Trading Strategies of Corporate Insiders[*]

Olga Klein[a] Ernst Maug[b] Christoph Schneider[c]

January 4, 2017

Abstract

We test two complementary theories of optimal trading strategies by analyzing transaction patterns of corporate insiders: Information-based theories predict that investors trade faster if they compete with others for exploiting the same information. Liquidity-based theories predict the opposite. Our analysis supports the predictions of liquidity-based models: insiders take longer to complete trades when they face competition from other insiders and they trade slower in less liquid markets. Insiders adapt to fluctuations in market liquidity. We identify informed trading using CARs, company news announcements, and insider trading pattern. Our results support the predictions of information-based models for trades classified as informed.

JEL classifications: G14, G34, G38

Keywords: Trade splitting, informed trading, block trading, insider trading, liquidity, Sarbanes-Oxley

[*] We thank Utpal Bhattacharya, Thierry Foucault, Craig Holden, Rik Sen, Eric Theissen, and Bohui Zhang as well as seminar participants at the BI Oslo, Karlsruhe Institute of Technology, University of Mannheim, National University of Singapore, Singapore Management University, Technical University Munich, the German Finance Association (DGF) meetings in Frankfurt, the EFMA meeting in Braga, and the conference of the TR/SFB 15 in Caputh for discussions and suggestions on earlier drafts of this paper. We thank the collaborative research centers SFB 504 "Rationality Concepts, Decision Making and Economic Modeling" and TR/SFB 15 "Governance and the Efficiency of Economic Systems" at the University of Mannheim and the Rudolf von Bennigsen-Foerder foundation for financial support.

[a] University of Warwick, Coventry CV4 7AL, UK. E-mail: Olga.Klein@wbs.ac.uk. Tel: +44 24 765 28956.

[b] University of Mannheim, 68131 Mannheim, Germany. E-mail: maug@uni-mannheim.de. Tel: +49 621 181 1952.

[c] University of Mannheim, 68131 Mannheim, Germany. E-mail: schneider@uni-mannheim.de. Tel: +49 621 181 1949.

1 Introduction

This paper evaluates theories of strategic trading, defined as the way in which investors break up large trades and allocate them over time. The literature has produced a range of models, which can be grouped according to the main motivation for strategic trading. The first group assumes that informed investors spread their trades over time in order to conceal their private information and manage the permanent price impact their trades have on the stock price, an argument that goes back at least to Kyle (1985).[1] The second group is based on trading motives that comprise portfolio-rebalancing and risk-sharing, which we summarize under the broad concept of liquidity motives ("allocational" motives in Vayanos (2001)). These theories share the notion that investors manage the temporary price impact their trades have on stock prices, a friction which may exist absent any informational motivations for trading, and which creates a cost for immediate execution and a trade-off between immediacy and the price at which an order is executed. To the best of our knowledge, Vayanos (1999) is the earliest model of dynamic trading strategies based on liquidity motives.[2]

The empirical literature in market microstructure has evaluated some of the specific implications of these models, but always has to face two empirical challenges, which we attempt to address in this paper. The first challenge is that large transaction databases do not provide identi-

[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 private information break up their trades over time. The most important extensions for our purposes are Holden and Subrahmanyam (1994), Foster and Viswanathan (1994, 1996), and Back, Cao and Willard (2000), who consider multiple competing traders. We discuss their models in more detail below.

[2] Grossman and Miller (1988) provide an early analysis of temporary price impact, but their model is not dynamic. Bertsimas and Lo (1998) have a model of dynamic trading, but assume a price process that only features permanent price impact, which is more consistent with information-based trading. 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), who involve temporary price impact, but assume that the price process is exogenous to the investor's trades. Vayanos (1999) derives prices and price impact endogenously from the model.

fiers for the investors who originated these transactions, so that direct analyses of trading strategies rely on small, hand-collected data sets (see Chan and Lakonishok (1995) and Keim and Madhavan (1995), who have data from 37, respectively, 21 institutions). We address this problem by investigating insider trades, for which large comprehensive data sets exist.

Second, models of strategic trading based on information-related motives and those based on liquidity-related motives often overlap in their predictions, making it difficult to distinguish them empirically. The reason is that investors will attempt to minimize temporary as well as permanent price impact independently of their trading motives. The focus of our analysis is on situations in which several investors trade simultaneously and therefore compete for the use of the same information, respectively, for liquidity in the same stock. In this particular context, theories of trading strategies generate distinct predictions depending on the main friction on which they are based. Information-based theories predict that competition among multiple informed investors leads to a "rat-race" effect, in which each informed investor trades faster. Intuitively, informed investors become competitors for the exploitation of the same informative signal and enjoy an informational advantage only as long as their information has not been incorporated into prices through the trades of other informed traders.[3] This happens, because informed insiders' trades move prices closer towards their fundamental values, so the trades of one insider impose a cost for waiting on all other insiders. By contrast, liquidity-based arguments imply the opposite: traders extend their trading horizons and trade more slowly if they know that other investors trade in the same direction at the same time, because competition for liquidity increases price impact and

[3] See also Foster and Viswanathan (1994, 1996), who 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. Back, Cao and Willard (2000) show that the "rat-race" effect obtains only if the signals of different insiders are sufficiently correlated. 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)).

therefore the costs of immediacy. This happens even in anonymous markets when liquidity-motivated trades have permanent price impact, because the market cannot distinguish between informed and uninformed trades. With liquidity-induced insider trades, price impact moves prices away from fundamental values and creates benefits from waiting and holding out until some point in the future when the market has learned the true information content of trades and prices have reverted to fundamental values.

We study a sample of 1.85 million transactions by more than 99,000 insiders in the United States. Insiders' trades provide an ideal testing ground for both groups of models, because insider transactions are well documented, permit the identification of multiple transactions by the same trader, and allow us to separate situations in which other insiders compete from situations in which only one insider trades.

In the first step, we show that most of these transactions indeed form sequences that result from breaking up larger trades and not just from random clustering of transactions. The main analysis focuses on the length of transaction sequences in terms of calendar time (trade duration), measured in days. We ignore how trades are distributed within a day for data reasons, which also helps us to avoid looking at trades broken up passively during the day; such a passive break-up may result if insiders place limit orders that are matched with multiple orders from other traders.[4] We use three different identification strategies to separate trades into informed trades and uninformed trades: (1) corporate news events (e.g., M&A and earnings announcements); (2) event-study returns after the disclosure of insider trades; (3) the classification of trades into opportunistic and routine trades proposed by Cohen, Malloy and Pomorski (2012). We then distinguish days

[4] For an analysis of how insiders use market orders or limit orders see Baruch, Panayides and Venkataraman (2013).

on which multiple insiders of the same firm trade in the same direction from those days on which only one insider trades.

Our main finding is that 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. Hence, the predominant concern of insiders in our sample is the management of temporary price impact and market liquidity. This conclusion is also supported by four later analyses. First, we show that those insiders who are arguably least informed, because they have no operational role in the firm, take the longest to complete their trades. Second, if insiders trade on the long side of the market, i.e. they buy when the market moves up or sell when the market moves down, then they take longer to complete their trades. Third, trade duration increases in less liquid markets, independently of the measure we chose to proxy for market liquidity. Fourth, we investigate how insiders adapt their trading strategies in response to changes in the liquidity of their firm's stock. We hypothesize that insiders 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. Several liquidity measures increase by a factor of about two on days when insiders do not trade compared to days when they trade. All observations taken together support the conclusion that liquidity-related motives such as portfolio rebalancing or risk sharing are the predominant concern for most insiders.

However, conclusions at the level of the entire sample may hide important differences across transactions. In most cases, we find trades are completed faster if insiders are more likely to be informed. More importantly, competition from other insiders reduces trade duration for informed trades for all classifications of informed trades. This result is in line with the predictions of the information-based models of Holden and Subrahmanyam (1992), Foster and Viswanathan (1994, 1996), Back, Cao and Willard (2000), and Kaniel and Liu (2006).

We contribute to the literature in several ways. To the best of our knowledge, we are the first to conduct empirical tests for the contrasting implications of information-based and liquidity-based strategic trading models. The paper closest to ours is Cho (2007), who uses structural estimation of several information-based models and makes inferences about the number of informed traders before earnings announcements. His inferences are based on matching moments for price volatility, volume, and market depth. His framework does not consider liquidity-based motivations for trading. In his experimental work, Schnitzlein (2002) shows that it may be critical for the predictions of information-based models that informed traders and dealers know how many informed traders are in the market. Cho (2007) and Schnitzlein (2002) are the only contributions we are aware of that explicitly focus on competition between traders, and both have a different focus and use methodologies different from ours.

There is a small empirical literature on trading strategies. Collin-Dufresne and Fos (2015) analyze the trading strategy of activist investors (Schedule 13D filers) and document liquidity timing, which is consistent with our evidence on corporate insiders. They conclude that strategic traders with long-lived information who can choose when and how to trade cannot be detected using standard adverse selection measures. Kacperczyk and Pagnotta (2016) examine options and equity market trades based on material and non-public information in SEC's insider trading litigation files. They argue in contrast to Collin-Dufrense and Fos (2015) that how information is revealed to markets does not depend on whether informed traders strategically time their trades or not. Kaniel and Liu (2006) investigate in their empirical analysis the strategic choice of limit and market orders by informed investors. They find that limit orders are more informative than market orders. Baruch, Panayides and Venkataraman (2016) analyze the trading strategies of corporate insiders before unscheduled news events. They relate the competition between insiders to the question of whether insiders use limit orders or market orders and hence to another aspect of insiders' trading strategies than the one analyzed in this paper.

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. We calculate abnormal returns from a market model, for which we require at least 100 stock return observations. We lose 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 computer-executed trades may influence our analysis. 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. One remaining concern is that some transactions are generated passively by matching large limit orders with several orders of other investors. To alleviate this concern we aggregate all transactions executed at the same price in the same direction by the same insider on the same day. In unreported regressions, we check whether our 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. 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.

2.2 Constructing transaction sequences

Definition of a transaction sequence. In our baseline analysis, we regard an individual transaction as a part of a transaction sequence if there is a subsequent (individual) transaction in the same direction and by the same insider within seven days. If two transactions in the same direction are separated by a transaction in the opposite direction, we start a new sequence.[5] Transaction sequences are the main objects of our analysis; defining a transaction sequence properly is therefore crucial and we undertake a number of robustness checks. First, we vary the length of the trading window from three to 14 days. Second, we use a definition based on the actual disclosure date of trades. In this case, a sequence stops if its first transaction is disclosed. The motivation for the latter definition is that trade splitting might only help insiders to conceal information as long as the first transaction in a sequence has not been disclosed. Betzer, Gider, Metzger and Theissen (2014) analyze the trade reporting of insiders before and after SOX. They find that be-

[5] This choice may appear problematic in the context of the model of Huddart, Hughes and Levine (2001), in which insiders play mixed strategies and may interrupt a sequence of transactions in the same direction with a transaction in the opposite direction to mislead the market. However, we find only 121 cases in which insiders change the direction of their trades within a week and conclude that this theoretical possibility is not relevant for our analysis.

fore SOX insiders frequently delayed reporting and even violated reporting requirements. Based on their event study results they argue that insiders who execute several trades before reporting are more likely to possess private information.

As noted above, disclosure requirements changed with the Sarbanes-Oxley act (SOX) on August 29, 2002 and the definition is adjusted accordingly. Using our baseline definition based on seven-day sequences, we obtain 207,414 transaction sequences. Finally, we exclude 10,713 sequences from our analysis where transactions across several days are executed at the same price, because these might be generated passively by matching large limit orders with several orders of other investors. Not excluding these sequences does not materially affect our results.

For all variables that can change over a transaction sequence, we assign the value of the variable associated with the first transaction to the whole sequence. We aggregate only *Stake*, defined as the number of shares traded by the insider scaled by the number of shares outstanding, and *Volume*, value of the transaction in $, over transaction sequences. We refer to a transaction as a single transaction if it does not belong to any sequence. Overall, the 1,849,513 insider transactions in our data set map into 455,484 trades. We identify 258,783 single transactions and 196,701 transaction sequences.

Figure 1 displays some characteristics of transaction sequences according to our benchmark definition. Panel A of Figure 1 shows a secular trend throughout our sample period towards more transaction sequences, which account for about 60% of all trades at the beginning of our sample period and for 95% before the onset of the financial crisis, which then led to a considerable drop in transaction sequences. 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 to about twelve 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*:

$$\text{(1)} \qquad Trade\ Duration\left(s\right) = \sum_{t=1}^{T} t \times SharesTraded_{s,t} \,/\, \sum_{t=1}^{T} SharesTraded_{s,t}.$$

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 transaction is equal to one. Given our definitions and sample construction, transaction sequences that are completed within one day also have a trade duration equal to one. Panel C of Figure 1 plots average trade duration, which increases from about 1.8 to 2.2 days in the period before Sarbanes-Oxley. After Sarbanes-Oxley, trade duration continuously decreases to 1.4 days until 2007. During the financial crisis of 2008, trade duration increases again to about 1.6 to 1.8 days.

Transaction sequences are broken-up trades. 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 sells 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. The only relevant aspect for our analysis is that a sequence of transactions should be regarded as the execution of one larger trade. In Appendix C (Table A1 Panel A) we show that conditional on the previous transaction being a sale (purchase), the next transaction is also a sale (purchase) in 98.8% (96.7%) of all cases. Unconditionally, 20.3% of all transactions are purchases and 79.7% are sales, and the difference between the conditional and the unconditional frequencies is statistically significant at the 0.01%-level based on a Chi-square test, which rejects the hypothesis that transaction sequences occur from random clustering. This result is confirmed in multivariate probit regressions (Appendix C Table A1 Panel B), where we control for several exogenous factors that might influence the direction of trades.

