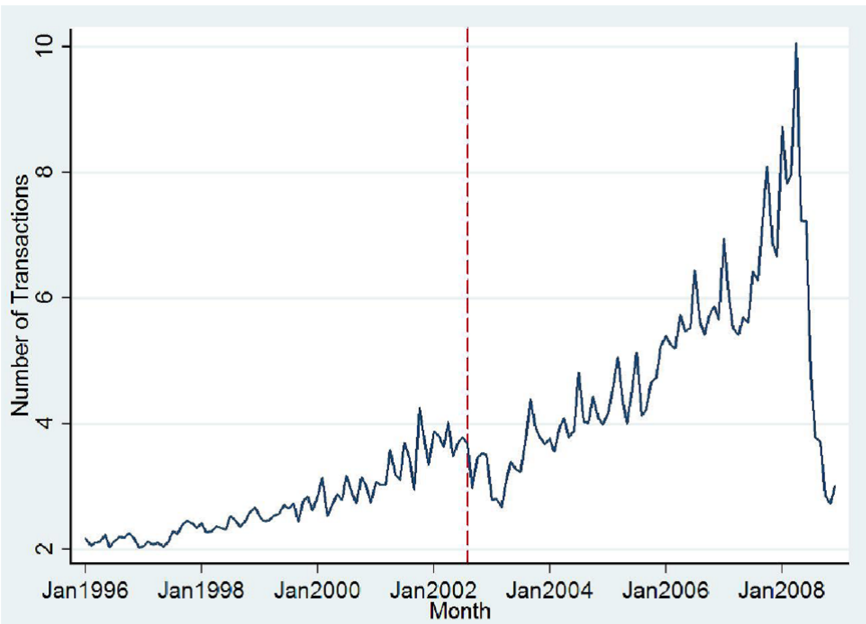
Figures

Figure IV.1: **Development of Trade Sequences over Time.** Panel A of this figure displays the development of the proportion of trading sequences of all insider transactions, Panel B the average number of transactions in a trading sequence, and Panel C the average trade duration of trading sequences over the sample period. Single trades are excluded from Panel C. The dashed vertical line marks the month when the Sarbanes-Oxley act came into force (August 2002).

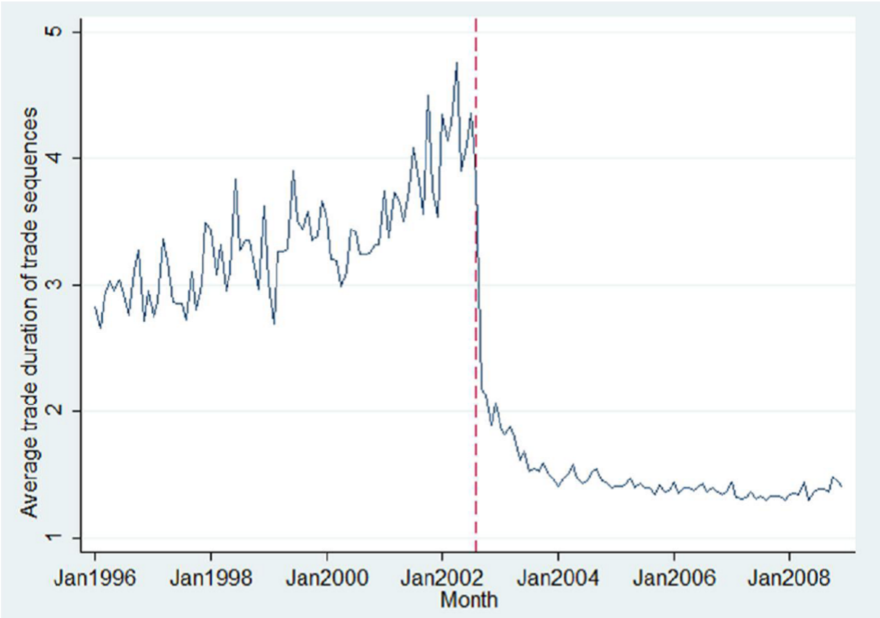
A. Proportion of Trade Sequences Relative to All Trades



B. Number of Transactions in a Trading Sequence



C. Average Trade Duration of Trading Sequences



Tables

Table IV.1: **Sample Design.** This table displays how our sample is constructed from raw Thomson Reuters Insider Filing database (IFDF) data to our final sample. We include all open market and private transactions in the IFDF database (Table One) between January 1, 1996 and December 31, 2008 in our initial data set. We report the losses of observations after matching the IFDF data with CRSP, because of missing information, and consistency checks.