The average trade duration for transaction sequences is 1.7 days (1.85 days pre-SOX and 1.58 days post-SOX) and varies between 1 and 4.75 days. Individual transactions in a transaction sequence are only about one half as large as single transactions (median size: \$27,160 vs. \$60,000 or 0.002% vs. 0.013% as a percentage of all shares outstanding). Transaction sequences are around four times larger than single transactions (median size: \$266,230 vs. \$60,000 or 0.053% 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 individual transactions because trades are our units of analysis.

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 distribute 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.[6] 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.

Informed trading with competition. Holden and Subrahmanyam (1994) show in the context of a Kyle (1985) model that insiders trade more intensely or faster if they compete for the use of the same information at the same time. Foster and Viswanathan (1996) and Back, Cao and Willard (2000) refine this argument by considering the possibility that insiders have information that is positively, but not perfectly correlated. Correlated signals do not alter the theoretical analysis qualitatively, because correlated signals can always be decomposed into a common component, on which insiders compete, and an idiosyncratic component, to which each insider has unique access. These models predict that insiders compete more intensely for the component of the information they have in common. We therefore have:

Hypothesis 1: *Trade duration decreases if several insiders compete for exploiting the same private information.*

Long-lived private information. Kaniel and Liu (2006) show that informed traders do not necessarily prefer faster execution, i.e., they do not favor market orders over limit orders. Their model distinguishes between short-lived and long-lived information and illustrates that it can be

[6] 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.

optimal for insiders with long-lived private information to use limit orders and bear execution risk in exchange for a better price.

Hypothesis 2: *Trade duration increases if insiders have more long-lived compared to short-lived private information.*

Liquidity trading. In contrast to informed trading, liquidity-based arguments predict that competition among insiders leads to an increase in trade duration. We develop this argument more formally in the context of a stylized model in Appendix B and provide the intuition here. The model follows the literature on liquidity-induced block trades and extends this literature to the case of multiple insiders who trade for liquidity reasons.[7] The model has two rounds of trading. We adopt the terminology of Bessembinder, Carrion, Tuttle and Venkataraman (2016) and distinguish between short-lived temporary price impact, which lasts for one period, and long-lived temporary price impact, which lasts for two periods. Our model is not information-based. As such, it does not feature permanent price impact. Trades have long-lived temporary price impact if the market is not "resilient" in the terminology of Bessembinder et al., i.e. if order books do not refill immediately and trades have price impact beyond the execution period. In our model, insiders liquidate stakes they do not sell in the two trading periods at the terminal date, at which prices will revert to fundamental values. However, shares held to the final date are subject to fundamental risk, which insiders try to reduce.

In this framework, assume there are two or more insiders who wish to sell a block of shares for liquidity reasons in order to diversify their portfolios. All insiders have a need to trade, for example, because they wish to reduce their exposure to the long-term uncertainty about the fun-

[7] The model borrows from Bessembinder (2003) and 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. See Appendix B for further discussions of this literature.

damental value of their stock. They do not have any information and trade simultaneously. Insider trades have short-lived and long-lived temporary impact on transaction prices, because trades are assumed to be anonymous and market participants cannot distinguish informed trades from uninformed trades.

In this context, trading faster creates benefits from immediate execution as well as costs from incurring additional price impact.[8] Consequently, each insider trades less and distributes her transactions over a longer period if other insiders trade simultaneously in the same direction. Intuitively, simultaneous trading by other insiders increases the slope of the residual demand function for each insider.[9] The increased price impact increases the costs of immediacy and therefore slows down trading by each insider. In our model, this effect is stronger if price impact is long-lived than if it is short-lived, because in the model, short-lived price impact increases costs for one period, whereas long-lived price impact increases trading costs in both periods. A final prediction of our model is that 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 3: *(1) Trade duration increases with the number of insiders who 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 to 3 shows that information-based and liquidity-based explanations have contrasting implications in a context in which multiple insiders trade at the same time. Interestingly, the "rat-race effect" modeled by Foster and Viswanathan (1994) does not obtain in

8 Note that the opposite happens in Vayanos' (1999) model. In his framework, additional traders *supply* liquidity and reduce price impact since their endowment shocks are uncorrelated, whereas in our setting, additional traders compete for the same liquidity. To the best of our knowledge, no model in the literature extends the liquidity-based argument to a multiple-trader context. We provide a simple version of such an extension in Appendix B.

9 A similar mechanism seems to be at work in Back, Cao and Willard (2000) who show that informed investors trade more slowly if their information is uncorrelated. With uncorrelated informed trading, investors do not compete for exploiting the same information, but they still compete for liquidity in the same stock.

this case, even though the price impact of trades can be long-lived and last beyond the execution period. In Foster and Viswanathan, trades are informed and their permanent price impact moves prices *towards* fundamental values. Accordingly, waiting has a cost, because it reduces the benefits from trading. By contrast, in the model we present in the appendix, insider trades are liquidity-motivated, even though market participants attribute some likelihood to the possibility that they are information motivated. Insiders can hold their shares until some final date at which prices have reverted to fundamental values. Hence, depending on the resilience of the market, prices may be distorted for multiple periods, but not indefinitely. Hence, the price impact of trades moves prices *away* from fundamental values and waiting has a benefit. The critical difference, which distinguishes the liquidity-model from information models is that some part of insiders' price impact, however long it may last, will be corrected within insiders' investment horizon.

4 Empirical analysis

In this section we present the core of our analysis. First, we develop our empirical approach and discuss the three different approaches we use to classify trades (Section 4.1). Next, we test Hypotheses 1 to 3 (Section 4.2). We test further hypotheses on the effects of stock market liquidity (Section 4.3) and information hierarchies (Section 4.4), comment on the control variables (Section 4.5), and finally distinguish between long-lived and short-lived information (Section 4.6).

4.1 Identification and trade classification

Testing the implications of the different 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 use three approaches to measure the information content of trades, all of which have been advocated in the literature. At the end of this section we reflect on the advantages and disadvantages of each approach.

Our first strategy to classify trades relies on corporate news events. More specifically, we use quarterly earnings announcements and M&A announcements for target firms. We find 47,505 insider trades within four weeks before earnings announcements, which is 10.43% of our sample. For these we set *Informed (Earnings)* equal to one. With four quarterly earnings announcements per year, our unconditional expectation, assuming a uniform distribution of trades throughout the year, would be that about one-third of trades happen during the four weeks before those announcements. Hence, insiders seem to avoid trading in the period immediately before earnings announcements. For M&A announcements, we define a trade as informed if it takes place within four weeks (28 days) before the announcement. Very few insiders trade before M&A announcements; for targets we classify only 856 insider trades as informed, which is only 0.19% of our sample. Again, we set *Informed (Target)* equal to one for these trades. These observations suggest insiders avoid trading during these periods of high public attention, most likely for regulatory and legal reasons. The limitation of the approach based on news announcements is the small number of trades we can unequivocally identify as information-based, which limits the power of our analysis, especially for the M&A sample.

Our second approach applies event-study methodology to disclosure day returns to measure the information content of insider trades (ex post). We calculate two-day cumulative abnormal returns (CARs), where the event date is the disclosure date *D* of the first transaction in a sequence (*CAR(D,D+1)*). We use the market model and proxy for the market return with the CRSP equally-weighted return index. The estimation window ranges over 200 trading days from 240 until 41 trading days prior to the disclosure day and we require at least 100 trading days for the parameter estimation. This approach is based on the general idea in the insider trading literature (e.g., Seyhun (1986), Fidrmuc, Goergen and Renneboog (2006)) that insiders' trading on private information leads to stronger market reactions at the disclosure date. Brochet (2010) uses cumulated abnormal returns after the disclosure date as measures for the information content of insider trades. We define a dummy variable *Informed (CAR)*, 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 CARs are positive (negative) for purchases (sales). Table 3 presents the results for the event study. Insider trades are informative, in line with prior literature. Disclosure day returns are significant across all event windows for the pooled sample. We find that purchases usually lead to stronger market reactions, in line with prior literature.

Third, and finally, we follow Cohen, Malloy and Pomorski (2012) (CMP) and classify information-based trades by using their distinction between "routine" and "opportunistic" trades. CMP use event-study methodology to show that *opportunistic trades* are on average more informed than routine trades. We adopt CMP's definition and classify an insider as a routine trader if she placed a trade in the same calendar month for at least three years in the past. All subsequent trades of the same insider-firm pair are defined as routine trades; for these we set *Informed (Opportunistic)* equal to zero. The remaining insider-firm pairs and all of their subsequent trades are classified as *opportunistic*; for these we set *Informed (Opportunistic)* equal to one.

We can apply the classification of CMP only to 15% of our sample, because their classification requires at least three years of data for each insider-firm pair. For this part of our sample, we classify 58.5% of all trades as opportunistic, compared to 45.2% in CMP's sample. We attribute this difference mainly to (1) different sample periods and (2) difference in units of analysis.[10]

[10] Our sample period is from January 1996 to December 2008. CMP's sample period starts much earlier, in January 1986, and ends in December 2007. If we use individual and not aggregated transactions as observations like CMP do in their summary statistics, we classify only 52.9% of all trades as opportunistic.

All three approaches to classifying trades as either informed or uninformed resolve a trade-off, which results from the ambiguity of assigning trades to either category. All three approaches are based on the notion that some trades are unambiguously information-based, whereas others are unambiguously liquidity-motivated. The three approaches differ in how they classify trades in the gray area in between, in which no clear classification based on observable variables is possible. The approach based on news announcements is the most conservative and classifies only those trades as informed that have a high probability of being based on inside information. Consequently, it probably classifies a significant number of information-based trades falsely as liquidity-based. In contrast, the CMP classification takes the opposite approach to categorizing trades in the gray area and assigns all trades that are not unambiguously routine to the category of opportunistic (informed) trades. In all likelihood, this approach misclassifies many liquidity-motivated trades as information-based. The event-study based classification strikes a middle ground between the other two approaches, by classifying more trades as information-based than the news-based approach and by also classifying fewer trades as information-based compared to the CMP approach.

Without observing an error-free benchmark we cannot establish which of the three classifications is superior for our purpose based on ex ante criteria and therefore proceed by discussing the results of all three classifications simultaneously. If we end up misclassifying too many trades, we would reduce the power of the tests and introduce attenuation bias, which biases our research design against finding support for our hypotheses.

4.2 Competition for liquidity vs. competition for information

We measure competition between insiders by counting the number of other insiders who trade during a sequence of a particular insider. We define *MultipleInsiders* as the number of other insiders who trade. It equals zero if there are no other insiders who are trading during a sequence of a particular insider. The average (median) value of *MultipleInsiders* is 0.757 (zero, see Table 2). In a robustness check reported in Appendix C (Table A5) we define *MultipleInsiders* as a dummy variable; the results remain qualitatively unchanged.

We perform the analysis once for each of our three trade classifications in Table 4. We present four different classifications, based on earnings announcements (columns (1), (2)), mergers and acquisition announcements (columns (3), (4)), cumulative abnormal returns (columns (5), (6)), and the CMP classification into opportunistic and routine trades (columns (7), (8)). We formulate additional hypotheses, which motivate the inclusion of additional explanatory variables below. We enter all these variables in one regression in order to avoid omitted variable bias. We group variables in Table 4 by the associated hypotheses and order them in the order in which we discuss them in the text.

The main coefficients of interest in Table 4 are those on *MultipleInsiders* and on the interaction of *MultipleInsiders* with *Informed*. Hypothesis 1 predicts that the coefficient on *MultiplerInsiders* should be negative, whereas Hypothesis 3 predicts the opposite. The coefficient on *MultipleInsiders* is always positive and highly significant. The presence of one additional insider who trades in the stock in the same direction increases trade duration on average by 1.5% except for the opportunistic/routine classification (columns (7) and (8)), where it is significantly larger (2.5% to 3%). Here, percentages express fractions of *TradeDuration*, which has a mean of 1.3 days, so an increase of 1.5% (2.5%) corresponds on average to 0.020 (0.033) trading days. Hence, the evidence is statistically strong, but economically modest and supports the prediction of Hypothesis 3 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.

Hypotheses 1 and 3 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* (see columns (2), (4), (6), and (8)) shows that this seems to be the case. The coefficient is significant and negative, with significant point estimates between -0.0088 and -0.0077 in three cases; for M&A related news this effect is insignificant, probably because this classification method identifies too few trades as informed, which creates attenuation bias. Hence, the results suggest that insiders trade faster if there is competition from other insiders *and* their trades exploit privileged information. The coefficient on the interaction terms is between 29% (column (8)) and 132% (column (4)) of the coefficient on *MultipleInsiders* for all regressions. Hence, we find strong evidence for the predictions 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 faster.

Hypothesis 3 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 find supporting evidence for this prediction. The coefficient on *Volatility* is always negative, and statistically highly significant in all cases, except for the opportunistic/routine classification, for which significance is at the 10% level. Economic significance of this effect is relatively small: the coefficient is between -0.0102 and -0.0092 for the six regressions where it is statistically significant. Hence, a one-standard deviation increase in *Volatility* reduces *TradeDuration* by about 0.4%. We conclude that the connection between volatility and the benefits from immediacy is relatively weak and suspect that the benefits from immediacy arise from other considerations.

4.3 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 long side of the market, i.e. they buy when other investors want to buy and they sell when other investors want to sell.

Hypothesis 4 (Stock liquidity): *(1) Trade duration increases in the illiquidity of the stock. (2) Trade duration increases if insiders trade on the long side of the market.*

Liquidity is a somewhat elusive concept and the literature has developed different measures. (See Goyenko, Holden and Trzcinka (2009) for a recent analysis of liquidity measures.) We wish to use a measure that can be calculated on a daily basis. To conserve space we only report results for the Amihud measure (*Amihud*) in Table 4. Table 6 presents the results for other liquidity measures (*EffectiveSpread*, *Turnover*, *PriceImpact*), which are discussed in Section 5. *Amihud* is defined as the ratio of the daily absolute return to the dollar trading volume on that day. We assign the value of *Amihud* on the first day of a transaction sequence to the whole sequence.

Consistent with Hypothesis 4, we observe significantly longer trade duration for less liquid stocks. On average, a one standard deviation increase in the *Amihud* liquidity measure (0.488 from Table 2) increases trade duration by about 2.1%, irrespective of the approach we use for identifying informed trading. Only with *Informed (Opportunistic)* do we find a slightly stronger effect (2.7%). Hence, the effect of a one-standard deviation change in *Amihud* has about the same economically moderate magnitude as the presence of one additional insider.

The variable *LongSide* intends to capture periods during which insiders are on the long side of the market, i.e., situations when insiders want to buy (sell) and there are more investors on the buy side (sell side) than on the opposing market side for this stock. We cannot measure the direction in which other traders want to trade directly and infer it from recent price movements instead.[11] 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 outperformed (underperformed) compared to all other stocks in the market. We capture this idea by defining the dummy variable *LongSide,* which equals one for purchases (sales) if the stock return of the firm in the previous calendar month was in the upper (lower) tercile of the stock returns of all firms in the sample. Hypothesis 4 predicts a positive sign for *LongSide*. In Table 4 the coefficient for *LongSide* is positive as predicted and highly significant, irrespective of our measure for informed trading, which supports the notion that insiders adapt their trading strategies to manage liquidity. Trade duration increases on average by about 3.1% if the insider is on the long side of the market, which corresponds to the impact of about two (one) additional insiders in columns (1) to (6) (columns (7), (8)). In addition, Table A2 in Appendix C shows that this effect is driven mostly by sales in a falling market rather than by purchases in a rising market. We find similar results for the other definitions of *Informed*.

4.4 Information hierarchies and the roles 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

[11] Using recent returns as measure for order imbalances is not perfect but allows us to proxy for situations when insiders are on the long-side of the market without much more computational intensive estimations.

(1986)). The empirical evidence on this hypothesis is mixed. Seyhun (1986) shows that the directors and officers trade on more valuable information than other insiders do. 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. 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.

The univariate analysis in Table 3 above generates the following ranking in terms of the absolute size of cumulative abnormal returns for CAR(D,D+1) and CAR(D,D+5): *CEO>Chairperson>Officer>Director>Other*, although the return differences between these groups are not always statistically significant. 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. For CARs measured over longer event windows, the ranking between *Chairperson* and *Officer* is reversed; for sales, we cannot observe a clear ranking.

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, because insiders at the top of the information hierarchy share their privileged information with fewer other insiders. In particular, we expect the CEO to have access to more unique information than other officers and directors. 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 trade faster.

Hypothesis* 5 *(Information Hierarchy): *Insiders at the bottom of the information hierarchy trade faster, whereas those at the top of the information hierarchy spread their trades over longer periods.*

We test this hypothesis by including dummy variables for all categories of insiders except the CEO in Table 4, so the coefficients for the four remaining insider groups have to be interpreted relative to the CEO of the company. We do observe large and negative coefficients for *Officer* and *Director*, showing that this group trades faster than the CEO, in line with the predictions of Hypothesis 5. The coefficient on *Chairperson* is positive and significant for all definitions of *Informed* except for *Informed (Opportunistic)*. Contrary to the predictions of Hypothesis 5, 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 4, 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 somewhat weaker results. CEOs trade slowly compared to officers and directors, which is consistent with Hypothesis 5, whereas insiders who have no operating role in the firm trade more slowly than all other groups of insiders, probably because they should not be considered insiders.

4.5 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. 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 size decile. Hence, the effects we observe in Table 5 obtain all *after* controlling for trade size.

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. This observation is surprising, since larger stocks are more liquid. We attribute this finding to the fact that we already control for the relevant aspects of firm size by including liquidity measures and transaction size, so that *LogMarketCap* picks up residual effects. 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 1.2% (with *Informed (Earnings)*) and 2.1% (with *Informed (Opportunistic)*) longer compared to sales; we provide sample splits for purchases and sales in Appendix C Table A2.

4.6 Long-lived versus short-lived information

In Table 5 we test Hypothesis 2, which predicts that trade duration increases if insiders have long-lived private information. In order to test this hypothesis we follow Cicero and Wintoki (2014) and separate *Informed* (*Opportunistic*) trades into *isolated trades* and *sequenced trades*. *Isolated trades* are all *opportunistic trades* that happen in isolated months, i.e., there are no trades by the same insider in the month before or after. *Sequenced trades* are *opportunistic trades* that occur in consecutive months. Cicero and Wintoki argue that insiders who possess short-lived private information are more likely to use *isolated trades*, whereas insiders with long-lived private information use *sequenced trades.* We define the dummy variable *LongLived* to equal one for *sequenced trades* and zero for *isolated trades*. This separation allows us to test whether both types of informed trading (short-lived and long-lived) have the same implications for *TradeDuration*. The results presented in columns (1) to (4) of Table 5 show that insiders possessing long-lived private information trade more slowly. Compared to informed trades based on short-lived private information *TradeDuration* increases by 13.4% (coefficient of *LongLived* in column (4)); compared to liquidity motivated trades, *TradeDuration* increases by 3.6% (sum of coefficients of *LongLived* and *Informed (Opportunistic)* in column (4)). These effects are quantitatively somewhat stronger than those of one additional insider or a one-standard deviation increase in *Amihud*. The results are in line with the model of Kaniel and Liu (2006), which predicts that insiders will trade more slowly when information is long-lived. The positive and significant interaction of *LongLived* and *MultipleInsiders* shows that trade duration increases even more (by about 2.2%) if insiders with long-lived private information face competition from other insiders. None of the models we consider above predicts this result, which makes it somewhat hard to interpret. However, if sufficiently long-lived information does not dissipate quickly in the market, insiders may not become subject to the "rat race" described in Foster and Viswanathan (1996). In this scenario, competition between insiders actually increases trade duration.[12]

5 Robustness checks

We perform a number of robustness checks to see if our results are sensitive to different measures of liquidity, alternative definitions for transaction sequences, and alternative definitions of *Informed*. Table presents results on robustness tests using different liquidity measures. Depending

[12] The definition of *sequenced trades* already implies that insiders trade based on this information for at least two consecutive months, which means information is not quickly observed by the market.

on the liquidity measure used, we find different effects of liquidity on trade duration. For *Turnover,* we find similar results to our benchmark specification with *Amihud*. However, for *EffectiveSpread* and *PriceImpact* the sign of the coefficient estimated is reversed and does not support Hypothesis 4 for all definitions of *Informed* except for *Informed (Opportunistic)*. However, these results are only significant at the 5%-level for *PriceImpact*; economic significance is weak. We have two potential explanations for this rather surprising result: (1) *EffectiveSpread* and *PriceImpact* could also capture informed trading, including informed trading by investors outside the firm. Insiders are likely to trade faster if they are afraid that other market participants have similar private information;[13] (2) in unreported results we find that *EffectiveSpread* and *PriceImpact* are highly correlated with *LogMarketCap* and transaction size, therefore it is possible that those variables already control for liquidity, and *EffectiveSpread* and *PriceImpact* may only pick up residual effects. Second, we split the sample for the pre- and post-SOX period (see Appendix C Table A2). Most coefficients are quite similar for both subsamples.

Third, we use alternative definitions of transaction sequences. Our baseline definition requires that all transactions of the sequence be executed within seven days of the first trade. This definition is arbitrary. We therefore vary the maximum length of a transaction sequence to three and 14 days (see Appendix C Table A3). For the coefficients on *Informed*, *MultipleInsiders*, and their interactions, we mostly observe a higher economic and statistical significance if we increase the maximum length of a trade. In a second step, we link the length of a transaction sequence to the disclosure date of the first trade in the sequence. If insiders split trades in order to hide their

[13] Mehta, Reeb and Zhao (2014) argue that managers often possess private information about business partners or competitors and exploit this private information by trading in the stocks of these companies. Their results imply that insiders have not only to fear insiders of their own company to exploit the same information but also others from outside the firm.

information, sequences should end when the first transaction is publicly disclosed. We do not observe qualitative changes if we define transaction sequences and trades accordingly.

Fourth, we report results for alternative definitions of *Informed (CAR)* based on abnormal returns (see Appendix C Table A4). Instead of our baseline definition, which uses CAR(D,D+1), we define *Informed (CAR)* based on CAR(D,D+5) to capture a delayed incorporation of information into prices after disclosure. Moreover, we also include the insider trading period, because some of the information may already be incorporated through insider trading during this time. All measures classify a similar percentage of trades as informed and our results are qualitatively unchanged. Finally, we rerun our regression with Cicero and Wintoki's definition of *isolated* and *sequenced trades* instead of *Informed (Opportunistic)*. Results are mostly unaffected by these variations.

6 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 break up 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 to minimize transaction costs. Liquidity timing in this sense has been documented for hedge funds (Cao, Chen, Liang and Lo (2013)) and activist shareholders (Norli, Ostergaard and Schindele (2014), Collin-Dufresne and Fos (2015)). Furthermore, if insiders trade, they should trade larger quantities on days on which liquidity is higher. This argument assumes that insiders can observe liquidity and time their trades accordingly. In Appendix B, we formally derive this argument in the context of a highly stylized model.

Hypothesis 6 (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 6. 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 transaction 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 higher liquidity than the equally-weighted average. Univariate results presented in the Appendix C (Table A6) are in line with the predictions of Hypothesis 6 and support the notion that insiders optimize their trades with respect to market liquidity.

In Table 7, we perform multivariate probit regressions in which the dependent variable equals one if an insider trades on a certain day and zero otherwise. 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 except *Turnover*.

We control for a number of effects: The lag of the trading dummy, 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. 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. We do not include the absolute stock return in regression (1), which uses *Amihud* as a liquidity measure, because *Amihud* is mechanically related to the absolute stock return. Additionally, we control for calendar months and day-of-the-week effects.

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. Overall, 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.[14]

7 Conclusion

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 trade simultaneously. 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. We apply three different methods to identify informed trades and find that these trades are completed significantly faster if multiple insiders compete for exploiting the same private information, which provides strong support for the predictions of information-based models with competition between insiders.

[14] In Appendix C (Table A7), we perform three additional robustness checks using multivariate OLS regressions with *Stake* as dependent variable to test the liquidity-timing hypothesis: (1) we add firm-fixed effects (Panel A); (2) we use first differences (Panel B); (3) split the sample at the median ratio of *Stake* over *Turnover* to alleviate reverse causality concerns. All three tests support the liquidity-timing hypothesis.

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 optimally adapt their trading strategies.

References

Alexander, Gordon J., and Mark A. Peterson, 2007, An Analysis of Trade-Size Clustering and Its Relation to Stealth Trading, *Journal of Financial Economics* 84, 435-471.

Almgren, Robert, and Neil Chriss, 2001, Optimal Execution of Portfolio Transactions, *Journal of Risk* 3, 5-39.

Almgren, Robert F., 2003, Optimal Execution with Nonlinear Impact Functions and Trading-Enhanced Risk, *Applied Mathematical Finance* 10, 1-18.

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

Back, Kerry, C. Henry Cao, and Gregory A. Willard, 2000, Imperfect Competition among Informed Traders, *Journal of Finance* 55, 2117-2155.

Baker, Malcolm, and Jeffrey Wurgler, 2006, Investor Sentiment and the Cross-Section of Stock Returns, *Journal of Finance* 61, 1645-1680.

Baruch, Shmuel, Marios Panayides, and Kumar Venkataraman, 2013, Informed Trading before Unscheduled Corporate Events: Theory and Evidence, *Working Paper, University of Utah*.

Baruch, Shmuel, Marios Panayides, and Kumar Venkataraman, 2016, Informed Trading before Unscheduled Corporate Events: Theory and Evidence, *Journal of Financial Economics (forthcoming)*.

Bernhardt, Dan, and Jianjun Miao, 2004, Informed Trading When Information Becomes Stale, *Journal of Finance* 59, 339-390.

Bertsimas, Dimitris, and Andrew W. Lo, 1998, Optimal Control of Execution Costs, *Journal of Financial Markets* 1, 1-50.

Bessembinder, Hendrik, 2003, Issues in Assessing Trade Execution Costs, *Journal of Financial Markets* 6, 233-257.

Bessembinder, Hendrik, Allen Carrion, Laura Tuttle, and Kumar Venkataraman, 2016, Liquidity, Resiliency and Market Quality around Predictable Trades: Theory and Evidence, *Journal of Financial Economics* 121, 142-166.

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

Betzer, André, Jasmin Gider, Daniel Metzger, and Erik Theissen, 2014, Stealth Trading and Trade Reporting by Corporate Insiders, *Review of Finance (forthcoming)*.