	Trans-actions	**%**	**Firms**	**Insider**
IFDF data	3,272,073	100.0%	18,380	151,523
Observations lost because of:				
Missing stock data on CRSP	300,033	9.2%		
Missing price or volume information on IFDF	9,587	0.3%		
Purchases and sales by the same insider on the same day	26,030	0.8%		
# shares traded > total # of shares traded at the same day	129,139	3.9%		
Insufficient data for event window or estimation period	297,050	9.1%		
Exclude transactions if # of shares traded is not a multiple of 10	470,437	14.4%		
Aggregate all transactions of the same stock in the same direction by the same insider on the same day and at the same price into one transaction	190,284	5.8%		
Final sample	1,849,513	56.5%	11,013	99,413

Table IV.2: **Summary Statistics.** This table displays descriptive statistics for all variables used in our analysis. Insider trading data are taken from IFDF, accounting data from Compustat, market data from CRSP, and intraday data from TAQ.

Variable	**N**	**Mean**	**Median**	**Standard deviation**	**Min**	**Max**
AfterEarn	471,241	0.210	0	0.407	0	1
Amihud	471,131	0.136	0.003	0.483	0.000	3.1
BeforeEarn	471,241	0.038	0	0.192	0	1
CEO	471,241	0.121	0	0.326	0	1
Chairman	471,241	0.027	0	0.163	0	1
Director	471,241	0.305	0	0.460	0	1
EffectiveSpread	429,190	1.91%	0.54%	4.52%	0.00%	50.00%
Informed, CAR(0;1)	471,241	0.140	0.000	0.346	0.000	1.000
Informed, CAR(0;5)	471,241	0.151	0.000	0.358	0.000	1.000
MarketCap (in million $)	471,241	4,844	548	21,549	0.1	571,816
MultipleInsiders	471,241	0.369	0	0.483	0	1
Officer	471,241	0.448	0	0.497	0	1
OtherInsider	471,241	0.099	0	0.298	0	1
PriceImpact	432,906	0.017	0.007	0.036	0.000	1
Purchase	471,241	0.314	0	0.464	0	1
ShortSide	471,241	0.270	0	0.444	0	1
SOX	471,241	0.568	1	0.495	0	1
Stake	471,241	0.098%	0.023%	0.272%	0.000%	20.694%
TradeDuration	471,241	1.296	1	0.843	1	20.58
Purchases	148,002	1.309	1	0.943	1	20.40
Sales	323,239	1.290	1	0.793	1	20.58
TradeSplitting	471,241	0.447	0	0.497	0	1
Purchases	148,002	0.375	0	0.484	0	1
Sales	323,239	0.481	0	0.500	0	1
Turnover	471,241	0.013	0.006	0.056	0.000	9
Volatility	471,063	0.509	0.400	0.403	0.009	19
Volume (in thousand $)	471,241	1100	128	12720	0.008	4,514,165

Table IV.3: **Existence of Trade Sequences.** Panel A of this table displays the percentage of transactions that are followed by a transaction in the same direction (separated for purchases and sales). Please note that the total number of transactions is reduced and the percentage of sales is different compared to the original sample because the first transaction of each individual insider in each firm can only be used as benchmark for the next transaction by the insider in the respective firm. The Chi^2-test on independence and the Fisher exact test are based on the contingency table expressing the relationship between sales and purchases conditional on the prior direction of trade. Panel B of this table presents results for Probit regressions with *Purchase* as dependent variable. See Appendix A for a definition of all variables. For each independent variable, the table displays the marginal effects (evaluated at the mean of the independent variables) and in parentheses, the t-statistic of the two-sided t-test for a coefficient equal to zero. In all regressions, t-statistics are based on heteroskedasticity-robust standard errors. Additionally, we report McFadden's R^2 and the p-values of the F-test with the null-hypothesis of the coefficient of *LagPurchase* being equal to its unconditional mean.