Brochet, Francois, 2010, Information Content of Insider Trades: Before and after the Sarbanes-Oxley Act, *The Accounting Review* 85, 419–446.

Cao, Charles, Yong Chen, Bing Liang, and Andrew W. Lo, 2013, Can Hedge Funds Time Market Liquidity?, *Journal of Financial Economics* 109, 493-516.

Chan, Louis K. C., and Josef Lakonishok, 1995, The Behavior of Stock Prices around Institutional Trades, *Journal of Finance* 50, 1147-1174.

Cho, Jin-Wan, 2007, Earnings Announcements, Private Information, and Strategic Informed Trading, *Journal of Financial Intermediation* 16, 117-149.

Cicero, David C., and M Babajide Wintoki, 2014, Insider Trading Patterns, *Working Paper, University of Alabama*.

Cohen, Lauren, Christopher Malloy, and Lukasz Pomorski, 2012, Decoding inside Information, *The Journal of Finance* 67, 1009-1043.

Collin-Dufresne, Pierre, and Vyacheslav Fos, 2015, Do Prices Reveal the Presence of Informed Trading?, *Journal of Finance* 70, 1555-1582.

Dubil, Robert, 2002, How Quickly Should You Liquidate Your Vested Stock?, *SSRN eLibrary*.

Fidrmuc, Jana P., Marc Goergen, and Luc Renneboog, 2006, Insider Trading, News Releases, and Ownership Concentration., *Journal of Finance* 61, 2931-2973.

Foster, F. Douglas, and S. Viswanathan, 1994, Strategic Trading with Asymmetrically Informed Traders and Long-Lived Information, *Journal of Financial and Quantitative Analysis* 29, 499-518.

Foster, F. Douglas, and S. Viswanathan, 1996, Strategic Trading When Agents Forecast the Forecasts of Others, *Journal of Finance* 51, 1437-1478.

Goyenko, Ruslan Y., Craig W. Holden, and Charles A. Trzcinka, 2009, Do Liquidity Measures Measure Liquidity?, *Journal of Financial Economics* 92, 153-181.

Grossman, Sanford J., and Merton H. Miller, 1988, Liquidity and Market Structure, *Journal of Finance* 43, 617-633.

He, Hua, and Harry Mamaysky, 2005, Dynamic Trading Policies with Price Impact, *Journal of Economic Dynamics and Control* 29, 891-930.

Henker, Thomas, and Jian-Xin Wang, 2006, On the Importance of Timing Specifications in Market Microstructure Research, *Journal of Financial Markets* 9, 162-179.

Hisata, Y., and Y. Yamai, 2000, Research toward the Practical Application of Liquidity Risk Evaluation Methods,, *Working Paper, Institute for Monetary and Economic Studies, Bank of Japan*.

Holden, Craig W., and Avanidhar Subrahmanyam, 1992, Long-Lived Private Information and Imperfect Competition, *Journal of Finance* 47, 247-270.

Holden, Craig W., and Avanidhar Subrahmanyam, 1994, Risk Aversion, Imperfect Competition, and Long-Lived Information, *Economics Letters* 44, 181-190.

Huberman, Gur, and Werner Stanzl, 2005, Optimal Liquidity Trading, *Review of Finance* 9, 165-200.

Huddart, Steven, John S. Hughes, and Carolyn B. Levine, 2001, Public Disclosure and Dissimulation of Insider Trades, *Econometrica* 69, 665-681.

Kacperczyk, Marcin T., and Emiliano Pagnotta, 2016, Chasing Private Information, *Working Paper, Imperial College Business School*.

Kaniel, Ron, and Hong Liu, 2006, So What Orders Do Informed Traders Use?, *The Journal of Business* 79, 1867-1913.

Keim, Donald B., and Ananth Madhavan, 1995, Anatomy of the Trading Process Empirical Evidence on the Behavior of Institutional Traders, *Journal of Financial Economics* 37, 371-398.

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

Lee, Charles M. C., and Mark J. Ready, 1991, Inferring Trade Direction from Intraday Data, *The Journal of Finance* 46, 733-746.

Lin, Ji-Chai, and John S. Howe, 1990, Insider Trading in the Otc Market., *Journal of Finance* 45, 1273-1284.

Mehta, Mihir N, David M Reeb, and Wanli Zhao, 2014, Shadow Insider Trading: Do Insiders Exploit Private Information About Stakeholders?, *Working Paper, Temple University*.

Norli, Oyvind, Charlotte Ostergaard, and Ibolya Schindele, 2014, Liquidity and Shareholder Activism, *Review of financial Studies (forthcoming)*.

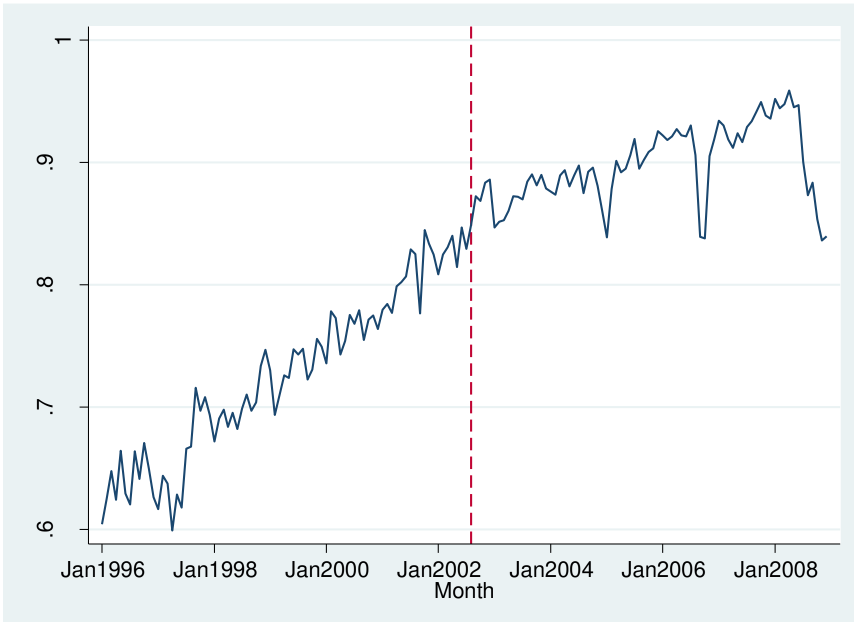
Obizhaeva, Anna A., and Jiang Wang, 2005, Optimal Trading Strategy and Supply/Demand Dynamics, *NBER Working Paper*.

Schied, Alexander, and Torsten Schöneborn, 2009, Risk Aversion and the Dynamics of Optimal Liquidation Strategies In illiquid Markets, *Finance and Stochastics* 13, 181-204.
Schnitzlein, Charles R., 2002, Price Formation and Market Quality When the Number and Presence of Insiders Is Unknown, *Review of Financial Studies* 15, 1077-1109.
Seyhun, Hasan Nejat, 1986, Insiders' Profits, Costs of Trading, and Market Efficiency, *Journal of Financial Economics* 16, 189-212.
Vayanos, Dimitri, 1999, Strategic Trading and Welfare in a Dynamic Market, *Review of Economic Studies* 66, 219-254.
Vayanos, Dimitri, 2001, Strategic Trading in a Dynamic Noisy Market, *Journal of Finance* 56, 131-171.

Figure 1: Development of transaction sequences over time

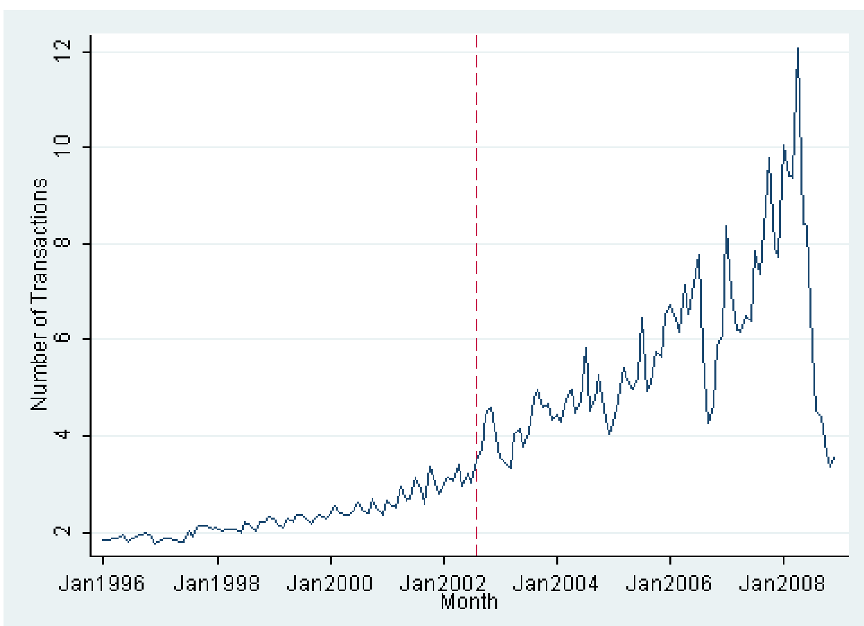
Panel A: Proportion of transaction sequences relative to all trades

The figure displays the development of the proportion of transaction sequences of all insider trades over the sample period. The dashed vertical line marks the month when the Sarbanes-Oxley act came into force (August 2002).



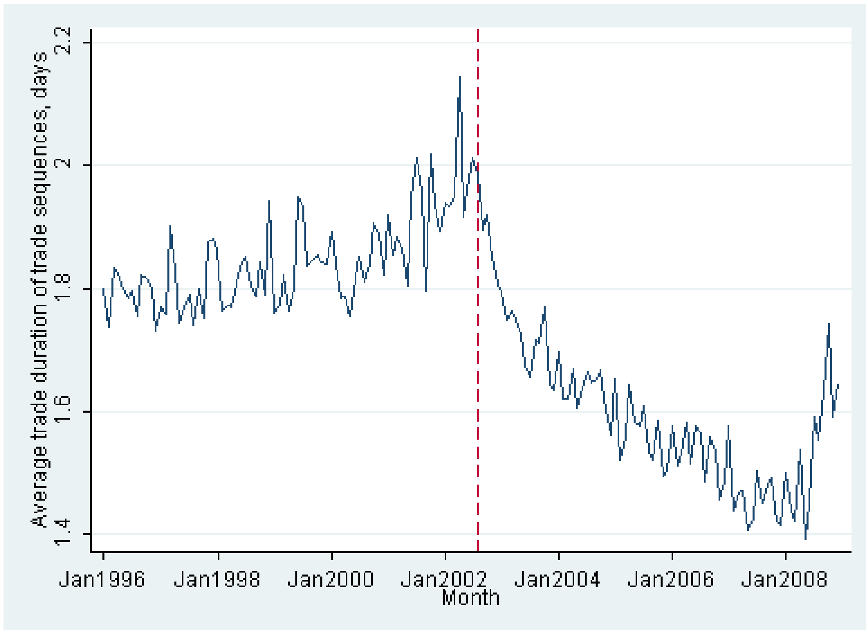
Panel B: Number of transactions in a transaction sequence

The figure displays the development of the average number of individual transactions in a transaction sequence over the sample period. The dashed vertical line marks the month when the Sarbanes-Oxley act came into force (August 2002).



Panel C: Average trade duration of transaction sequences

The figure displays the development of the average trade duration of transaction sequences over the sample period. Single transactions are excluded. The dashed vertical line marks the month when the Sarbanes-Oxley act came into force (August 2002).



Tables

Table 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 dataset. 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 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	455,484	0.203	0	0.403	0	1
Amihud	455,373	0.138	0.003	0.488	0.000	3.1
BeforeEarn	455,484	0.039	0	0.194	0	1
CEO	455,484	0.121	0	0.326	0	1
Chairperson	455,484	0.027	0	0.163	0	1
Director	455,484	0.310	0	0.463	0	1
EffectiveSpread	410,092	1.97%	0.55%	4.62%	0.00%	50.00%
Informed (Earnings)	455,484	0.104	0	0.306	0	1
Informed (Target)	455,484	0.002	0	0.043	0	1
Informed (CAR)	455,484	0.139	0	0.346	0	1
Informed (Opportunistic)	68,837	0.585	1	0.492	0	1
Long-lived	68,837	0.216	0	0.411	0	1
MarketCap (in million $)	455,484	4,808	548	21,507	0.1	571,816
MultipleInsiders	455,484	0.757	0	1.648	0	44
Officer	455,484	0.444	0	0.497	0	1
Other	455,484	0.097	0	0.296	0	1
PriceImpact	414,151	0.017	0.007	0.037	0.000	1
Purchase	455,484	0.320	0	0.466	0	1
LongSide	455,484	0.277	0	0.447	0	1
SOX	455,484	0.500	1	0.500	0	1
Stake	455,484	0.098%	0.023%	0.260%	0.000%	30.024%
TradeDuration	455,458	1.300	1	0.652	1	4.375
Purchases	145,578	1.276	1	0.644	1	4.375
Sales	309,880	1.312	1	0.655	1	4.375
Turnover	455,484	0.013	0.006	0.056	0.000	9
Volatility	455,313	0.522	0.409	0.413	0.009	19
Volume (in thousand $)	455,484	1128	123	11004	0.010	2,355,720

Table 3: 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 (-240, -41). In the lower panel, the table reports the CARs for five different insider groups. The table displays the CAR and, in round brackets, the t-statistic of the two-sided t-test for the null-hypothesis that the respective CAR equals zero. The t-statistic for the difference between CEO and the four other insider groups.is reported in square brackets.

	CAR(D,D+1)		**CAR(D,D+5)**		**CAR(D,D+20)**		**CAR(D,D+40)**	
	purchases	**sales**	**purchases**	**sales**	**purchases**	**sales**	**purchases**	**sales**
All	0.0082	-0.0014	0.0187	-0.0050	0.0256	-0.0152	0.0267	-0.0244
	(6.22)	(-2.59)	(8.19)	(-5.30)	(5.97)	(-8.60)	(4.46)	(-9.91)
CEO	0.0135	-0.0015	0.0299	-0.0049	0.0425	-0.0162	0.0498	-0.0265
	(3.31)	(-1.40)	(4.21)	(-2.56)	(3.20)	(-4.55)	(2.69)	(-5.35)
Chairperson	0.0116	-0.0004	0.0228	-0.0035	0.0289	-0.0132	0.0423	-0.0218
	(1.58)	(-0.16)	(1.78)	(-0.82)	(1.21)	(-1.64)	(1.27)	(-1.94)
	[0.39]	[-0.80]	[0.83]	[-0.55]	[0.85]	[-0.65]	[0.33]	[-0.74]
Officer	0.0089	-0.0014	0.0222	-0.0053	0.0360	-0.0164	0.0461	-0.0281
	(2.76)	(-1.65)	(3.96)	(-3.69)	(3.44)	(-6.11)	(3.15)	(-7.49)
	[1.29]	[-0.18]	[1.23]	[0.27]	[0.55]	[0.08]	[0.23]	[0.37]
Director	0.0076	-0.0012	0.0171	-0.0051	0.0263	-0.0136	0.0259	-0.0218
	(3.51)	(-1.04)	(4.57)	(-2.53)	(3.76)	(-3.63)	(2.65)	(-4.17)
	[2.09]	[-0.29]	[2.59]	[0.10]	[1.75]	[-0.69]	[1.85]	[-0.92]
Other	0.0058	-0.0021	0.0132	-0.0046	0.0109	-0.0129	0.0043	-0.0140
	(2.56)	(-1.07)	(3.38)	(-1.37)	(1.49)	(-2.07)	(0.42)	(-1.61)
	[2.64]	[0.36]	[3.28]	[-0.12]	[3.32]	[-0.70]	[3.43]	[-1.92]

Table 4: Determinants of Trade Duration

The table presents results for OLS regressions with *LogTradeDuration* as the dependent variable. The definition of *Informed* in Columns (1) and (2) is based on earnings announcements. An insider trade is classified as informed if it takes place within 28 days before an earnings announcement. Columns (3) and (4) report results for the definition of *Informed*, based on M&A announcements. An insider trade is classified as informed if it takes place in a target firm within 28 days before an M&A announcement. Columns (5) and (6) report results for the definition of *Informed*, based on event study returns, and Columns (7) and (8) for the definition of *Informed* following Cohen, Malloy and Pomorski (2012) for the subsample where it is available. 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. Standard errors allow for clustering at the firm level. All regressions include calendar year dummies, industry dummies, and dummies for each stake decile.

	Definition of Informed:	Earnings Announcements		M&A Target Insiders		Event study returns		Opportunistic	
		LogTradeDuration							
		(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
H.1 & H.2 & H.3	MultipleInsiders	0.0146	0.0153	0.0145	0.0145	0.0145	0.0156	0.0251	0.0305
		(10.28)	(10.58)	(10.24)	(10.24)	(10.25)	(10.70)	(10.27)	(7.28)
	Informed	0.0196	0.0250	-0.0131	-0.0026	-0.0162	-0.0096	-0.0522	-0.0462
		(6.47)	(8.35)	(-0.48)	(-0.09)	(-8.62)	(-3.81)	(-7.69)	(-6.43)
	MultipleInsiders		-0.0077		-0.0191		-0.0088		-0.0088
	*Informed		(-2.43)		(-0.94)		(-2.61)		(-2.06)
	Volatility	-0.0092	-0.0092	-0.0102	-0.0102	-0.0094	-0.0094	-0.0165	-0.0162
		(-2.87)	(-2.87)	(-3.16)	(-3.16)	(-2.93)	(-2.92)	(-1.75)	(-1.73)
H.4	LongSide	0.0315	0.0314	0.0316	0.0316	0.0315	0.0316	0.0257	0.0258
		(15.78)	(15.82)	(15.93)	(15.93)	(15.94)	(16.01)	(6.01)	(6.04)
	Amihud	0.0437	0.0436	0.0436	0.0436	0.0435	0.0434	0.0533	0.0533
		(17.81)	(17.79)	(17.72)	(17.75)	(17.70)	(17.66)	(7.20)	(7.21)
H.5	Chairperson	0.0325	0.0323	0.0325	0.0325	0.0324	0.0324	0.0331	0.0332
		(2.87)	(2.86)	(2.87)	(2.87)	(2.86)	(2.86)	(1.39)	(1.38)
	Officer	-0.0384	-0.0384	-0.0394	-0.0393	-0.0394	-0.0393	-0.0329	-0.0329
		(-6.67)	(-6.75)	(-6.90)	(-6.90)	(-6.92)	(-6.93)	(-3.50)	(-3.50)
	Director	-0.0202	-0.0203	-0.0209	-0.0209	-0.0210	-0.0209	0.0063	0.0064
		(-3.62)	(-3.67)	(-3.78)	(-3.78)	(-3.80)	(-3.80)	(0.59)	(0.59)
	Other	0.1160	0.1159	0.1172	0.1171	0.1170	0.1169	0.1424	0.1429
		(13.05)	(13.08)	(13.26)	(13.26)	(13.26)	(13.27)	(6.04)	(6.04)
Controls	LogMarketCap	0.0224	0.0223	0.0222	0.0222	0.0222	0.0222	0.0205	0.0204
		(19.04)	(19.01)	(18.85)	(18.85)	(18.93)	(18.92)	(7.60)	(7.57)
	SOX	-0.0252	-0.0249	-0.0256	-0.0256	-0.0251	-0.0252	-0.0593	-0.0589
		(-2.98)	(-2.95)	(-3.03)	(-3.03)	(-2.97)	(-2.98)	(-4.11)	(-4.10)
	Purchase	0.0115	0.0117	0.0111	0.0111	0.0121	0.0121	0.0210	0.0211
		(3.12)	(3.16)	(2.99)	(2.99)	(3.24)	(3.26)	(1.98)	(1.99)
	Observations	420,814	420,814	420,814	420,814	420,814	420,814	65,719	65,719
	R^2	0.271	0.271	0.271	0.271	0.271	0.271	0.291	0.291
	Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	StakeDecile FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 5: Short vs. long-lived information

The table presents results for OLS regressions with *LogTradeDuration* as the dependent variable. The definition of *Informed* follows Cohen, Malloy and Pomorski (2012) for the subsample where it is available. Columns (1) to (4) include a measure for long-lived private information, *LongLived*. Following Cicero and Wintoki (2014) this variable is 1 for all *opportunistic trades* that spread over multiple consecutive months (*sequenced trades*), and 0 otherwise. 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. Standard errors allow for clustering at the firm level. All regressions include calendar year dummies, industry dummies, and dummies for each stake decile.

		LogTradeDuration			
Definition of Informed:		Opportunistic			
		(1)	**(2)**	**(3)**	**(4)**
H.1 & H.2 & H.3	MultipleInsiders	0.0251	0.0224	0.0247	0.0302
		(10.66)	(8.86)	(10.43)	(7.09)
	Informed			-0.1092	-0.0984
				(-16.72)	(-14.54)
	MultipleInsiders *Informed				-0.0160
					(-3.69)
	LongLived	0.0926	0.0833	0.1493	0.1344
		(11.47)	(9.60)	(19.98)	(17.03)
	MultipleInsiders *LongLived		0.0137		0.0219
			(3.01)		(4.91)
	Volatility	-0.0209	-0.0211	-0.0149	-0.0146
		(-2.21)	(-2.23)	(-1.65)	(-1.63)
H.4	LongSide	0.0298	0.0299	0.0244	0.0249
		(7.11)	(7.16)	(5.94)	(6.06)
	Amihud	0.0574	0.0574	0.0518	0.0519
		(7.94)	(7.94)	(7.37)	(7.38)
H.5	Chairperson	0.0406	0.0410	0.0318	0.0324
		(1.70)	(1.71)	(1.36)	(1.38)
	Officer	-0.0305	-0.0307	-0.0166	-0.0168
		(-3.19)	(-3.21)	(-1.83)	(-1.85)
	Director	0.0124	0.0124	0.0189	0.0189
		(1.12)	(1.11)	(1.83)	(1.83)
	Other	0.1503	0.1502	0.1370	0.1377
		(6.10)	(6.10)	(5.92)	(5.94)
Controls	LogMarketCap	0.0230	0.0229	0.0229	0.0227
		(8.69)	(8.68)	(8.95)	(8.87)
	SOX	-0.0504	-0.0503	-0.0515	-0.0506
		(-3.56)	(-3.55)	(-3.71)	(-3.67)
	Purchase	0.0237	0.0236	0.0331	0.0332
		(2.22)	(2.21)	(3.22)	(3.23)
	Observations	65,719	65,719	65,719	65,719
	R^2	0.297	0.297	0.313	0.314
	Year FE	Yes	Yes	Yes	Yes
	Industry FE	Yes	Yes	Yes	Yes
	StakeDecile FE	Yes	Yes	Yes	Yes

Table 6: Trade duration: Robustness checks

This table presents results for OLS regressions with *LogTradeDuration* as the dependent variable. Results for three different liquidity measures are reported: (1) *EffectiveSpread*, (2) *Turnover*, and (3) *PriceImpact*. The header of the table reports the measure used for each column. Coefficients for each of the liquidity measures are reported in the line *Liquidity Measure*. Panel A displays results for the definition of *Informed* based on earnings announcements and M&A announcements. Panel B presents results for the definition of *Informed*, based on event study returns and opportunistic trades following Cohen, Malloy and Pomorski (2012) for the subsample where it is available. 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. Standard errors allow for clustering at the firm level. All regressions include calendar year dummies, industry dummies, and dummies for each stake decile.

Panel A: Earnings and M&A Announcements

		LogTradeDuration					
Definition of Informed:		Earnings Announcements			M&A Target Insiders		
Liquidity measure:		Effective Spread	Turnover	Price Impact	Effective Spread	Turnover	Price Impact
		(1)	(2)	(3)	(4)	(5)	(6)
H.1 & H.2 & H.3	MultipleInsiders	0.0156	0.0161	0.0155	0.0147	0.0153	0.0147
		(9.84)	(10.85)	(9.87)	(9.57)	(10.62)	(9.60)
	Informed	0.0256	0.0250	0.0252	-0.0124	0.0013	-0.0139
		(8.24)	(8.43)	(8.19)	(-0.44)	(0.05)	(-0.49)
	MultipleInsiders	-0.0089	-0.0079	-0.0085	-0.0035	-0.0047	-0.0060
	*Informed	(-2.66)	(-2.49)	(-2.57)	(-0.20)	(-0.25)	(-0.34)
	Volatility	-0.0048	0.0040	-0.0051	-0.0060	0.0030	-0.0062
		(-1.38)	(1.13)	(-1.48)	(-1.70)	(0.84)	(-1.79)
H.4	LongSide	0.0307	0.0308	0.0305	0.0308	0.0310	0.0307
		(14.68)	(15.40)	(14.72)	(14.78)	(15.50)	(14.83)
	Liquidity Measure	-0.0253	-0.4168	-0.0424	-0.0247	-0.4162	-0.0417
		(-1.41)	(-3.69)	(-2.14)	(-1.38)	(-3.69)	(-2.10)
H.5	Chairperson	0.0383	0.0330	0.0377	0.0387	0.0332	0.0380
		(3.13)	(2.91)	(3.11)	(3.14)	(2.91)	(3.12)
	Officer	-0.0395	-0.0391	-0.0394	-0.0404	-0.0400	-0.0402
		(-6.61)	(-6.85)	(-6.59)	(-6.74)	(-7.00)	(-6.71)
	Director	-0.0216	-0.0215	-0.0218	-0.0222	-0.0220	-0.0224
		(-3.72)	(-3.88)	(-3.76)	(-3.82)	(-3.98)	(-3.86)
	Other	0.1112	0.1143	0.1111	0.1125	0.1155	0.1124
		(12.05)	(12.94)	(12.07)	(12.23)	(13.12)	(12.25)
Controls	LogMarketCap	0.0175	0.0184	0.0180	0.0173	0.0182	0.0178
		(13.99)	(16.18)	(14.64)	(13.85)	(16.04)	(14.48)
	SOX	-0.0239	-0.0242	-0.0237	-0.0246	-0.0249	-0.0244
		(-2.74)	(-2.85)	(-2.71)	(-2.82)	(-2.94)	(-2.79)
	Purchase	0.0162	0.0132	0.0169	0.0156	0.0127	0.0163
		(4.22)	(3.57)	(4.42)	(4.06)	(3.40)	(4.27)
	Observations	379,645	420,851	383,263	379,645	420,851	383,263
	R^2	0.271	0.272	0.269	0.270	0.272	0.269