A. Univariate Analysis

	(1)	(2)	(3)	(4)
Observations	All without first for each person	Only within 183 days of each other	Only within 40 days of each other	Only within 2 days of each other
Same Direction				
Sales	98.78%	99.75%	99.89%	99.98%
Purchases	96.75%	99.00%	99.53%	99.89%
% Sales / Total	81.43%	82.24%	82.95%	85.31%
# of observations	1,727,012	1,612,035	1,511,706	1,268,502
Chi^2-test (p-value)	0.00%	0.00%	0.00%	0.00%
Fisher exact test (p-value)	0.00%	0.00%	0.00%	0.00%

B. Probit Regressions

	(1)	(2)	(3)	(4)	(5)
LagPurchase	0.9400	0.9273	0.9373	0.9398	0.9249
	(800.32)	(645.32)	(767.59)	(798.47)	(620.80)
Sentiment		0.0187			0.0169
		(30.12)			(28.56)
StockTercile			-0.0268		-0.0343
			(-92.29)		(-73.36)
RunupCAR				-0.0061	0.0103
				(-3.91)	(4.89)
Observations	1,727,012	1,016,682	1,726,953	1,719,955	1,010,552
Pseudo R^2	0.844	0.824	0.850	0.844	0.829
LagPurchase =0.202	0.0%	0.0%	0.0%	0.0%	0.0%

Table IV.4: **Event Study Analysis of Disclosure Day Returns.** This table reports the cumulative abnormal returns (CAR) of insider purchases and sales for four different intervals after the disclosure date. The CARs are estimated using the market model, the estimation period for the parameters is (-220, -21). The sample is split into the pre- and post-SOX (after August 28, 2002) period. In the lower panel, the table reports the CARs for five different insider groups. The table displays the CAR and, in parentheses, the t-statistic of the two-sided t-test for the null-hypothesis that the respective CAR equals zero.

	CAR(0;1)		**CAR(0;5)**		**CAR(0;20)**		**CAR(0;40)**	
	purchases	**sales**	**purchases**	**sales**	**purchases**	**sales**	**purchases**	**sales**
All	0.0081	-0.0014	0.0186	-0.0050	0.0259	-0.0151	0.0276	-0.0243
	(6.17)	*(-2.57)*	*(8.20)*	*(-5.27)*	*(6.09)*	*(-8.57)*	*(4.64)*	*(-9.88)*
Pre-SOX	0.0029	-0.0022	0.0125	-0.0089	0.0219	-0.0276	0.0294	-0.0492
	(1.35)	*(-1.45)*	*(3.36)*	*(-3.40)*	*(3.14)*	*(-5.64)*	*(3.02)*	*(-7.20)*
Post-SOX	0.0133	-0.0011	0.0248	-0.0037	0.0299	-0.0110	0.0257	-0.0161
	(8.87)	*(-2.16)*	*(9.54)*	*(-4.04)*	*(6.17)*	*(-6.47)*	*(3.79)*	*(-6.79)*
CEO	0.0135	-0.0015	0.0297	-0.0049	0.0425	-0.0161	0.0504	-0.0265
	(3.31)	*(-1.41)*	*(4.22)*	*(-2.57)*	*(3.23)*	*(-4.54)*	*(2.74)*	*(-5.34)*
Chairman	0.0110	-0.0004	0.0225	-0.0034	0.0291	-0.0130	0.0416	-0.0217
	(1.50)	*(-0.14)*	*(1.77)*	*(-0.79)*	*(1.23)*	*(-1.62)*	*(1.26)*	*(-1.94)*
Officer	0.0088	-0.0013	0.0218	-0.0053	0.0361	-0.0164	0.0466	-0.0280
	(2.74)	*(-1.63)*	*(3.94)*	*(-3.67)*	*(3.48)*	*(-6.11)*	*(3.22)*	*(-7.48)*
Director	0.0075	-0.0012	0.0171	-0.0050	0.0268	-0.0135	0.0269	-0.0216
	(3.49)	*(-1.04)*	*(4.61)*	*(-2.52)*	*(3.86)*	*(-3.62)*	*(2.77)*	*(-4.14)*
Other	0.0057	-0.0020	0.0131	-0.0045	0.0112	-0.0127	0.0055	-0.0138
	(2.53)	*(-1.05)*	*(3.37)*	*(-1.35)*	*(1.54)*	*(-2.04)*	*(0.53)*	*(-1.59)*

Table IV.5: **Determinants of Trade Duration.** Models (1) and (2) of the table present results for OLS regressions with cumulative abnormal returns of the disclosure day and the next trading day CAR(0;1) as the dependent variable. The event window starts on the disclosure date of the first transaction of a series of split trades or the disclosure date of a non-split trade. Models (3) to (7) of the table present results for OLS regressions with *LogTradeDuration* as the dependent variable. See Appendix A for a definition of all variables. For each independent variable, the table displays the slope estimate and, in parentheses, the t-statistic of the two-sided t-test for the null-hypothesis that the respective coefficient equals zero. In all regressions, t-statistics are based on heteroskedasticity-robust standard errors. All regressions include calendar year dummies, industry dummies, and dummies for each stake decile.