Panel B: Event Study Returns and Opportunistic

		LogTradeDuration					
Definition of Informed:		**Event study returns**			**Opportunistic**		
Liquidity measure:		**Effective Spread**	**Turnover**	**Price Impact**	**Effective Spread**	**Turnover**	**Price Impact**
		(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
H.1 & H.2 & H.3	MultipleInsiders	0.0159	0.0164	0.0159	0.0310	0.0321	0.0310
		(10.04)	(10.90)	(10.07)	(7.14)	(7.32)	(7.13)
	Informed	-0.0106	-0.0093	-0.0102	-0.0449	-0.0479	-0.0448
		(-3.97)	(-3.80)	(-3.84)	(-6.23)	(-6.69)	(-6.21)
	MultipleInsiders	-0.0097	-0.0082	-0.0097	-0.0095	-0.0082	-0.0096
	*Informed	(-2.65)	(-2.53)	(-2.66)	(-2.18)	(-1.87)	(-2.19)
	Volatility	-0.0050	0.0036	-0.0053	-0.0117	0.0053	-0.0110
		(-1.43)	(1.04)	(-1.53)	(-1.19)	(0.56)	(-1.11)
H.4	LongSide	0.0308	0.0309	0.0306	0.0235	0.0255	0.0236
		(14.84)	(15.58)	(14.90)	(5.57)	(6.02)	(5.61)
	Liquidity Measure	-0.0263	-0.4131	-0.0408	0.0972	-1.0754	0.0073
		(-1.47)	(-3.67)	(-2.06)	(1.50)	(-5.95)	(0.12)
H.5	Chairperson	0.0385	0.0331	0.0379	0.0371	0.0326	0.0370
		(3.13)	(2.90)	(3.11)	(1.52)	(1.37)	(1.52)
	Officer	-0.0404	-0.0400	-0.0403	-0.0332	-0.0333	-0.0332
		(-6.77)	(-7.02)	(-6.75)	(-3.45)	(-3.55)	(-3.45)
	Director	-0.0223	-0.0221	-0.0225	0.0050	0.0039	0.0049
		(-3.85)	(-4.01)	(-3.90)	(0.45)	(0.36)	(0.44)
	Other	0.1122	0.1153	0.1121	0.1471	0.1400	0.1469
		(12.24)	(13.14)	(12.26)	(6.06)	(5.97)	(6.06)
Controls	LogMarketCap	0.0174	0.0183	0.0179	0.0178	0.0174	0.0176
		(13.93)	(16.13)	(14.58)	(6.41)	(6.69)	(6.37)
	SOX	-0.0240	-0.0244	-0.0238	-0.0600	-0.0609	-0.0599
		(-2.75)	(-2.89)	(-2.73)	(-4.00)	(-4.27)	(-3.99)
	Purchase	0.0168	0.0137	0.0175	0.0311	0.0273	0.0317
		(4.36)	(3.65)	(4.55)	(2.79)	(2.55)	(2.84)
	Observations	379,645	420,851	383,263	63,140	65,720	63,185
	R^2	0.271	0.272	0.269	0.292	0.295	0.292

Table 7: 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 insiders trade, and 0 otherwise. Regressions include all non-trading days within a transaction 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. Standard errors allow for clustering at the firm level. All regressions include calendar month dummies.

	Trading			
	Amihud	**Effective Spread**	**Turnover**	**Price Impact**
	(1)	**(2)**	**(3)**	**(4)**
LagTrading	0.3480	0.3487	0.3450	0.3447
	(146.4)	(136.4)	(144.9)	(136.1)
Liquidity measure	-0.0063	-0.2451	0.3408	-0.3109
	(-40.86)	(-37.43)	(19.66)	(-39.19)
Absolute return		0.1598	0.0904	0.1693
		(38.15)	(12.95)	(42.04)
% change in market volume	0.0126	0.0099	0.0090	0.0105
	(15.93)	(11.86)	(11.61)	(12.74)
BeforeEarn	-0.0283	-0.0295	-0.0280	-0.0289
	(-43.28)	(-42.36)	(-43.19)	(-42.12)
AfterEarn	0.0223	0.0224	0.0216	0.0225
	(45.54)	(42.86)	(44.74)	(44.01)
Monday	0.0063	0.0073	0.0059	0.0071
	(9.06)	(9.57)	(8.66)	(9.49)
Tuesday	0.0041	0.0043	0.0040	0.0042
	(8.77)	(8.57)	(8.79)	(8.50)
Wednesday	0.0005	0.0008	0.0006	0.0007
	(1.16)	(1.49)	(1.20)	(1.40)
Thursday	0.0003	0.0003	0.0002	0.0003
	(0.65)	(0.64)	(0.53)	(0.56)
Observations	7,382,052	6,504,796	7,487,992	6,610,461
R^2	0.149	0.153	0.150	0.152
Calendar month FE	Yes	Yes	Yes	Yes

Appendix

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
Chairperson	1 if trade is executed by the chairperson 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 chairperson) 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 midpoint and P_t is the price at which a transaction is executed; observations with *EffectiveSpread*>0.5 are set to missing values	TAQ
Informed, CAR	1 if the disclosure date *CAR(D,D+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 -240 to -41	CRSP
Informed, Opportunistic	1 for all opportunistic trades, following the definition of Cohen, Malloy and Pomorski (2012), zero otherwise	IFDF
Informed, Target	1 for all trades by insiders of target firms that take place within 28 days of a takeover announcement, zero otherwise	IFDF, SDC
Informed, Earnings	1 for all trades that take place within 28 days of an earnings announcement, zero otherwise	IFDF, Compustat
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	Number of insiders if more than one insider trades on any day during a given transaction sequence in the same direction, zero otherwise	IFDF

Variable	Description	Source
Officer	1 if trade is executed by an officer (not including the CEO)	IFDF
Other	1 for all insiders who are not classified as an officer, chair-person, director, or CEO	IFDF
PriceImpact	The measure of price impact of each trade after 5 minutes, defined as $2\lvert Q_{t+5} - Q_t \rvert / Q_t$, 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
LongLived	1 for all opportunistic trades that spread over multiple consecutive months (sequenced trades), according to the classification of Cicero and Wintoki (2014), zero otherwise	IFDF
LongSide	1 for purchases if *StockTercile*=3; 1 for sales if *StockTercile*=1; zero otherwise	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
SOX	1 if trade is executed after August 28, 2002, zero otherwise	IFDF
Stake	Number of shares traded by insider / total number of shares outstanding	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 transaction sequence	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	Value of the transaction in thousand $	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 i wishes to sell a block of Q^i 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 trades by adjusting the price, which may deviate from the fundamental value. We adopt the terminology of Bessembinder, Carrion, Tuttle and Venkataraman (2016) and define price impact as temporary and short-lived if it lasts only for one period, the execution period. Similarly, price impact is temporary and long-lived it if lasts for two periods. We follow the literature and simply assume a price-impact function, which is not derived from first principles.[15]

Price formation. The price of the shares in period t is established as a function of the quantity traded by all insiders at that point:

(2) $$p_1 = p_0 - \lambda_1 \sum_{i=1}^{i=I} q_1^i,\ p_2 = p_0 - \theta \sum_{i=1}^{i=I} q_1^i - \lambda_2 \sum_{i=1}^{i=I} q_2^i$$

Hence, the price process includes one-period ("short-lived") as well as two-period ("long-lived") temporary price impact. There is no permanent price impact, i.e. trades do not affect the fundamental value p_0. The parameter θ, which determines the impact of trading in period 1 on the price in period 2 corresponds to the resiliency parameter in Bessembinder, Carrion, Tuttle and Venkataraman (2016) and measures the long-lived temporary price impact beyond the period in which the trade is executed. The price-impact function relies on the following assumptions:

1. There is a sufficient ex-ante possibility that some market participants are informed, so that market makers expect informed trades and react with longer-term changes in the stock price.
2. Trading is anonymous and can therefore have a long-lived price impact for uninformed trades until the market learns that these trades were, in fact, uninformed. Only then will the stock price revert back to the fundamental value p_0. In our model this happens after period 2. Effectively, we assume that the market cannot resolve until after period 2 whether trades in period 1 should be attributed to informational or to liquidity reasons.
3. Insiders have no information and their trades are therefore not related to changes in fundamental value and they do not compete for the use of private information. Insiders

[15] Models that analyze optimal strategies to trade large blocks usually employ price impact functions that feature some combination of temporary price changes attributable to microstructure reasons and permanent price changes attributable to changes in the fundamental value of the stock. See Almgren and Chriss (2001), Bessembinder, Carrion, Tuttle and Venkataraman (2016), 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.

can wait until all long-lived temporary price impact has faded and value all shares they do not sell and hold until the terminal period at the shares' fundamental value p_0.

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 and the slope parameters are common knowledge.

Insiders' objective. Each insider maximizes the following objective:

$$p_1 q_1^i + p_2 q_2^i + p_0\left(Q - q_1^i - q_2^i\right) - \frac{\rho}{2}\left(Q - q_1^i - q_2^i\right)^2. \tag{3}$$

The objective builds on prior literature.[16] The first two terms of the objective represent 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 third term represents the fundamental value of her remaining shares after the two periods and after the stock price has reverted to its fundamental value. 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.[17] 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 optimal trading strategies chosen at time 0 are time-consistent.[18]

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 restate the objective by inserting the definition for p_t from (2) into (3):

$$\begin{aligned} &\left(p_0 - \lambda_1\left(q_1^i + Q_1^{-i}\right)\right)q_1^i + \left(p_0 - \theta\left(q_1^i + Q_1^{-i}\right) - \lambda_2\left(q_2^i + Q_2^{-i}\right)\right)q_2^i \\ &\qquad + p_0\left(Q - q_1^i - q_2^i\right) - \frac{\rho}{2}\left(Q - q_1^i - q_2^i\right)^2. \end{aligned} \tag{4}$$

---

16 E.g., Huberman and Stanzl (2005).

17 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). Grossman and Miller (1988) and Vayanos (2001) endogenize price impact and assume an exponential utility function and normal distributions, which implies mean-variance behavior and is therefore similar.

18 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 significantly more complex.

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

$$
\begin{aligned}
&p_0 - \lambda_1 Q_1^{-i} - 2\lambda_1 q_1^i - \theta q_2^i - p_0 + \rho\left(Q - q_1 - q_2\right) = 0, \\
&p_0 - \lambda_2 Q_2^{-i} - 2\lambda_2 q_2^i - p_0 + \rho\left(Q - q_1 - q_2\right) = 0.
\end{aligned} \tag{5}
$$

Of particular interest for us is the solution for q_1^i, the quantity traded in period 1, from solving the system of equations (5):

$$
q_1 = \frac{\left(2\lambda_2 - \theta\right)\rho Q^i - \lambda_1\left(2\lambda_1 + \rho\right)Q_1^{-i} + \left(\rho + \theta\right)\lambda_2 Q_2^{-i}}{4\lambda_1\lambda_2 + 2\rho\left(\lambda_1 + \lambda_2\right)}. \tag{6}
$$

Hence, the response of insider i to the contemporaneous trades of others, Q_1^{-i} is negative and depends only on the short-lived price impact λ_1, but not on long-lived price impact θ. The contemporaneous trades of other traders, Q_1^{-i}, have no influence on how long-lived price impact influences current trading decisions. The influence of Q_1^{-i} works only through short-lived price impact λ_1.

From symmetry, we have that the quantities traded by all insiders are the same. We can therefore drop the superscript I and use $q_t^i = q_t$ and $Q^i = Q$ for all i and t. To simplify, let $Q_1^{-i} = \left(I - 1\right)q_1^i$, and express the first order conditions as:

$$
\begin{aligned}
&-\left(I + 1\right)\lambda_1 q_1 - \theta q_2 + \rho\left(Q - q_1 - q_2\right) = 0, \\
&-\left(I + 1\right)\lambda_2 q_2 + \rho\left(Q - q_1 - q_2\right) = 0.
\end{aligned} \tag{7}
$$

Upon solving, we obtain:

$$
\begin{aligned}
q_1 &= \frac{\lambda_2\rho - \dfrac{\rho\theta}{I+1}}{\lambda_1\lambda_2\left(I+1\right) + \rho\left(\lambda_1 + \lambda_2\right) - \dfrac{\rho\theta}{I+1}} Q, \\
q_2 &= \frac{\lambda_1\rho}{\lambda_1\lambda_2\left(I+1\right) + \rho\left(\lambda_1 + \lambda_2\right) - \dfrac{\rho\theta}{I+1}} Q.
\end{aligned} \tag{8}
$$

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.

Long-lived price impact is modeled here with the parameter θ. It measures the (lack of) resilience of the market in the terminology of Bessembinder, Carrion, Tuttle and Venkataraman (2016). If θ becomes larger, then the impact of trading in period 1 on prices in period 2 increases. Higher temporary long-lived price impact induces insiders to shift their trades from period 1 to period 2, which is intuitive: if temporary long-lived price impact increases, insiders trade more cautiously at the beginning in order not to move future prices against themselves. Hence, higher temporary long-lived price impact increases the cost of immediacy, because with long-lived price impact, trading today has not only short-term costs, but also long-term costs.

Appendix C: Additional tables (not for publication)

Table A1: Existence of trade sequences

Panel A: Univariate analysis

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 Chi²-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.

	(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
Chi²-test (p-value)	0.00%	0.00%	0.00%	0.00%
Fisher exact test (p-value)	0.00%	0.00%	0.00%	0.00%

Panel B: Probit regressions

The table presents results for Probit regressions with *Purchase* as the 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.

	(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	0.0%	0.0%	0.0%	0.0%	0.0%

Table A2: Trade duration: Sample splits

This table presents results for OLS regressions with *LogTradeDuration* as the dependent variable. Panel A reports results separately for purchases and sales, and Panel B separately for pre- and post-SOX periods. The definition of *Informed* in Columns (1) and (2) is based on earnings announcements. An insider trade is classified as informed if it takes place within 28 days before an earnings announcement. Columns (3) and (4) report results for the definition of *Informed*, based on M&A announcements. An insider trade is classified as informed if it takes place in a target firm within 28 days before an M&A announcement. Columns (5) and (6) report results for the definition of *Informed*, based on event study returns, and Columns (7) and (8) for the definition of *Informed* following Cohen, Malloy and Pomorski (2012) for the subsample where it is available. 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. Standard errors allow for clustering at the firm level. All regressions include calendar year dummies, industry dummies, and dummies for each stake decile.

Panel A: Purchases vs. sales

		LogTradeDuration							
	Definition of Informed:	**Earnings Announcements**		**M&A Target Insiders**		**Event study returns**		**Opportunistic**	
		purchases	sales	purchases	sales	purchases	sales	purchases	sales
		(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
H.1 & H.2 & H.3	MultipleInsiders	0.0065	0.0211	0.0056	0.0207	0.0067	0.0217	0.0168	0.0346
		(3.77)	(10.48)	(3.02)	(10.65)	(3.32)	(11.98)	(2.01)	(8.50)
	Informed	-0.0028	0.0322	-0.0003	-0.0042	-0.0139	-0.0072	-0.0409	-0.0461
		(-0.65)	(8.67)	(-0.01)	(-0.12)	(-5.23)	(-1.70)	(-3.34)	(-5.67)
	MultipleInsiders *Informed	-0.0073	-0.0031	-0.0037	-0.0188	-0.0069	-0.0090	-0.0139	-0.0056
		(-2.01)	(-0.73)	(-0.14)	(-0.63)	(-2.37)	(-1.58)	(-1.60)	(-1.34)
	Volatility	-0.0111	-0.0040	-0.0110	-0.0058	-0.0102	-0.0053	-0.0201	-0.0107
		(-2.79)	(-0.90)	(-2.79)	(-1.30)	(-2.59)	(-1.18)	(-1.22)	(-0.95)
H.4	LongSide	0.0086	0.0414	0.0088	0.0417	0.0084	0.0418	0.0104	0.0277
		(3.21)	(15.66)	(3.24)	(15.87)	(3.10)	(16.05)	(1.17)	(5.75)
	Amihud	0.0473	0.0675	0.0474	0.0671	0.0474	0.0670	0.0642	0.0573
		(18.58)	(12.96)	(18.59)	(12.84)	(18.60)	(12.85)	(8.08)	(4.83)
H.5	Chairperson	0.0097	0.0404	0.0096	0.0404	0.0092	0.0404	0.0032	0.0425
		(0.71)	(2.72)	(0.71)	(2.70)	(0.68)	(2.70)	(0.09)	(1.47)
	Officer	-0.0351	-0.0384	-0.0350	-0.0403	-0.0348	-0.0404	-0.0275	-0.0289
		(-7.74)	(-5.08)	(-7.74)	(-5.35)	(-7.71)	(-5.38)	(-1.93)	(-2.65)
	Director	-0.0414	-0.0077	-0.0416	-0.0091	-0.0418	-0.0092	-0.0324	0.0227
		(-8.71)	(-1.00)	(-8.74)	(-1.19)	(-8.80)	(-1.20)	(-2.55)	(1.70)
	Other	0.1443	0.0851	0.1437	0.0861	0.1426	0.0861	0.1393	0.1270
		(12.30)	(7.41)	(12.24)	(7.56)	(12.23)	(7.58)	(3.94)	(4.64)
Controls	LogMarketCap	0.0309	0.0194	0.0309	0.0190	0.0311	0.0190	0.0339	0.0162
		(20.40)	(13.02)	(20.46)	(12.71)	(20.57)	(12.77)	(8.06)	(5.08)
	SOX	-0.0218	-0.0218	-0.0221	-0.0229	-0.0217	-0.0222	-0.0784	-0.0451
		(-2.16)	(-1.86)	(-2.19)	(-1.96)	(-2.16)	(-1.90)	(-3.35)	(-2.67)
	Observations	129,016	291,798	129,016	291,798	129,016	291,798	11,225	54,494
	R^2	0.348	0.249	0.347	0.248	0.348	0.248	0.408	0.280
	Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	StakeDecile FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Pre- vs. post-SOX

		LogTradeDuration							
Definition of Informed:		**Earnings Announcements**		**M&A Target Insiders**		**Event study returns**		**Opportunistic**	
		Pre-SOX	Post-SOX	Pre-SOX	Post-SOX	Pre-SOX	Post-SOX	Pre-SOX	Post-SOX
		(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
H.1 & H.2 & H.3	MultipleInsiders	0.0160	0.0145	0.0150	0.0140	0.0166	0.0146	0.0297	0.0323
		(7.56)	(9.34)	(7.26)	(9.35)	(8.30)	(8.72)	(3.71)	(7.37)
	Informed	0.0159	0.0309	-0.0355	0.0171	0.0023	-0.0213	-0.0586	-0.0402
		(4.31)	(7.17)	(-0.81)	(0.45)	(0.60)	(-8.34)	(-4.40)	(-5.10)
	MultipleInsiders	-0.0098	-0.0058	0.0788	-0.0393	-0.0117	-0.0057	-0.0014	-0.0135
	*Informed	(-2.10)	(-1.70)	(0.70)	(-2.16)	(-2.37)	(-1.82)	(-0.17)	(-2.85)
	Volatility	-0.0007	-0.0190	-0.0010	-0.0208	-0.0010	-0.0190	-0.0103	-0.0123
		(-0.19)	(-4.14)	(-0.26)	(-4.51)	(-0.24)	(-4.12)	(-0.74)	(-1.18)
H.4	LongSide	0.0367	0.0256	0.0368	0.0259	0.0369	0.0259	0.0425	0.0200
		(13.19)	(9.79)	(13.21)	(9.99)	(13.37)	(10.02)	(4.38)	(4.64)
	Amihud	0.0399	0.0559	0.0400	0.0560	0.0399	0.0555	0.0466	0.0600
		(14.45)	(14.40)	(14.40)	(14.46)	(14.39)	(14.29)	(4.71)	(6.61)
H.5	Chairperson	0.0250	0.0373	0.0252	0.0375	0.0251	0.0375	0.0587	0.0028
		(1.98)	(2.28)	(1.98)	(2.28)	(1.97)	(2.29)	(1.77)	(0.12)
	Officer	-0.0382	-0.0375	-0.0385	-0.0390	-0.0385	-0.0391	-0.0376	-0.0324
		(-7.72)	(-4.40)	(-7.78)	(-4.55)	(-7.80)	(-4.60)	(-2.47)	(-3.01)
	Director	-0.0261	-0.0132	-0.0262	-0.0146	-0.0262	-0.0149	0.0102	0.0075
		(-5.00)	(-1.64)	(-5.01)	(-1.80)	(-5.02)	(-1.86)	(0.62)	(0.60)
	Other	0.1148	0.1154	0.1153	0.1168	0.1150	0.1161	0.0805	0.1619
		(11.58)	(8.89)	(11.61)	(9.01)	(11.62)	(8.97)	(2.65)	(5.64)
Controls	LogMarketCap	0.0276	0.0171	0.0276	0.0168	0.0276	0.0168	0.0232	0.0201
		(20.47)	(9.80)	(20.50)	(9.59)	(20.55)	(9.62)	(6.30)	(6.17)
	Purchase	0.0211	0.0013	0.0209	-0.0003	0.0210	0.0027	0.0241	0.0170
		(4.60)	(0.26)	(4.54)	(-0.05)	(4.58)	(0.54)	(1.59)	(1.38)
	Observations	205,406	215,408	205,406	215,408	205,406	215,408	15,281	50,438
	R^2	0.282	0.264	0.282	0.263	0.282	0.264	0.323	0.289
	Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	StakeDecile FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A3: Trade Duration: Additional Robustness Checks (1)

This table repeats the analysis of Table 4 of the paper with *LogTradeDuration* as the dependent variable. Results for three alternative definitions of a transaction sequence are presented: (1) the maximum length of a transaction sequence is limited to 3 days; (2) the maximum length of a transaction sequence is limited to 14 days; (3) the maximum length of a transaction sequence is limited by the disclosure date of its first transaction or 40 days, whichever is earlier. Panel A displays results for the definition of *Informed* based on earnings announcements and M&A announcements. Panel B presents results for the definition of *Informed*, based on event study returns and opportunistic trades following Cohen, Malloy and Pomorski (2012) for the subsample where it is available. 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. Standard errors allow for clustering at the firm level. All regressions include calendar year dummies, industry dummies, and dummies for each stake decile.

Panel A: Earnings and M&A Announcements

		LogTradeDuration					
Definition of Informed:		**Earnings Announcements**			**M&A Target Insiders**		
Definition of transaction sequence:		**3-Day Period**	**14-Day Period**	**Disclosure Date**	**3-Day Period**	**14-Day Period**	**Disclosure Date**
		(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
H.1 & H.2 & H.3	MultipleInsiders	0.0064	0.0208	0.0150	0.0060	0.0203	0.0152
		(8.45)	(11.15)	(6.97)	(7.80)	(10.74)	(7.20)
	Informed	0.0102	0.0393	0.0152	0.0061	-0.0104	-0.0289
		(4.89)	(9.78)	(4.37)	(0.34)	(-0.36)	(-1.33)
	MultipleInsiders *Informed	-0.0040	-0.0040	0.0028	0.0065	-0.0245	-0.0012
		(-2.36)	(-0.81)	(0.54)	(0.33)	(-1.16)	(-0.07)
	Volatility	-0.0014	-0.0155	0.0003	-0.0017	-0.0171	-0.0005
		(-0.63)	(-4.14)	(0.08)	(-0.81)	(-4.55)	(-0.16)
H.4	LongSide	0.0170	0.0341	0.0276	0.0170	0.0343	0.0277
		(9.26)	(14.95)	(15.79)	(9.25)	(15.02)	(15.85)
	Amihud	0.0188	0.0551	0.0346	0.0187	0.0549	0.0344
		(11.73)	(20.49)	(15.36)	(11.66)	(20.39)	(15.26)
H.5	Chairperson	0.0071	0.0311	0.0337	0.0072	0.0314	0.0339
		(1.08)	(2.38)	(3.47)	(1.08)	(2.39)	(3.47)
	Officer	-0.0339	-0.0452	-0.0253	-0.0343	-0.0463	-0.0257
		(-7.84)	(-8.87)	(-6.12)	(-7.88)	(-9.03)	(-6.15)
	Director	-0.0156	-0.0289	-0.0082	-0.0158	-0.0296	-0.0085
		(-3.70)	(-5.22)	(-1.91)	(-3.74)	(-5.32)	(-1.97)
	Other	0.0674	0.1255	0.1085	0.0678	0.1280	0.1096
		(12.24)	(12.26)	(14.80)	(12.30)	(12.49)	(14.87)
Controls	LogMarketCap	0.0132	0.0262	0.0165	0.0131	0.0258	0.0163
		(15.81)	(19.54)	(15.72)	(15.68)	(19.32)	(15.57)
	SOX	-0.0204	-0.0292	-0.1346	-0.0207	-0.0301	-0.1347
		(-3.93)	(-3.31)	(-18.42)	(-4.00)	(-3.40)	(-18.45)
	Purchase	0.0003	0.0163	0.0006	0.0001	0.0157	0.0003
		(0.12)	(4.00)	(0.16)	(0.04)	(3.80)	(0.08)
	Observations	508,143	372,548	427,269	508,143	372,548	427,269
	R^2	0.189	0.292	0.274	0.189	0.292	0.274

Panel B: Event Study Returns and Opportunistic

		LogTradeDuration					
Definition of Informed:		**Event study returns**			**Opportunistic**		
Definition of transaction sequence:		**3-Day Period**	**14-Day Period**	**Disclosure Date**	**3-Day Period**	**14-Day Period**	**Disclosure Date**
		(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
H.1 & H.2 & H.3	MultipleInsiders	0.0059	0.0219	0.0180	0.0134	0.0432	0.0293
		(6.36)	(11.65)	(9.99)	(5.05)	(8.29)	(7.43)
	Informed	-0.0063	-0.0100	-0.0009	-0.0208	-0.0602	-0.0245
		(-3.16)	(-3.30)	(-0.53)	(-3.86)	(-6.42)	(-3.88)
	MultipleInsiders	0.0007	-0.0116	-0.0109	-0.0033	-0.0156	-0.0080
	*Informed	(0.26)	(-2.90)	(-7.17)	(-1.18)	(-3.00)	(-1.92)
	Volatility	-0.0015	-0.0162	-0.0005	-0.0064	-0.0271	-0.0066
		(-0.68)	(-4.32)	(-0.15)	(-1.15)	(-2.61)	(-0.82)
H.4	LongSide	0.0170	0.0343	0.0277	0.0134	0.0306	0.0197
		(9.24)	(15.06)	(15.91)	(5.00)	(6.46)	(5.75)
	Amihud	0.0187	0.0546	0.0344	0.0234	0.0685	0.0311
		(11.66)	(20.26)	(15.23)	(4.80)	(8.57)	(5.26)
H.5	Chairperson	0.0071	0.0313	0.0339	0.0223	0.0363	0.0479
		(1.07)	(2.38)	(3.48)	(1.76)	(1.38)	(2.92)
	Officer	-0.0343	-0.0463	-0.0258	-0.0265	-0.0265	-0.0142
		(-7.88)	(-9.02)	(-6.17)	(-4.26)	(-2.43)	(-2.35)
	Director	-0.0158	-0.0296	-0.0084	0.0069	0.0148	0.0208
		(-3.74)	(-5.33)	(-1.96)	(0.87)	(1.11)	(2.58)
	Other	0.0678	0.1277	0.1095	0.0810	0.1562	0.1043
		(12.31)	(12.49)	(14.88)	(6.38)	(5.06)	(7.78)
Controls	LogMarketCap	0.0131	0.0259	0.0162	0.0119	0.0238	0.0106
		(15.72)	(19.39)	(15.63)	(5.71)	(7.79)	(4.81)
	SOX	-0.0206	-0.0294	-0.1341	-0.0349	-0.0602	-0.1856
		(-3.96)	(-3.33)	(-18.62)	(-3.91)	(-3.87)	(-12.04)
	Purchase	0.0004	0.0170	0.0011	0.0096	0.0241	0.0034
		(0.16)	(4.10)	(0.29)	(1.29)	(1.98)	(0.41)
	Observations	508,143	372,548	427,269	78,720	56,512	73,179
	R^2	0.189	0.292	0.275	0.204	0.312	0.273