		LogTradeDuration					CAR(0,1)	
		all	purchases	sales	pre-SOX	post-SOX	purchases	sales
		(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*
	LogTradeDuration						-0.0037	0.0014
							(-5.21)	(3.98)
H.1 & H.2	MultipleInsiders	0.0531	0.0428	0.0568	0.0763	0.0270	0.0052	-0.0004
		(48.47)	(18.43)	(45.95)	(33.14)	(27.36)	(12.14)	(-2.37)
	Informed	-0.0054	-0.0063	-0.0063	0.0009	-0.0051		
		(-3.60)	(-2.58)	(-3.24)	(0.29)	(-3.42)		
	MultipleInsiders	-0.0173	-0.0207	-0.0122	-0.0274	-0.0125		
	*Informed	(-6.24)	(-4.57)	(-3.44)	(-4.87)	(-4.99)		
	Volatility	0.0025	0.0041	0.0046	0.0071	-0.0078	0.0073	-0.0012
		(1.34)	(1.47)	(1.84)	(2.18)	(-4.39)	(7.36)	(-1.41)
H.3	ShortSide	0.0231	0.0041	0.0312	0.0376	0.0129	-0.0020	-0.0007
		(19.66)	(1.98)	(21.96)	(14.93)	(12.20)	(-4.74)	(-3.21)
	EffectiveSpread	0.0342	0.0498	0.0256	0.0085	0.1226	-0.0125	0.0069
		(2.50)	(2.67)	(1.29)	(0.55)	(5.42)	(-2.90)	(2.44)
H.4	Chairman	0.0313	0.0155	0.0341	0.0313	0.0186	-0.0027	0.0008
		(8.04)	(2.17)	(7.41)	(4.12)	(5.39)	(-1.99)	(1.45)
	Officer	-0.0313	-0.0327	-0.0328	-0.0288	-0.0286	0.0004	0.0001
		(-19.94)	(-11.23)	(-17.67)	(-7.54)	(-20.92)	(0.59)	(0.32)
	Director	-0.0118	-0.0289	-0.0025	-0.0185	-0.0078	-0.0018	-0.0002
		(-7.15)	(-10.27)	(-1.20)	(-4.72)	(-5.33)	(-2.78)	(-0.59)
	Other	0.1024	0.1111	0.0823	0.1683	0.0798	-0.0056	-0.0007
		(37.25)	(22.98)	(24.38)	(27.44)	(32.50)	(-6.60)	(-1.59)
	LogMarketCap	0.0110	0.0128	0.0096	0.0250	0.0042	0.0001	-0.0002
		(32.23)	(19.66)	(23.79)	(36.44)	(13.15)	(0.62)	(-3.48)
	SOX	-0.1353	-0.1077	-0.1524			0.0028	-0.0038
		(-30.71)	(-15.54)	(-27.38)			(1.83)	(-5.36)
	Purchase	0.0053			0.0393	0.0006		
		(4.07)			(15.99)	(0.51)		
	BeforeEarn	0.0262	-0.0063	0.0377	0.0417	0.0126	0.0006	0.0019
		(9.81)	(-1.20)	(12.36)	(7.11)	(5.28)	(0.68)	(3.81)
	AfterEarn	-0.0005	0.0005	0.0012	0.0096	-0.0069	0.0007	0.0006
		(-0.49)	(0.24)	(0.87)	(4.28)	(-6.88)	(1.57)	(2.94)
	Observations	397,823	115,258	282,565	153,098	244,725	115,258	282,565
	R^2	0.270	0.333	0.252	0.317	0.178	0.022	0.005
	Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	StakeDecile FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table IV.6: **Trade Duration: Robustness Checks.** The table presents results for OLS regressions with *LogTradeDuration* as the dependent variable. Panel A: Models (1) and (2) show results for sample splits with respect to listings on different exchanges. Models (3) and (4) display results for stocks with different liquidity levels. The High Spread group includes illiquid stocks with the effective spread above its median level across all stocks. Remaining (more liquid) stocks belong to the Low Spread group. Model (5) reports results for all trading series when multiple insiders are trading the same stock and Model (6) includes all remaining observations. Panel B: Models (1) to (3) control for different liquidity measures. The header of the table reports the measure used for each column. Coefficients for each of the liquidity measures are reported in the line *LiquidityMeasure*. Model (4) uses an alternative definition of a trading sequence: the maximum length of a trading sequence is limited to 7 days. Model (5) uses an alternative definition of *Informed*, based on CAR[0;5] instead of CAR[0;1]. Liquidity measure used in Models (4) and (5) is the effective spread. See Appendix A for a definition of all variables. For each independent variable, the table displays the slope estimate and, in parentheses, the t-statistic of the two-sided t-test for the null-hypothesis that the respective coefficient equals zero. In all regressions, t-statistics are based on heteroskedasticity-robust standard errors. All regressions include calendar year dummies, industry dummies, and dummies for each stake decile.

A. Sample Splits

		LogTradeDuration					
		NYSE	NASDAQ	High Spread	Low Spread	Mult Insiders	No Mult Insiders
		(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
H.1 & H.2	MultipleInsiders	0.0429	0.0587	0.0588	0.0480		
		(26.90)	(39.38)	(31.21)	(39.04)		
	Informed	-0.0071	-0.0035	-0.0071	-0.0028	-0.0218	-0.0054
		(-3.37)	(-1.64)	(-3.01)	(-1.57)	(-9.07)	(-3.58)
	MultipleInsiders *Informed	-0.0152	-0.0188	-0.0203	-0.0158		
		(-3.87)	(-4.89)	(-4.59)	(-4.76)		
	Volatility	-0.0079	0.0073	0.0008	-0.0005	0.0042	-0.0030
		(-2.33)	(3.25)	(0.33)	(-0.17)	(1.30)	(-1.38)
H.3	ShortSide	0.0188	0.0245	0.0258	0.0196	0.0337	0.0172
		(10.63)	(15.80)	(14.20)	(13.84)	(14.54)	(13.21)
	EffectiveSpread	0.0298	0.0902	0.0086	2.4068	0.0979	0.0198
		(1.24)	(5.27)	(0.61)	(4.41)	(3.22)	(1.39)
H.4	Chairman	0.0256	0.0338	0.0149	0.0474	0.0392	0.0265
		(4.71)	(6.27)	(2.54)	(9.34)	(5.25)	(6.11)
	Officer	-0.0201	-0.0366	-0.0345	-0.0297	-0.0365	-0.0250
		(-8.55)	(-17.48)	(-13.36)	(-15.77)	(-12.49)	(-14.10)
	Director	-0.0018	-0.0178	-0.0203	-0.0039	-0.0202	-0.0057
		(-0.69)	(-8.15)	(-7.80)	(-1.88)	(-6.33)	(-3.05)
	Other	0.1223	0.0863	0.1048	0.0887	0.0982	0.1047
		(29.31)	(23.60)	(26.66)	(23.71)	(20.34)	(31.74)
	LogMarketCap	0.0074	0.0138	0.0131	0.0132	0.0170	0.0062
		(14.21)	(26.85)	(21.39)	(25.54)	(25.82)	(16.22)
	SOX	-0.0959	-0.1639	-0.1428	-0.1292	-0.2002	-0.0953
		(-14.96)	(-27.36)	(-23.73)	(-20.37)	(-24.97)	(-18.75)
	Purchase	0.0046	0.0048	0.0083	0.0004	0.0092	0.0046
		(2.32)	(2.67)	(4.41)	(0.25)	(3.34)	(3.19)
	BeforeEarn	0.0223	0.0279	0.0214	0.0292	0.0543	0.0128
		(5.38)	(8.03)	(5.28)	(8.77)	(10.01)	(4.35)
	AfterEarn	-0.0033	0.0022	0.0015	-0.0025	0.0037	-0.0044
		(-2.16)	(1.45)	(0.83)	(-1.93)	(1.92)	(-3.45)
	Observations	171,645	226,098	194,174	203,649	148,952	248,871
	R^2	0.292	0.264	0.270	0.250	0.293	0.242
	Year FE	Yes	Yes	Yes	Yes	Yes	Yes
	Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
	StakeDecile FE	Yes	Yes	Yes	Yes	Yes	Yes

B. Different Liquidity Measures and Alternative Definition of Trade Sequences

		LogTradeDuration				
		Amihud	Turnover	Price Impact	7-Day Period	Informed: CAR(0,5)
		(1)	*(2)*	*(3)*	*(4)*	*(5)*
H.1 & H.2	MultipleInsiders	0.0545	0.0559	0.0529	0.0542	0.0523
		(50.82)	(50.68)	(48.47)	(47.11)	(47.40)
	Informed	-0.0052	-0.0047	-0.0051	-0.0104	-0.0053
		(-3.53)	(-3.14)	(-3.39)	(-6.39)	(-3.60)
	MultipleInsiders *Informed	-0.0152	-0.0153	-0.0170	-0.0238	-0.0102
		(-5.62)	(-5.65)	(-6.19)	(-8.39)	(-3.79)
	Volatility	-0.0035	0.0104	0.0026	-0.0058	0.0024
		(-2.03)	(5.51)	(1.41)	(-3.32)	(1.30)
H.3	ShortSide	0.0241	0.0236	0.0230	0.0306	0.0231
		(21.04)	(20.47)	(19.70)	(24.43)	(19.66)
	LiquidityMeasure	0.0481	-0.3985	-0.0310	-0.0120	0.0343
		(36.25)	(-7.32)	(-2.00)	(-1.04)	(2.50)
H.4	Chairman	0.0254	0.0265	0.0313	0.0383	0.0312
		(6.75)	(7.04)	(8.11)	(9.23)	(8.02)
	Officer	-0.0310	-0.0317	-0.0311	-0.0380	-0.0313
		(-20.06)	(-20.51)	(-19.93)	(-22.07)	(-19.95)
	Director	-0.0103	-0.0116	-0.0120	-0.0182	-0.0119
		(-6.35)	(-7.16)	(-7.28)	(-10.05)	(-7.17)
	Other	0.1086	0.1070	0.1025	0.1157	0.1024
		(40.30)	(39.69)	(37.42)	(39.16)	(37.22)
	LogMarketCap	0.0160	0.0118	0.0113	0.0160	0.0110
		(47.19)	(35.55)	(33.29)	(44.48)	(32.26)
	SOX	-0.1375	-0.1373	-0.1351	-0.0231	-0.1353
		(-32.27)	(-32.27)	(-30.69)	(-4.84)	(-30.72)
	Purchase	0.0000	0.0022	0.0063	0.0180	0.0052
		(-0.02)	(1.73)	(4.85)	(13.63)	(3.97)
	BeforeEarn	0.0257	0.0273	0.0258	0.0297	0.0263
		(9.81)	(10.43)	(9.69)	(10.98)	(9.82)
	AfterEarn	0.0001	-0.0001	-0.0004	-0.0086	-0.0006
		(0.13)	(-0.07)	(-0.35)	(-7.35)	(-0.53)
	Observations	435,992	436,031	401,125	387,949	397,823
	R^2	0.274	0.274	0.268	0.269	0.270
	Year FE	Yes	Yes	Yes	Yes	Yes
	Industry FE	Yes	Yes	Yes	Yes	Yes
	StakeDecile FE	Yes	Yes	Yes	Yes	Yes

Table IV.7: **Liquidity Timing: Univariate Analysis.** Panel A of this table presents results of the univariate test on liquidity timing, based on differences in liquidity on the days when insiders trade. Column 1 reports the trade-size-weighted mean of the liquidity measure, where the weight of each day in the trading sequence is the proportion of trade, executed on this day. Column 2 reports the equally-weighted mean of the liquidity measure over all days in the trading sequence, on which insiders actually trade. Column 3 reports the ratio of (2) to (1) in percent. Column 4 displays the t-statistic of the two-sided t-test on the equality of two means. Column 5 shows the number of trading sequences for each liquidity measure. Panel B presents results of the univariate test on liquidity timing, based on differences in liquidity between trading and non-trading days within a sequence. Trading days include days within a trading sequence when an insider actually trades, whereas non-trading days include remaining days in between, up to 20 non-trading days before the start of a trading sequence and up to 20 non-trading days after the end of a trading sequence. Column 1 reports the equally-weighted mean of the liquidity measure on trading days and Column 2 on non-trading days. Column 3 reports the ratio of (2) to (1) in percent. Column 4 displays the t-statistic of the two-sided t-test on the equality of two means. Column 5 shows the number of trading sequences for each liquidity measure.

A. Trading Days Only

	Mean		**Relative difference**		
	Trade-size-weighted	Equally-weighted	%	t-statistic	N
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
EffectiveSpread	0.0156	0.0160	2.6%	18.00	193,926
Amihud	0.1264	0.1363	7.8%	47.43	208,013
Turnover	0.0138	0.0132	-4.3%	-29.22	210,768
PriceImpact	0.0154	0.0153	-0.6%	-1.04	193,145

B. Trading Days vs Non-Trading Days

	Mean		**Relative difference**		
	Trading Days	Non-trading days	%	t-statistic	N
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
EffectiveSpread	0.0172	0.0336	95.3%	-118.79	96,508
Amihud	0.1337	0.2944	120.2%	-107.52	150,338
Turnover	0.0119	0.0093	-21.8%	111.52	150,342
PriceImpact	0.0158	0.0273	72.8%	-98.02	96,758

Table IV.8: **Liquidity Timing: Determinants of Stake Traded.** Panel A of this table presents results for OLS regressions with the number of shares traded by an insider on a particular day divided by the total number of shares outstanding *(Stake)* in percent as the dependent variable. Regressions include all non-trading days within a trading sequence as well as up to 20 non-trading days before the first trading day in a sequence and up to 20 non-trading days after the last trading day in a sequence. The dependent variable (*Stake*) equals 0 for non-trading days. The header of the table reports the liquidity measure used for each column. Coefficients for each of the liquidity measures are reported in the line *LiquidityMeasure*. Panel B presents results for OLS regressions with the difference in the number of shares traded by an insider on a particular day from the number of shares traded on the previous day, divided by the total number of shares outstanding, *D.Stake* (in percent), as the dependent variable. Coefficients for the first differences of each of the liquidity measures are reported in the line *D.LiquidityMeasure*. Panel C of this table presents results for OLS regressions with *Stake* as the dependent variable. The sample includes only days, on which insiders actually trade. The table displays results for insider trades, for which stake traded, scaled by the daily turnover of the stock, (*Stake/Turnover*) is below the median of the whole sample. Coefficients for each of the liquidity measures are reported in the line *LiquidityMeasure*. See Appendix A for a definition of all variables. For each independent variable, the table displays the slope estimate and, in parentheses, the t-statistic of the two-sided t-test for the null-hypothesis that the respective coefficient equals zero. In all regressions, t-statistics are based on heteroskedasticity-robust standard errors. All regressions include calendar month dummies and weekday dummies. Regressions in Panels A and C additionally include firm-fixed effects.

A. Levels

	Stake, %			
	Effective Spread	**Amihud**	**Turnover**	**Price Impact**
	(1)	*(2)*	*(3)*	*(4)*
LagStake	0.3260	0.2894	0.2895	0.3262
	(2.96)	*(3.40)*	*(3.40)*	*(2.98)*
Liquidity measure	-0.0023	-0.00001	0.3577	-0.0110
	(-5.37)	*(-1.35)*	*(1.72)*	*(-4.34)*
Absolute Return	0.2039		0.5497	0.2021
	(3.41)		*(1.10)*	*(3.38)*
% Change in Market	0.0232	0.0245	0.0142	0.0240
Volume	*(1.42)*	*(2.10)*	*(1.01)*	*(1.47)*
BeforeEarn	-0.0219	-0.0147	-0.0162	-0.0218
	(-3.65)	*(-1.58)*	*(-1.99)*	*(-3.64)*
AfterEarn	0.0131	0.0155	0.0134	0.0131
	(2.12)	*(3.33)*	*(2.91)*	*(2.10)*
Observations	2,515,693	3,780,048	3,841,074	2,518,672
R^2	0.137	0.095	0.095	0.138
Calendar month FE	Yes	Yes	Yes	Yes
Week day FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

B. Differences

	D.Stake, %			
	Effective Spread	**Amihud**	**Turnover**	**Price Impact**
	(1)	*(2)*	*(3)*	*(4)*
D.Liquidity measure	-0.0007	0.0000	0.6583	-0.0015
	(-7.15)	(-1.83)	(2.76)	(-2.70)
D.Absolute Return	0.2064		0.7167	0.2038
	(4.06)		(1.42)	(4.00)
% Change in Market	0.0229	0.0274	0.0196	0.0233
Volume	(1.06)	(1.70)	(1.24)	(1.07)
BeforeEarn	0.0014	0.0108	0.0079	0.0020
	(0.26)	(1.18)	(0.97)	(0.38)
AfterEarn	0.0040	0.0045	0.0061	0.0036
	(0.52)	(0.83)	(1.11)	(0.47)
Observations	2,328,758	3,613,227	3,711,439	2,332,119
R^2	0.0001	0.0001	0.0001	0.0001
Calendar month FE	Yes	Yes	Yes	Yes
Week day FE	Yes	Yes	Yes	Yes

C. Stake/Turnover Below Median

	Stake, %			
	Effective Spread	Amihud	Turnover	Price Im-pact
	(1)	(2)	(3)	(4)
LagStake	0.0530	0.0742	0.0566	0.0531
	(3.54)	(6.04)	(4.69)	(3.55)
Liquidity measure	-0.0664	-0.0131	0.6104	-0.0030
	(-9.29)	(-14.60)	(4.27)	(-0.31)
Absolute Return	0.2381		0.0536	0.2363
	(11.75)		(1.21)	(11.69)
% Change in Market	0.0026	0.0066	0.0008	0.0025
Volume	(2.66)	(6.72)	(0.79)	(2.57)
BeforeEarn	-0.0007	-0.0012	-0.0011	-0.0007
	(-1.29)	(-1.74)	(-2.02)	(-1.32)
AfterEarn	0.0007	0.0003	0.0000	0.0007
	(1.37)	(0.58)	(-0.10)	(1.39)
Observations	138,347	155,293	155,293	138,582
R^2	0.405	0.351	0.463	0.404
Calendar month FE	Yes	Yes	Yes	Yes
Week day FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

Table IV.9: **Liquidity Timing: Determinants of Insider Trading Days.** The table presents results for Probit regressions with *Trading* as the dependent variable. *Trading* is equal to 1 for days on which insider trade, and 0 otherwise. Regressions include all non-trading days within a trading sequence as well as up to 20 non-trading days before the first trading day in a sequence and up to 20 non-trading days after the last trading day in a sequence. The header of the table reports the liquidity measure used for each column. Coefficients for each of the liquidity measures are reported in the line *Liquidity measure*. See Appendix A for a definition of all variables. For each independent variable, the table displays the marginal effects (evaluated at the mean of the independent variables) and, in parentheses, the t-statistic of the two-sided t-test for the null-hypothesis that the respective coefficient equals zero. In all regressions, t-values are based on heteroskedasticity-robust standard errors. All regressions include calendar month dummies.

	Trading			
	Effective Spread	**Amihud**	**Turnover**	**Price Impact**
	(1)	*(2)*	*(3)*	*(4)*
LagTrading	0.3411	0.3285	0.3334	0.3723
	(111.9)	(114.8)	(113.2)	(111.5)
Liquidity measure	-0.5059	-0.0094	0.0735	-0.7573
	(-43.68)	(-34.88)	(4.81)	(-41.76)
Absolute Return	0.2091		0.2155	0.2742
	(18.04)		(19.58)	(20.47)
% Change in Market	0.0154	0.0153	0.0138	0.0207
Volume	(8.94)	(10.84)	(9.52)	(10.18)
BeforeEarn	-0.0625	-0.0520	-0.0539	-0.0749
	(-40.55)	(-39.42)	(-39.39)	(-40.55)
AfterEarn	0.0190	0.0242	0.0264	0.0241
	(17.41)	(28.73)	(30.33)	(18.82)
Monday	0.0105	0.0071	0.0069	0.0122
	(10.46)	(8.39)	(7.89)	(10.31)
Tuesday	0.0070	0.0059	0.0062	0.0080
	(8.45)	(8.48)	(8.67)	(8.22)
Wednesday	-0.0003	-0.0002	-0.0001	-0.0005
	(-0.34)	(-0.24)	(-0.11)	(-0.56)
Thursday	-0.0016	-0.0016	-0.0017	-0.0020
	(-2.05)	(-2.49)	(-2.50)	(-2.28)
Observations	2,522,015	3,789,579	3,850,702	2,525,013
R^2	0.138	0.116	0.114	0.131
Calendar month FE	Yes	Yes	Yes	Yes

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Erklärung

Hiermit erkläre ich, die vorliegende Arbeit selbstständig angefertigt zu haben. Ich habe alle Hilfsmittel vollständig und deutlich angegeben.

Olga Lebedeva

Kurzlebenslauf

Olga Lebedeva

Schulausbildung und akademischer Werdegang

2008-2012	UNIVERSITÄT MANNHEIM
	Wissenschaftlicher Mitarbeiterin am Lehrstuhl für Corporate Finance (Professor Ernst Maug, Ph.D.) und Doktorandin am Center for Doctoral Studies in Business
2011	WHARTON SCHOOL DER UNIVERSITÄT PENNSYLVANIA
	Forschungsaufenthalt
2006-2008	OTTO-VON-GUERICKE UNIVERSITÄT MAGDEBURG
	Masterstudium, Abschluss als M.Sc. "Economics and Finance"
2005	UNIVERSITÄT MAASTRICHT (Maastricht/Niederlanden)
	Austauschstudentin
2002-2006	KIEW-MOHYLA AKADEMIE (Kiew/Ukraine)
	Bachelorstudium, Abschluss als BA "Economics"
2002	Abitur, Gymnasium 99, Zaporizhya, Ukraine