Table A4: Trade Duration: Additional Robustness Checks (2)

The table presents results for OLS regressions with *LogTradeDuration* as the dependent variable. Columns (1) to (3) present results for three alternative definition of *Informed* based on event study returns: (1) *Informed* is based on a longer disclosure 6-day window, CAR(D,D+5), (2) a 6-day window around the trading date, CAR(T,T+5), and (3) the CAR between the trading date and one day after the disclosure date, CAR(T,D+1), instead of the 2-day benchmark definition. In columns (4) and (5), *Informed* is 1 for all opportunistic trades that happen in isolated months (*Isolated*), according to the classification of Cicero and Wintoki (2014), and 0 otherwise. Column (6) also includes a measure for long-lived private information, *LongLived*. Following Cicero and Wintoki (2014) this variable is 1 for all opportunistic trades that spread over multiple consecutive months (sequenced trades), and 0 otherwise. 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. Standard errors allow for clustering at the firm level. All regressions include calendar year dummies, industry dummies, and dummies for each stake decile.

		LogTradeDuration				
Definition of Informed:		**CAR (D,D+5)**	**CAR (T,T+5)**	**CAR (T,D+1)**	**Isolated**	**Isolated**
		(1)	**(2)**	**(3)**	**(4)**	**(5)**
H.1 & H.2 & H.3	MultipleInsiders	0.0167	0.0156	0.0160	0.0322	0.0302
		(11.16)	(9.47)	(9.72)	(9.50)	(7.09)
	Informed	-0.0034	-0.0125	-0.0097	-0.1115	-0.0984
		(-1.42)	(-6.81)	(-3.21)	(-20.63)	(-14.54)
	MultipleInsiders	-0.0106	-0.0038	-0.0078	-0.0181	-0.0160
	*Informed	(-3.52)	(-1.99)	(-2.09)	(-5.06)	(-3.69)
	LongLived					0.0360
						(3.63)
	MultipleInsiders					0.0059
	*LongLived					(1.05)
	Volatility	-0.0097	-0.0093	-0.0092	-0.0133	-0.0146
		(-3.01)	(-2.90)	(-2.86)	(-1.47)	(-1.63)
H.4	LongSide	0.0317	0.0319	0.0320	0.0237	0.0249
		(16.04)	(16.11)	(16.11)	(5.71)	(6.06)
	Amihud	0.0433	0.0436	0.0436	0.0507	0.0519
		(17.61)	(17.74)	(17.75)	(7.13)	(7.38)
H.5	Chairperson	0.0325	0.0325	0.0325	0.0302	0.0324
		(2.86)	(2.87)	(2.86)	(1.29)	(1.38)
	Officer	-0.0393	-0.0393	-0.0392	-0.0174	-0.0168
		(-6.86)	(-6.85)	(-6.82)	(-1.92)	(-1.85)
	Director	-0.0209	-0.0210	-0.0209	0.0172	0.0189
		(-3.77)	(-3.78)	(-3.75)	(1.67)	(1.83)
	Other	0.1167	0.1168	0.1168	0.1356	0.1377
		(13.21)	(13.22)	(13.22)	(5.89)	(5.94)
Controls	LogMarketCap	0.0221	0.0223	0.0223	0.0220	0.0227
		(18.88)	(18.97)	(18.97)	(8.47)	(8.87)
	SOX	-0.0251	-0.0247	-0.0251	-0.0530	-0.0506
		(-2.98)	(-2.93)	(-2.98)	(-3.82)	(-3.67)
	Purchase	0.0121	0.0124	0.0125	0.0325	0.0332
		(3.26)	(3.34)	(3.36)	(3.16)	(3.23)
	Observations	420,814	420,814	420,814	65,719	65,719
	R^2	0.271	0.271	0.271	0.312	0.314
	Year FE	Yes	Yes	Yes	Yes	Yes
	Industry FE	Yes	Yes	Yes	Yes	Yes
	StakeDecile FE	Yes	Yes	Yes	Yes	Yes

Table A5: Alternative definition of *MultipleInsiders*

This table repeats the analysis of Table 4 of the paper with *MultipleInsiders* defined as a dummy variable, equal to 1 if more than one insider trades on the same day in the same direction, and zero otherwise. 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. Standard errors allow for clustering at the firm level. All regressions include calendar year dummies, industry dummies, and dummies for each stake decile.

		LogTradeDuration			
	Definition of Informed:	**Earnings Announcements**	**M&A Target Insiders**	**Event Study Returns**	**Opportunistic**
		(1)	**(2)**	**(3)**	**(4)**
H.1 & H.2 & H.3	MultipleInsiders	0.0534	0.0518	0.0549	0.0643
		(21.01)	(18.65)	(18.19)	(6.75)
	Informed	0.0251	-0.0076	-0.0083	-0.0488
		(9.49)	(-0.30)	(-4.61)	(-6.49)
	MultipleInsiders	-0.0126	-0.0189	-0.0217	-0.0072
	*Informed	(-1.76)	(-0.33)	(-5.36)	(-1.72)
	Volatility	-0.0100	-0.0110	-0.0101	-0.0146
		(-3.17)	(-3.45)	(-3.20)	(-1.56)
H.4	LongSide	0.0323	0.0324	0.0324	0.0264
		(16.42)	(16.53)	(16.55)	(6.19)
	Amihud	0.0439	0.0438	0.0437	0.0532
		(17.99)	(17.91)	(17.87)	(7.25)
H.5	Chairperson	0.0335	0.0337	0.0336	0.0341
		(2.90)	(2.90)	(2.89)	(1.40)
	Officer	-0.0378	-0.0387	-0.0387	-0.0324
		(-6.21)	(-6.34)	(-6.36)	(-3.43)
	Director	-0.0176	-0.0182	-0.0182	0.0087
		(-3.04)	(-3.13)	(-3.14)	(0.80)
	Other	0.1220	0.1233	0.1230	0.1468
		(13.57)	(13.75)	(13.76)	(6.30)
Controls	LogMarketCap	0.0222	0.0220	0.0221	0.0209
		(18.47)	(18.24)	(18.31)	(7.66)
	SOX	-0.0247	-0.0253	-0.0247	-0.0567
		(-2.93)	(-3.00)	(-2.94)	(-3.99)
	Purchase	0.0131	0.0126	0.0137	0.0226
		(3.49)	(3.35)	(3.63)	(2.14)
	Observations	420,814	420,814	420,814	65,719
	R^2	0.272	0.271	0.272	0.291
	Year FE	Yes	Yes	Yes	Yes
	Industry FE	Yes	Yes	Yes	Yes
	StakeDecile FE	Yes	Yes	Yes	Yes

Table A6: Liquidity Timing: Univariate Analysis

Panel A: Trading days only

The table presents results of the univariate test on liquidity timing, based on differences in liquidity on the days when insiders trade. Column (1) reports trade-size-weighted mean of the liquidity measure, where the weight of each day in the transaction 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 transaction 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 transaction sequences for each liquidity measure.

	Mean		**Relative difference**		
	Trade-size-weighted	Equally-weighted	%	t-statistic	N
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Amihud	0.1271	0.1366	7.5%	45.31	194,302
EffectiveSpread	0.0156	0.0159	1.9%	13.23	180,040
Turnover	0.0145	0.0139	-4.1%	-28.16	196,675
PriceImpact	0.0154	0.0154	-0.3%	-1.86	179,440

Panel B: Trading days vs. non-trading days

The table 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 transaction 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 transaction sequence and up to 20 non-trading days after the end of a transaction sequence. Column (1) reports trade-size-weighted mean of the liquidity measure, where the weight of each day in the transaction sequence is the proportion of trade, executed on this day. Column (2) reports equally-weighted mean of the liquidity measure over all days in the transaction 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 transaction sequences for each liquidity measure.

	Mean		**Relative difference**		
	Trading Days	Non-trading days	%	t-statistic	N
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Amihud	0.1351	0.3386	150.6%	-119.94	193,218
EffectiveSpread	0.0159	0.0293	84.3%	-148.03	179,603
Turnover	0.0117	0.0091	-22.2%	127.97	193,226
PriceImpact	0.0152	0.0247	62.5%	-119.47	179,963

Table A7: Liquidity timing: Determinants of stake traded

Panel A: Levels

The 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 transaction 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 zero 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 *Liquidity Measure*. 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. Standard errors allow for clustering at the firm level. All regressions include calendar month dummies, weekday dummies and firm-fixed effects.

	Stake, %			
	Amihud	**Effective Spread**	**Turnover**	**Price Impact**
	(1)	**(2)**	**(3)**	**(4)**
LagStake	0.2053	0.2072	0.2024	0.2059
	(8.86)	(8.01)	(8.55)	(7.91)
Liquidity Measure	-0.0017	-0.03047	0.7061	-0.0249
	(-23.73)	(-23.86)	(21.33)	(-17.40)
Absolute return		0.0953	0.0260	0.0978
		(5.14)	(1.68)	(5.35)
% change in market volume	0.0017	-0.0001	-0.0037	0.0000
	(4.40)	(-0.13)	(-7.83)	(-0.01)
BeforeEarn	-0.0019	-0.0020	-0.0021	-0.0020
	(-13.97)	(-15.62)	(-16.14)	(-15.61)
AfterEarn	0.0029	0.0028	0.0015	0.0029
	(12.83)	(10.65)	(6.58)	(10.83)
Observations	7,109,356	6,265,385	7,210,819	6,367,313
R^2	0.055	0.057	0.059	0.056
Calendar month FE	Yes	Yes	Yes	Yes
Week day FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

Panel B: Differences

The table 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. Regressions include all non-trading days within a transaction 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 the first differences of each of the liquidity measures are reported in the line Δ liquidity measure. 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. Standard errors allow for clustering at the firm level. All regressions include calendar month dummies and weekday dummies.

	ΔStake, %			
	Amihud	**Effective Spread**	**Turnover**	**Price Impact**
	(1)	**(2)**	**(3)**	**(4)**
Δ liquidity measure	-0.0016	-0.0277	1.2506	-0.0198
	(-21.40)	(-17.59)	(22.66)	(-9.00)
Δ absolute return		0.0554	-0.0452	0.0585
		(9.69)	(-8.65)	(10.36)
% change in market volume	0.0015	0.0008	-0.0036	0.0009
	(3.62)	(1.85)	(-7.94)	(2.18)
BeforeEarn	0.0001	0.0001	-0.0008	0.0001
	(0.52)	(1.13)	(-7.52)	(0.85)
AfterEarn	0.0006	0.0007	0.0014	0.0006
	(8.05)	(8.29)	(17.15)	(7.92)
Observations	7,041,608	6,065,466	7,210,642	6,207,586
R^2	0.002	0.001	0.007	0.001
Calendar month FE	Yes	Yes	Yes	Yes
Week day FE	Yes	Yes	Yes	Yes

Panel C: Stake/Turnover below median

The 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. 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. 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 slope estimate and, in parentheses, the t-statistic of the two-sided t-test for the null-hypothesis that the respective coefficient equals zero. Standard errors allow for clustering at the firm level. All regressions include calendar month dummies, weekday dummies, and firm-fixed effects.

	Stake, %			
	Amihud	**Effective Spread**	**Turnover**	**Price Impact**
	(1)	**(2)**	**(3)**	**(4)**
LagStake	0.0434	0.0416	0.0343	0.0418
	(8.16)	(7.28)	(7.43)	(7.30)
Liquidity measure	-0.0115	-0.02905	0.9872	-0.0080
	(-14.39)	(-6.85)	(35.65)	(-1.94)
Absolute return		0.1233	0.0136	0.1228
		(21.29)	(3.04)	(21.06)
% change in market volume	0.0064	0.0037	-0.0030	0.0037
	(10.45)	(5.98)	(-5.26)	(5.99)
BeforeEarn	-0.0001	-0.0006	-0.0008	-0.0006
	(-0.19)	(-1.24)	(-1.89)	(-1.29)
AfterEarn	0.0021	0.0022	0.0005	0.0022
	(7.92)	(8.13)	(2.26)	(8.07)
Observations	228,639	208,674	228,639	208,960
R^2	0.311	0.336	0.434	0.335
Calendar month FE	Yes	Yes	Yes	Yes
Week day FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes